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Regional Inequality and Spatial Dependence in Sweden

A spatial analysis of regional convergence in Sweden 1980-2022

by

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Abstract Regional inequality is a growing concern in developed countries, as country-level convergence may obscure increasing disparities within countries. This thesis aims to address this concern by examining the dynamics of regional convergence in Sweden from 1980-2022. The study employs spatial data analysis and econometric methods to examine the spatial dynamics of income and spillover effects between regions, providing a comprehensive and up-to-date understanding of regional inequality in Sweden. The analysis of per-worker income growth among Swedish regions reveals a nuanced picture of β- and σ- convergence. Overall, the findings indicate β- convergence throughout the period, with notable convergence occurring between 1980-1994. However, between 1995-2008 convergence slowed, and from 2009-2022, a diverging pattern emerged. Examining σ-convergence confirms an overall decrease in the dispersion of regional incomes and an increase in dispersion in later decades. Moreover, the divergence since the beginning of the 2000s seems to be primarily driven by within-regional inequality. The application of spatial econometric methods uncover significant spillovers during the first two periods, indicating that regional growth was positively influenced by the economic performance of neighboring regions. Furthermore, exploratory spatial data analysis reveals that regional incomes have been influenced by spatial dependence and clustering, although to a limited degree and primarily during the 1990s and 2000s. Overall, spatial clustering does not seem to be associated with increasing regional dispersion of income.

Keywords: regional inequality, convergence, spatial dependence, spatial econometrics, Sweden

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Introduction

In recent years, regional economic disparities have become a growing concern in developed countries, in particular for the European Union (EU) and its member states. While many countries have experienced growth and development in recent decades and the regional disparities between member states have narrowed, these gains seem to be increasingly unevenly distributed across regions. This has led to persistent gaps within countries in terms of income, employment, and productivity (Iammarino et al., 2019; Balakrishnan et al., 2022) which may undermine European social and economic cohesion objectives (European Commission, 2021). This development of convergence on a national level but divergence on a sub-national level poses a challenge for policymakers to balance this emerging trade-off between *intra-country* and *inter-country* disparities (Higgins, 1992) and some authors have linked this development to rising social unrest and political extremism (Dijkstra et al., 2020).

Sweden is no exception to this development. Despite Sweden's high level of economic development and social welfare, regional disparities in Sweden have increased since the 1980's (Enflo and Rosés, 2015; André et al., 2021; OECD, 2022). In 2020, Sweden was among ten out of thirty-three OECD countries that became more polarized in terms of the ratio of per capita GDP between its top and bottom 20% of regions (OECD, 2022). The issue of regional inequality is of great relevance for Swedish policymakers who recently released a national strategy for sustainable regional development (Government, 2021).

The concept of convergence has been a common framework used to understand regional disparities. Convergence refers to the neoclassical prediction that poorer economies should grow faster than richer ones, leading to a narrowing of income gaps over time (Abramovitz, 1986). The empirical literature is vast and well-researched on a national level starting with the works of Baumol (1986) and has led to multiple influential studies of regional convergence within countries (e.g. Barro and Sala-i Martin, 1991, 1992). There has been a wide range of applications with varying results, mainly due to differences in methodology, data, and the chosen time period. However, there have been significant improvements in methodology with the use of spatial econometric techniques in the convergence models that take geographical factors into account (Rey and Montouri, 1999; Rey and Janikas, 2005). Geographical location has been shown to be an important factor for economic outcomes with the emergence of endogenous growth theory and new economic geography (Lucas, 1988; Krugman, 1991). These theories highlight how economic activity tends to cluster in specific geographical areas, leading to regional disparities in development and productivity.

This thesis aims to contribute to a deeper understanding of regional convergence by focusing on the Swedish context. First, the thesis builds upon and expands existing research on regional income convergence in Sweden. To achieve this, a comprehensive dataset covering the period of 1980-2022 is utilized, enabling an up-to-date analysis of convergence and divergence patterns among regions in Sweden. Second, a key objective of this study is to examine the impact of spatial dependence on Sweden's convergence process. This allows for gaining unique insights into the specific characteristics of the Swedish experience but also contributes to existing literature that has explored this relationship within other countries. Incorporating spatial techniques allows for accounting for spatial spillovers between regions and improves the accuracy and reliability of estimates in the models and can also help identify and visualize spatial patterns and clusters. In this way, the role of agglomeration economies and other spatial factors can be better accounted for and help policymakers target interventions and resources more effectively.

In sum, this thesis aims to answer two main questions: i) what are the convergence/divergence patterns between Swedish regions during the period 1980-2022? and, ii) what is the role of spatial dependence in the regional growth process in Sweden? In light of these questions, special attention will be paid to the temporal dynamics of the convergence process and the changing importance of spatial factors in shaping regional disparities over time.

To achieve these goals, this study adopts a methodological structure similar to Rey and Montouri (1999), Royuela and García (2015) and Artelaris (2021), who investigated spatial dependence in the convergence process in the US, Colombia, and Greece respectively. The study employs spatial research methods such as exploratory spatial data analysis (ESDA) and spatial econometrics. These methods offer the ability to incorporate spatial dependence into regression analysis and to identify spatial patterns in the data. This way the role of spatial effects in the regional growth process can be assessed and can provide valuable insights into the mechanisms driving convergence or divergence over time. No previous research has used such methods to study this relationship in Sweden during this time period.

The thesis is structured as follows. Chapter 2 reviews both the theoretical and empirical literature on regional convergence and its potential influence of spatial effects. Section 3 presents the methodology and section 4 discusses the data used and its limitations. Section 5 presents the empirical results of the study, and Section 6 concludes with a discussion of the findings, their implications for policy, and suggestions for future research.

2

Literature Review

2.1 Theoretical Foundation

The theoretical foundation for studying regional convergence has various predictions. While the neoclassical growth theory predicts convergence, the endogenous growth theory and new economic geography (NEG) instead suggest that regions could exhibit divergence due to different key assumptions about the drivers of economic growth.

2.1.1 Neoclassical Growth Theory

In general terms, convergence can be defined as the narrowing of differences among economies in the development of certain economic variables. The mechanism behind convergence rests on the assumption within the neoclassical growth theory based on the work of Solow (1956) and Swan (1956) of decreasing returns to capital and exogenous technological growth rate. The law of diminishing returns drives a "catch-up" process which means that less developed regions will experience higher marginal returns on new investment, allowing them to grow faster than more developed regions until they reach equilibrium (steady state). This is referred to as the *unconditional convergence hypothesis* and assumes that the only difference between rich and poor economies is the capital stock (Abramovitz, 1986).

However, Barro and Sala-i Martin (1992) and Mankiw et al. (1992) relaxed this assumption and suggested that economies will converge to different steady-states due to differences in characteristics such as factor endowments, preferences, technology, and institutions. This phenomenon is known as *conditional convergence* and could lead to the concept of club convergence where distinct groups of regions exhibit similar income dynamics and convergence patterns. However, it can be argued that regions within a country are more homogeneous than between different countries or between regions in different countries as they share many similarities such as institutional frameworks and policy environments. This homogeneity can allow for the application of the unconditional convergence hypothesis, which posits that all regions will converge to the same steady state (Barro and Sala-i Martin, 1995).

2.1.2 Endogenous Growth and New Economic Geography

With the emergence of the endogenous growth theory, the neoclassical assumptions of diminishing returns to capital came under scrutiny. Romer (1986) and Lucas (1988) demonstrated that the returns on investments in innovation (R&D), can support continuous technological growth and increasing returns to factors. In this way, technological growth becomes an endogenous factor and regions with high income can sustain a higher growth rate indefinitely by investing in R&D and human capital. As a result, these models do not necessarily predict convergence between regions, as the neoclassical theory does.

The new economic geography (NEG) literature, pioneered by Krugman (1991); Puga (1999) among others, questioned the neoclassical assumption as well. The concept of geographical concentration of economic activities, i.e. agglomeration economies, has been known at least since Marshall (1890) who argued that the concentration of firms and industries in specific areas leads to positive externalities such as knowledge spillovers, labor market pooling, and shared infrastructure contribute to economic growth. However, while NEG models further emphasized the importance of such spatial externalities, Krugman (1991) also argued that these agglomeration forces can lead to a 'core-periphery pattern' where an economy is divided into two parts: a central, prosperous area (the core) that benefits from agglomeration and a surrounding, less developed area (the periphery).

The combination of endogenous growth theory and NEG models gives a mutual relationship between economic growth and agglomeration. The prediction of whether such models will result in regional convergence or divergence relies on the assumptions about how technological knowledge spreads: globally or locally. With a global spread of technological knowledge, geography does not impact growth and higher growth will be linked to the convergence of regional incomes (Baldwin and Martin, 2004). However, with a local spread, the concentration of economic activity in specific areas can both increase growth but also widen income disparities between regions. This could lead to a scenario of a trade-off between regional equity and overall economic growth [1] where the benefits of agglomeration (with reduced cost of innovation and faster growth) are reserved for the core region, while core and periphery regions are lagging.

2.2 Empirical Research

The empirical research on convergence is vast and well-researched which has been at the heart of a broad debate in the growth literature for a long time. Empirical studies differ widely due to a variety of factors such as theoretical frameworks, model specification, treatment of cross-sectional-heterogeneity, time-and entity selection, and methodology (see surveys such as Abreu et al., 2005; Islam, 2003). In an extensive survey, Islam (2003) provides a summary of the often encountered dichotomies and the different methodologies used to understand convergence. For this study, the relevant previous research focuses on unconditional convergence using a cross-sectional approach within an economy, specifically examining growth rate through β- and σ- convergence.

[1] See how this relates to the discussion of the trade-off between intra-national and inter-country disparities (Higgins, 1992).

The unconditional convergence was initially tested by Baumol (1986). Although the study received criticism, it gave rise to numerous subsequent studies that further explored the phenomenon. There are several ways to examine unconditional convergence, but β- and σ- convergence is the most commonly applied (Barro and Sala-i Martin, 1995). β-convergence refers to the tendency for economies with lower initial levels (poorer economies) of development to experience higher growth rates, allowing them to catch up with economies that started at higher levels (richer economies). This is based on the assumption that all economies share technological progress equally, allowing them to grow at the same growth rate in the steady state (Islam, 2003). [2] A widespread belief is that convergence should exhibit a 2% rate on average (although various studies have found this number Abreu et al. (2005) emphasizes that this should not be interpreted as a natural constant).

In contrast, σ- convergence measures the distribution of income over time. Quah et al. (1992); Quah (1993) argued that β- convergence does not necessarily imply a reduction in the distribution of income measured by σ- convergence: it is possible to observe a β convergence even though there is a diverging trend in distribution. This means that even though poorer regions have grown faster than richer ones, the dispersion might still increase.

Furthermore, the focus has also shifted from cross-country analysis to regions operating at a sub-national scale (within-country convergence)(e.g., Barro and Sala-i Martin, 1991; Sala-i Martin, 1996). Whereas the conditional convergence has been seen to be a more realistic assumption than the unconditional at the country level (Mankiw et al., 1992; Barro and Sala-i Martin, 1992), the unconditional convergence can arguably still be applicable when studying within-country convergence, as regions within a country can be considered more homogeneous in terms of similarities in factors such as institutional frameworks, policy, and market conditions (Barro and Sala-i Martin, 1995).

Given that regions typically display a greater deal of openness than countries, various forms of interdependencies between regions, such as labor and capital flows along with trade, a growing literature emerged that recognized the importance of geographic factors and spatial effects on regional income patterns compared to studies on an international level, a notion that also aligned better with the theoretical framework of endogenous growth and NEG models (Rey, 2001; Rey and Janikas, 2005). This led to the emergence of using spatial methods such as spatial econometrics for estimating β- convergence or the use of exploratory spatial data analysis to better understand σ- convergence (Rey and Montouri, 1999; Abreu et al., 2004).

One of the first to apply spatial econometrics to growth is Rey and Montouri (1999) which studied US regional income patterns over the 1929-94 period. Some studies have looked at the integration of regions at the EU level (Dall'Erba et al., 2008; De Dominicis, 2014; Artelaris, 2015; Panzera and Postiglione, 2022). Other studies that used spatial econometrics to within-country convergence among regions are Gezici and Hewings (2004) on Turkey 1980-97, Royuela and García (2015) on Colombia 1975-2005, and Artelaris (2021) on Greece 1981-2015. Each one found a significant impact of spatial effects on the convergence process but in different ways.

[2] The essential difference to convergence in terms of income *level* is that it assumes that all economies have identical aggregate production functions, implying that their steady-state income levels are also identical (Islam, 2003).

2.2.1 Previous Research in Sweden

The most comprehensive studies on regional inequality and convergence in Sweden have been conducted by Enflo and Rosés (2015) and Enflo et al. (2018). They investigated regional convergence/divergence patterns over the course of 140 years between 1860-2000. By dividing the process of regional convergence into three major periods they found evidence of convergence in the first period (1860-1940). This was followed by an even more intense period of convergence in the second period (1940-80). During the last period (1980-2000) regional incomes diverged. Instead of attributing the compression of regional inequality to neoclassical convergence forces due to diminishing returns to capital and technological catching-up, but rather structural change. [3]

They attribute the divergence of regional inequality since the 80s to growth in metropolitan areas and the structural change towards increased importance of the service sector and knowledge-intensive industries (Enflo et al., 2018). Other studies have also found a close connection between economic growth and the resurgence of major urban areas since the 80s in Sweden (Lundquist et al., 2008) and the emergence in the private service sector (Henning, 2020). Enflo and Henning (2020) also points out that cities with higher education institutions have managed to fare quite well, although it may not always be reflected in the total GDP figures at the county ("län") level.

One of the few studies that have studied regional growth with spatial effects is Gustavsson and Persson (2003) which analyzed determinants of economic growth for Swedish regions between 1911-1993. They found that the growth rate of income per capita is strongly positively related to the growth rate of income per capita in neighboring counties.

[3] Convergence across regions due to structural change refers to the process where overall labor productivity increases as resources shift from low-productivity to high-productivity sectors, and regions with different income levels specialize in these sectors, leading to regional convergence in labor productivity (Enflo and Rosés, 2015).

3

Methods

This section explains how the regional inequality dynamics in Sweden are examined. The method employed follows a similar structure to previous studies looking at within-country (i.e. regional) convergence with spatial dependence (Rey and Montouri, 1999; Royuela and García, 2015; Artelaris, 2021).

The first line of analysis is a cross-sectional β- convergence approach, where only the absolute convergence will be tested. Although previous research has suggested that homogeneity is a reasonable assumption when studying within-country convergence (Barro and Sala-i Martin, 1995), there's also reason to believe that region-specific factors such as differences in education, infrastructure, or labor market structure could impact growth, leading to multiple steady-state paths, i.e. conditional convergence. However, due to the limited research on convergence with spatial effects in Sweden, studying absolute convergence can serve as a foundation for future research.

The second line of analysis is the σ- convergence approach and inequality analysis, which assess the dispersion of income across regions. This is done using both a parametric- and non-parametric approach to examine the development over time. Lastly, the role of spatial autocorrelation in regional growth is explored, exposing patterns of spatial dependence and clustering by using ESDA and spatial econometric techniques. This gives insights into how the region's neighbor's income might influence each other in the convergence process.

These methods combined are meant to provide a comprehensive understanding of the development of regional inequality, convergence, and spatial dependence in Sweden.

3.1 The Regression Approach: β-convergence

As previously discussed, the unconditional β-convergence model is the most commonly applied to test whether poor regions grow faster than rich regions. To test this form of convergence, numerous studies starting with Baumol (1986) have employed a cross-sectional OLS specification as follows:

$$\left(\frac{1}{T}\right) ln\left(\frac{y_{i,t+T}}{y_t}\right) = \alpha + \beta ln(y_{i,t}) + \epsilon_{i,t} \tag{3.1}$$

where the LHS is the annualized growth rate with $y_{i,t}$ as GDP is per worker in the region i in year t. α and β are parameters to be estimated, where α is the intercept and β is the coefficient associated with initial GDP per worker. $\epsilon_{i,t}$ is a stochastic error term that follows a normal distribution with mean zero and variance σ^2, denoted as $\epsilon_{i,t} \sim N(0, \sigma^2 I)$. This assumption allows for random deviations from the expected values in the regression.

A negative estimate of β can be interpreted in support of convergence since that would suggest that the growth rates in per-worker incomes over the T year period were negatively correlated with starting incomes. According to neoclassical growth theory, this negative correlation is expected, as economies that are further away from their steady state are predicted to experience higher growth rates. The convergence process is characterized by its convergence speed:

$$\gamma = -\frac{\ln(1-\beta)}{T}$$

and its half-life:

$$\tau = \frac{\ln(2)}{\gamma}$$

The convergence speed tells us how quickly the economies are reaching their steady state and the half-life time (measured in years) that is necessary for economies to fill half of the variation that separates them from the steady state.

3.2 The Distributional Approach: σ- convergence

σ- convergence implies a decline in the distribution of an economic variable. Plenty of different measures have been used to measure regional inequality over time, for example, standard deviation, the coefficient of variation (CV), the Theil index, the Gini index, etc. The choice here is to follow measures used in similar research: the CV complemented with the Theil decomposition (Royuela and García, 2015; Artelaris, 2021). The CV is simply calculated as $CV = \mu/\sigma$, where σ represents the standard deviation and μ represents the mean for all regions. The CV is a useful measure as it captures both the dispersion and relative variability of regional incomes.

The decomposed Theil index which is useful when studying inequalities at the sub-national level and helps evaluate the decomposition of overall inequality (De Dominicis, 2014). It can be decomposed as follows:

$$T = \sum_{g=1}^{m} s_g log(n/n_g s_g) + \sum_{g=1}^{m} s_g \sum_{i \in g} s_{i,g} log(n_g s_{i,g}) \tag{3.2}$$

where n_g is the number of observations in group g, $s_g = \sum_{i\in g} y_{i,g} / \sum_i^n y_i$ is the share of total income accounted for by group g, and $s_{i,g} = y_{i,g} / \sum_{i=1}^{n_g} y_{i,g}$ is region i's share of group g's income. The first term on the RHS of equation 3.2 is the 'between-group' component of inequality, while the second term is the 'within-group' component of inequality. Simplified this means:

$$T = T_B + T_W \tag{3.3}$$

where T_B measures the distance between the mean incomes of the aggregate groups and T_W measures distances between the incomes of regions belonging to the same group. Rey and Janikas (2005) explains that this decomposition allows the analysis to consider the amount of spatial polarisation for a given level of inequality. He argues that this is important as it is entirely possible for a general decline in σ-convergence to coexist with increasing polarization within the income distribution.

3.2.1 Distribution Dynamics: Stochastic Kernels

Another common approach is to evaluate the changes in the distributional dynamics through a non-parametric approach. Stochastic kernels that provide additional insights compared to regular - and σ-convergence that do not capture the full dynamics of the distribution (Quah, 1993). This method allows us to study how the distribution of income changes over time and how individual regions shift within the distribution. Here, the formation of clusters within the distribution can be identified, which can help determine whether there are groups of regions that are converging towards different steady states, possibly giving an indication of the presence of club convergence. The formula for the stochastic kernels, as shown by Magrini (2007) can be expressed as:

$$f_{X(t+s)} = M_{t,s} f_{X(t)} \tag{3.4}$$

This describes how the probability density function (PDF) of the variable X evolves over time. It relates the PDF of X at a future time $t + s$ to the PDF of X at an earlier time t. The stochastic kernel, $M_{t,s}$ describes how the PDF of X changes over time. To further assess convergence, a contour plot of the stochastic kernels is used to visualize the joint distribution of two variables (the 3D relationship in two dimensions) (Royuela and García, 2015) This can give an indication of whether regions are maintaining their relative positions over time.

3.3 Incorporating Spatial Effects

The analysis of spatial data often requires considering spatial autocorrelation, which captures the dependence between neighboring regions. One common approach to account for this autocorrelation is by utilizing a spatial weight matrix (Anselin and Bera, 1998). This matrix is then used for the ESDA and the spatial regression models.

3.3.1 Spatial Weight Matrix

The spatial weight matrix represents the spatial adjacency between regions and defines the structure and intensity of spatial effects. In order to capture the spatial relationships between Swedish regions, the choice of this matrix is crucial. There are several options including binary contiguity (such as queen and rook), k-nearest neighbors, and distance-based weighting.

Binary contiguity matrices are the most simple where regions are considered neighbors if they share a boundary (rook) or a point (queen). These types of matrices can be a good starting point when studying spatial relationships and Gustavsson and Persson (2003) used such a matrix in Sweden. An issue with this matrix is the island of Gotland cannot be assigned weights since it is disconnected from the mainland. K-nearest neighbors, on the other hand, allow for a fixed number of neighbors for each region which ensures a degree of uniformity in the connectivity structure. However, the process of selecting the appropriate 'k' is not straightforward and might connect regions that are geographically distant but rank as 'nearest' due to a lack of alternatives.

The main choice in this thesis is a distance-based spatial weight matrix which is the second most common matrix applied in the spatial convergence literature after contiguity (Abreu et al., 2004). Such a matrix allows for the fact that all regions can potentially interact with the strength of the interaction diminishing with distance. The chosen matrix utilizes the 'minimum threshold distance' to ensure that all regions are connected, creating an inversely weighted matrix that acknowledges the heterogeneity of spatial relationships across regions. To ensure robustness in the results, the regressions will be tested with both a distance-based matrix and a Queen contiguity matrix. However, the ESDA will be based solely on the distance-based matrix due to limited space and time. For a formal discussion on the matrices, see Appendix A.

3.3.2 Exploratoty Spatial Data Analysis (ESDA)

Global Spatial Autocorrelation

In order to detect the presence of spatial patterns and autocorrelation, exploratory data analysis (ESDA) is used. There exist a few different ways to measure spatial autocorrelation, but Moran's I is the most commonly used for the purposes used here (e.g., Rey and Montouri, 1999; Rey and Janikas, 2005). Moran's I is an index that measures the extent of spatial clustering or dispersion of observations and ranges from -1 (indicating strong negative autocorrelation) to 1 (indicating strong positive autocorrelation). The calculation of Moran's I is calculated as:

$$I = \frac{N}{W} \cdot \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n} (x_i - \bar{x})^2} \tag{3.5}$$

where I is the Moran's I statistic, N is the number of regions, W is the sum of all spatial weights, w_{ij} is an element in the spatial weight matrix that represents a weight between regions i and j, x_i and x_j are the values of the variable for regions i and j respectively, and $\bar{x}$ represents the mean value of the variable across all regions.

Local Spatial Autocorrelation

While Moran's I measure global spatial autocorrelation, local indicators of spatial association (LISA) statistics provide local measures of spatial autocorrelation. LISA maps visually represent these statistics and provide insights into the local clusters where similar values of the variable cluster together. The local statistics of spatial patterns are calculated as local Moran's I statistic. For a region i it is calculated as:

$$I_i = \frac{z_i}{\sum_{j=1}^{n} \left(\frac{z_j^2}{N}\right)} \sum_{j \in J_i}^{n} w_{ij} z_j \tag{3.6}$$

where z_i is the standardized value of x_i and J_i is the number of regions in neighboring region i (Royuela and García, 2015).

3.3.3 Spatial Dependence Models

As discussed in chapter 2, the regional convergence process might exhibit spatial dependence. Spatial autocorrelation, if not adequately accounted for, can lead to the misspecification of traditional models such as the absolute convergence model in equation 3.1. Anselin (1988) have shown that spatial dependence can manifest in two primary ways: through the error process (nuisance dependence) or directly by values of the dependent variable in neighboring locations (substantive dependence). The way these are incorporated in the models and what they imply for the non-spatial specification is covered more in-depth in Appendix B.

Spatial Error Model

Nusiance spatial dependence or spatial error dependence arises when the residuals of a model exhibit spatial autocorrelation, indicating that there exist spatial factors that are not included in the model and create a pattern in the errors. This will violate the assumption of independence of the error term and result in inefficient OLS estimations of the β- convergence models. The incorporation of spatial dependence into the absolute convergence model in 3.1 can be done via a spatial error term (in vector notation) as:

$$\left(\frac{1}{T}\right) ln\left(\frac{y_{t+T}}{y_t}\right) = \alpha + \beta ln(y_t) + \epsilon_t \quad \text{where} \quad \epsilon_t = \lambda W \epsilon_t + u_t \tag{3.7}$$

where $\lambda W \epsilon_t$ represents the spatial error component which incorporates the spatial dependence by multiplying the error term ϵ_t by the spatial weight matrix W and the spatial autoregressive coefficient λ. The spatial weight matrix defines the spatial relationship between observations, and λ captures the strength of the spatial dependence, meaning that if $\lambda = 0$ then the model becomes the regular OLS specification. The error term u_t will then be $u_i \sim N(0, \sigma^2 I)$.

Spatial Lag Model

The second form of spatial dependence is substantive, where the dependent variable in a given location is directly influenced by the values of the dependent variable in neighboring locations. This type of spatial dependence suggests that there is an interactive process between locations. This is illustrated in the equation:

$$\left(\frac{1}{T}\right) ln\left(\frac{y_{t+T}}{y_{i,t}}\right) = \alpha + \beta ln(y_t) + \rho W \left[\left(\frac{1}{T}\right) ln\left(\frac{y_{t+T}}{y_t}\right)\right] + \epsilon_t \tag{3.8}$$

where the third term on the RHS represents the spatial lag component of the model: it incorporates the spatial dependence by multiplying the lagged dependent variable by the spatial weight matrix W and the spatial autoregressive coefficient ρ. Similarly, to the spatial error model, the spatial weight matrix defines the spatial relationship between observations, and ρ captures the strength of the spatial dependence, and when $\rho = 0$ it becomes the regular OLS specification.

The spatial econometric literature has suggested that OLS estimation is unsuitable for models with spatial dependence. In the presence of spatial error autocorrelation, OLS estimators lose efficiency, and in the case of a spatial lag specification, they become inconsistent. Hence, maximum likelihood techniques are commonly recommended to address these issues (Anselin, 1988). Furthermore, there is a number of different alternative spatial models such as SDM, SAC, SLX, or the spatial cross-regressive model. However, following Royuela and García (2015), only the spatial error and spatial lag models will be considered due to the difficulty to disentangle which model is more relevant and also more difficult to interpret.

4

Data

4.1 Source Material

The data used in this study is collected from the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy (ARDECO) (ARDECO, 2023). This database contains variables for EU regions with Nomenclature of Territorial Units for Statistics (NUTS), including those of Sweden, at various statistical scales such as NUTS 1-3. The primary source of data within ARDECO is the Statistical Office of the European Commission (Eurostat), supplemented by data from other relevant sources. The data is provided in euros, and the national currency has been converted using a fixed euro conversion rate. The choice of using ARDECO is that it allows for a long time period between 1980-2022.

4.2 Variables: GDP per worker

The most common approach in the convergence literature is to study GDP per capita. However, there are compelling reasons to use GDP per worker as some authors have suggested (De Dominicis, 2014; Panzera and Postiglione, 2022; Boldrin and Canova, 2001). They argue that using GDP per capita may introduce a potential distortion by the spatial scale in the measurement of variables. This is because GDP is estimated at workplaces, while people are counted based on their residential location, which can result in individuals working across administrative boundaries (Eurostat, 2022). GDP per worker does not suffer from the same problem. It also avoids counting residents who do not contribute to the production efforts such as retirees (Boldrin and Canova, 2001). Note that this does come with the drawback of not being as good a measure of living standards as GDP per capita for the same reason of not accounting for non-working individuals such as children and retirees.

There are important distinctions when interpreting GDP per worker as opposed to GDP per capita. GDP per worker is rather a measure of labor productivity and how much each worker produces on average. This can help to shed light on the sources of economic growth in a different way than GDP per capita. A rising GDP per worker suggests that the efficiency of the region's labor force is improving. This could be due to factors such as education and skills or more effective use of capital. A stagnant/declining GDP per worker can on the other hand imply capital shortages or a mismatch between workers' skills. This thesis will use GDP per employed [1] rather than the entire workforce which will provide a representation of the productivity of the labor force that's actively engaged in employment. The data on GDP is at constant prices (i.e. real GDP) with reference year 2015. GDP per worker is calculated as constant GDP divided by employed (thousands).

4.3 Data Limitations

Using the ARDECO dataset comes with the issue that the data is denominated in Euros. As Sweden has not adopted the euro and continues to use the Swedish Krona (SEK) there is a potential effect of exchange rate fluctuations between the SEK and euro that should be taken into consideration. Factors such as differences in inflation and interest rates could introduce some degree of variation in the data that does not reflect the real economic performance or productivity of Swedish regions. However, despite this potential source of bias, the potential impact of exchange rate fluctuations should be relatively constant across all Swedish regions. Therefore, the relative differences and trends, which are the primary focus of this study, should remain valid.

The division of geographical units can pose a problem known as the Modifiable Areal Unit Problem (MAUP) (Openshaw, 1984). MAUP refers to the statistical bias that arises due to the risk of these regions being arbitrarily decided and not representing the *true* functional economic-geographical areas. Both excessively high and low aggregation levels can either hide functional economic units or divide them inappropriately. In the case of this thesis, the usage of NUTS-3 regions might be associated with the problem of high aggregation, which could potentially conceal important spatial interactions occurring at lower aggregation scales, such as municipalities. However, the choice of studying NUTS-3 regions is a common approach in regional studies and aligns with the available data and existing literature in the field (e.g. Royuela and García, 2015; Artelaris, 2021). While there may be limitations to the level of spatial granularity, the use of NUTS-3 regions allows for a broader analysis of regional convergence and provides a reasonable compromise between data availability and capturing regional variations. Moreover, the correspondence of NUTS-3 units to the 21 Swedish counties ("län") helps in maintaining some level of meaningful regional representation. [2]

Lastly, it has been highlighted by Artelaris (2021) among others that convergence or divergence trends can be heavily dependent upon the selection of time period which poses a high risk of misleading the results. One of the reasons for this is the potential effect of business cycles, which can significantly influence the regional growth dynamics Rodríguez-Pose and Fratesi (2007). In order to address this concern, the long-run analysis is complemented by examining different sub-periods. This approach allows for the potential effect of economic cycles and illuminates the variations in convergence rates depending on the period chosen. A key advantage of studying within-country dynamics is the synchronization of business cycles, which

[1] Throughout the thesis, GDP per employed will be referred to as GDP per worker.

[2] There have been some changes in the Swedish counties during the studied period. 1997 Kristianstad County and Malmöhus County merged into Skåne County, and in 1998 where Gothenburg Bohus County, Älvsborg County, and Skaraborg County were merged into Västra Götaland County (with the exception of the municipalities of Habo and Mullsjö, which were transferred to Jönköping County). The NUTS regional units correspond with the counties following these changes.

provides a more robust basis for such analysis compared to cross-country comparisons (Petrakos et al., 2005). The selection of sub-periods is done in a similar vein as Artelaris (2021) to reflect periods between large crises that have had significant impacts on the economy, namely the crises of 1990-94 and 2008-09. Coincidentally, this divides the into almost equal lengths of 14, 13, and 13 years respectively which makes them sufficiently comparable.

4.4 Sweden As a Case Study

Sweden presents itself as an interesting case study for investigating regional convergence between its regions during the period of 1980-2022. Most notable is that the topic of regional dispersion is highly relevant for Swedish policymakers, where in March 2021, the government unveiled its 2021-2030 National strategy for sustainable regional development throughout the country (Government, 2021). Also on the EU level, one of the principal aims of the EU's regional policy is its cohesion policy to gradually reduce the gaps between regions (European Commission, 2021). Sweden's highly decentralized governance means that regional and local governments play a significant role in implementing development policies (André et al., 2021). [3]

Furthermore, the studied time period is characterized by significant structural shifts in the Swedish economy, transitioning from a manufacturing-based economy to a more knowledge-intensive and service-oriented one. Radical economic and policy changes, such as liberalization, deregulation, and EU membership, could have affected the distribution of economic growth across regions. Sweden has also experienced severe business cycles with the financial crises of 1990-94 and 2007-08.

Incorporating spatial effects into the analysis of regional convergence in Sweden is particularly interesting due to Sweden's diverse geography and spatial heterogeneity which offers a diverse context. First, Sweden is characterized by densely populated urban areas in the south [4] and vast, sparsely populated areas in the north. While urban areas often are hubs of economic activity, attracting investment, talent, and businesses, the peripheral areas could face challenges related to accessibility, labor market dynamics, or economic diversification. Second, there is a diverse mix of industrial sectors in Sweden which has a notable spatial component: resource-based industries and energy production in the north, and a strong manufacturing base with industries such as automotive and electronics in the south and central parts. Also, Sweden's largest cities such as Stockholm, Gothenburg, and Malmö are in turn characterized by a knowledge-based economy concentrated with service industries.

[3] Sweden is among the most decentralized OECD countries, and sub-national governments account for more than 70% of general government final consumption, the highest share in the (OECD, 2022).

[4] 88% of the Swedish population lives in urban areas all located in the south of Sweden (SCB, 2022)

5

Empirical Analysis

In the literature review in chapter 2, previous theoretical and empirical studies emphasized the importance of spatial externalities and interactions in shaping the convergence process. The methodology presented in chapter 3 illustrated how spatial dependence can be incorporated in convergence models by utilizing spatial econometric models and ESDA to avoid misspecified models and detect spatial autocorrelation. This section will have the following structure.

First, the results from σ- convergence and the presence of spatial dependence in the data are presented. Results from ESDA will convey if we can see the clustering of regions in terms of real GDP per worker by utilizing both global and local Moran's I. To visualize the spatial autocorrelation, a time-series plot, Moran's I scatterplots, and LISA-cluster maps are utilized. The σ- convergence will be presented in the form of the CV and Theil decomposition in time-series plots. The non-parametric estimates will be presented with univariate density- and contour plots. Also, the relationship between spatial clustering and σ- convergence will be evaluated.

Second, the results from the regressions estimating the cross-sectional β- convergence will be presented. These analyses will help identify the role of spatial effects in the convergence/divergence where econometric models incorporating spatial lag or spatial error specifications are employed to account for dependencies in the data. Different spatial weight matrices will be tested and special attention to the temporal dynamics will be paid. [1]

5.1 σ- Convergence and Exploratory Spatial Data Analysis

In Figure 5.1 the evolution of spatial autocorrelation measured by Moran's I (right axis) and the regional inequality measured by the CV (left axis) is displayed over time. The plot reveals some interesting patterns. The trend in Moran's I shows an initial increase, peaking in 2009, followed by a subsequent decline. The majority of years exhibit positive spatial autocorrelation, although not particularly high (consistently below 0.2) and prior to 1993 and after 2015, there are some years with negative spatial autocorrelation. However, approximately half of the years are statistically significant at a 10% significance level, while only around one-third are

[1] The analysis is conducted using Python with the package PySAL to conduct the spatial analysis developed by Rey and Anselin (2007).

significant at a 5% level. The significant years are primarily within the period of positive spatial autocorrelation observed in the 1990s and 2000s and in particular between 1995-2006.

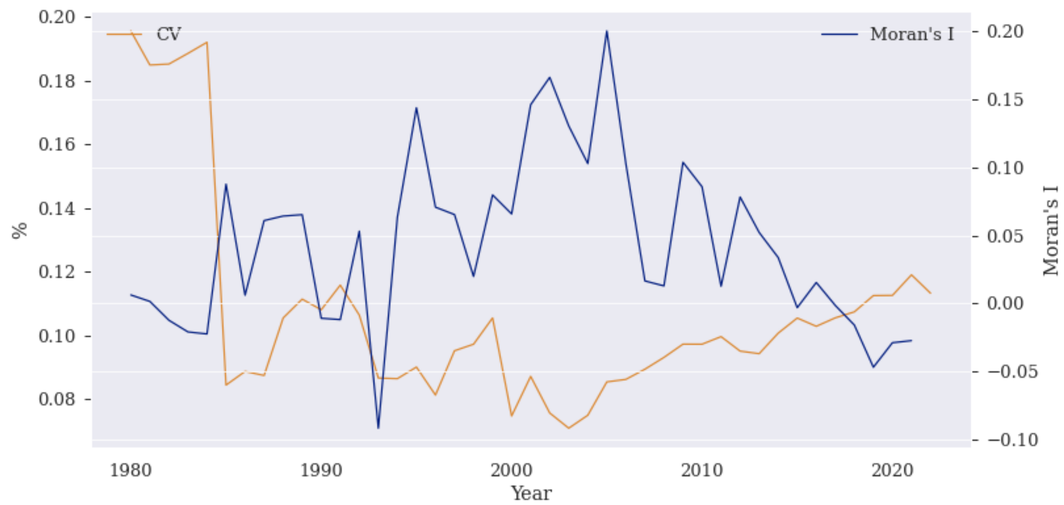

Figure 5.1: Coefficient of Variation (CV) (left axis) and Moran's I (right axis), 1980-2022

The results of the CV in Figure 5.1 are a bit puzzling. First, between 1984-1985 there is a substantial drop, between 1985-2003 there is a volatile but decreasing trend which then steadily increases after 2003 until it reaches its highest point in 2021 since 1984.

There is an unexpected negative significant correlation between the CV and Moran's I (Pearson: -0.49, $p < 1\%$), despite the literature suggesting a positive correlation (Rey and Janikas, 2005). Although there is assumed to be a lagged effect in moves of spatial autocorrelation on σ- convergence, a positive (non-significant) correlation is not seen until a 9-year lagged value of Moran's I (Pearson: 0.05, $p > 10\%$). The consequence of this result is the opposite of what Rey and Montouri (1999) and Rey and Janikas (2005) found in the case of the USA and what Royuela and García (2015) found in Colombia. While Artelaris (2021) also found a negative (non-significant) relationship for NUTS-3 regions in Greece he found a positive relationship between NUTS-2 regions, which is not the case for Sweden. [2] However, these results should be taken with caution since the values of Moran's I are mostly insignificant indicating weak or no spatial autocorrelation which makes the results unreliable. [3]

In Figure 5.2 the Theil decomposition of regional inequality is presented. [4] This shows how much of the overall regional inequality is due to inter-regional inequality (between NUTS-3) and intra-regional inequality (within NUTS-1). NUTS-1 consists of three large regions: East Sweden, South Sweden, and North Sweden. The general

[2] CV and Moran's I not presented for NUTS-2 regions due to the limited number of observations (8 NUTS-2 regions) and because the NUTS-2 level of Stockholm is composed solely of Stockholm län at the NUTS-3 level (meaning there is no internal variation within the region). However, they are nonetheless negatively correlated (non-significant) as well.

[3] The use of different weight matrices such as Queen contiguity provide similar results.

[4] For the same reason mentioned in a previous footnote 1, NUTS-1 regions are considered because the NUTS-2 level of Stockholm is composed solely of Stockholm län at the NUTS-3 level.

trend is that inter-regional inequality has historically been the main source of inequality, but intra-regional inequality seems to be the main source of the increasing inequality since around the early 2000s.

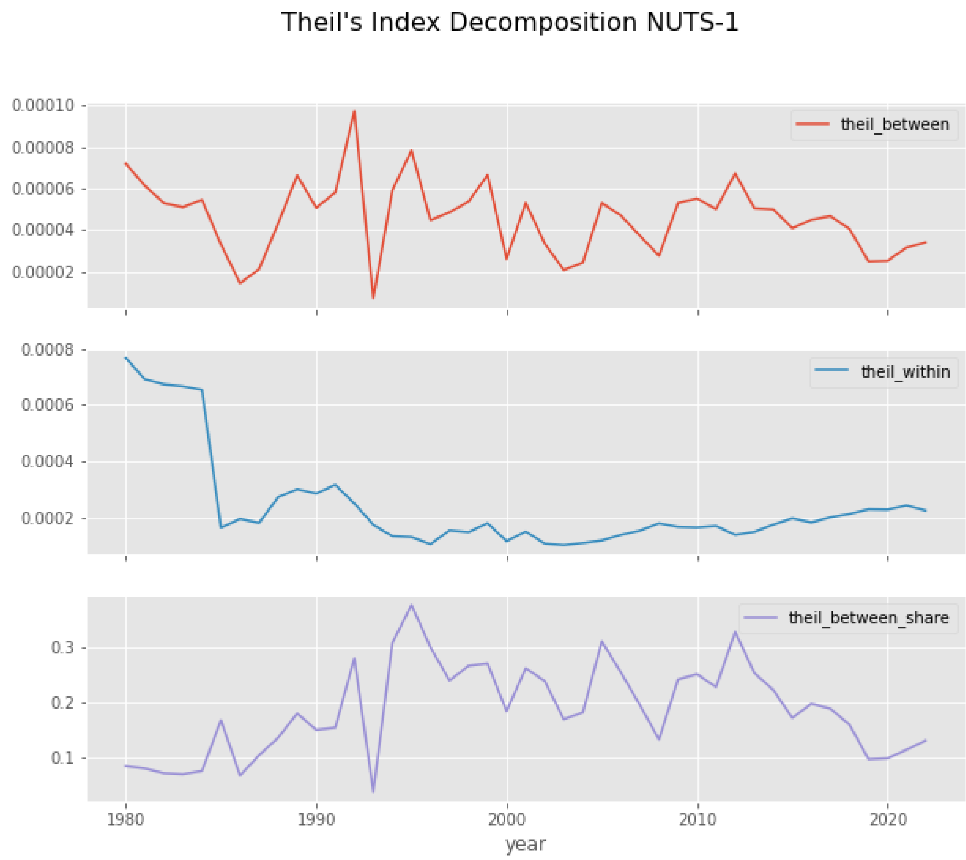

Figure 5.2: Theil Decomposition of between- and within regional inequality, 1980-2022

Figure 5.3 displays Moran's scatterplots for four years: 1980, 1995, 2010, and 2022. Each data point represents a region, with the x-axis representing to the standardized real per-worker GDP in each region (z), and the y-axis representing the spatial lag (Wz) (i.e., the average value of neighboring regions). A positive slope indicates positive spatial autocorrelation, implying clustering of similar values. The dotted blue lines divide the observations into four quadrants:

- Upper-Right Quadrant (High-High): above-average income regions surrounded by others with above-average income.
- Upper-Left Quadrant (Low-High): below-average income regions surrounded by others with above-average income
- Lower-Right Quadrant (High-Low): above-average income regions surrounded by others with above-average income
- Lower-Left Quadrant (Low-Low): below-average income regions surrounded by others with below-average income

These findings visually represent what we saw in Figure 5.1. Only in 1995, there is significant ($p < 5\%$) clustering and weak in 2010 ($p < 10\%$) with most values falling in the High-High (HH) or Low-Low (LL) quadrants.

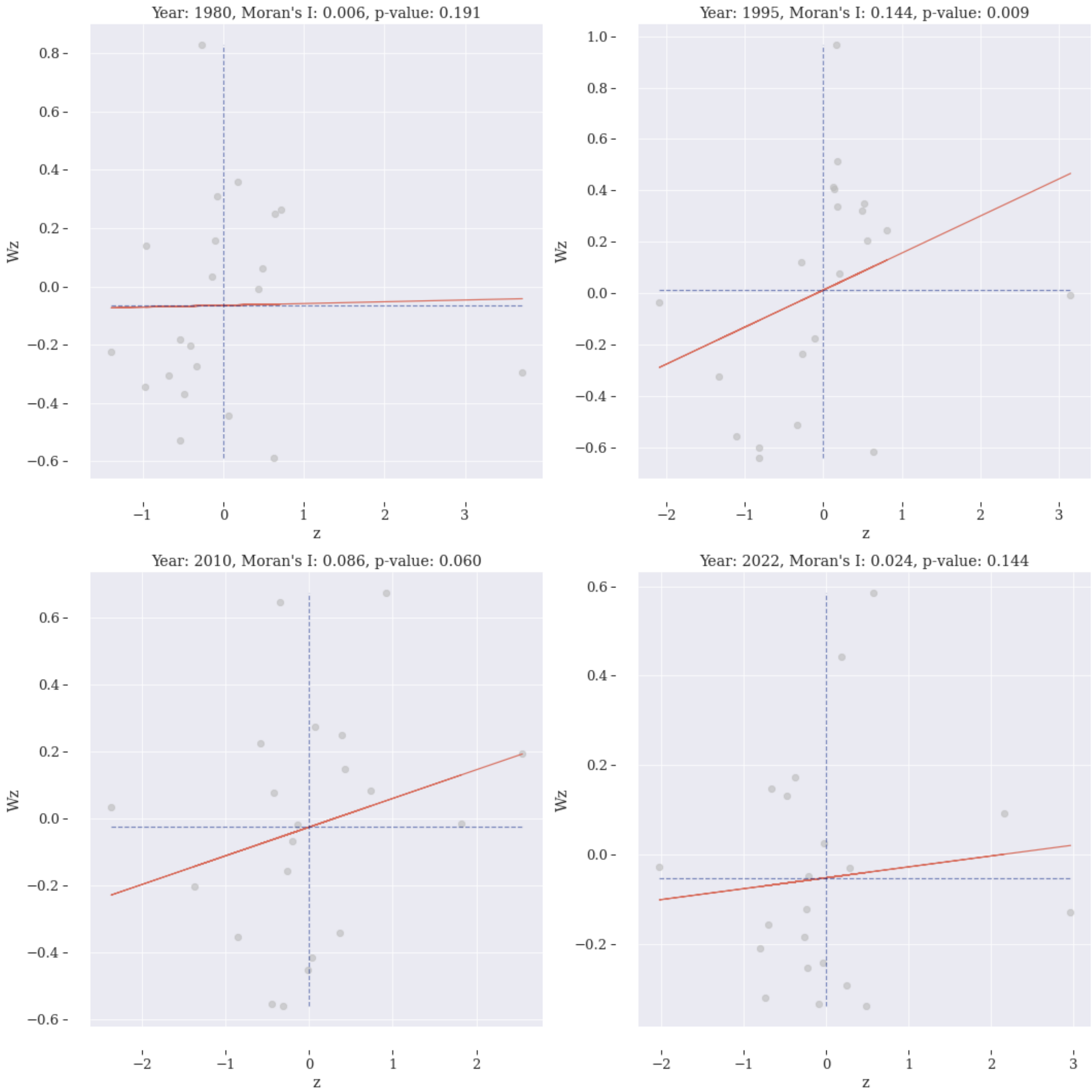

Figure 5.3: Global Moran's I Scatterplot of real GDP per worker in 1980, 1995, 2010 and 2022

Figure 5.4 presents the LISA maps which offer additional insights into the localized clusters. Here, we can see some interesting changes in the distribution. In 1980, large parts of southern Sweden were characterized by LL clusters (i.e. corresponding to the lower-left quadrant in the figures in 5.3), indicating lower-income regions were surrounded by similarly less prosperous regions. Over time, the LL clusters disappear, suggesting overall economic improvement in the south. Västra Götaland's transitions to an HL-cluster, indicating that the region becomes a higher-income region compared to its neighbors. Also, Kalmar's transition to an LL cluster suggests a relative decrease in its economic prosperity compared to its surroundings.

In 1995 there is a significant HH-clustering observed around Stochholm (Uppsala and Södermanland) and parts of northern Sweden. Uppsala's transition from an LH cluster signifies an economic transformation and alignment with its surrounding regions. Uppsala's proximity to Stockholm could suggest benefits from spillover effects and agglomeration economies. As of 2022, there is not much significant local clustering.

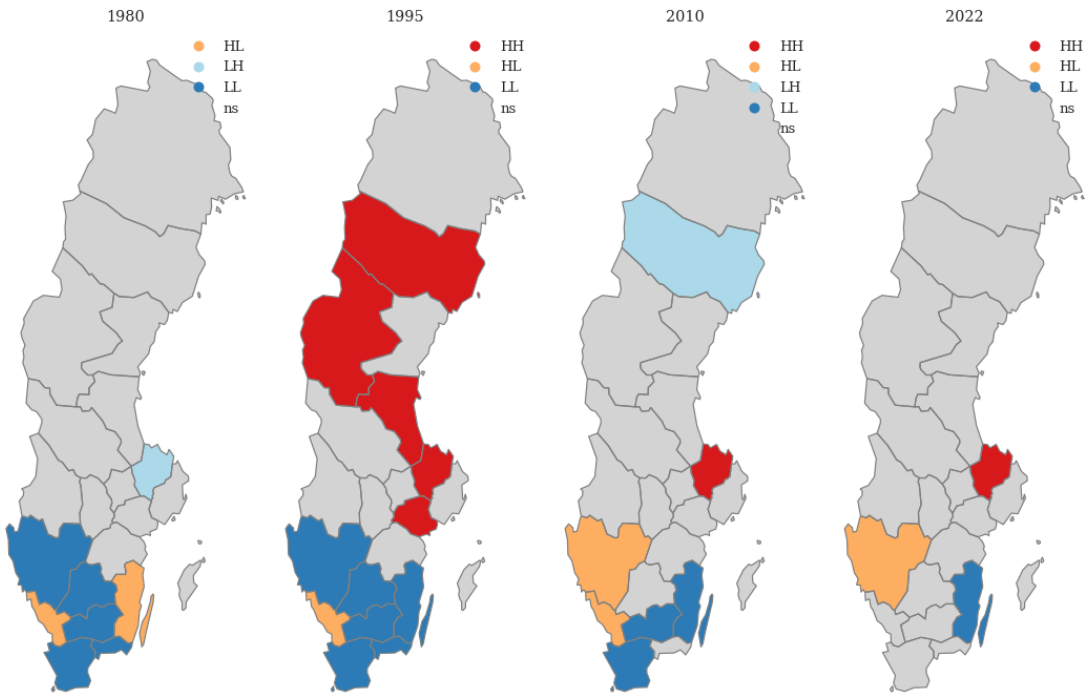

Figure 5.4: LISA cluster maps of real GDP per worker in 1980, 1995, 2010 and 2022

5.1.1 Distribution Dynamics

Next, the kernel density estimates offer insights into the dynamics of the distribution. This allows for exploring how regions move within the distribution over time and whether specific groups of clusters emerge. In Figure 5.5 the univariate kernel density estimates (KDE) of relative per-worker GDP in the years 1980, 1995, 2010, and 2022 are depicted. We can see some significant changes in the distribution.

The general picture is that in 1980, the distribution was the most dispersed with a significant tail and with the highest density to the left of 0, indicating that most regions had a less-than-average per-worker GDP. By 1995 the distribution is more peaked and shifted to the right, indicating a less dispersed per-worker GDP. There is also an emergence of a secondary mode, indicating the development of a bimodal distribution. This could be due to the emergence of a group of regions that have experienced above-average growth rates. By 2010 and 2022, we see a gradually more dispersed pattern and the secondary mode becoming more pronounced.

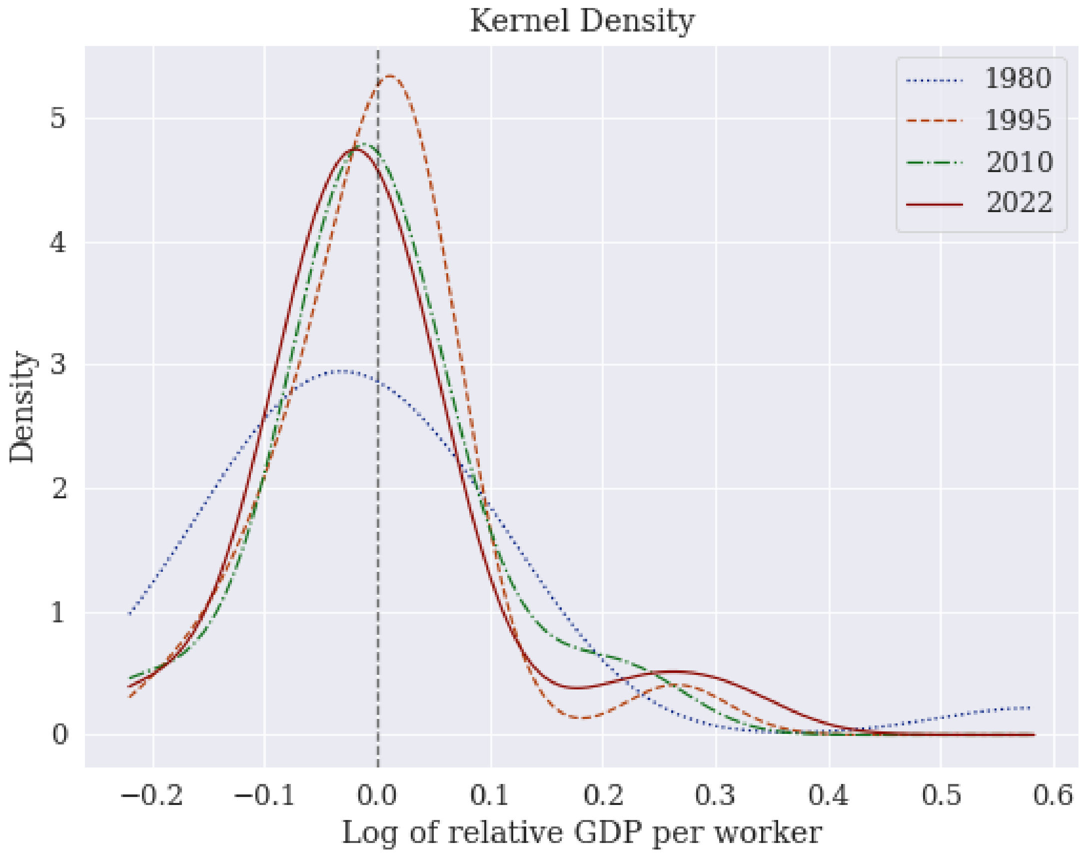

Figure 5.5: Univariate Kernel Density estimate of relative GDP per worker in 1980, 1995, 2010 and 2022

Figure 5.6 below displays a contour plot of the stochastic kernel and shows the relative GDP per worker in two different time frames: between the entire period 1980-2022 (left figure) and 1995-2022 (right figure). The relative per worker in the initial year is on the x-axis and the last year is on the y-axis. The 45-degree line is particularly relevant in the context of convergence. If a region lies above the 45-degree line, it indicates that its relative GDP per worker in 2022 is higher than in 1980, implying divergence of a widening gap. Conversely, if a region is located below the 45-degree diagonal it suggests convergence. A majority of regions lying below could suggest a general trend of convergence and vice versa.

In the left figure (1980-2022), the highest density is mainly above the 45-degree line indicating that a majority of the regions have seen a higher relative GDP per worker in 2022 than in 1980. There are some clear outliers: Stockholm (SE110) is seen to have a relatively high per-worker GDP in 1980 but has not grown as much by 2022. Norrbotten County (SE332) seems to be an upward outlier and Gotland County (SE214) has fallen behind. In the right figure (1995-2022), the density is highest below the diagonal line and less above, which indicates higher growth for a smaller proportion of regions. For the outliers, the trend looks similar, although Stockholm has performed above-average growth. Compared to the entire period from 1980 to 2022, there is a wider distribution along the diagonal. This greater variability in GDP per worker suggests less convergence within this time frame.

These findings might give some intuition as to which regions have driven the increase in intra-regional inequality within the NUTS-1 regions seen in the Theil decomposition in 5.2.

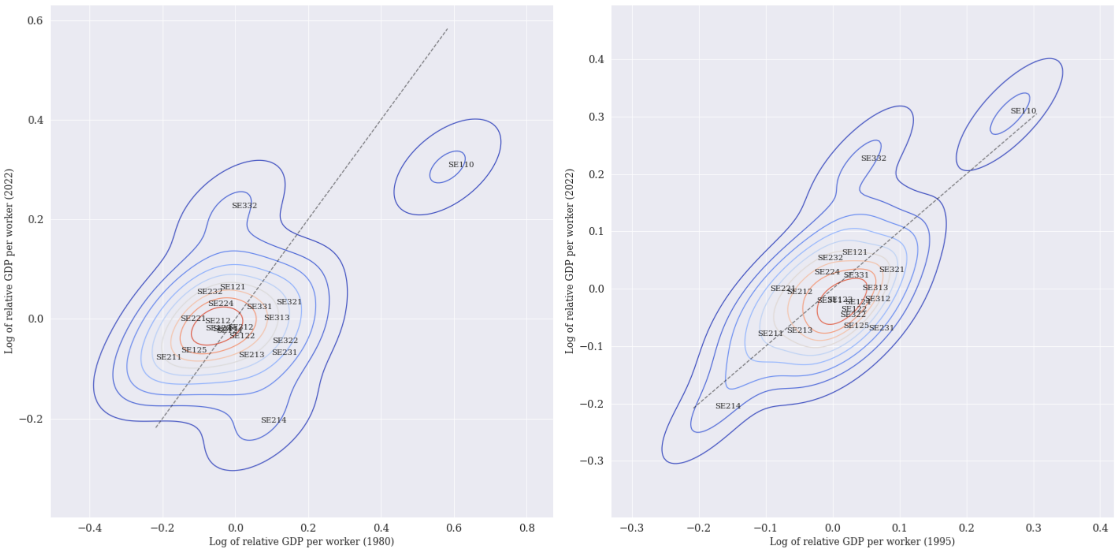

Figure 5.6: Contour Plot of relative per worker GDP, 1980-2022 (left figure) and 1995-2022 (right figure)

5.2 β-convergence

The long-run cross-section estimates are presented in Table 5.1 which highlights the convergence and the role of spatial dependence in shaping regional growth. The preliminary results from the non-spatial OLS model in the first column demonstrate convergence, with a negative significant coefficient for initial GDP per worker in 1980, a convergence speed of around 2.5 % (which aligns well with commonly seen 2% convergence speed (Abreu et al., 2005)), and a half-life of 27.5 years. The value of R^2 indicates that 58% of the variation in annual regional growth can be explained by initial developmental levels in 1980. Furthermore, there is no indication of heteroskedasticity or non-normality as seen in the Breusch-Pagan and Jarque-Bera statistics.

In order to determine the most suitable model specification in the presence of spatial dependence, a set of spatial diagnostics tests is performed on the non-spatial model. These tests follow the commonly used decision rule by Anselin and Florax (1995) and Anselin et al. (1996). The tests include the Lagrange Multiplier (LM) test and their robust versions (R-LM). As discussed in the model specifications of the spatial error (3.7) and the spatial lag (3.8) there can exist nuisance spatial dependence (captured through the error process) and substantive spatial dependence (represented by a spatial lag in the dependent variable). These tests are employed to assess the type of autocorrelation that may be present in the model. The LM test (LMERR) detects the presence of error dependence, while the LMLAG test examines the presence of a spatially lagged dependent variable. Their robust versions (R-LMERR and R-LMLAG) test whether spatial dependence is robust against the other type of dependence.

Table 5.1: β-cross-section estimates, OLS, SLM and SEM 1980-2022

	OLS (Distance)	OLS (Queen)	SLM (Queen)	SEM (Queen)
Constant	0.0767***		0.0712***	0.0773***
	(0.0115)		(0.0101)	(0.0111)
Log GDPpw in 1980	-0.0156***		-0.0153***	-0.0158***
	(0.0031)		(0.0026)	(0.0029)
Convergence Speed (%)	2.55		2.45	2.58
Half-Life (years)	27.5		28.6	27.2
Lambda (λ)				-0.0812
				(0.3091)
Rho (ρ)			0.2554***	
			(0.0933)	
Observations	21	21	21	21
R^2/Pseudo R^2	0.5800		0.6876	0.5792
AIC	-195.564		-198.716	-194.856
Moran's I	0.404	0.234		
LMLAG	0.347	4.906**		
R-LMLAG	0.542	5.871**		
LMERR	0.029	0.017		
R-LMERR	0.224	0.981		
Likelihood Ratio			2.9181*	0.5124

Note: *p<0.1; **p<0.05; ***p<0.01

The spatial diagnostics yielded some interesting results. When the distance-based spatial weight matrix was used on the non-spatial OLS model, the spatial diagnostics test did not indicate any significant spatial autocorrelation. However, when testing different weight matrices, the Queen contiguity spatial weight matrix gave different results [5] where the diagnostics on the OLS model showed significant substantive spatial dependence indicated by the LMLAG and R-LMLAG statistics. Similarly to the distance-based, the SEM does not reveal any significant spatial autocorrelation.

The SLM based on the Queen contiguity matrix is presented in the column and the SEM is presented in column 4 for comparison. [6] First, in terms of convergence, the spatial models suggest a similar convergence speed to the OLS specification with the SLM suggesting slightly lower (2.45%) and the SEM slightly higher (2.58%). The

[5] The k-nearest neighbor matrix was also tested for different values of k but the results were insignificant.

[6] The SEM and SLM based on the distance-matrix is not presented due to the insignificant spatial diagnostics. However, the results did not have vastly different results in terms of convergence. Also, the second column is blank because they are identical to column one except for the spatial diagnostic tests.

spatial coefficient in the SLM (ρ) suggests a positive substantive dependence while the SEM shows a (negative) non-significant nuisance dependence. The Akaike information criterion (AIC) is lower for the SLM than both the OLS- and SEM specification, indicating a better fit. [7] Lastly, the likelihood ratio compares the fit of spatial models to the non-spatial OLS model by evaluating the improvement achieved when adding the spatial coefficients. Although the likelihood ratio is only significant at the $P < 10\%$ level for the SLM model compared to the OLS specification, the overall evidence suggests that the SLM is arguably the preferred specification.

It is important to note the different implications between the distance-based weight matrix and the Queen Contiguity weight matrix: it suggests that the spatial structure of the relationship might be influenced by a contiguity defined by shared borders rather than a distance-based decay. This would imply that growth tends to be more localized and concentrated around direct neighboring regions and is not necessarily linked to pure geographical distance. Furthermore, the significant spatial lag dependence suggests that regions are influenced by the growth of their neighbors, which might imply the existence of spatial spillover effects playing an important role in regional growth dynamics. Note however that Gotland is treated as a separate unit since it has no borders.

In the next Table 5.2 the different time periods are presented: 1980-94, 1995-2008, 2009-22. When looking at the OLS estimates in the first column it is evident that the period of 1980-94 is the main driver of the convergence pattern seen in 5.1 with a negative significant coefficient for initial GDP per worker in 1980, a convergence speed of around 7.3 %, and a half-life of only 10 years. The value of R^2 indicates that 75% of the variation in annual regional growth between 1980-94 can be explained by initial developmental levels in 1980. When looking at the other two subsequent periods the patterns are very different. Between 1995-2008 shown in column 2, there is no significant coefficient for initial GDP per worker (initial GDP 1995) and with very low explanatory power (8.8%). The last period between 2009-2022 (column 3) is even showing a (non-significant) divergence pattern, with no explanatory power (0%).

The spatial diagnostics of LMLAG and R-LMLAG indicate the presence of substantive spatial dependence in the first period of 1980-94 using the Queen contiguity matrix. [8] The fourth column shows how there is positive significant spatial dependence (ρ) and that the convergence is slightly lower (7%). The AIC indicates a better fit than the OLS, but the likelihood ratio is only significant at $p < 10\%$.

Interestingly, the spatial diagnostics for the second period during 1995-2008 also indicate substantive spatial dependence, although at somewhat lower significance. Also here the AIC indicates a better fit and the likelihood ratio is significant at $p < 5\%$. Altogether, this supports the SLM as a better-specified model than the OLS for the period of 1995-2008. In the last period, no significant spatial dependence is observed, regardless of the choice of the spatial weight matrix.

[7] The AIC is a preferred tool for model comparison as it, unlike R^2 balances the model's fit with its complexity (numbers of parameters), which is useful when comparing OLS and ML (Anselin et al., 1996).

[8] For the distance-based matrix as well as for the k-nearest neighbor matrices, the results were insignificant and therefore not presented here.

Table 5.2: β-cross-section estimates, OLS and SLM in subperiods 1980-1994, 1995-2008, 2009-2022

		Non-spatial (Queen)			SLM (Queen)	
	1980-1994	1995-2008	2009-2022	1980-1994	1995-2008	2009-2022
	OLS	OLS	OLS	ML	ML	ML
Constant	0.194***	0.095*	0.008	0.1817***	0.1219***	-0.0016
	(0.022)	(0.053)	(0.038)	(0.017)	(0.0473)	(0.0381)
Log of initial GDPpw	-0.046***	-0.017	0.0006	-0.0418***	-0.0258**	0.0034
	(0.006)	(0.013)	(0.009)	(0.004)	(0.012)	(0.009)
Annual Convergence Speed (%)	7.26	1.98	-0.06	7.06	3.15	-0.33
Half-Life (years)	9.9	35.3	-1174.7	10.16	22.4	-208.1
Rho (ρ)				0.4408***	0.3414**	-0.2564
				(0.0953)	(0.1529)	(0.2486)
Observations	21	21	21	21	21	21
R^2/Pseudo-R^2	0.757	0.088	0.000	0.8707	0.2694	0.0644
AIC	-167.793	-161.226	-173.838	-177.136	-162.180	-172.239
Moran's I						
LMLAG	8.583***	3.774**				
R-LMLAG	9.170***	4.282**				
LMERR						
R-LMERR						
Likelihood Ratio				3.6123*	9.6576**	0.4011

Note: *p<0.1; **p<0.05; ***p<0.01

6

Conclusion

The aim of this thesis has been first to explore and expand upon existing research concerning regional inequality and the convergence process in Sweden. This has been done by employing an up-to-date dataset of GDP per worker, to investigate convergence in terms of labor productivity between 1980-2022. Secondly, and most importantly, the role of spatial effects on this development has been thoroughly examined. The role of spatial dependence in both β- and σ-convergence has been assessed with commonly applied techniques within the field of spatial econometrics and convergence: exploratory spatial data analysis and spatial econometric methods.

There are two contrasting views within the theoretical framework. The neoclassical growth theories have led to the prediction of convergence that poorer regions should grow faster than richer ones, leading to a "catch-up" process. In contrast, endogenous growth theory does not rely on the same assumptions of diminishing returns to scale as the neoclassical model, thus convergence does not necessarily need to occur. In the NEG framework, there might even be a divergence pattern depending on the nature of spatial spillovers. If localized spillover effects can concentrate economic activities and growth in particular regions, driven by agglomeration benefits, this could then lead to the emergence of a "high-income core" and a "low-income periphery". Consequently, rather than witnessing an equalization of income levels, we may observe persistent or even increasing regional inequality.

The main findings of this thesis have been the following. First, the distributional analysis demonstrated the existence of a general σ- convergence, although with a clear upwards trend during the later years which today is larger than in 1985. The rising intra-regional ("within-region") inequality seems to be the dominant source for the upwards trend (in contrast to what Artelaris (2021) found in Greece). The stochastic kernels affirm the notion of σ- convergence but also point to an emergence of a bimodal distribution taking place in later periods. This could be related to the increased intra-regional inequality seen and is indicative of the possibility of "convergence clubs".

Second, the ESDA revealed some significant spatial autocorrelation, mainly in the 1990s and 2000s. In contrast to previous findings (Rey and Janikas, 2005; Royuela and García, 2015; Artelaris, 2021), this did not seem to be positively correlated to moves in σ-convergence, giving no reason to expect that spatial clustering is associated with rising inequality, if anything the opposite seems to be the case. Moreover, the LISA maps showed that there were some tendencies of localized spatial autocorrelation, especially in the form of persistent "cold spots" in southern Sweden early on and some small indication of "hot spots" concentrated around Stockholm.

Lastly, β- convergence was found during the overall period, but when dividing the entire period into sub-periods to allow for variations in the temporal dynamics and consider cyclical effects, different patterns emerged. The overall convergence was mainly due to strong convergence in the period of 1980-94 while 1995-2008 showed slow convergence and 2009-2022 showed divergence (or at least no convergence). The regressions based on the distance-based weight matrix showed no indication of spatial dependence in the convergence process. However, when using a Queen contiguity matrix, the spatial lag model indicated that the convergence process seems to be associated with the presence of spatial dependence. This suggests that the economic performance in one region has been influenced by its neighbor's economic performance. The nature of the spatial interactions, therefore, seems to be due to the connectivity of regions rather than due to physical distance.

This could imply that spillover effects are driven by mechanisms driven by the direct connectivity and interactions between regions. Such mechanisms could include factors such as cross-border trade, shared infrastructure, or joint development projects.

How can we explain these findings of an overall convergence during the period, strong convergence in the period of 1980-94, slow convergence in 1995-2008, and divergence (or at least no convergence) in 2009-2022? The notion of overall convergence in terms of β- and σ- convergence in Sweden during this time is not supported in previous literature. Although there is no study specifically on this entire time period, Enflo and Rosés (2015); Enflo et al. (2018) showed that the divergence started in 1980 and Gustavsson and Persson (2003) showed that there was no strong absolute β-convergence in the 1980s.

One potential explanation for this is the usage of per-worker GDP rather than per capita. A divergence in terms of per capita income but convergence in terms of labor productivity could be due to differences in capital intensity where some regions might have more capital per worker, allowing them to produce more output with the same level of labor productivity. It could also be due to demographic differences where regions with a larger non-working population will have lower GDP per capita but could still have high labor productivity. This is not an impossibility, as, for example, Norrbotten County which we have seen has performed above-average growth in terms of labor productivity (see the contour plot in chapter 5), has had a negative population growth between 1994-2011 but have simultaneously seen significant growth in employment between 2000-2011 (Ejdemo et al., 2014)

Another explanation is that there seems to be an anomaly taking place between 1984-85 where there is a sudden drop in the dispersion in per worker GDP (see Figure 5.1). This might be due to problems in the data provided by ARDECO. However, due to the credibility of the European Commission as an institution for reliable data and to avoid cherry-picking the data, the choice has been to proceed with the entire time period and analyze it at face value. In an attempt to circumvent the potential effect of the anomalies in the early period of the data, the thesis has a focus on studying different sub-periods and providing information on the development during later periods as well.

Nonetheless, the first period of 1980-94 could possibly give an indication of a neoclassical catch-up process but with significant positive substantive spatial autocorrelation, suggesting that neighboring regions exhibited similar growth patterns. Through the theoretical lens of endogenous growth and NEG, this could indicate that technological knowledge through spatial interactions and spillover effects has spread globally during this time and that there is no trade-off between regional equity and overall economic growth taking place.

During the second period of 1995-08, convergence slowed down compared to the previous period. However, when accounting for positive substantive spatial autocorrelation, the convergence becomes more apparent. This is particularly interesting, as this highlights the importance of considering spatial dependencies when analyzing regional convergence, which otherwise would be ”hidden” in a misspecified OLS model. However, the slower convergence does suggest that development levels are worse at explaining subsequent growth, which does give an indication that there could be other factors at play such as effects from the economic shock of 1990-94, globalization, or the radical economic and policy changes taking place at the time, such as liberalization, deregulation, and EU membership.

The last period in 2009-2022 exhibits a pattern of divergence, or at least a notable lack of convergence. This notion is in line with later reports from the OECD (André et al., 2021; OECD, 2022), and Enflo and Henning (2020) findings of increased dispersion between Swedish regions in terms of per capita GDP since the early 2000s. The presence of this non-convergence pattern challenges the neoclassical theory of absolute convergence, but the endogenous growth/NEG framework may also face limitations in explaining this trend. The fact that spatial dependence seems to be inversely related to regional dispersion, especially after 2009, and no significant indications of spatial dependence of local nature were observed, there is no indication of the core-periphery pattern. However, it is important to note that this observation serves as preliminary evidence rather than a formal test of this pattern. This later divergence trend might instead be due to structural factors as suggested by Enflo and Rosés (2015) where changes in economic structure, industry composition, or specialization patterns across regions could be the main cause for divergence unrelated to spatial factors. Similarly, as in the period before, the crisis of 2008-09 might also have played a part in shaping the regional growth patterns.

Lastly, it is plausible that the decline in spatial clustering and divergence in incomes between regions is influenced by external factors such as globalization and trade liberalization. The increased economic integration and globalized supply chains could have led to the dispersion of economic activities and a reduction in industry concentration and income among regions in Sweden. This would suggest that while NEG models may not explain the Swedish experience at the national level, they may provide insights when considering the global context.

6.1 Policy Implications and Future Research

In light of these findings, the slowdown of convergence and the presence of divergence trends could pose a challenge for policymakers. The finding of decreased spatial dependence in the growth process might suggest that policymakers do not necessarily need to focus on the geographical location of regions, but it might be more fruitful for Swedish policymakers to investigate the role of factors such as structural factors of industry shifts, changes in economic structure or the effect of crises. However, with this said, that does not mean that geography and spatial dependence should be discarded. As seen during previous periods, spatial factors are seen to have played an important part in the convergence process and might do in the future. Furthermore, if the decrease is due to global factors such as the integration within the EU, the question might rather be a question for policymakers in the EU.

Regarding future research, the natural extension of this thesis is to investigate the conditional convergence to see if regions converge to different steady-states which is determined by region-specific factors, where spatial effects might be more pronounced. This could be done by adding explanatory variables such as human capital or industrial composition, or through the use of panel data techniques. In the analysis of the non-parametric approach, the stochastic kernels revealed an emerging bimodality in the distribution which could represent different convergence clubs. These clubs might potentially be composed of regions with similar structural characteristics, implying a convergence to unique steady-states.

Also, studying regions at the NUTS-3 level has the disadvantage of possibly masking economic activity by administrative boundaries (see discussion of the MAUP in chapter 4) at a higher degree of granularity where spatial dependence might be much more pronounced. The economic development of Sweden's larger urban areas and University cities have been subject to spatial spillovers and agglomeration in a way that larger regions have not. This could also reveal further insights into the rural-urban gap. Studying administrative units such as municipalities would therefore be a logical progression for future research.

As a concluding remark, it is important to emphasize that even though there is a significant trend in rising dispersion between Swedish regions since the 80s, Sweden can still be considered a regionally equal country by international standards. As summarized by Enflo and Henning (2020), one might pose the question: are growing regional disparities during times of economic growth and transformation an issue or merely a natural consequence of the economic transformation process, self-correcting through market forces and equalization effects? Nevertheless, even if market forces and equalization effects can correct these disparities, the transition period can be lengthy and fraught with challenges

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Appendix A

Spatial Weight Matrices

The distance-based spatial weight matrix is constructed based on the geographical distance [1] between observations, taking into consideration both the distance decay effect and a distance threshold. Each entry in a distance matrix D, denoted as $d_{i,j}$ represents the spatial Euclidean distance between observation i and observation j. Each of these distances is then transformed using a Gaussian distance decay function. The weight $w_{i,j}$ between two observations i and j is given by:

$$w_{ij} = d_{ij}^{-\alpha} \tag{A.1}$$

where α is a distance decay parameter set equal to $\alpha = -2$. This results in weights that decrease as the distance between observations increases. A threshold is applied to ensure that only "local" effects are considered: any pair of observations i and j where $d_{i,j}$ exceeds this threshold are given a weight of zero. In addition, the weights matrix is row-standardized as $w_{ij} = \frac{w_{i,j}}{\sum_j w_{i,j}}$. This is a common approach in order to ensure that it is the relative and not the absolute distance that matters and ensures that all weights are between 0 and 1(Anselin, 1988). In sum, we can define the distance-based weight matrix as (not row-standardized):

$$W = \begin{cases} w_{i,j} = 0 & \text{if} \quad i = j \\ w_{i,j} = d_{ij}^{-2} & \text{if} \quad d_{i,j} \leq T \\ w_{i,j} = 0 & \text{if} \quad d_{i,j} > T \end{cases} \tag{A.2}$$

where T is the threshold distance which determines the maximum distance at which two observations are considered to have a spatial relationship. It is set to the minimum threshold distance from a shapefile provided by Eurostat (Eurostat, Accessed 2023) based on the function min_threshold_dist_from_shapefile in the module libpysal.weights. This function gets the maximum nearest neighbor distance between observations in the shapefile. Distance is based on polygon centroids [2]and is defined using coordinates in shapefile which are assumed to be projected and not geographical coordinates. In other words, the center point of each polygon is used

[1]There are other ways to define distance such as 'institutional' or 'socio-economic' distances which take factors beyond geography into account (Arbia et al., 2010). However, the advantage of using purely geographical-based measures is that they are strictly exogenous (Anselin and Bera, 1998).

[2]A polygon is a two-dimensional geometric shape representing a specific area or region. The centroid of this polygon is its geometric center, often used as a representative single point for the spatial feature the polygon represents.

to represent its location, and distances are measured in the projected coordinate system of the shape file. See the right figure in figure A.1 for a visual representation.
The Queen contiguity matrix has a simpler expression (not row-standardized):

$$W_{=}\begin{cases} w_{i,j} = 1 & \text{if} \quad i \neq j \quad \text{and} \quad i \quad \text{and} \quad j \quad \text{are neighbors} \\ w_{i,j} = 0 & \text{otherwise} \end{cases} \tag{A.3}$$

Where "neighbors" are defined as observations that share either a common border (edge) or a vertex (corner), according to the Queen contiguity rule, which states the regions are considered adjacent and thus "neighbors" if they touch at any point, including corners (see figure A.1).

Figure A.1: Spatial Weights Maps: Distance-based (left) and Queen-based (right)

Appendix B

Spatial Model Specifications

In conventional β- convergence models, the assumption is that the error terms between spatial units (e.g. regions) are independent as:

$$E[\epsilon_t \epsilon_t'] \tag{B.1}$$

However, Rey and Montouri (1999) explains that when dealing with spatially organized units, this assumption may be overly restrictive where spatial spillovers across unit boundaries can create spatial dependence, thus violating the independence assumption. Instead, when the dependence works through the error process from different spatial units he suggests that the error terms would be expressed as (in vector notation):

$$\begin{aligned} \epsilon_t &= \lambda W \epsilon_t + u_t, \\ \epsilon_t &= (I - \lambda W)^{-1} u_t. \end{aligned} \tag{B.2}$$

where ρ is a scalar spatial error coefficient, W represents spatial weights, and $u_t \sim N(0, \sigma^2 I)$. The error term would then display spatial covariance, resulting in a non-spherical covariance matrix:

$$E[\epsilon_t \epsilon_t'] = (I - \lambda W)^{-1} \sigma^2 I (I - \lambda W)^{-1} \tag{B.3}$$

Thus, inferences based on the OLS estimates will be inefficient in this spatial error model. Maximum likelihood (ML) or a general method of moments (GMM) estimation has instead been recommended (Anselin, 1988). Substituting B.2 into the absolute convergence equation in 3.1 will result in the spatial error model in equation 3.7.

The way that substantive spatial dependence can be accounted for is by including a spatially lagged dependent variable (in matrix form) (Anselin, 1988):

$$\begin{aligned} y &= X\beta + \rho W y + \epsilon \\ y(I - \rho W) &= X\beta + (I - \rho W)^{-1} u \\ y &= (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} u \end{aligned} \tag{B.4}$$

The absolute convergence model specified with a spatial lag in 3.8 will thus suffer from endogeneity in the form of simultaneity through the spatial lag if estimated with OLS (Rey and Montouri, 1999) and have therefore also been suggested to be estimated by ML or instrumental variables estimation (GIV) (Anselin, 1988).