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The Geography of Average Income and Inequality: Spatial Evidence from Austria

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The Geography of Average Income and Inequality. Spatial Evidence from Austria.*

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Abstract: This paper investigates the nexus between regional income levels and inequality. We present a novel small-scale inequality database for Austrian municipalities to address this question. Our dataset combines individual tax data of Austrian wage tax payer on regionally disaggregated scale with census and geographical information. This setting allows us to investigate regional spillover effects of average income and various measures of income inequality. Using this data set we find distinct regional clusters of both high average wages and high earnings inequality in Austria. Furthermore we use spatial econometric regressions to quantify the effects between income levels and a number of inequality measures such as the Gini and 90/10 quantile ratios.

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

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0 Introduction

The distribution of income and its nexus to a wide range of social, political and economic aspects has generated a large body of literature. Income inequality can be connected to multiple phenomena, most prominently its relation to economic growth, investment as well as private and public consumption. Furthermore, it has been shown that inequality affects socioeconomic parameters like health, crime rates, voter participation or attitudes towards redistribution and also has consequences for political power and democratic stability. Given these manifold effects of inequality, there is growing interest in understanding the main drivers of inequality.

The greater part of articles on income inequality use common measures, such as the Gini index, to assess the dimension of income disparities at a national level. These conventional measures clearly bear the advantage of intuitive comprehension and simple comparability of the results. However, they ignore the geographic dimension of inequality and potential neighborhood effects which may lead to biased results (Goodchild and Janelle, 2004). There is a growing empirical literature on the spatial dynamics of income inequality confirming that economic inequality is a regional phenomenon (Fan and Casetti, 1994; Rey and Montouri, 1999; Beblo and Knaus, 2001; Akita, 2003; Hoffmeister, 2009). Moreover, some studies focus on the interdependency of geographic and social segregation based on regional inequality and income concentration (Watson, 2009; Bailey et al., 2013).

However, only few articles investigate which socioeconomic factors correlate with the income distribution on a regional level. In this paper, we explore the drivers of wage inequality on a disaggregated regional scale in Austria and extend this analysis by accounting for spatial neighborhood effects of inequality. Using census data on municipality level combined with wage data from tax registers, we analyze the effects of differences in the socioeconomic structures on income disparities using spatial econometric methods. We particularly focus on the role of differing wage levels between municipalities and their relation to income inequality, that is, whether high average wages are equally distributed among the population. Our findings suggest that high levels of average wages are driven by a lift-off at the top tail of the distribution. The detachment of high earnings translates into higher inequality within Austrian municipalities.

The remainder of this article is structured as follows. First, we provide an overview of related studies on the spatial distribution of income, inequality and possible determinants in section 1. Furthermore, we summarize applied research focused on income inequality in Austria and how we extend this literature. Section 2 introduces the dataset and motivates the need for a spatial analysis. In section 3, we describe the measures used to detect spatial clusters, the estimation strategy as well as the treatment of spatial effects. Subsequently, section 4 presents the results from the econometric exercise and describes the main findings. Finally, section 5 concludes.

1 Income Inequality and Spatial Effects

The greater part of regional inequality analyses has dealt with (sub-)national income levels, mainly in terms of GDP per capita adjusted by purchasing power parities. In this context, the bulk of literature has stressed the role of welfare regimes (Gottschalk and Smeeding, 1997; Beblo and Knaus, 2001; Hoffmeister, 2009) or skill-biased technological change (Acemoglu, 1998) for the stratification of income between countries. Since we explore spatial effects on a small-scale level of municipalities, macroeconomic developments can hardly serve as an explanation for the varying inequality measures between single units of observation. Therefore, other explanatory approaches for the spatial dynamics of inequality have to be considered.

On a disaggregated scale, income inequality and spatial segregation are mainly linked via housig market segregation in so far as higher income groups may outbid lower income groups in the competition for better neighborhoods (Banzhaf and Walsh, 2008). This can lead to positive feedback effects, since richer families might produce positive neighborhood externalities which rises the relative price of high-income neighborhoods further (Watson, 2009; Bailey et al., 2013). While the canonical model of Meltzer and Richard (1981) predicts that higher inequality leads to more redistribution, empirical evidence suggests that increasing spatial segregation and rising income disparities between regions worsen social cohesion and limit the success of redistribution policies. For instance, 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 one's absolute economic position but rather on a comparison to 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, and spatial segregation fortifies these attitudes.

As stated before, the well-investigated macroeconomic covariates of income inequality are only partly useful to detect disparities on sub-national levels. On a small geographic scale, the explanations range from structural to institutional factors with a variety of socio-demographic variables. However, there is a set of recurring justifications for the level of inequality that enfolds education (Rodríguez-Pose and Tselios, 2009), ethnicity (Borjas and Ramey, 1994; Watson, 2009), labor market parameters (Fortin and Lemieux, 1997) and the structure of the population (Perugini and Martino, 2008; Baum-Snow and Pavan, 2013) which have to be considered in such analyses.

While the empirical literature provides rich evidence of spatial patterns in income inequality measures (Fan and Casetti, 1994; Chakravorty, 1996; Rey and Montouri, 1999; Beblo and Knaus, 2001; Akita, 2003; Rey, 2004; Shorrocks and Wan, 2005; Ezcurra, Pascual, and Rapún, 2007; Novotný, 2007; Ramajo, Márquez, Hewings, and Salinas, 2008; Hoffmeister, 2009; Rey and Sastré-Gutiérrez, 2010), the spatial correlation of the crucial factors generally remains underexposed. As a consequence, the identification of the drivers of inequality could lead to biased results. For instance, Rodríguez-Pose and Tselios (2009) constitute positive relationships between per capita income, educational level and income inequality, while controlling for spatial spillover effects of inequality. Perugini and Martino (2008) provide evidence that higher income inequality leads to more regional growth, however, the effects are lower and less significant when controlling for spatial distortions. Recently, the nexus between urbanization and income disparities has been investigated, where there is a strong monotonic relationship between city size and inequality (Baum-Snow and Pavan, 2013; Behrens and Robert-Nicoud, 2014). These contributions clearly demonstrate the importance to take spatial spillover effects into account.

While a number of scholars have dealt with income inequality in Austria, there is no comprehensive analysis of its spatial dimension. Hoffmeister (2009) observes spatial differences in European income inequality including Austria between 1995 and 2000. However, income inequality is decomposed in only three NUTS1 regions (i.e. Southern, Western and Eastern Austria). The within-region inequality 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. Based on these findings it seems essential to gain a better understanding of Austria's particularly high level of within region inequality. Newly available register data allow us to investigate regional inequality and its covariates on a disaggregated scale.

2 Data and Descriptive Analysis

We use a new inequality database based on wage tax data for all Austrian municipalities including the 23 districts of Vienna for the years 2009-2011. This dataset includes approximately 6.4 million tax payers, of which roughly 4.1 million are economically active, that is, not retired. These persons can be attributed to $2,356$ municipalities and the 23 districts of Vienna, which leaves us with a total of $2,379$ regional observations. On the whole, Austrian wage tax data covers about 90% of income tax payers but leaves out self-employed individuals.

A distinct feature of this data source is the broad range of available earnings inequality measures on such a disaggregated geographic scale, such as the Gini index, the 90/10, 90/Median and Median/10 ratios. While this paper focuses on the economically active part of the distribution, these variables are also available for the total population including retirees. Analyzing inequality via a set of measures (as opposed to one single indicator) has several advantages, but is empirically often limited by data constraints. First, prominent measures such as the Gini index can be sensitive to changes in the middle of the distribution, and therefore lead to an under– or overestimation of effects. Second, deviations in such aggregated measures can hardly provide insights into the actual changes in the distribution, i.e. which segment of the distribution caused the observed reaction in the measure. Given these considerations, our choice of inequality measures targets different parts of the distribution (overall, upper, middle, lower) to facilitate the interpretation of the results.

To calculate these four inequality measures, gross wages are defined as all income received in a year, including supplementary payments and social security contributions.

Table 1: Descriptive statistics for municipality inequality measures, 2009-2011

	Minimum	Mean	Median	Maximum	Std. Dev.	Var. Coef.
Avg. Wages	17,360	31,482	31,005	68,399	4,209	13.4
Gini	0.155	0.325	0.324	0.555	0.0289	8.87
90/10	1.56	5.2	5.14	31.6	0.826	15.9
90/50	1.26	1.9	1.88	4.6	0.171	9
50/10	1.16	2.74	2.71	14.9	0.369	13.4

Source: Wage tax data 2009–2011; own calculations

As can be seen in Table 1, the various inequality measures vary considerably between municipalities for the pooled period of 2009-2011. While the Gini index is rather stable in terms of the coefficient of variation, the 90/10 ratio as well as the other ratios prove to be more responsive. This is also shown by the minima and maxima of the inequality measures. The Gini index varies in a narrow interval of 0.16 for the most equal municipalities and an upper bound of roughly 0.56. Strong deviations are found for the 90/10 ratio, where the income share of richest 10% compared to the bottom 10% varies by a factor of about 20 between the most equal and unequal municipalities (1.56 and 31.6 respectively). While not shown in the table, the time dimension does not seem to have very strong effects on these measures. Especially for very small municipalities we find a few extreme outliers related to persons with high incomes moving into (or out of) these regions. The following analysis will therefore use 3-year averages to smooth such statistical noise.

Figure 1 graphically depicts the dispersion of inequality measures by federal states. Especially the capital Vienna in the east incorporates extreme outliers: the 11^{th} district on the lower side and the 1^{st} district on the upper. These two regions associated with large differences in average income, which gives a first intuition on the relation of average income and inequality. Furthermore, we can depict strong differences between Austrian federal states, most strikingly the example of *Burgenland* at the Hungarian border, which covers a comparably homogeneous set of municipalities in terms of inequality.

The explanatory variables for the regression analysis are mostly drawn from the register-based labour market statistics 2009 which are a predecessor of the Austrian register-based census conducted in 2011. This source provides detailed information on the socioeconomic characteristics for the economically active population of Austrian municipalities. For our estimations, we use a number of relevant variables such as the population density of a region which among other things serves as a proxy for urbanization. Other potential determinants of income inequality are adopted from the existing literature and include the share of native-born individuals as well as information on ongoing and attained education. With the exception of population density and average income all our variables are defined as shares relative to total population of the municipality. We include the share of females to control for wage-gap and part-time effects that could affect regional inequality measures. The proportion of commuters may be an indicator for income transfers from high income regions to rural areas even if average education levels

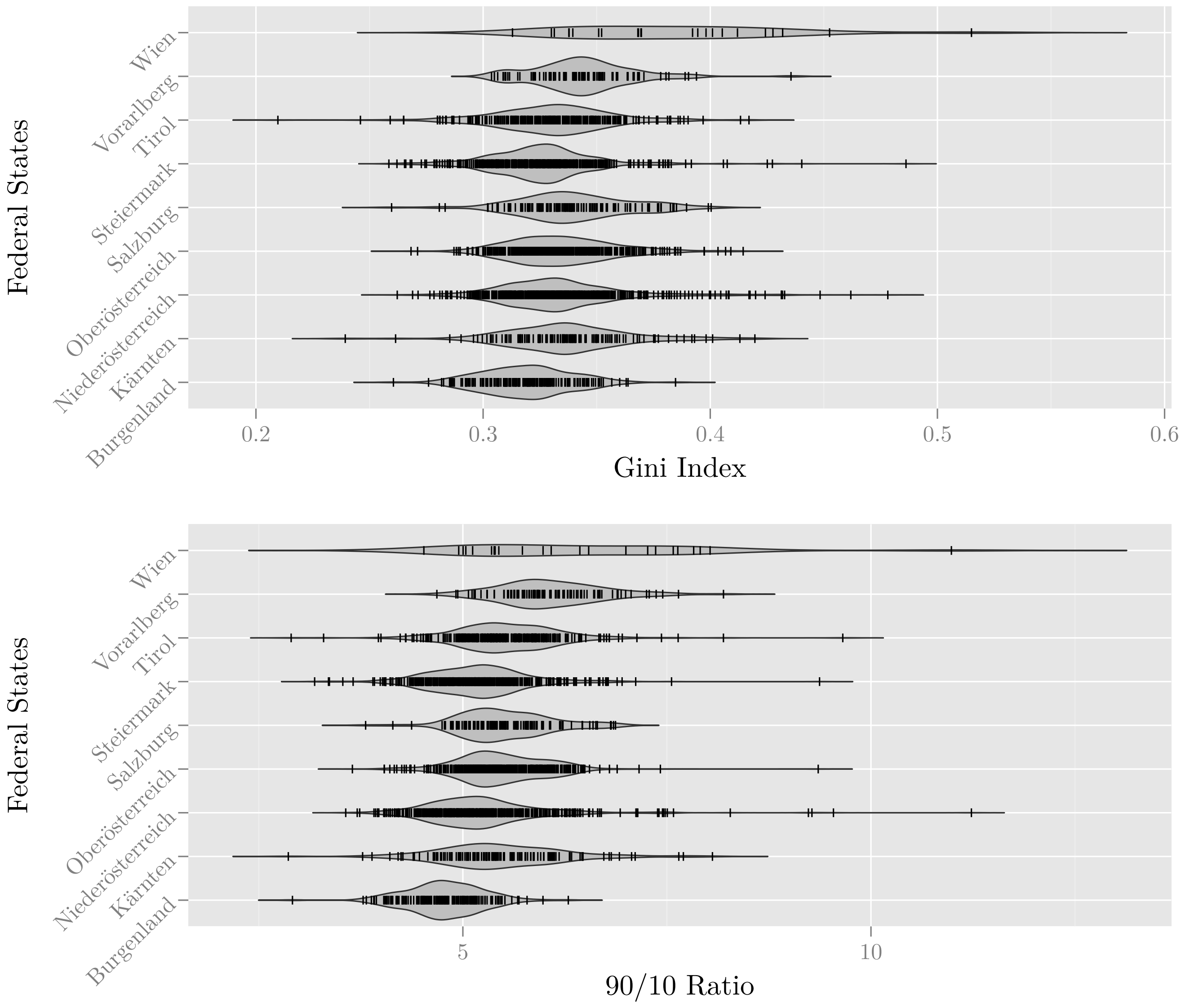


Figure 1: Beanplots for Municipality Inequality Measures Aggregated by Federal States (Mean 2009-2011)

remain low (Tinbergen, 1972). Finally, the logarithm of average income is expected to contribute positively to inequality since there is evidence that productivity gains are particularly unequally distributed (cf. Dew-Becker and Gordon, 2005). Table A.1 provides a detailed overview of the used variables and their source.

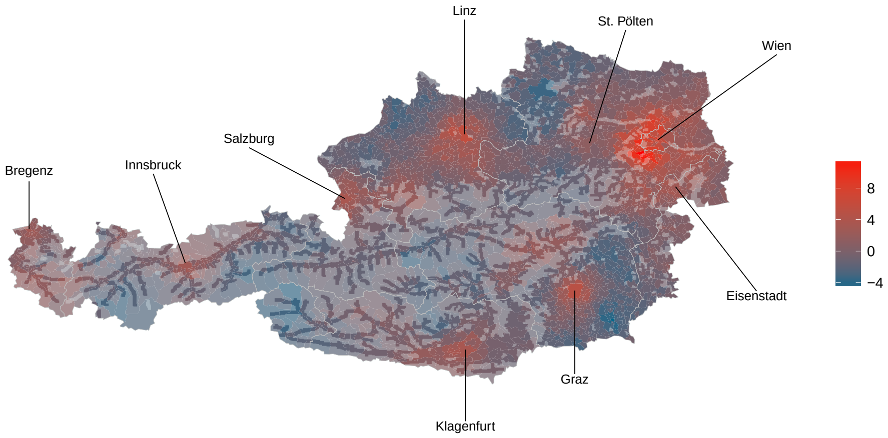
Spatial dependence in income-related statistics is often measured through Moran's I which is used to test the null hypothesis that spatial autocorrelation of a variable is zero (Rey, 2004; Ord and Getis, 1995). Since Moran's I is a global indicator and assumes homogeneity across the spatial sample, local measures are more powerful to reveal spatial non-stationarity. Anselin (1995) designs a class of local indicators of spatial association (LISA) like local Moran's I, while Ord and Getis (1995) developed a "G statistic". These measures provide information on regional clustering ("hot" or "cold" spots). The diagnostic tool applied in this paper is the Z-score of the Getis-Ord G statistic which denotes

$$G_i(d) = \frac{\sum_j w_{ij}(d)y_j - W_i\bar{y}(i)}{s(i)\{[(n-1)S_{1i} - W_i^2]/(n-2)\}^{\frac{1}{2}}}, \quad i \neq j \tag{1}$$

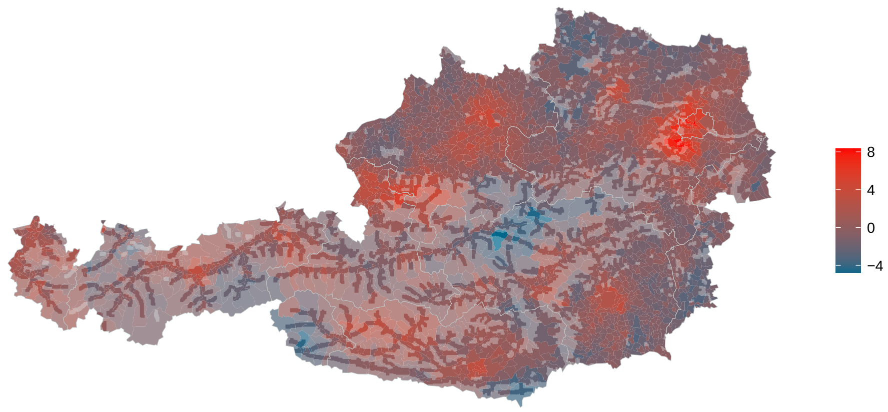
where y is the variable under consideration, n the number of observations, w_{ij} is a so-called spatial weight matrix which is an indicator for the adjacency of regions i and j. The sum of weights is written as $W_i = \sum_{i\neq j} w_{ij}(d)$, where $S_{1i} = \sum_j w_{ij}^2$. $\bar{y}$ and s^2 are the usual sample mean and variance. The spatial weight matrix incorporates spatial relationships via multiple weighting possibilities (e.g. inverse distance, fixed distance, k nearest neighbors, contiguity). We apply the concept of first-order contiguity with row-standardization, but additionally make our inference more robust using other weighting strategies. Positive values of G_i indicate local pockets of high values of y, while negative figures signal a concentration of low y values.

Figure 2a shows the results for the local spatial association of average earnings while figure 2b presents the same map for the Gini index. Blue shaded areas represent regions considered as *cold spots* of income or inequality, whereas red shaded regions imply spatial patterns of high values (*hot spots*). For Austria, the heat map of average earnings shows strong positive spatial patterns for urban areas, specifically for the eastern part of the country, as can be seen in Figure 2a. High wages are especially concentrated in Vienna and its suburbs which reach far into the neighboring state of Lower Austria.

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, where, again, Vienna leads the ranking (see Figure 2b). This evidence mirrors the findings of Baum-Snow and Pavan (2013) who uncover a positive relationship between wage inequality and city size in the United States. However, the spillover effects for the Gini index seem to be more dispersed compared to income, so that new hot spots emerge in this figure. For instance, strong spatial autocorrelation of high inequality is evident in large parts of the West (Vorarlberg) and in the South (Carinthia). The cold spots are found in regions like Northern Styria, Southern Burgenland as well as in Northern Lower Austria. In general, this visual evidence suggests a link between both inequality



(a) Average wages



(b) Wage inequality (Gini)

Figure 2: Local Indicators of Spatial Association

and average earnings.

To sum up, the analysis of local indicators of spatial association shows distinct hot spots of high inequality or high average wages in urban areas whereas we find cold spots mainly in rural regions.

3 Econometric Approach

Our data permits us to estimate specifications using the average over 2009-2011 for four inequality measures (Gini Index, 90/10, 90/Median and Median/10 point ratios) as endogenous variables. On the RHS we include the 2009 levels of the census variables already described above and listed in Table A.1. As discussed above, inequality measures are spatially correlated, so standard OLS estimates are inconsistent and possibly suffer from omitted variable bias. Different estimation strategies allow the incorporation of spatial autocorrelation to some extent.

We consider two approaches here, the Spatial Lag Model as well as the Spatial Error Model. While the former assumes a direct 'lag' of the neighboring observations of the endogenous variable, the error model assumes spatial dependence in the disturbances. Both can be written nested as

$$y_i = \alpha + \rho W y_i + X\beta + \nu \qquad \nu = \lambda W \nu_i + \epsilon_i \tag{2}$$

where $\epsilon \sim N(0,\sigma^2)$, W an $N \times N$ spatial weights matrix and $\lambda = 0$ for the spatial lag or $\rho = 0$ for the error model. The choice of the most appropriate estimation method is based on Lagrange Multiplier tests, which check for error dependence and a missing spatial lag respectively (Anselin, Bera, Florax, and Yoon, 1996). Our estimation approach closely follows LeSage and Pace (2009), where the process is separated into two steps: First, the autoregressive parameter is found by maximum likelihood optimization and then used for GLS estimation of the rest of the model.

The weight matrix is a non-negative matrix used to describe the strength of the spatial interaction for cross-sectional units. The weights depend on the properties of the data as well as on theoretical considerations concerning spatial patterns. Its specification therefore needs to be addressed carefully. To make our analysis more robust, we consider multiple spatial weights matrices. For the baseline regressions we define neighbors via Queen-style contiguity, where neighbors share a common border or corner. Alternative k-nearest-neighbor weights of different order did not change the quality of our statements and are therefore not shown in the results section.

4 Econometric Analysis of Regional Inequality Determinants

Our analysis departs from the standard OLS model, which may be subject to misspecification and uses Lagrange Multiplier tests to evaluate alternative estimation approaches, such as spatial lag or error models. For this exercise, we regress the explanatory variables mentioned in section 2 on three year averages of the Gini Index. In a further step we then incorporate other inequality measures, namely the 90/10, 90/Median, and Median/10 ratios into our analysis. In a framework where we assume that income inequality is positively related to average earnings in a municipality, this strategy allows us to investigate which part of the income distribution drives this effect. Our main assumption will be that this phenomenon can be explained through developments within the highest incomes. In this scenario one would thus expect a moderate positive effect through higher average incomes in the Gini regressions. A strong effect should be seen for those ratios that include the 90$^{\text{th}}$ percentile point. On the other hand, we would expect no effect at the Median/10 ratio.

Controlling for other covariates, we hypothesize that a high share of Austrian citizens decrease inequality due to the income gap between natives and immigrants. Furthermore, a considerable proportion of marginal and part-time employment should increase inequality since these jobs are

Table 2: (Robust) Lagrange Multiplier Tests for different model specifications

	Gini		**90/10**		**90/50**		**50/10**	
	Stat.	p-val.	Stat.	p-val.	Stat.	p-val.	Stat.	p-val.
LMerr	225.78	0.00	289.86	0.00	198.39	0.00	165.95	0.00
LMlag	118.36	0.00	240.75	0.00	137.07	0.00	201.03	0.00
RLMerr	109.00	0.00	52.74	0.00	61.32	0.00	0.57	0.45
RLMlag	1.58	0.21	3.64	0.06	0.00	0.99	35.64	0.00

Source: Wage tax data 2009–2011; own calculations

typically attributed to lower wages. The effect of education is theoretically ambiguous since it may lead to a higher wage segregation between high and low education. However, rising educational attainments could reduce the income gap in regions with already high inequality. A similar argument can be made for the share of females in the workforce and persons commuting to nearby cities.

The Lagrange Multiplier (LM) test statistics based on the OLS results are shown in Table 2. The standard tests to distinguish lag and error specifications are both highly significant with a preference for the error specification in all models except for the 50/10 ratio. In a case where both tests are equally significant, robust versions of these LM tests (RLM) can be computed, which extend the preference for the error model - again with the exception of the 50/10 ratio. Accordingly, our following estimation strategy will focus on the error model but we additionally report results for the lag specification to make our findings more robust.

In table 3 we report results for the Gini coefficient as dependent variable using OLS as well as a spatial error and lag approach. These results are based on the municipality dataset and use Queen-style contiguity weights. Both the λ and ρ parameter capture a spatial effect in the error and lag specification respectively. Their signs are positive and diminishing as expected. Thus, we are confirmed that estimation procedures of regional inequality should control for spatial spillover effects to avoid biased results. The following interpretation of the results will therefore focus on the spatial error model.

With regard to our hypotheses, a high share of natives is correlated with reduced inequality within a municipality, which is most likely an income effect of social stratification. Both of the two indicators for atypical employment (part-time work and marginal employment) exhibit strong correlation with the inequality measures. Marginal employment shows large and significant effects on the inequality measures that are more sensitive at the tails of the distribution. Part-time work, however, is increasingly present in the Austrian labor market and therefore even affects the Gini, which is more sensitive to changes in the middle of the distribution. In fact, the share of part-time employment reaches up to a third of all employees in some municipalities.

Secondary education is consistently high for most Austrian municipalities and does not exhibit drastic correlations with inequality, which is why we find a low significant coefficient only in

Table 3: Model comparison of municipality income inequality, 2009-2011

	Gini		
	OLS	Spatial Error	Spatial Lag
Constant	-0.97***	-1.12***	-0.94***
	(0.055)	(0.059)	(0.055)
Pop. Density	0.00	-0.01	-0.00
	(0.012)	(0.014)	(0.011)
AT Citizen	-0.08***	-0.08***	-0.06***
	(0.012)	(0.013)	(0.011)
Marginal Emp.	0.24***	0.20***	0.20***
	(0.032)	(0.033)	(0.031)
Secondary Edu.	-0.01	-0.03**	-0.02
	(0.010)	(0.012)	(0.010)
Tertiary Edu.	0.08***	0.04*	0.06***
	(0.015)	(0.016)	(0.015)
Share Female	-0.09***	-0.06**	-0.08***
	(0.021)	(0.021)	(0.020)
Secondary Sector	-0.05***	-0.06***	-0.04***
	(0.008)	(0.009)	(0.008)
Tertiary Sector	-0.03***	-0.04***	-0.03***
	(0.007)	(0.008)	(0.007)
Avg. Income (ln)	0.13***	0.15***	0.12***
	(0.005)	(0.006)	(0.005)
City Commuters	-0.02***	-0.02***	-0.02***
	(0.004)	(0.005)	(0.004)
Part-time	0.22***	0.22***	0.21***
	(0.012)	(0.012)	(0.012)
λ		0.42***	
		(0.027)	
ρ			0.25***
			(0.024)
Observations	2379	2379	2379

*****: Significant at 0.1%; ****: Significant at 1%; ***: Significant at 5%

Table 4: Spatial Error Estimation of Municipality Income Inequality, 2009-2011

	90/10	90/50	50/10
λ	0.45***	0.39***	0.37***
	(0.026)	(0.028)	(0.028)
Constant	-15.59***	-3.72***	3.71***
	(1.879)	(0.376)	(1.029)
Pop. Density	-0.47	-0.24**	0.01
	(0.449)	(0.088)	(0.240)
AT Citizen	-1.45***	-0.57***	-0.22
	(0.408)	(0.081)	(0.222)
Marginal Emp.	11.24***	0.39	4.93***
	(1.052)	(0.211)	(0.579)
Secondary Edu.	-0.53	-0.11	0.06
	(0.374)	(0.074)	(0.202)
Tertiary Edu.	2.90***	0.69***	0.69*
	(0.521)	(0.104)	(0.285)
Share Female	-3.23***	-0.01	-2.01***
	(0.652)	(0.132)	(0.362)
Secondary Sector	-3.14***	-0.28***	-1.33***
	(0.283)	(0.056)	(0.154)
Tertiary Sector	-2.67***	-0.13*	-1.19***
	(0.259)	(0.052)	(0.141)
Avg. Income (ln)	2.39***	0.60***	0.05
	(0.182)	(0.036)	(0.099)
City Commuters	-0.74***	0.03	-0.38***
	(0.158)	(0.030)	(0.082)
Part-time	5.63***	0.70***	2.10***
	(0.389)	(0.078)	(0.214)
Observations	2379	2379	2379

***: Significant at 0.1%; **: Significant at 1%; *: Significant at 5%

the Gini specification. This differs notably for tertiary education, since this variable is more volatile from a regional perspective. Tertiary education positively and consistently correlates with inequality for all evaluated inequality measures, however, less strong at the top of the distribution.

Commuters are a large and very heterogeneous group of the working population. We find that a large share of commuters appears to be connected to lower inequality. This could theoretically be linked to less developed regions where a large share of persons is forced to commute to nearby cities.

Most importantly the relation of average earnings and the observed inequality measures has to be stressed. The data support the view that the two factors are positively correlated, as can bee seen in the regression on the overall inequality measured via the Gini index. This setup in itself, however, does not reveal the full picture. In fact, there appear to be differences between changes in inequality that are focused on the top versus the bottom half of the distribution. If higher income was distributed evenly among residents of a municipality, this should not affect inequality measures. However, our observation implies that the spread in income levels mainly occurs in those segments of the income distribution that increase the Gini index. This could be due to two major reasons: First, there is a widening gap between low income earners and the rest of the population. In this case many individuals participate in rising income levels, while a subgroup does not, which would indeed point at high inequality. Another explanation could be that average wage levels are driven by exorbitant income levels for the upper tail of the distribution, which would be reflected in the mean but not the median. In such a world, most of the population would receive below-average incomes vis-a-vis a small elite.

To test for such effects, we make our analysis more robust using different income distribution measures in table 4. As the regression for the 90/10 ratio shows, the changes in inequality seem to be related to the tails of the distribution. The 90/50 ratio then indicates that the inequality of the top to the median is higher for higher mean wage levels. As a counterfactual, the analysis regarding the 50/10 measure – which does not include changes in the top – remains insignificant for average earnings. This confirms that inequality within municipalities is mainly driven by changes in top incomes.

To sum up, we detect spatial spillover effects in our small-scale inequality data and apply spatial econometric techniques to control for possible biases in an OLS specification. The signs of the OLS estimates do not differ in the spatial error and spatial lag models, however, the size of the coefficients varies. We can show the differences in the relationship of wage inequality and the explanatory variables with alternative measures of income inequality.

5 Conclusion

This paper uses individual wage tax data to investigate geographically disaggregated wage inequality in Austria. We find strong spatial patterns in the inequality measures for roughly 2,380 Austrian municipalities especially in cities and suburban areas. Given these findings, the estimation of the relation between inequality and important socioeconomic characteristics may be biased if they neglect spatial spillover effects.

We thus apply spatial regressions to inequality measures derived from a rich wage tax dataset. We find a broad variation of inequality measures in Austrian municipalities where descriptive statistics already highlight spatial hot and cold spots of inequality in contiguous regions. By means of local indicators of spatial autocorrelation (LISA), we show a distinct disparity between urban and rural areas. The results for wage inequality and average wages are similar, hence indicating a strong correlation between both measures.

The econometric exercise reveals small-scale relationships which have not yet been investigated for Austria. The consideration of spatial effects provides additional insights into the dynamics of income inequality. We find that regionally specific characteristics such as marginal employment and part-time jobs increase inequality. Most notably, the effect of tertiary education has a positive influence on inequality. This is especially important in urban areas and their exurbs, since there is a significant spread between locals and highly qualified top earners moving to suburban regions. Finally, we show that municipalities with higher average earnings also exhibit higher inequality, mainly driven by the upper tail of the income distribution. This evidence suggests that productivity gains are distributed unequally which increases inequality along with higher average incomes (cf. Dew-Becker and Gordon, 2005).

Our findings have important policy implications. The development of rising spatial inequality may cause externalities via housing prices to the disfavor of the local population. There is evidence of feedback effects since richer families entail positive neighborhood externalities that drive housing prices and vice versa (Watson, 2009). At worst, this leads to segregation and social separation between income groups. Spatial segregation may erode the social bases for redistribution policies and consequently explain the path-dependent nature of welfare regimes (Bailey et al., 2013).

The related question of the nexus between regional inequality and housing prices is still an open task for Austria. Especially in city suburbs, commuter-driven housing price surges may endanger the continuity of established municipal structures like educational institutions, public infrastructure, volunteer work and vivid private associations that contribute to high living standards. Needless to say, increased mobility and the ease of communication have entailed more complex spatial patterns, but the neighborhood context and small-scale social interaction are still an essential reference point in our daily lives.

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A Data Appendix

Table A.1: List of variables

Variable	**Description**	**Source**
Gini Index (*dependent*)	Gini Index of individual gross wages for all Austrian municipalities	WTD
Percentile Ratios (*dependent*)	Precentile ratios of gross wages (90/10, 90/Median, Median/10)	WTD
Population density	Number of inhabitants with respect to municipality area	Census
Natives	Share of inhabitants who are born in Austria	Census
Secondary Education	Share of persons with completed secondary education (ISCED level 2+3)	Census
Tertiary Education	Share of persons with completed tertiary education (ISCED level 5+6)	Census
Share Female	Share of women	Census
2^{nd} Sector	Share of persons employed in industrial sector	Census
3^{rd} Sector	Share of persons employed in services sector	Census
Log. Average Income	Annual average gross wages	WTD
Share Commuters	Share of persons living and working in different municipalities	Census
Marginal Employment	Share of persons in marginal employment according to their social security status (*Geringfügigkeit*)	Census
Part-time workers	Share of persons in part-time employment according to self-assessment	Census

WTD: Austrian wage tax data (*Lohnsteuerstatistik*, Full Microdataset), Statistics Austria
Census: *Volkszählung* (2001), *Abgestimmte Erwerbsstatistik* (2009, 2010), *Registerzählung* (2011), Statistics Austria

B Regression Appendix

Table B.2: Spatial Lag Estimation of Municipality Income Inequality, 2009-2011

	Gini	90/10	90/50	50/10
Constant	-0.94***	-11.81***	-3.06***	2.59**
	(0.055)	(1.683)	(0.343)	(0.924)
Pop. Density	-0.00	-0.33	-0.24***	0.00
	(0.011)	(0.356)	(0.072)	(0.194)
AT Citizen	-0.06***	-1.32***	-0.40***	-0.40*
	(0.011)	(0.356)	(0.073)	(0.193)
Marginal Emp.	0.20***	9.98***	0.21	4.58***
	(0.031)	(0.984)	(0.197)	(0.535)
Secondary Edu.	-0.02	-0.42	-0.08	0.06
	(0.010)	(0.307)	(0.062)	(0.168)
Tertiary Edu.	0.06***	2.75***	0.75***	0.51*
	(0.015)	(0.467)	(0.095)	(0.255)
Share Female	-0.08***	-4.25***	-0.06	-2.40***
	(0.020)	(0.630)	(0.128)	(0.344)
Secondary Sector	-0.04***	-2.48***	-0.17***	-1.14***
	(0.008)	(0.249)	(0.050)	(0.135)
Tertiary Sector	-0.03***	-2.02***	-0.06	-0.96***
	(0.007)	(0.227)	(0.045)	(0.124)
Avg. Income (ln)	0.12***	1.83***	0.46***	0.09
	(0.005)	(0.163)	(0.034)	(0.087)
City Commuters	-0.02***	-0.70***	-0.01	-0.27***
	(0.004)	(0.110)	(0.023)	(0.061)
Part-time	0.21***	4.95***	0.62***	1.86***
	(0.012)	(0.364)	(0.073)	(0.198)
ρ	0.25***	0.35***	0.28***	0.35***
	(0.024)	(0.024)	(0.025)	(0.026)
Observations	2379	2379	2379	2379

***: Significant at 0.1%; **: Significant at 1%; *: Significant at 5%