Spatial Dynamics of Income Inequality in Austria

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Income inequality is generally assessed by using a number of different methods that often neglect the impact of location on the results. The use of spatial methods to shed light on regional income inequality has been applied on a small set of countries, mostly due to the problem of data availability. Using a tax dataset of all Austrian wage earners including geographic information, we analyze spatial dynamics of income inequality in Austria. We obtain results for spatial dependence on different geographical levels. Using this information we investigate clusters of high income earners and the distribution of income and inequality regarding regional units.

Keywords: Regional inequality, spatial dependence, spatial autoregressive model
JEL Classifications: C21, D31, J31

1. Introduction

Income inequality has recently been the subject of a great deal of attention in economic research. Particularly since the outburst of the massive economic eruptions in 2008 the unequal distribution of income has been a popular explanation for the intensity of the crisis. Numerous books and articles have been published using the familiar measures of inequality to assess the dimension of income disparities (Galbraith, 2012; Stiglitz, 2012). The computation of conventional measures and the descriptive illustration of inequality have the advantage of intuitive comprehension and simple comparability of the results. However, one important property of the subject is being ignored: the geographic location of inequality and possible spill–over effects (Goodchild and Janelle, 2004, p. 3). While the application of spatial methods has a long tradition in urban and land use planning, economists have been recognizing the applicability of spatial methods in their discipline only recently. The growing number of studies with a spatial perspective shows evidence of a paradigm shift towards thinking spatially in economics.

Studies on income inequality in Austria have been scarce compared to the state of research in other countries, especially due to the lack of useful longterm datasets (Berka, Moser, Humer, and Altzinger, 2011; Atkinson, 2008). The two major administrative sources for the measurement of inequality in Austria are social security data and tax data. The first dataset is top–coded at the upper earnings ceiling which is a decisive limitation for inequality analyses. The income data in the administrative records of the Austrian tax register is unfortunately partitioned in three different statistics. In consequence of these

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limitations, there has been only a small number of studies on the longterm development of income inequality in Austria (Christl, 1980; Chaloupek, 1981; Guger and Marterbauer, 2005; Berka, Moser, Humer, and Altzinger, 2011). Some important insights into the mechanics of inequality remained still unrevealed, like the spatial dynamics of inequality. With the present contribution, we aim to narrow the research gap.

2. Existing Evidence

Income inequality and spatial segregation are mainly linked through the housing system, where higher income groups may outbid lower income groups in the competition for better neighborhoods. This may lead to “feedback effects”, since richer families might produce positive neighborhood externalities and the relative price of high-income neighborhoods increases (Bailey et al., 2013; Watson, 2009). The increasing spatial segregation along with rising income disparities is held to be accountable for worsening social cohesion and limits the success of policies promoting redistribution. Bailey et al. (2013) argue that if growing segregation undermines the bonds of solidarity between rich and poor, support for redistributive policies weakens which further fuels rising inequality. A theoretical explanation for this vicious circle is given by the relative deprivation hypothesis. Accordingly, attitudes are not based on knowledge about the absolute economic position but rather on a comparison with a reference group or the immediate social network. Hence, the neighborhood context shapes attitudes in addition to individual opinions (social contagion). More affluent people are already less likely to support redistribution, however, spatial segregation fortifies these attitudes via the relative deprivation hypothesis.

While residential patterns are empirically evident, the theoretical foundation of spatial segregation between city centers and suburbs is ambiguous. Since there is (at least for the U.S.) empirical evidence of relative suburbanization of the rich, the theoretical justification is the high income elasticity of the demand for land (Watson, 2009, p. 823). However, given that housing close to city centers implies lower commuting costs and the rich have higher opportunity costs for commuting time, living in the city center should be more desirable for affluent individuals.

Another rationale for the exploration of spatial relationships is given by Galbraith (2012, p. 41). He shows that there may be only a few subnational geographical units contributing to the overall development of inequality. For instance, only fifteen of more than 3,000 counties accounted for all of the rise in income inequality measured from 1994 to 2000 in the United States. Thus, if they had been removed from the dataset the rise in overall inequality would not have occurred at all. Out of the 15, only five counties contributed about half of the rise in total inequality in the late 1990s. The five counties are Santa Clara, San Francisco, and San Mateo in California associated with Silicon Valley; King County, Washington, home to Microsoft; and New York, the financial capital of the country. These figures impressively certify the importance of a spatial decomposition of inequality measures in order to correctly assess the actual scope of income inequality.

In general, Shorrocks and Wan (2005, p. 59) suggest the application of spatial methods
especially where “income inequality has been rising over time and where average incomes vary considerably across regions or provinces.” Empirical regression models most often contain regional dummies to account for the significance of location for income inequality, however, less attention is paid to the quantitative influence of spatial factors on income inequality. Shorrocks and Wan carry out a spatial decomposition of inequality measures into a between–group and a within–group component which is the standard procedure (see also Bourguignon, 1979; Shorrocks, 1980; Cowell, 1980; Lambert and Aronson, 1993). The intuitive explanation for the between–group component is the amount of inequality that is observed if all individuals in a certain area would earn the regional mean income. In most studies on regional income inequality, special attention is paid to the between–regions component, expressed as a proportion of overall inequality (Novotný, 2007, p. 565).

While, to the best knowledge of the authors, there is no analysis of spatial income inequality for the case of Austria and only a few articles on the European Union. Hoffmeister (2009) analyzes spatial patterns in EU income inequality between 1995 and 2000 with data from the Luxembourg Income Study (LIS) for roughly 230,000 households in 18 countries. The results reveal that the degree of income inequality converged on all geographic levels in the period under investigation. The convergence takes place between Member States of the EU–15 and the ten new Member States as well as between individuals within the Member States. The convergence of within–country inequality is explained by increasing inequality in the social–democratic welfare states of Scandinavia, accompanied by a decline in the Mediterranean countries. In the years 1999/2000, almost a quarter of the personal income inequality in the EU–25 could be ascribed to inequality between regions. The remaining three quarters were caused by within–country income disparities and reflects different social policies of local governments.

Hoffmeister also included Austria into the analysis. By means of the mean logarithmic deviation (MLD), the income inequality for three NUTS1 regions (i.e. Southern, Western and Eastern Austria) was calculated and decomposed. The within–region component accounts for 99.3% of total inequality, while the between–region component only causes 0.7% which is the smallest value in the whole sample. Hence, obviously the differences in inequality between regions are negligible in Austria. The highest inequality measure in Austria is displayed in Eastern Austria which incorporates the capital city Vienna. The scholar finds that regions including larger urban agglomeration show the highest levels of personal inequality (e.g. Hamburg and Berlin in Germany, London in the United Kingdom).

Another European study is conducted by Ezcurra, Pascual, and Rapún (2007). The scholars detect spatial non–stationarity by exploiting the European Community Household Panel (ECHP) for the years 1993 to 2000 on a NUTS1 level. Ezcurra, Pascual, and Rapún attest a positive spatial relationship of income inequality between adjacent areas, i.e. the spatial autocorrelation measures display a similar degree of income dispersion in neighbouring regions. The most egalitarian income distributions are found in the Scandinavian countries, Germany, Austria and Northern Italy. High degrees of income dispersion, on the contrary, are located in Southern Europe (Portugal, Spain, Greece) and in countries identified with the liberal welfare state (United Kingdom and Ireland).
These results are conform with Beblo and Knaus (2001), besides, in their study differences between countries only account for roughly 10% of total Euroland income inequality.

3. Data and Methods

3.1. Wage tax data

The subject matter of this article is income inequality in Austria and its spatial dynamics. Thus, at least regional per-capita income over a certain time period would be required. We are able to analyze a full dataset of the Austrian wage tax statistics for the years 1996 to 2010 with more than six million observations each year. Moreover, the place of residence as well as the place of work are available along with some socioeconomic characteristics like sex and age.

One problem of wage tax data for the analysis of income inequality is evident. Wage is only one income component neglecting all other types of income inequality, however, wages account for roughly 70% of the national income. One additional aspect to consider is the possibility of (legal) ways of tax avoidance as well as (illegal) fiscal evasion which are more present at higher incomes and could therefore potentially lead to an underestimation of inequality (see Berka, Moser, Humer, and Altzinger, 2011, p. 520). A decisive advantage of tax data (compared to social security data, for instance) is that the income information is not truncated at the tails of the distribution. The Austrian wage tax statistics provides detailed information on the gross wages of employees. However, if an employee derives additional income from self-employed activities, these earnings are not comprised in the wage tax data.

In general, the application of spatial methods on a certain geographical scale is determined by the degree of data aggregation. For instance, the availability of per-capita income data on a county level would limit the spatial analysis to this scale. Since we have individual data for every employed individual in Austria including the place of residence, we are able to choose any desirable spatial scale. In this paper, we derive spatial inequality measures on a municipality level. It is worth noting, however, that the spatial scale may influence the degree of inequality between the regional units (Novotný, 2007, p. 566).

3.2. Regional inequality measurement

Amongst a variety of inequality measures, the most popular gauge for regional income inequality is the Theil index which belongs to the family of the general entropy indices (Theil, 1967). The rationale for preferring Theil’s T statistic to other measures is the possibility to additively decompose inequality into subgroup components, provided that the groups are mutually exclusive and completely exhaustive (MECE). Particularly for data with a certain degree of aggregation or any underlying hierarchy (e.g. municipalities within regions within states), this measure is the appropriate choice for the assessment
of inequality (Conceicao, Galbraith, and Bradford, 2001; Cowell, 1980; Shorrocks, 1980). The Theil index is given as

\[ T_T = \frac{1}{n} \sum_{i=1}^{n} \frac{y_i}{\mu_Y} \cdot \log \left( \frac{y_i}{\mu_Y} \right) \]  

(1)

where \( n \) is the number of individuals, \( y_i \) is the income of person \( i \) and \( \mu_Y \) is the average income of the total population. The lower bound of Theil’s \( T \) is 0 which indicates perfect equality. A Theil index of 1 implies that the distribution of the underlying system is around 82:18 (which is slightly more unequal than Pareto’s famous 80:20-principle and means that 82% of the resources belong to 18% of the population and vice versa). If \( m \) are the MECE regional aggregations, \( Y = \sum_{i=1}^{m} Y_i \) is the total income of the population and \( Y_i \) is the total income in group \( i \), the equation can be rewritten as

\[ T_T = \sum_{i=1}^{m} \frac{Y_i}{Y} \cdot \log \left[ \frac{Y_i}{Y} / \left( \frac{1}{m} \right) \right] \]  

(2)

The interpretation of Theil’s \( T \) is a comparison between a group’s share of population and its share of income. If a group’s share of income equals its share of the population this would not contribute to inequality. If every group has exactly the income corresponding to its population size, the Theil index is \( \log(1) = 0 \) and indicates perfect equality. The lower boundary of \( T \) is zero, whereas the upper boundary, i.e. all income is concentrated in one region, is \( \log(m) \) (Novotný, 2007).

The application of the Theil index on regional income inequality requires the decomposition of the index. The additive decomposition of the measure into a between-group (\( T_B \)) and a within-group (\( T_W \)) component denotes

\[ T_T = \sum_{i=1}^{m} \frac{Y_i}{Y} \cdot \log \left[ \frac{Y_i}{Y} / \left( \frac{n_i}{n} \right) \right] + \sum_{i=1}^{m} \frac{Y_i}{Y} \cdot \sum_{g \in i} \psi_{ig} \]  

(3)

with

\[ \psi_{ig} = \frac{y_{ig}}{Y_i} \cdot \log \left( \frac{y_{ig}}{Y_i} / \left( \frac{1}{n_i} \right) \right) \]  

(4)

Note that the index \( i \) in the between-group component \( T_B \) refers to the group and \( n_i \) labels the number of observations in that aggregate. The index \( g \) in the within-group component \( T_W \) displays the next lower aggregate in the hierarchy (e.g. individuals within a municipality, cities within a region) and counts all group members from 1 to \( n_i \). \( T_W \) is a weighted average of the Theil indices for each group, where only the inequality between
members of a certain group is taken into account. In a spatial framework, $T_W$ is associated with intraregional inequality, whereas $T_B$ is considered to be interregional inequality.

As stated above, Theil’s T is not bounded between 0 and 1 like most common inequality indices which complicates the comparability of different values. Hence, a simple transformation results in the Atkinson index, denoting

$$A(\varepsilon = 1) = 1 - \exp(-T_T).$$

Since the Atkinson index ranges between 0 and 1 the transformation can be called a normalization of Theil’s T (under the assumption of log-normality of the income distribution). We use the standardized Theil’s T for interregional comparisons, while the inequality decomposition is based on the common Theil index.

### 3.3. Spatial dependence

There are mainly two statistical instruments to detect the existence of spatial autocorrelation of inequality: Moran’s I and Geary’s C, which are inversely related to each other. Moran (1950, p. 21) derived a measure of spatial autocorrelation in a two dimensional scheme which denotes

$$I = \left( \frac{n}{\sum_i \sum_j w_{ij}} \right) \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

where $n$ is the number of spatial objects, $w_{ij}$ is an element of a spatial contiguity matrix\(^1\), $y_i$ is the average income in region $i$ and $\bar{y}$ is the overall average income. Moran’s I is bounded by the interval $[-1,1]$, where $-1$ indicates perfect dispersion, 1 means perfect correlation and 0 shows a random spatial pattern. Inference for Moran’s I is calculated by subtracting the expected value and dividing by the standard error. Since Moran’s I is a global indicator and assumes homogeneity across the spatial sample, local measures are more useful to reveal spatial non-stationarity. Anselin’s (1995) local indicators of spatial association (LISAs), like the local Moran’s $I$ or the Getis-Ord $G$ (Ord and Getis, 1995) provide information on regional clustering (“hot” or “cold spots”). Local Moran’s $I$ measures the product of the deviations from the arithmetic mean in region $i$ and the mean of the deviations in all adjacent regions. The product then is standardized by the average of the squared deviations from the mean, resulting in

\(^1\)The spatial-weights matrix $w_{ij}$ quantifies spatial relationships with a multitude of weighting possibilities (e.g. inverse distance, fixed distance, $k$ nearest neighbors, contiguity). The concept of first-order contiguity defines

$$w_{ij} = \begin{cases} 1, & \text{if regions } i \text{ and } j \text{ share a common border and } i \neq j \\ 0, & \text{otherwise} \end{cases}$$
\[ I_i = \frac{(x_i - \bar{x}) \sum_{j=1}^{n} w_{ij} \cdot (x_j - \bar{x})}{\sum_{j=1}^{n} (x_j - \bar{x})^2 / n}, \]  

where \( x_i \) may either refer to per capita income or to the degree of income inequality in region \( i \). This measure identifies local clusters of inequality (or local pockets of non-stationarity respectively).

To reveal the effects of multiple regional characteristics on income inequality, we first of all consider a standard regression model in the form

\[ y = X\beta + \epsilon. \]  

If the explanatory variables in \( X \) fully determine the variability in \( y \), we do not recognize any spatial pattern beyond the structural similarities of adjacent regions which are explicitly controlled for, and hence \( E(\epsilon_i \epsilon_j) = 0 \) for neighboring \( i \) and \( j \). However, if the structural model in equation (8) is insufficient to explain spatial dependences there will be statistically significant spatial residual autocorrelation (cf. Baller et al., 2001).

The literature proposes two alternative approaches with regard to spatial distortions. The spatial effects model includes a so-called spatial lag of the dependent variable, i.e. a weighted average of the observations in neighboring regions. In a spatial disturbance model, by contrast, spatial dependence is incorporated in the error term and indicates the spatial influence of omitted covariates.

A spatial autoregressive error process can be written as

\[ \epsilon = \lambda W\epsilon + u, \]  

where \( W \) is a (row-standardized) spatial weights matrix, \( \lambda \) is a spatial autoregressive coefficient and \( u_i \) are i.i.d. errors. Including the error term in regression equation (8) yields

\[ y = X\beta + (I - \lambda W)^{-1} u. \]  

Spatial effects models (or spatial lag models) additionally control for the influence of the dependent variable in neighboring regions by including spatially lagged variables. The model subsumes the spatial error model in (10) takes the form

\[ y = \rho Wy + X\beta + u \]  

(Structural form)

\[ y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1} u \]  

(Reduced form)

The scalar \( \rho \) equals the degree of spatial dependence and \( Wy \) is the spatial lag vector.
4. Results

To address the interrelation between average income levels and earnings inequality within and between regions we calculate Theil’s T statistic and Moran’s I on municipality level for Austria. While we also present time trends for the two measures described above, the reference period for the remaining calculations is 2010. For this year the total adult population addressed by the dataset (14 years and older) is 7,150,149 persons for the whole country. The size of municipalities varies in a broad range from 39 persons (Gramais, Tyrol) in rural areas to 213,000 (Graz) in cities.\(^2\) Table 1 provides information on the variability of the calculated average income and inequality statistics.

<table>
<thead>
<tr>
<th></th>
<th>Obs</th>
<th>Min.</th>
<th>1st Qu.</th>
<th>Median</th>
<th>Mean</th>
<th>3rd Qu.</th>
<th>Max.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Income</td>
<td>2379</td>
<td>16600</td>
<td>24500</td>
<td>26600</td>
<td>27000</td>
<td>28900</td>
<td>52400</td>
</tr>
<tr>
<td>Average Population</td>
<td>7150149</td>
<td>39</td>
<td>817</td>
<td>1360</td>
<td>3010</td>
<td>2330</td>
<td>213000</td>
</tr>
<tr>
<td>Theil’s T</td>
<td>2379</td>
<td>0.14</td>
<td>0.21</td>
<td>0.23</td>
<td>0.24</td>
<td>0.25</td>
<td>0.66</td>
</tr>
<tr>
<td>Std. Theil’s T</td>
<td>2379</td>
<td>0.13</td>
<td>0.19</td>
<td>0.20</td>
<td>0.21</td>
<td>0.22</td>
<td>0.48</td>
</tr>
</tbody>
</table>

Figure 1 plots the average earnings as taken from the Austrian wage tax register using an overlay for population density and topology to mask out badlands, mountains etc. As expected, higher income is concentrated around the major cities, which is particularly true for Vienna. Furthermore, high income clusters seem to decay with distance from urban regions. An exception to this observation are the Viennese suburbs in the south, south-west and north, which exhibit exceptionally high average incomes.

A visual comparison of this map with figure 2 gives a first insight into the correlation of average income and income distribution as measured by standardized Theil’s T (or Atkinson index). While the inequality measure varies less than the average incomes and is also less concentrated, high values of inequality seem to appear in similar regions as high average income. Even though there is no striking pattern, first visual impressions suggest higher average wages as well as larger income inequality in urban and suburban areas.

This evidence is especially strong for Viennese districts. Figure 5 plots both mean income and Theil’s T side by side for all 23 districts. With the exception of the two districts north-east of the Danube, Floridsdorf and Donaustadt, most districts are found to be in the same quintile for both measures. For instance, the 13\(^{th}\) and the 19\(^{th}\) districts (Hietzing in the west and Döbling in the north) exhibit income levels in the highest quintile, that is more than €39,000. At the same time they both are subject to above-average income inequality, with a standardized Theil statistic of more than 0.3. Simmering (Vienna’s 11\(^{th}\)

\(^2\)While Vienna is the Austrian largest city, the data allow analyses on its 23 districts directly.
district) in the south does not only face rather low average earnings for an urban region, in addition to that the income distribution is exceptionally equal.

As already described in section 3.3, spatial correlation of wages as well as of inequality can be expressed by the Moran’s I statistic. Figure 3 plots both measures against their spatially lagged dependants for all Austrian municipalities. The spatial autocorrelation is very strong for the mean gross wages, while it is much weaker for Theil’s T with a Moran’s I coefficient of 0.25 (compared to 0.61 for average income). In these figures, we included a third dimension to reveal an interesting association between regional income inequality and educational attainments. The colors in the plots represent the proportion of persons with tertiary education in a municipality. As anticipated, visual evidence shows that places with higher shares of tertiary education have higher average earnings and are surrounded by municipalities that also have above-average wage levels. This relationship will further be investigated in the regression analysis below.

Figure 4 shows the movements of both Theil’s T and the corresponding Moran’s I for the period between 2004 and 2010. Income inequality for overall Austria has been fairly persistent for these years though experiencing a slight increase up to the beginning of the economic crisis in 2007, followed by a minor decrease to a value of roughly 0.26. Similarly, spatial autocorrelation experienced a level shift in 2006 and since remained constant at about 0.23 from then on.

Figures 6 and 7 show the results for the local indicators of spatial association. Blue shaded areas represent regions considered as cold spots of income and inequality, whereas red regions exhibit strong spatial patterns of high values or hot spots. The heat map of average earnings shows especially strong positive spatial patterns for the cities in Eastern and
Southern Austria. High wages are particularly concentrated in Vienna and its suburbs, while Graz and Linz show similar patterns. In parts of Lower Austria (Waldviertel) in the North and Styria (Südost-Steiermark) in the South, there is a high degree of spatial autocorrelation of below-average earnings.

To a certain extent, the spatial patterns for income inequality and average earnings are very similar. High levels of inequality are concentrated around the major cities, with Vienna again leading the ranking. However, the spill-over effects seem to be in a narrower range. There are some new hot spots emerging in this figure. For instance, strong spatial autocorrelation of high inequality is evident in big parts of Vorarlberg in the West and in Carinthia in the South. The cold spots are found in Northern Styria (Liezen and Östliche Obersteiermark) as well as in Northern Lower Austria (Waldviertel and Weinviertel). In general, this analysis suggests that regions with high average earnings also exhibit more pronounced inequality. (tbc)
Figure 3: Scatter Plot for Spatial Autocorrelation

Figure 4: Theil’s T and Moran’s I over time
<table>
<thead>
<tr>
<th></th>
<th>Theil’s T (ln)</th>
<th>90/10 Ratio (ln)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>OLS</td>
<td>SAR</td>
</tr>
<tr>
<td>Constant</td>
<td>-3.24***</td>
<td>-2.88***</td>
</tr>
<tr>
<td>Avg. Income (ln)</td>
<td>0.18***</td>
<td>0.18***</td>
</tr>
<tr>
<td>Population (ln)</td>
<td>-0.01***</td>
<td>-0.01***</td>
</tr>
<tr>
<td>Share Female</td>
<td>-0.2</td>
<td>-0.03</td>
</tr>
<tr>
<td>Tertiary Edu.</td>
<td>2.05***</td>
<td>1.77***</td>
</tr>
<tr>
<td>Primary Sector</td>
<td>0.22**</td>
<td>0.24***</td>
</tr>
<tr>
<td>Tertiary Sector</td>
<td>-0.33***</td>
<td>-0.28***</td>
</tr>
<tr>
<td>Foreign Born</td>
<td>0.5***</td>
<td>0.4***</td>
</tr>
<tr>
<td>$\rho$</td>
<td>---</td>
<td>0.31***</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>Spatial Lag (ln)</td>
<td>---</td>
<td>---</td>
</tr>
</tbody>
</table>

***: Significant at 0.1%; **: Significant at 1%; *: Significant at 5%  
SAR: ML Autoregressive Lag Model; SEM: ML Autoregressive Error Model
5. Concluding remarks (to be written)
References


Bailey, N. et al. (2013): “Living apart, losing sympathy? How neighbourhood context affects attitudes to redistribution and to welfare recipients”. In: Environment and Planning A 45 (advanced online publication).


A. Appendix

Figure 5: Average income and inequality (Std. Theil’s T) in districts of Vienna
Figure 6: Heat map of average wages in Austria

Figure 7: Heat map of earnings inequality in Austria