ECONOMIC STRUCTURE OF THE POLISH ECONOMY- DYNAMIC EXTERNALITIES AND SPATIAL EFFECTS REVISITED

A THESIS

Presented to

The Faculty of the Department of Economics and Business

The Colorado College

In Partial Fulfillment of the Requirement for the Degree

Bachelor of Arts

By

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May 2013

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Abstract

The objective of this paper is to test how the local economic structure (local sectoral specialization and diversity, competition, average firms size and total employment density) affects the 2004-2006 local employment growth in 379 administrative regions of Poland. In particular, we estimate a reduced form equation as in Combes (2000) for four different sectors of economy (agriculture, hunting, forestry and fishing, industry and construction, market services, non-market services). We find evidence for both MAR and Jacobs externalities in the services sectors. Industrial sectors tend to be influenced only by MAR externalities. Furthermore, we examine and find the issue of spatial correlation in our data. Hence, spatially lagged and error models are used with no major change in the overall effects. Moreover, we learn that even for very short periods of time, dynamic externalities tend to be helpful in terms of explaining changes in local employment growth. To the best of our knowledge, this is the first study of this kind to analyze both industrial and services sector of Eastern European economy.

KEY WORDS: (Dynamic Externalities, Marshall-Arrow-Romer, Jacobs, Spatial Autocorrelation, Spatial Lag and Spatial Error Model)

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ACKNOWLEDGEMENTS

Writing this thesis has been a challenging and difficult yet rewarding process and I am very thankful to everyone who provided me with any support and advice in the meantime. In particular, I'd like to thank my thesis advisor, prof. Pedro de Araujo, for all the help, knowledge, and guidance he provided me with throughout. I would also like to acknowledge Matt Gottfried in the GIS lab for helping me with learning spatial analysis software.

CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

Geographic concentration of economic activities, is referred to as agglomeration. It is argued that firms benefit from locating close to one another (O'Sullivan (2003)). There are two types of factors affecting the growth of aglomeration economies: exogenous and endogenous. The first type refers to factors such as availability of natural resources or the specific geographic conditions that can aid in explaining historical trends in the distribution of existing agglomerations, yet those factors are not useful in explaining the further employment growth of already established industries (Douth (2010)). Endogenous factors are those of agglomeration economies that are responsible for generating new employment growth in the cities. Henderson (1997) distinguishes two different types of endogenous forces: urbanization economies externalities, first described by Jacobs (1969) and localization economies externalities, MAR, discussed in the work of Marshall (1890). Those two forces are commonly referred to as the dynamic externalities.

Marshall (1890) proposed that when a particular branch of industry is already settled in a given location, it will almost certainly stay there in the long-run. This would be due to the so-called localization economies, which allows for knowledge sharing between specialists within the same field.

The second type of dynamic externalities describes influences resulting form the process of urbanization, which we will refer to as the urbanization economies. Jacobs (1969) proposes that if many different industries start in the same location in a similar time, then they should benefit from exchanging knowledge between one another. The most common way of measuring a proxy for Jacob's externalities is to include an inverse relative Hirschman-Herfindahl Index (HHI), (Beaudry and Schiffauerova (2008)), which for any given region, is calculated as in Henderson, Kuncoro, and Turner (1995) and Combes (2000) by taking the inverse of an HHI of sectoral concentration based on the share of all sectors, except the one considered.

Both MAR and Jacobs externalities give a theoretical framework for explaining why and how agglomeration economies have positive effects on and influence the productivity and employment growth of regions. Nevertheless, the literature on the subject remains inconclusive as to whether Marshallian specialization or Jacobian diversification externalities favors local employment growth.

While most researchers agree that agglomeration economies are very important in explaining the direction and magnitude of economic activity, it is yet to be settled which forces determine it. Despite the extensive theoretical and empirical discussion in the literature, studies about this topic in developing/transitioning countries such as Poland are still not widely present.

This is an interesting area of study as one can elaborate on the underlying economic structure of those countries that tend to have a very different economic past than the one of most of the "western world". Furthermore, an analysis of this kind could possibly lead to different conclusions than those of the empirical studies done for France (Combes (2000)), Germany (Blien and Suedekum (2004)) and other developed countries.

A more comprehensive understanding of agglomeration economies is essential for policy makers who are responsible for creating reforms and policies, in particular those relating to employment and effectiveness of financial resource management. Hence, primary purpose of this paper is to elaborate on, if, and how Jacobs and or Marshall-Arrow-Romer (MAR) externalities impact regional employment growth in Poland, which to the best of our knowledge has not been investigated.

Most of the empirical studies about this topic focus on measuring economic growth by taking employment growth as a proxy indicator, (Beaudry and Schiffauerova (2008)). Nonetheless, the use of employment growth as an indicator of economic growth is frequently disputed and its popularity is most certainly a direct result of the fact that data on total employment is often readily available, (Beaudry and Schiffauerova (2008)). Moreover, the choice of this indicator is based on the assumption that labor is a homogenous input and it can move freely across the country, thus it should have a positive correlation with the actual growth in income per capita (Beaudry and Schiffauerova (2008)). We follow this methodology and use two-year employment growth rates between the years 2004 and 2006 as a proxy for urban growth.

Furthermore, it is proposed that the spatial effects of agglomeration can play a role in local employment growth (Mion (2004), Ketelhohn (2006), Batisse (2002), Carvajal and Watanabe (2004), Paci and Usai (1999)). Consequently, this study investigates the issue of spatial autocorrelation and uses several strategies to model how different types of spatial dependence impact local employment growth.

We use a sample that consists of 379 county-level entities (later referred to as ”powiats”) from 2004 to 2006. By considering all the data in the sample collectively, we learn that density, specialization and competition significantly influence two-year employment growth rates. We find some evidence for both localization and urbanization effects and our findings are in line with the work of Combes (2000), although the evidence for Marshall externalities tend do dominate across all the sectors considered. Moreover, we realize that there are significant differences between industrial and services sectors. Lastly, our findings show that although the data we used manifests some degree of spatial dependence, elasticity estimates across different specifications do not tend to change by significant amounts.

The remainder of this paper will be organized as follows. Chapter 2 outlines the theories about dynamic externalities. Chapter 3 describes the data and modeling strategy. Chapter 4 elaborates on specification problems, while Chapter 5 presents and discusses results. Chapter 6 concludes.

CHAPTER 2

DYNAMIC EXTERNALITIES

Agglomeration Externalities: Marshall versus Jacobs

Beginning with Romer (1986) and Lucas (1988), terms like economies of scale and network effects became widely used in urban economics. Closely related to those, is the idea of economies of agglomeration, which has been predominant in the recent explanations of economic growth. Cities form and grow to exploit economies of agglomeration. Moreover, for an agglomeration economy to maintain stability and sustain positive outcomes, it requires clustering to create positive externalities, commonly referred to as "knowledge spillovers", (Romer (1987b)). Literature distinguishes two types of externalities: static and dynamic. The first type is based on the immediate information spillovers about the current market conditions whereas the latter deals with the role of prior accumulation on current productivity and hence employment, (Henderson, Kuncoro, and Turner (1995)). While static externalities help explain existing cities and agglomerations, they are not useful in terms of generating the process of economic growth. On the other hand, dynamic externalities simultaneously explain the existing local industrial structure and economic growth.

Glaeser, Kallal, Scheinkman, and Shleifer (1992) distinguish three types of dynamic externalities, two of which are pertinent to this study, namely Marshall-Arrow-Romer (MAR) and Jacobs externalities. This paper, therefore, contributes to literature by building on existing methodology while introducing a new and unique data set for a transition economy, Poland. Below we describe both MAR and Jacobs externalities in more detail.

Marshall-Arrow-Romer Externalities

According to the theory of MAR externalities, the higher specialization of a particular industry within a specific region facilitates knowledge spillovers among the firms within that industry. Furthermore the geographic proximity of the firms should provide lower transaction costs and promote sharing of common knowledge. In this setting, knowledge can be transmitted between the firms either through the exchange of ideas or via movement of specialized labor between the firms. Glaeser, Kallal, Scheinkman, and Shleifer (1992) suggest that the existence of MAR externalities can be captured by a positive relationship between the industrial specialization and industrial growth. Yet there exists a possibility that too many firms from the same industry concentrated in a certain geographical area may have an adverse impact on the growth of that specialized industry due to intra-industry competition for labor, markets and infrastructure. A situation like that would imply the opposite of what MAR theory suggest. Several studies, including Combes (2000), conclude that there is not much evidence to support the MAR hypothesis in general. Others, find that they exist and have a strong positive impact on industrial growth (de Lucio, Herce, and Golcolea (2002)).

Jacobs Externalities

Jacobs (1969), by contrast, argues that higher diversity of a particular industry within a given region is responsible for knowledge spillovers between complementary rather than similar industries. The ideas developed by firms in one industry can be translated and applied in the remaining industries. Quigley (1998) proposes that the exchange of complementary knowledge across diverse firms and economic agents facilitates innovation thus increasing returns and giving rise to urbanization or "diversification" externalities. In other words, though the stock of innovation of a given sector mainly begins and diffuses within and from that sector, a part of that stock is generated externally, in the sectors that are complementary to the one in question.

Glaeser, Kallal, Scheinkman, and Shleifer (1992) suggest that the existence of Jacobs externalities can be captured by a positive relationship between "urban variety" (diversification) and industrial growth captured by the growth in employment. The argument for Jacobs externalities is found to be positive and significant by many, (Glaeser, Kallal, Scheinkman, and Shleifer (1992), Combes (2000), Dekle (2002), Greunz (2004), Paci and Usai (1999), Batisse (2002), Makhloufi (2007)).

In a review, Beaudry and Schiffauerova (2008) summarizes the results of 67 articles on impact of dynamic externalities on local growth. They find that 70% of these studies suggests the existence of Marshall externalities and their positive influence on employment, thus economic growth. A similar proportion of this same set of studies (75%) verifies the presence of Jacobs externalities, indicating beneficial impacts of diversification of economic activity within agglomerations on economic growth. Table (2.1) summarizes the proxies used for both specialization and diversity as well as control variables in terms of the directions necessary for either MAR or Jacobs externalities to exist.

Table 2.1: Sources of Spillovers

	MAR	**Jacobs**
Variables of Interest		
Specialization	+	-
Diversity	-	+
Controls		
Competition	+	-
Density	+	
Size	+	

Despite the existing evidence for positive impact of both types of externalities, there are cases where negative effects can be found, (Glaeser, Kallal, Scheinkman, and Shleifer (1992), Blien and Suedekum (2004), Neffke, Henning, Boschma, Lundquist, and Olander (2011), Beaudry and Schiffauerova (2008), de Lucio, Herce, and Golcolea (2002)).

Furthermore, studies in this subject using data from developing/transitioning countries are still not widely present. In particular, this area requires more attention in order to better understand how do these forces behave in a setting where past market-based economic activities were minimal or non-existent. Thus, it would be interesting to see if the differences in the "initial conditions" alter the validity of theories and findings discussed above if analyzed for developing/transitioning countries. Implications of this extension to the literature can be important and findings could aid policymakers in determining the directions of future policies and reforms concerning employment and their effectiveness. The empirical model is presented in the following section.

CHAPTER 3

MODELING STRATEGY, MEASUREMENT AND DATA

Data and Model

In this paper, we use an administrative database provided by the Central Statistical Office of Poland and publicly available[1]. More specifically, we work with a cross-sectional database published in the Aggregated Studies for the years 2005 and 2007[2]. The sample units are 379 administrative regions as defined in the acts passed by the Polish parliament in 1998. Cross-sections for both years include information on population, total area in km^2, investment, number of firms and employment by sectors and regions for the years 2004 and 2006. Descriptive statistics for the explanatory variables calculated using the above information can be found in the appendix. Employment is observed for 379 regions and in 4 different industries, encompassing:

[1] $http://www.stat.gov.pl/gus/index_ENG_HTML.htm$
[2] $http://www.stat.gov.pl/gus/5840_732_PLK_HTML.htm$

- agriculture, hunting, forestry and fishing, (Sector I)
- industry and construction, (Sector II)
- market services, (Sector III)
- non-market services, (Sector IV)

In accordance to other studies (Illy, Hornych, Schwartz, and Resenfeld (2009)), agriculture, fishing, hunting, forestry and mining should be excluded from the analysis since employment of these industries is not influenced by agglomeration economies, i.e. those activities have no significant impact on growth in urban areas. Nevertheless we perform analysis on that sector to verity the above hypothesis.

Also, this paper examines the effects of localization and urbanization economies on urban growth. We proxy urban growth by the employment growth rate of administrative regions over the two year period from 2004 to 2006. Thus, in our empirical model, the dependent variable, $y_{z,s}$ represents local employment growth of sector s in region z and is defined as follows:

$$y_{z,s} = \frac{emp_{z,s,2006}/emp_{z,s,2004}}{emp_{s,2006}/emp_{s,2004}} \tag{3.1}$$

Where $emp_{z,s}$ is the employment of each region in sector s, and $z = 1, 2, \ldots, 379$ is an index for the region. The growth rate $y_{z,s}$ is normalized by the total employment to ensure comparability across regions.

Hence, our reduced form equation follows Combes (2000) and is defined as:

$$\begin{aligned} ln(y_{z,s}) = \alpha_0 + \alpha_1 \ln(spec_{z,s}) + \alpha_2 \ln(div_{z,s}) + \alpha_3 \ln(den_z) \\ + \alpha_4 \ln(comp_{z,s}) + \alpha_5 \ln(size_{z,s}) + \epsilon_{z,s} \end{aligned} \tag{3.2}$$

Where $spe_{z,s},\ div_{z,s},\ size_{z,s},\ comp_{z,s}$ and den_z are independent variables that capture specialization, diversity, size, competition and total density of employment. We measure those as in Combes (2000) and Blien and Suedekum (2004) with the exception of $comp_{z,s}$, for which we define an alternative metric due to data limitations. In what follows, we provide a justification for using specification (equation 3.2) by defining the variables that have an impact on employment growth via location and urbanization externalities.

Description of Variables

According to Combes (2000) there are several variables of interest that we need to consider in order to determine which kind of underlying economic structure fosters local employment growth or whether it has any impact at all.

Specialization

The specialization conjecture argues that increased presence of a particular industrial sector within any given geographic region, that is of a considerable size, leads to a greater volume of knowledge diffusion among firms operating in that sector.

Consequently, this produces more and better research, development, and more innovation. Historically, firms operating in the same sector tend to locate near one another, which is just a consequence of cost-benefit analysis, a classic example of that is the evolution of Silicon Valley. Being located near large input and output markets reduces the costs that any given firm must bear. In other words, firms benefit from externalities that are exogenous to their industry, but also from those that are internal to the sector. Advantages include the sharing of a specific labor market, implicit information, but also the links within the sector itself. In that sense, the measure of local sectoral specialization acts as a proxy for MAR externalities (table 2.1).

$$spec_{z,s} = \frac{emp_{z,s}/emp_z}{emp_s/emp} \tag{3.3}$$

One way of measuring specialization is to calculate the ratio of the employment share of sector s in region z divided by this very same ratio calculated for the entire country as in Combes (2000). In this paper we follow this methodology and calculate the specialization index as in equation (3.3) above.

Diversity

Jacobs (1969) emphasizes the external nature of the sources of knowledge spillovers to the sectors in which economic activities in question take place. She builds her theory based on the notion of diversity and variety of industries within the boundaries of a geographic unit arguing that these are the primary sources of greater returns on the exchange of economic knowledge across firms.

In her view, a diversified industrial environment is a must for the efficient spread of technological and knowledge externalities, thereby stimulating local economic growth (table 2.1). Combes (2000) points out that if innovations flow throughout the local economy and can be incorporated and used by noncompeting firms, then industrial heterogeneity tends to boost local economies. On the other hand, she elaborates that the beneficial effects of industrial heterogeneity require that innovations of one sector be used in another sector.

The most common way of measuring a proxy for Jacobs externalities is to include an inverse relative Hirschman-Herfindahl Index (HHI), (Beaudry and Schiffauerova (2008)), which for any given region, is calculated as in Henderson, Kuncoro, and Turner (1995) by taking the inverse of an HHI of sectoral concentration based on the share of all sectors, except the one considered (Combes (2000)). In this paper, we use the same diversity measure derived by calculating a variant of Hirshman-Herfindahl-index as in (equation 3.4).

$$div_{z,s} = \frac{1/\sum_{S'=1,s'\neq s}^{S}(emp_{z,s'}/(emp_z - emp_{z,s})^2}{1/\sum_{s'=1,s'\neq s}^{S}(emp_{s'}/(emp - emp_s))^2} \tag{3.4}$$

The value of the diversity index increases with the greater local diversity faced by sector s. Its maximum value in sector occurs when all surrounding sectors account for an identical employment share (i.e. the denominator of the sum in equation (3.4) is as small as possible). Furthermore, a positive coefficient on the natural log transformation on this index suggests the existence of Jacobs externalities.

Density

For a country as a whole, it is certain that both rural as well as urban areas are considered. Hence, it is intuitive that the size of the local economy should also impact the rate at which the agglomeration forces operate in different regions. The size of the local economy is an important explanation of the uneven distribution of activities in the U.S. (Ciccone and Hall (1996)) and can be interpreted as yet another form of urbanization economies. Combes (2000) for example, argues that “the level and quantity of information exchanges in spillovers are sufficiently important only when the number of firms, and thus the potential commentaries, is high enough". In the majority of cases, a higher number of firms is expected to be associated with greater physical areas.

$$den_{z,s} = \frac{emp_z}{area_z} \tag{3.5}$$

Thus, it is important to incorporate and control for the differences in the regions areas, as bigger regions most definitely will experience greater employment. Hence, we analyze the impact of employment density (table 2.1), which we measure as in Combes (2000) and Ciccone and Hall (1996) according to equation (3.5), where area is measured in kilometers squared.

Average Firm Size

Finally, we need to define our competition indicators. First, is the average firm size as in hUallachain and Satterthwaite (1992) and Combes (2000) who define it by taking the inverse of number of firms per worker and interpret it as the average size of plants located in region z.

$$size_{z,s} = \frac{emp_{z,s}/number\ of\ firms_{z,s}}{emp_s/number\ of\ firms_s} \tag{3.6}$$

The choice of this variable is motivated in Combes (2000) who argues that scale economies are not necessarily internal to the firms and proposes that if scale economies are external to them, then it is only the size of the city that determines the degree of scale economies (equation (3.6)). This is supported in Caballero and Lyons (1992) who find very little evidence of internal economies of scale while find evidence for external ones in four countries they consider. Once again, we follow the methodology of both Combes (2000) and hUallachain and Satterthwaite (1992), which is designed to test for internal economies of scale. Furthermore, we normalize it by the average size of plants in that sector for an entire country.

Competition

The other measure of competition, reflects the the degree of market power within a given sector and region. The effects on the employment growth of the size of local markets are contingent upon the degree of competition in these markets, (Combes (2000)). The literature on the subject justifies including this competition variable based on the notion that competition should stimulate innovative activities and promote city-industry growth. Thus a positive coefficient on that variable is expected. Following the methodology introduced in Combes (2000) we would like to calculate the competition variable as in equation (3.7). In that case, competition would be captured by the inverse of HHI of productive concentration, calculated using the employment shares of the plants in the given sector s and in the same region z, and as in the case of other variables, standardized by dividing it with the indicator's value at the national level.

$$comp_{z,s} = \frac{1/\sum_{i\in z}(emp_{z,s,i}/emp_{z,s})^2}{1/\sum_{i}(emp_{s,i}/emp_{s})^2} \tag{3.7}$$

Unfortunately, our data does not allow to observe the plant level employment (i denotes a particular plant). An alternative measurement is suggested in Panne (2004) where the degree of local competition is measured in the following way:

$$comp_{z,s} = \frac{firms_{z,s}/emp_{z,s}}{firms_{s}/emp_{s}} \tag{3.8}$$

This measure relates the number of firms per worker per industry s per region z to its national equivalent and refers to Jacobs (1969) notion of labor market competition: high values are associated with increased level of industry-specific labor market competition. Alternatively, it can be read as Marshall's (1890) notion of competition, relating low values to large firm size and market power. Nevertheless, the above metric has a perfect negative correlation with the measure of size discussed above, thus we need to develop an alternative metric for competition, which is defined as:

$$comp_{z,s} = \frac{investment_{z,s}/firms_{z,s}}{investment_{z,s}/firms_{z,s}} \tag{3.9}$$

Where investment is given in millions of 2004 polish zloty. The role of this competition variable is to capture the degree of market power within a given sector and region. Thus we believe that it is justified to think about the market power in terms of the average value of monetary resources invested per firm. We conjecture that high values of the above metric are associated with large firm size and market power thus relating to Marshall's (1890) notion of competition in the way opposite to Panne (2004), (see table 2.1).

As we have shown, all elements of the local economic structure (competition, density, diversity, specialization and size) are likely to affect information spillovers and market-based forces (as in table 2.1). Thus, depending which sector of economy we would like to analyze, it is the role of empirical studies such as this one to show what the dominant effects are.

CHAPTER 4

SPECIFICATION PROBLEMS

Due to the lack of available data, we substitute the competition variable with our own, which may make our model less comparable to similar studies that follow precisely the methodology in Combes (2000). However, we believe that our specification is robust enough, and therefore comparable to Combes (2000), Blien and Suedekum (2004), Panne (2004), Henderson (1997), He and Pan (2010), Glaeser, Kallal, Scheinkman, and Shleifer (1992), Cigano and Schivardi (2004), Illy, Hornych, Schwartz, and Resenfeld (2009) and Dekle (2002).

We start by performing a standard set of diagnostics tests. Pearson correlation coefficients are calculated for the five explanatory variables, indicating a somewhat high degree of correlation between size and specialization measures, thus in this case; the issue of multicollinearity can pose a risk of affecting the results of the empirical model via inefficient standard errors. Hence, we also calculate VIFs in order to better assess the degree in which multicollinearity affects these standard errors. Variance inflation factor (VIF), quantifies the severity of multicollinearity in an ordinary least squares regression by producing an index that measures how much the variance (the square of the estimate's standard deviation) of an estimated regression coefficient is increased because of collinearity. Thus, we analyze the magnitude of multicollinearity by considering the size of each VIF, where the common rule of thumb is that a VIF>10 indicates that multicollinearity is high, (Kutner, Nachtschein, and Neter (2004)). We find none of them to exceed 10 (see appendix). Next, we test for heteroskedasticy and obtain the Breusch-Pagan/Cook-Weisberg test statistic equal to 28.79 (p-value< 0.01). This test can be less-well behaved in small samples, (Davidson and MacKinnon (1983)). Because our sample size is small, we still fit the model with robust standard errors.

Spatial Autocorrelation

Spatial correlation is designed to measure the degree to which a set of spatial features and their associated data values tend to be clustered together in space (positive spatial autocorrelation) or dispersed (negative special autocorrelation), (Anselin and Berra (1998)). The data used in this study consists of spatially distributed regions, thus it is justified to investigate the possibility of spatial clustering, (Ketelhohn (2006) and Anselin (1988)). To obtain latitude and longitude measures, for simplicity, we use the midpoint of each region's location. To identify spatial dependence, we use Moran's I, with the test statistic given by:

$$I = \frac{N}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(X_i - \bar{X})(X_j - \bar{X})}{\sum_j (X_i - \bar{X})^2} \tag{4.1}$$

Where N is the number of spatial units indexed by i and j; X is the variable of interest, $\bar{X}$ is the mean of X, and w_{ij} is an element of a matrix of spatial weights.[3] The main problem that arises with this test is that the results are highly influenced by the choice of weight matrix.

[3]Negative (positive) values indicate negative (positive) spatial autocorrelation. Values range from -1 (indicating perfect dispersion) to +1 (perfect correlation). A zero value indicates a random spatial pattern. The null hypothesis in the Moran's I test is: random special pattern

The nature of the data dictates spatial weights based on distance as there is no information on the parcels borders, (Farahmand, Akbari, and Abootalebi (2012)). Hence, we proceed by using the matrix that assigns weights between each pair of regions based upon the Euclidean distances between them[4]. With the exception for the third sector, all the P-values calculated for the Moran's I test are small (see appendix), meaning that the distribution in this data is nonrandom and manifests some degree of spatial dependence.

There are two different types of spatial correlation. The first one can occur if that correlation is present in the dependent variable (also known as a spatial lag process). The second is due to spatial correlation in the errors. Failure to correct for a spatial lag process, when it exists, results in biased coefficient estimates. Failure to correct for spatially correlated errors results in inefficient coefficient estimates, (Anselin and Berra (1998)). To choose an appropriate specification for these data, a series of Lagrange Multiplier tests are used (see appendix). In general terms, this test checks for the misspecification of either form by taking the restricted model[5] as a null hypothesis and the more general as the alternative, thus considering the situation as an omitted variable problem, (Anselin (1988)). Results suggest that for all the groups[6] both of the methods described can be used. A discussion of the results follows.

[4]Weights for those regions that are more than 200 kilometers appart are set to equal zero

[5]restricted model is the one that does not account for either spatial error or spatial lag process

[6]with the exception of manufacturing; nevertheless we proceed by estimating both models regardless

CHAPTER 5

EMPIRICAL RESULTS AND DISCUSSION

The specification in equation (3.2) is used in all estimations performed. The model is estimated for regions of Poland for years 2004 to 2006. Notice that we use the natural log transformations for both dependent and independent variables as in Blien and Suedekum (2004), thus the estimated coefficients are interpreted as elasticities. In the OLS results we use four different specifications: the so called global regression, global regression with industry specific dummy variables, by sector regression, and finally a variation of the last one combining sectors I with II and III with IV, and calling them manufacturing and services respectively, (Combes (2000)).

First, our estimates are robust to the type of estimation technique implemented. Moreover, the estimated elasticities of the independent variables appear to be fairly consistent with those of Combes (2000) and Blien and Suedekum (2004). In the case of the global regression (table 5.1), we find that density, specialization and competition have statistically significant impacts on employment growth. Density and size have negative elasticities, which suggests no localization effects, while the positive estimate for competition suggests otherwise. As expected, specialization has a positive impact for the employment growth in agriculture, hunting, forestry and fishing (table 5.2) thus indicating that the localization

Table 5.1: Global Regression

	OLS	Spatial Lag	Spatial Error
Density	-0.0075339***	-0.0075491***	-0.0076533***
	(0.001935)	(0.0018480)	(0.0018365)
Diversity	-0.0134068	-0.0148186	-0.0145700
	(0.0161569)	(0.0127772)	(0.0128063)
Specialization	0.012987**	0.0126754***	0.0130784***
	(0.0049728)	(0.0043852)	(0.0044420)
Size	-0.0191136***	-0.0183960***	-0.0191007***
	(0.0053148)	(0.0056012)	(0.0057526)
Competition	0.0048238**	0.0047847**	0.0049753
	(0.0023881)	(0.0021852)	(0.0021863)
Intercept	0.026808***	0.0264588***	0.0267835***
	(0.0072853)	(0.0073296)	(0.0075585)
F	8.68	n/a	n/a
Wald statistic	n/a	1.6606	2.6141
P-value	0.0000	0.19752	0.10592

*p-value<0.10, **p-value<0.05, ***p-value<0.01

economies are strong in those industries.

Industry and construction (table 5.3) tend to be negatively influenced by the higher employment density, which is indicative of the fact that because density favors information spillovers, the induced productivity gains can have a negative effect on employment (Combes (2000)). Furthermore, the average firm size has a negative impact on employment growth. This is somehow counter-intuitive as one may think that larger plant size would grow faster, especially in the traditional industries, such as gas and oil, metallurgy, chemicals, manufacturing etc. Moreover, this result is very different to what both Combes (2000) and Blien and Suedekum (2004) find in their studies. This can indicate the absence of internal economies of scale, yet we have to exert caution, given the reduced form nature of our estimates, (Moretti (2004)). Using our competition coefficient (for which higher value indicates more market power) and its positive elasticity, we find some evidence for

Table 5.2: Sector I

	OLS	Spatial Lag	Spatial Error
Density	0.0013343	0.0018902	0.00175776
	(0.007846)	(0.0046431)	(0.00444965)
Diversity	0.0151685	0.0186925	0.01945992
	(0.0258813)	(0.0263752)	(0.02595810)
Specialization	0.0139179	0.0145082**	0.01480926**
	(0.0126349)	(0.00624940	(0.00599325)
Size	-0.0026201	-0.0025510	-0.00240164
	(0.00665650	(0.0045313)	(0.00424015)
Competition	0.0007752	0.0007358	0.00078884
	(0.0030633)	(0.0021253)	(0.00210345)
Intercept	-0.0082314	-0.0106201	-0.00917598
	(0.0266371)	(0.0160824)	(0.01526344)
F	2.27	n/a	n/a
Wald statistic	n/a	1.2556	3.1921
P-value	0.0475	0.26249	0.073994

*p-value<0.10, **p-value<0.05, ***p-value<0.01

localization externalities in industry and construction.

Market services (table 5.4) has positive elasticity of employment density. This is consistent with the fact that density favors information spillovers, and in this case the induced productivity gains positively affect employment. This is opposite to what we see in agriculture and industry. A statistically significant and positive elasticity of diversity in market services produces evidence for urbanization economies as defined in Jacobs (1969). However, the estimates for size and competition tells us that it is more likely for the market services to benefit from the presence of MAR externalities. In other words, market services are interesting because we find that they benefit from a mix of both types of dynamic externalities although the channels through which MAR impacts employment growth are very different than in the case of sectors I and II.

Similarly, for non-market services (table 5.5), we find evidence for both Jacobs and

Table 5.3: Sector II

	OLS	Spatial Lag	Spatial Error
Density	-0.0128688**	-0.0131303**	-0.0135728**
	(0.0049776)	(0.0055826)	(0.0055089)
Diversity	0.0066521	0.0027517	0.0010591
	(0.047623)	(0.0487263)	(0.0487659)
Specialization	0.0266046	0.0270065	0.0295431
	(0.026789)	(0.0237667)	(0.0245809)
Size	-0.0897702***	-0.0892889***	-0.0916349***
	(0.0247568)	(0.0194953)	(0.0199167)
Competition	0.0340361**	0.0341158***	0.0351524***
	(0.0139134)	(0.0097169)	(0.0097248)
Intercept	0.0691266***	0.0671349***	-0.0135728***
	(0.0166576)	(0.0178024)	(0.0055089)
F	8.40	n/a	n/a
Wald statistic	n/a	0.98335	1.8703
P-value	0.0000	0.32137	0.17144

*p-value<0.10, **p-value<0.05, ***p-value<0.01

Table 5.4: Sector III

	OLS	Spatial Lag	Spatial Error
Density	0.0153247**	0.0151672**	0.0157315**
	(0.0070552)	(0.0073092)	(0.0074498)
Diversity	0.0582312*	0.0553777	0.0525029
	(0.0384767)	(0.0391879)	(0.0396273)
Specialization	-0.03171	-0.0315555*	-0.0308506
	(0.019677)	(0.0174918)	(0.0181914)
Size	-0.0991203***	-0.0997417***	-0.1020462***
	(0.0274691)	(0.0205930)	(0.0209408)
Competition	0.0444227***	0.0443144***	0.0442977***
	(0.0129814)	(0.0083365)	(0.00834180
Intercept	-0.049302	-0.0486251*	-0.0529020*
	(0.0303262)	(0.0293866)	(0.0301481)
F	4.05	n/a	n/a
Wald statistic	n/a	0.86335	1.4653
P-value	0.0014	0.3528	0.2261

*p-value<0.10, **p-value<0.05, ***p-value<0.01

Table 5.5: Sector IV

	OLS	**Spatial Lag**	**Spatial Error**
Density	0.0009689	0.00174233	0.00252371
	(0.0025558)	(0.00200155)	(0.00206589)
Diversity	0.0229206*	0.02434361	0.02706903*
	(0.0131113)	(0.01448031)	(0.01484586)
Specialization	-0.0128175	-0.01457500*	-0.01343895
	(0.0130828)	(0.01014908)	(0.01063827)
Size	-0.0410096*	-0.03733925***	-0.03823290***
	(0.0214051)	(0.01083024)	(0.01133492)
Competition	0.001016	0.00090407	0.00091974
	(0.0085821)	(0.00210121)	(0.00210248)
Intercept	0.003755	0.00075077	-0.00049698
	(0.0085821)	(0.00817472)	(0.00857093)
F	1.95	n/a	n/a
Wald statistic	n/a	5.0321	3.7772
P-value	0.0863	0.024882	0.051956

*p-value<0.10, **p-value<0.05, ***p-value<0.01

MAR externalities, although the latter appear to be more statistically significant and consistent throughout all estimation techniques. Services, when considered collectively, have negative and positive elasticities for size and competition variables respectively (table 5.7), thus showing an evidence for the presence of localization economies. For sectors I and II combined, we only find density to be statistically significant and negative (table 5.6), which is consistent with the findings for both sectors I and II.

Our results indicate that the dynamic externalities may be important in explaining employment growth of agglomeration economies in Poland. We find evidence for MAR externalities in agriculture, hunting, forestry and fishing as indicated by the coefficient of the specialization variable. Our competition coefficient for industry and construction gives us some evidence for localization externalities in that sector as well. Furthermore, we find that different sectors of the economy tend to benefit from different types of dynamic external-

Table 5.6: Agriculture, Indsutry, Construction and Manufacturing

	OLS	**Spatial Lag**	**Spatial Error**
Density	-0.013395***	-0.01340074***	-0.01343583**
	(0.00316)	(0.00294342)	(0.00294625)
Diversity	-0.012794	-0.01330488	-0.01283357
	(0.0272609)	(0.01899743)	(0.01899281)
Specialization	0.0029379	0.00286031	0.00285705
	(0.0070085)	(0.00589257)	(0.00592269)
Size	-0.0069657	-0.00667928	-0.00675448
	(0.0059217)	(0.00670426)	(0.00677884)
Competition	0.0008234	0.00079998	0.00093758
	(0.003557)	(0.00337696)	(0.00338572)
Intercept	0.0484763***	0.04814991***	0.04861707***
	(0.0113393)	(0.01124088)	(0.01130081)
F	6.95	n/a	n/a
Wald statistic	n/a	0.18588	0.25159
P-value	0.0000	0.6637	0.61596

*p-value<0.10, **p-value<0.05, ***p-value<0.01

Table 5.7: Services

	OLS	**Spatial Lag**	**Spatial Error**
Density	-0.0009198	-0.00071504	-0.00069299
	(0.0026275)	(0.00307534)	(0.00312555)
Diversity	-0.0077906	-0.00965060	-0.01260750
	(0.020739)	(0.01958892)	(0.01981883)
Specialization	0.0126177	0.01217353	0.01500944*
	(0.0117968)	(0.00958057)	(0.01003013)
Size	-0.0491632***	-0.04891797***	-0.05240535***
	(0.017497)	(0.01240984)	(0.01287256)
Competition	0.00698*	0.00693680**	0.00701333**
	(0.0043423)	(0.00328346)	(0.00328136)
Intercept	-0.0002124	-0.00072509	-0.00243498
	(0.0120549)	(0.01265056)	(0.01322559)
F	2.36	n/a	n/a
Wald statistic	n/a	3.1169	4.2691
P-value	0.0387	0.077485	0.038811

*p-value<0.10, **p-value<0.05, ***p-value<0.01

ities. This is manifested in the difference between manufacturing and services sectors and presents itself in the fact that services tend to benefit from Jacobs externalities while more traditional industries do not experience a comparable degree of this phenomenon. Moreover, we learn that it is likely for very different sectors to benefit from the same type of dynamic externalities. However, the channels through which this process takes place is not the same.

Moreover, we believe that this paper contributes to the empirical literature on urban growth by shedding light on the fact that even short periods of time can be useful in terms of studying the role of dynamic externalities in explaining local employment growth.

We also believe that a better understanding of the role of dynamic externalities in developing and transitioning countries can be important for ultimately applying wise local development policies. The finding that dynamic externalities may have almost an immediate effect can be of special interest for local policy makers aiming at promoting higher growth in employment and thus local economic development.

CHAPTER 6

CONCLUSION

In this study, we examine the effects of agglomeration economies on employment growth in Poland and also account for spatial dependencies in both the dependent variables as well as in our controls. Our results support the Marshallian view of benefits resulting form localization economies for both industrial and services sectors. Furthermore, services experience some degree of Jacobs diversification benefits and thus, to some extent, prove the hypothesis of urbanization economies. Quite surprisingly and despite the data being of a spatially dependent nature, we do not find particularly different elasticity estimates across the different models.

There are several extensions to this analysis that may be worth pursuing. First, this type of study can be improved by using data including more information than the one we use in here. Due to the nature of the data available to us[7] we could only perform the analysis presented. Quite clearly the time period of only two years is somewhat limited. Nevertheless, our results are in line with those studies that utilized longer time periods to perform similar inferences on the directions and magnitudes of the impact of economic structures on local employment growth. From this, we learn that it is possible that dynamic externalities can

[7] $http://www.stat.gov.pl/gus/5840_732_{P}LK_{H}TML.htm$

in fact impact local economies even in a time period as short as two years.

This is noteworthy because, as previously mentioned, findings of this type can aid policymakers in deciding on taxation rules. This is turn, can encourage new growth in investment, employment or in the number of firms in certain industries while not in the others. As we show, the outcomes of these reforms can have almost an immediate and positive influence on the economy via employment growth, which can be of a substantial value to those in charge.

Moreover, we recommend implementing methods described with longer data series and panel methodology, as in Henderson (1997), (Combes (2000)). This would allow to distinguish between the short and long run impacts of economic structure on local employment growth. We also suggest considering methods that would help in distinguishing between productivity and output effects and between market-based effects and information spillovers.

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APPENDIX

Descriptive Statistics

Table 6.1: Descriptive Statistics

	Num. of Obs.	Mean	St. dev.	Min	Max
Competition	1454	-0.7422513	1.066029	-4.11252	2.960387
Density	1512	3.470351	1.330752	1.299123	7.27305
Diversity	1512	-0.2070584	0.194429	-0.8547524	0.0189808
Size	1512	-0.1791681	0.6041214	-3.027412	2.234001
Specialization	1512	-0.2230761	0.8192345	-4.571526	1.291759

Table 6.2: Pearson's correlation coefficients among explanatory variables

	Competition	Density	Diversity	Size	Specialization
Competition	1.0000				
Density	0.2716	1.0000			
Diversity	-0.0327	-0.2788	1.0000		
Size	0.1574	0.0973	-0.0719	1.0000	
Specialization	0.1259	-0.115	0.1979	0.6886	1.0000

Table 6.3: Variance Inflation factors

	Variance Inflation Factor	**1/VIF**
Density	1.23	0.814591
Diversity	1.34	0.746155
Specialization	2.29	0.436667
Size	2.18	0.459227
Competition	1.27	0.789121
Industry		
2	1.72	0.582996
3	1.79	0.558029
4	1.86	0.538776

Moran's I Test Results

Table 6.4: Moran's I based on the inverse distance weight matrix

	Moran's I	**St. deviate**	**Expectation**	**Variance**	**P-value**
Sector I	0.0453958820	3.0504	-0.0026525199	0.000248106	0.002285
Sector II	0.0197996650	1.3993	-0.0026525199	0.0002574582	0.1617
Sector III	0.0123352342	0.9334	-0.0026525199	0.0002578062	0.3506
Sector IV	0.0359256505	2.4528	-0.0026525199	0.0002473861	0.01418
all sectors	1.123071e-02	2.951	-6.618134e-04	1.624124e-05	0.003168
Manufacturing	1.2287123e-02	1.6954	-1.324503e-03	6.445508e-05	0.08999
Services	1.580028e-02	2.1216	-1.324503e-03	6.454427e-05	0.03304

Lagrange Multiplier Test Results

Table 6.5: LM Test for Spatial Lag and Spatial Error Models

	I	II	III	IV	all	manufacturing	services
LM_{lag}	2.3612	0.943	0.7828	3.3488	1.7659	0.1821	3.1911
P-value	0.1244	0.3315	0.3763	0.06725	0.1839	0.6696	0.07404
LM_{error}	5.2726	1.5193	1.1168	1.824	2.3303	0.1942	3.8553
P-value	0.02166	0.2177	0.2906	0.1768	0.1269	0.6595	0.04959

Result Tables

Table 6.6: OLS Estimates for the Manufacturing versus Services Differences in Economic Structures' Impact on Employment Growth

	Manufacturing	Services
Density	-0.013395***	-0.0009198
	(0.002216)	(0.0026275)
Diversity	-0.012794	-0.0077906
	(0.0272609)	(0.020739)
Specialization	0.0029379	0.0126177
	(0.0070085)	(0.0117968)
Size	-0.0069657	-0.0491634***
	(0.0059217)	(0.017497)
Competition	0.0008234	0.00698*
	(0.003557)	(0.0043423)
Intercept	0.0484763***	-0.0002124
	(0.0113393)	(0.0120549)
N	728	726
F	6.95	2.36
Probability > F	0.0000	0.0387
R-sq	0.0425	0.0265
Root MSE	0.08605	0.08199

*p-value<0.10, **p-value<0.05, ***p-value<0.01

Table 6.7: OLS Estimates for the Sectoral Differences in Economic Structures' Impact on Employment Growth

	Global OLS	OLS with industry dummy variables	Sector			
			I	**II**	**II**	**IV**
Density	-0.0075339***	-0.0070559***	0.0013343	-0.0128688**	0.0153247**	0.0009689
	(0.001935)	(0.0019113)	(0.007846)	(0.0049776)	(0.0070552)	(0.0025558)
Diversity	-0.0134068	0.0013943	0.0151685	0.0066521	0.0582312	0.0229206*
	(0.0161569)	(0.0170675)	(0.0258813)	(0.047623)	(0.0384767)	(0.0131113)
Specialization	0.012987**	0.012309**	0.0139179	0.0266046	-0.03171	-0.0128175
	0.0049728	0.0049712	0.0126349	0.026789	0.019677	0.0130828
Size	-0.0191136***	-0.0208511***	-0.0026201	-0.0897702***	-0.0991203***	-0.0410096*
	(0.0053148)	(0.0053293)	(0.0066565)	(0.0247568)	(0.0274691)	(0.0214051)
Competition	0.0048238**	0.0042788*	0.0007752	0.0340361**	0.0444227***	0.001016
	(0.0023881)	(0.0026051)	(0.0030633)	(0.0139134)	(0.0129814)	(0.0085821)
Industry dummies						
Sector II		0.0257452***				
		(0.006219)				
Sector III		0.003097				
		(0.0067308)				
Sector IV		0.0164759***				
		(0.0045732)				
Intercept	0.026808***	0.0159224**	-0.0082314	0.0691266***	-0.049302	0.003755
	(0.0072853)	(0.0064212)	(0.0266371)	(0.0166576)	(0.0303262)	(0.0085821)
N	1454	1454	350	378	378	348
F	8.68	7.17	2.27	8.40	4.05	1.95
Probability > F	0.0000	0.0000	0.0475	0.0000	0.0014	0.0863
R-sq	0.0253	0.0389	0.1107	0.1027	0.1053	0.0787
Root MSE	0.08443	0.08392	0.04003	0.10853	0.1017	0.04177

*p-value<0.10, **p-value<0.05, ***p-value<0.01

Table 6.8: Spatial Lag Regression Estimates for the Sectoral Differences in Economic Structures' Impact on Employment Growth

	Sectors				
	all	**I**	**II**	**III**	**IV**
Density	-0.0075491***	0.0018092	-0.0131303**	0.0151672**	0.00174233
	(0.0018480)	(0.00464310)	(0.0055826)	(0.0073092)	(0.00200155)
Diversity	-0.0148186	0.0186925	0.0027517	0.0553777	0.02434361*
	(0.0127772)	(0.0263752)	(0.0487263)	(0.0391879)	(0.01448031)
Specialization	0.0126754***	0.0145082**	0.0270065	-0.0315555*	-0.01457500*
	(0.0043852)	(0.0062494)	(0.0237667	(0.0174918)	(0.01014908)
Size	-0.0183960***	-0.0025510	-0.0892889***	-0.0997417***	-0.03733925***
	(0.0056012)	(0.0045313)	(0.0194953)	0.0205930)	(0.01083024)
Competition	0.0047847**	0.0007358	0.0341158***	0.0443144***	0.00090407
	(0.0021852)	(0.0021253)	(0.0097169)	(0.0083365)	(0.00210121)
Intercept	0.0264588***	-0.0106201	0.0671349***	-0.0486251*	0.00075077
	(0.0073296)	(0.0160824)	(0.0178024)	(0.0293866)	(0.00817472)
Rho	0.18227	-0.18027	0.14142	0.13771	0.31848
LR test value	1.6309	1.7404	0.93064	0.80012	3.7133
P-value	0.20158	0.18708	0.3347	0.37106	0.053982
Asymptotic st. error	0.14145	0.16088	0.14262	0.14821	0.14198
z-value	1.2886	-1.1205	0.99164	0.92917	2.2432
P-value	0.19752	0.26249	0.32137	0.3528	0.024882
Wald statistic	1.6606	1.2556	0.98335	0.86335	5.0321
P-value	0.19752	0.26249	0.32137	0.3528	0.024882
Log likelihood	1534.787	633.603	306.5823	331.072	616.1906
ML residual variance	0.0070873	0.0015647	0.01155	0.010147	0.0016874
N	1454	350	378	378	348
LM test value	0.84595	1.7609	1.0624	1.0096	0.041875
P-value for LM tests	0.3577	0.18451	0.30266	0.31499	0.83786

*p-value<0.10, **p-value<0.05, ***p-value<0.01

Table 6.9: Spatial Error Regression Estimates for the Sectoral Differences in Economic Structures' Impact on Employment Growth

	Sectors				
	all	**I**	**II**	**III**	**IV**
Density	-0.0076533***	0.00175776	-0.0135728**	0.0157315**	0.00252371
	(0.0018365)	(0.00444965)	(0.0055089)	(0.0074498)	(0.00206589)
Diversity	-0.0145700	0.01945992	0.0010591	0.0525029	0.02706903*
	(0.0128063)	(0.02595810)	(0.0487659)	(0.0396273)	(0.01484586)
Specialization	0.0130784***	0.01480926**	0.0295431	-0.0308506	-0.01343895
	(0.0044420)	(0.00599325)	(0.0245809)	(0.0181914)	(0.01063827)
Size	-0.0191007***	-0.00240164	-0.0916349***	-0.1020462***	-0.03823290***
	(0.0057526)	(0.00424015)	(0.0199167)	(0.0209408)	(0.01133492)
Competition	0.0049753**	0.00078884	0.0351524***	0.0442977***	0.00091974
	(0.0021863)	(0.00210345)	(0.0097248)	(0.0083418)	(0.00210248)
Intercept	0.0267835***	-0.00917598	0.0704355***	-0.0529020*	-0.00049698
	(0.0075585)	(0.01526344)	(0.0181446)	(0.0301481)	(0.00857093)
Lambda	0.24078	-0.30451	0.2052	0.18323	0.29466
LR test value	2.3148	4.132	1.6094	1.2306	2.468
P-value	0.12815	0.04208	0.20458	0.26729	0.11619
Asymptotic st. error	0.14892	0.17044	0.15005	0.15137	0.15161
z-value	1.6168	-1.7867	1.3676	1.2105	1.9435
P-value	0.10592	0.073994	0.17144	0.2261	0.051956
Wald statistic	2.6141	3.1921	1.8703	1.4653	3.7772
P-value	0.10592	0.073994	0.17144	0.2261	0.051956
Log likelihood	1535.129	634.7988	306.9217	331.2872	615.5679
ML residual variance	0.0070815	0.0015496	0.011516	0.010127	0.0016948
N	1454	350	378	378	348

*p-value<0.10, **p-value<0.05, ***p-value<0.01

Table 6.10: Manufacturing versus Services

	Spatial Lag		Spatial Error	
	Manufacturing	**Services**	**Manufacturing**	**Services**
Density	-0.01340074***	-0.00071504	-0.01343583**	-0.00069299
	(0.00294342)	(0.00307534)	(0.00294625)	(0.00312555)
Diversity	-0.01330488	-0.00965060	-0.01283357	-0.01260750
	(0.01899743)	(0.01958892)	(0.01899281)	(0.01981883)
Specialization	0.00286031	0.01217353	0.00285705	0.01500944
	(0.00589257)	(0.00958057)	(0.00592269)	(0.01003013)
Size	-0.00667928	-0.04891797***	-0.00675448	-0.05240535***
	(0.00670426)	(0.01240984)	(0.00677884)	(0.01287256)
Competition	0.00079998	0.00693680**	0.00093758	0.00701333**
	(0.00337696)	(0.00328346)	(0.00338572)	(0.00328136)
Intercept	0.04814991***	-0.00072509	0.04861707***	-0.00243498
	(0.01124088)	(0.01265056)	(0.01130081)	(0.01322559)
Rho	0.064288	0.25633	n/a	n/a
Lambda	n/a	n/a	0.079837	0.2988
LR test value	0.18186	2.938	0.21789	3.7282
P-value	0.66978	0.086516	0.64066	0.053502
Asymptotic st. error	0.14911	0.14519	0.15917	0.14461
z-value	0.43114	1.7655	0.50159	0.14461
P-value	0.6637	0.077485	0.61596	0.038811
Wald statistic	0.18588	3.1169	0.25159	4.2691
P-value	0.6637	0.077485	0.61596	0.038811
Log likelihood	755.7401	790.1746	755.7581	790.5696
ML residual variance	0.0073416	0.0066279	0.0073408	0.0066162
N	728	726	728	726

*p-value<0.10, **p-value<0.05, ***p-value<0.01

Moran’s I Plots

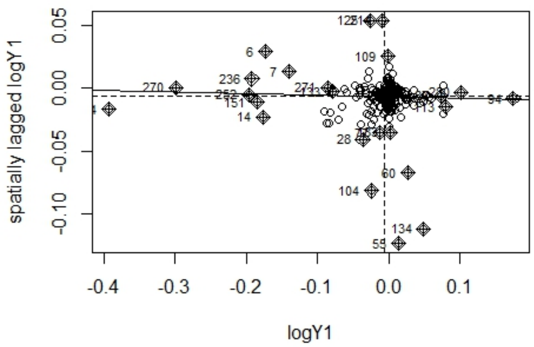

Figure 6.1: Moran’s I for Sector I

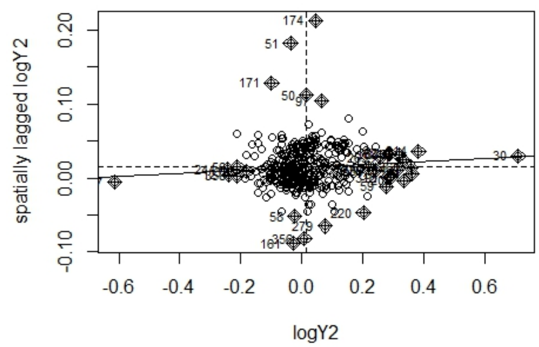

Figure 6.2: Moran’s I for Sector II

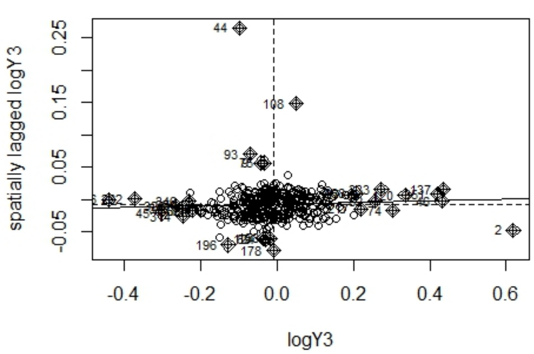

Figure 6.3: Moran’s I for Sector III

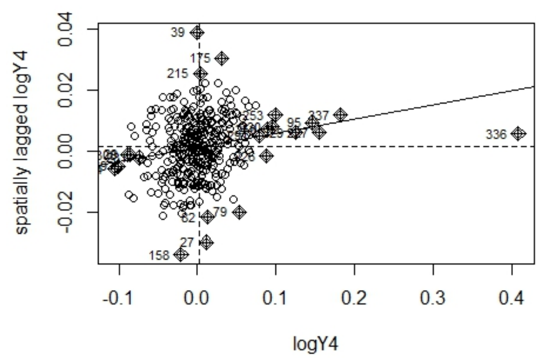

Figure 6.4: Moran’s I for Sector IV

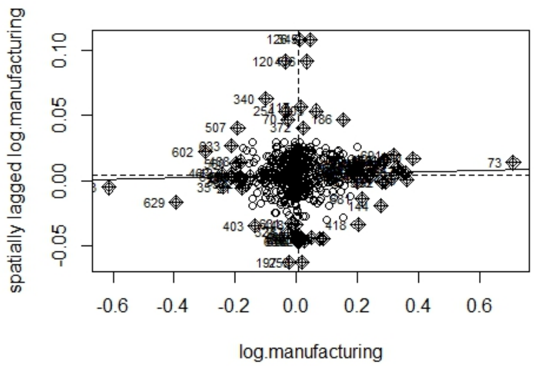

Figure 6.5: Moran's I for I and II

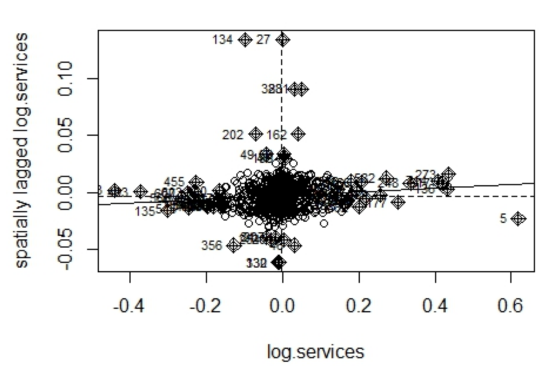

Figure 6.6: Moran's I for Services

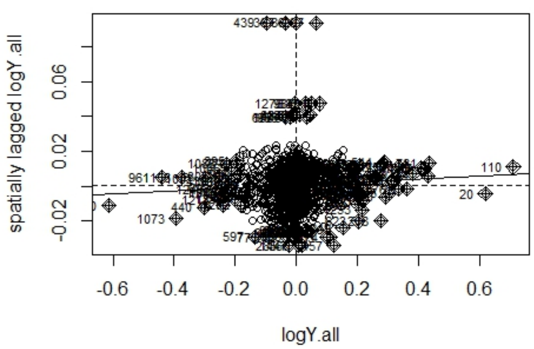

Figure 6.7: Moran's I for all sectors

R code

```
# Special dependence code for thesis
# Open the special dependence package(if not yet installed, type: install.packages("spdep
   "))
library(spdep)

# Generating the matrix of region point coordiantes or Spatial points object
coords1<-cbind(sector1$Longitude,sector1$Latitude)
coords2<-cbind(sector2$Longitude,sector2$Latitude)
coords3<-cbind(sector3$Longitude,sector3$Latitude)
coords4<-cbind(sector4$Longitude,sector4$Latitude)
coords.all<-cbind(alldata$Longitude,alldata$Latitude)
coords.m<-cbind(manufacturing$Longitude,manufacturing$Latitude)
coords.s<-cbind(services$Longitude,services$Latitude)

mydata1<-sector1
mydata2<-sector2
mydata3<-sector3
mydata4<-sector4
mydata.all<-alldata
mydata.m<-manufacturing
mydata.s<-services

depvar1<-cbind(mydata1$lnY)
depvar2<-cbind(mydata2$lnY)
depvar3<-cbind(mydata3$lnY)
depvar4<-cbind(mydata4$lnY)
depvar.all<-cbind(mydata.all$lnY)
depvar.m<-cbind(mydata.m$lnY)
depvar.s<-cbind(mydata.$lnY)

#OLS regressions withouth robust standards errors
ols1<-lm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata1)
```

```
summary(ols1)
ols2<-lm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata2)
summary(ols2)
ols3<-lm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata3)
summary(ols3)
ols4<-lm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata4)
summary(ols4)
ols.m<-lm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.m)
summary(ols.m)
ols.s<-lm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.s)
summary(ols.s)
#Global OLS regression
ols.global<-lm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.all)
summary(ols.global)

# SPATIAL ANALYSIS BASED ON DISTANCE WEIGHT MATRIX #
# First I use the binary weights #
# Binary spatial weight matrices based on distance (with lower and upper bounds for
    distance)
nb1<-dnearneigh(coords1,d1=0,d2=200,row.names=NULL,longlat=TRUE)
nb2<-dnearneigh(coords2,d1=0,d2=200,row.names=NULL,longlat=TRUE)
nb3<-dnearneigh(coords3,d1=0,d2=200,row.names=NULL,longlat=TRUE)
nb4<-dnearneigh(coords4,d1=0,d2=200,row.names=NULL,longlat=TRUE)
nb.all<-dnearneigh(coords.all,d1=0,d2=200,row.names=NULL,longlat=TRUE)
nb.m<-dnearneigh(coords.m,d1=0,d2=200,row.names=NULL,longlat=TRUE)
nb.s<-dnearneigh(coords.s,d1=0,d2=200,row.names=NULL,longlat=TRUE)


# NOTE: I set the upper bound to 200 kilometers, (Poland is approx. 600x600km, so I take 1
    /3 for the simplicity of the later computations)

listw11<-nb2listw(nb1,style="W")
listw22<-nb2listw(nb2,style="W")
listw33<-nb2listw(nb3,style="W")
```

```
listw44<-nb2listw(nb4,style="W")
listw.all1<-nb2listw(nb.all,style="W")
listw.m<-nb2listw(nb.m,style="W")
listw.s<-nb2listw(nb.s,style="W")

# Now I create the 1/distance weights (The inverse distnace weights,idw)
dist1<-nbdists(nb1,coords1,longlat=TRUE)
dist2<-nbdists(nb2,coords2,longlat=TRUE)
dist3<-nbdists(nb3,coords3,longlat=TRUE)
dist4<-nbdists(nb4,coords4,longlat=TRUE)
dist.all<-nbdists(nb.all,coords.all,longlat=TRUE)
dist.m<-nbdists(nb.m,coords.m,longlat=TRUE)
dist.s<-nbdists(nb.s,coords.s,longlat=TRUE)

idw1<-lapply(dist1,function(x) 1/x)
idw2<-lapply(dist2,function(x) 1/x)
idw3<-lapply(dist3,function(x) 1/x)
idw4<-lapply(dist4,function(x) 1/x)
idw.all<-lapply(dist.all,function(x) 1/x)
idw.m<-lapply(dist.m,function(x) 1/x)
idw.s<-lapply(dist.s,function(x) 1/x)

listw111<-nb2listw(nb1,glist=idw1,style="W")
listw222<-nb2listw(nb2,glist=idw2,style="W")
listw333<-nb2listw(nb3,glist=idw3,style="W")
listw444<-nb2listw(nb4,glist=idw4,style="W")
listw.all2<-nb2listw(nb.all,glist=idw.all,style="W")
listw.m1<-nb2listw(nb.m,glist=idw.m,style="W")
listw.s1<-nb2listw(nb.s,glist=idw.s,style="W")
summary(unlist(listw111$weights))

# Moran's I test
# Using binary weights
moran.test(depvar1,listw11,randomisation=TRUE,zero.policy=NULL,alternative="two.sided")
```

```
moran.test(depvar2,listw22,randomisation=TRUE,zero.policy=NULL,alternative="two.sided")
moran.test(depvar3,listw33,randomisation=TRUE,zero.policy=NULL,alternative="two.sided")
moran.test(depvar4,listw44,randomisation=TRUE,zero.policy=NULL,alternative="two.sided")
moran.test(depvar.all,listw.all1, randomisation=TRUE,zero.policy=NULL,alternative="two.sided")

# Using idw weights
moran.test(depvar1,listw111,randomisation=TRUE,zero.policy=NULL,alternative="two.sided")
moran.test(depvar2,listw222,randomisation=TRUE,zero.policy=NULL,alternative="two.sided")
moran.test(depvar3,listw333,randomisation=TRUE,zero.policy=NULL,alternative="two.sided")
moran.test(depvar4,listw444,randomisation=TRUE,zero.policy=NULL,alternative="two.sided")
moran.test(depvar.all,listw.all2,randomisation=TRUE,zero.policy=NULL,alternative="two.sided")

# Moran's Plots (using binary weights)
logY1<-mydata1$lnY
logY2<-mydata2$lnY
logY3<-mydata3$lnY
logY4<-mydata4$lnY
logY.all<-mydata.all$lnY
log.manufacturing<-mydata.m$lnY
log.services<-mydata.s$lnY

moran.plot(logY1,listw11)
moran.plot(logY2,listw22)
moran.plot(logY3,listw33)
moran.plot(logY4,listw44)
moran.plot(logY.all,listw.all1)
moran.plot(log.manufacturing,listw.m)
moran.plot(log.services,listw.s)

# Moran's Plots (using idw weights)
moran.plot(logY1,listw111)
moran.plot(logY2,listw222)
```

```
moran.plot(logY3,listw333)
moran.plot(logY4,listw444)
moran.plot(logY.all,listw.all2)
moran.plot(log.manufacturing,listw.m1)
moran.plot(log.services,listw.s1)

# Lagrange multiplier test for spatial lag and spatial error dependencies
# Binary weights
lm.LMtests(ols1,listw11,test=c("LMlag","LMerr"))
lm.LMtests(ols2,listw22,test=c("LMlag","LMerr"))
lm.LMtests(ols3,listw33,test=c("LMlag","LMerr"))
lm.LMtests(ols4,listw44,test=c("LMlag","LMerr"))
lm.LMtests(ols.global,listw.all1,test=c("LMlag","LMerr"))
lm.LMtests(ols.m,listw.m,test=c("LMlag","LMerr"))
lm.LMtests(ols.s,listw.s,test=c("LMlag","LMerr"))

# IDW weights
lm.LMtests(ols1,listw111,zero.policy=NULL,test=c("LMlag","LMerr"))
lm.LMtests(ols2,listw222,test=c("LMlag","LMerr"))
lm.LMtests(ols3,listw333,test=c("LMlag","LMerr"))
lm.LMtests(ols4,listw444,test=c("LMlag","LMerr"))
lm.LMtests(ols.global,listw.all2,test=c("LMlag","LMerr"))
lm.LMtests(ols.m,listw.m1,test=c("LMlag","LMerr"))
lm.LMtests(ols.s,listw.s1,test=c("LMlag","LMerr"))

# Spatial lag model
# Binary weights
spatial.lag11<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata1,listw11)
summary(spatial.lag11)
spatial.lag22<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata2,listw22)
summary(spatial.lag22)
spatial.lag33<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata3,listw33)
summary(spatial.lag33)
spatial.lag44<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata4,listw44)
```

```
summary(spatial.lag44)
spatial.lag.all1<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.all,listw.all1)
summary(spatial.lag.all1)

# IDW weights
spatial.lag111<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata1,listw111)
summary(spatial.lag111)
spatial.lag222<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata2,listw222)
summary(spatial.lag222)
spatial.lag333<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata3,listw333)
summary(spatial.lag333)
spatial.lag444<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata4,listw444)
summary(spatial.lag444)
spatial.lag.all2<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.all,listw.all2)
summary(spatial.lag.all2)
spatial.lag.m<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.m,listw.m1)
summary(spatial.lag.m)
spatial.lag.s<-lagsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.s,listw.s1)
summary(spatial.lag.s)

# Spatial error model
# Binary weights
spatial.error11<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata1,listw11)
summary(spatial.error11)
spatial.error22<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata2,listw22)
summary(spatial.error22)
spatial.error33<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata3,listw33)
summary(spatial.error33)
spatial.error44<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata4,listw44)
summary(spatial.error44)
spatial.error.all1<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.all,listw.all1)
```

```
summary(spatial.error.all1)

# IDW weights
spatial.error111<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata1,listw111)
summary(spatial.error111)
spatial.error222<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata2,listw222)
summary(spatial.error222)
spatial.error333<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata3,listw333)
summary(spatial.error333)
spatial.error444<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata4,listw444)
summary(spatial.error444)
spatial.error.all2<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.all,listw.
    all2)
summary(spatial.error.all2)
spatial.error.m<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.m,listw.m1)
summary(spatial.error.m)
spatial.error.s<-errorsarlm(lnY~lnDen+lnSpec+lnDiv+lnSize+lnkomp,data=mydata.s,listw.s1)
summary(spatial.error.s)
```

STATA code

```
******multicollinearity*****
corr lnkomp lnden lndiv lnspec lnsize
quietly regress lnspec lnden lndiv lnsize lnkomp
di 1-e(r2)
quietly regress  lnden lndiv lnsize lnkomp lnspec
di 1-e(r2)
quietly regress   lndiv lnsize lnkomp lnspec lnden
di 1-e(r2)
quietly regress   lnsize lnkomp lnspec lnden lndiv
di 1-e(r2)
quietly regress   lnkomp lnspec lnden lndiv  lnsize
di 1-e(r2)
regress lny lnden lndiv lnspec lnsize lnkomp i.industry
estat vif

****heteroskedasticity*******
hettest
predict res1, r
plot res1 lny

***** regressions by sector s*****
***** GLOBAL REGRESSION ******
reg lny lnden lndiv lnspec lnsize lnkomp,r

****** GLOBAL REGRESSION BY SECTORS *****
reg lny lnden lndiv lnspec lnsize lnkomp i.industry,r

****** BY SECTORS *******
reg lny lnden lndiv lnspec lnsize lnkomp if industry==1,r
reg lny lnden lndiv lnspec lnsize lnkomp if industry==2,r
reg lny lnden lndiv lnspec lnsize lnkomp if industry==3,r
reg lny lnden lndiv lnspec lnsize lnkomp if industry==4,r
```

```
****** MANUFACTURING VS. SERVICES *******
*** manufacturing *****
reg lny lnden lndiv lnspec lnsize lnkomp if industry==1&2,r
*** services *****
reg lny lnden lndiv lnspec lnsize lnkomp if industry==3&4,r
```