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Evidence from Swedish Micro Data

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Evidence from Swedish Micro Data

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Abstract

The new economic geography predicts that the wage gap will increase with accessibility to markets but does not consider the impact of spatial proximity. In contrast, urban economic theory explains wage differences by density without accounting for accessibility. Using a rich Swedish micro-panel, we empirically examine the two rival theories for males and females separately, controlling for individual, firm and regional characteristics. The regression results indicate that wage dispersion is correlated with both accessibility to markets and density. However, the urban economic theory has greatest explanatory power when we control for factors such as occupation, ethnical background, skill, firm size, technical change, ownership, commuting time, unobserved heterogeneity and spatial autocorrelation.

Key words: New economic geography, urban economics, spatial econometrics, micro panel data

JEL classification: C21, R12, R23, J30

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1. Introduction

It has been empirically well documented since the mid-1970s that nearly all modern economies have experienced a significant increase in wage inequality (Juhn et al. 1993; Berman et al. 2000; Aghion et al. 2000). Acemoglu (2002) argues that technological development is the dominant cause of growing wage differentials and that several other reasons for the changing wage structure are in fact the consequences of accelerated technological development. The introduction of advanced technologies, particularly the widespread diffusion of computers, has led to an increasing demand for skilled workers that, in turn, has generated a rise in the wages of skilled workers relative to those of unskilled workers. Focusing on wage inequalities in a geographical context, Combes et al. (2008) show that spatial differences in the skill composition of the workforce may explain the primary disparities in wages across areas. In a recent study for Sweden, Andersson et al (2013) distinguish between workers with routine and non-routine skills and find that agglomeration economics are significant only for workers with non-routine job tasks where there is no such an effect for workers with skills associated routine job tasks.
Moreover, recent studies suggest that wage inequality is caused by trade liberalization, which enhances the dispersion of revenues in firms (Akerman et al. 2013). Other studies argue that globalization promotes foreign direct investment (FDI), results in accelerated growth and has historically reduced spatial patterns of wage dispersion both within and between countries (Bhagwati 2004; Loungani 2005; Das 2005; and Baddeley and Fingleton 2008).

Controlling for the skill composition of the workforce and focusing on gender differences, this paper aims to explain municipal-level wage disparities using two different theoretical approaches. First, the new economic geography (NEG) provides a theoretical foundation for understanding spatial wage inequality at both the national and the international level (see Fujita et al. 1999). Based on this theory, a wage equation links nominal wages to market access.

The other hypothesis that may explain the increased wage gap has been derived from findings in various branches of urban economics (UE). The presence of a large variety of spatial proximity and employment density across various locations, regions and countries is supposed to be associated with wage inequalities (Fujita and Thisse 2009). Recently, an increasing number of empirical studies have investigated the explanatory power of UE theories with respect to the spatial variation in wages (Combes, Duranton and Overman 2005; Brakman, Garretsen, and Van Marrewijk 2009; Fingleton 2011; Fingleton and Longhi 2013).

A number of recent studies, including Fingleton and Longhi (2013), Ottaviano (2011), Venables (2011) and Combes et al. (2011), emphasize the need for observations at the micro-level and the need to incorporate individual heterogeneity into the analysis to foster a deeper understanding of agglomeration economics. Few studies employ micro-level datasets to examine the differences in wages across space[2]. To fill this gap, the present paper aims to identify the endowments that generate wage differences across space and to test the explanatory power of NEG and UE after controlling for unobserved individual-level and firm-level heterogeneity.

The analysis uses unique Swedish matched employer-employee data on firms throughout the economy and all workers in the Swedish manufacturing and service sectors. We observe approximately 4 million unique individuals at approximately 500,000 firms in 290 municipalities for the period 2001-2008. We consider an extensive range of characteristics of both the individual workers and firms. In addition, we use detailed regional data, including estimations of market accessibility and commuting time. In the regression analyses, we use regression models that account for both unobserved fixed effects and spatial correlation.

The rich Swedish micro-panel data set enables us to properly address worker and firm heterogeneity. First, in estimating the wage equation, we control for individual and firm characteristics and include area-year fixed effects. Second, employment density and market access measures are used as explanatory variables to explain the wage disparities captured by the area-year fixed effects estimated in the wage equation. A generalized spatial panel 2SLS model is used to capture spatial correlation. The main finding is that urbanization economies measured by employment density have greater explanatory power than measures of market access (as a proxy for NEG). In addition, the results show that individual characteristics such as skills play the primary role in explaining spatial wage differentials.

The remainder of the paper is organized as follows. Section 2 presents the theoretical foundations for the study. Section 3 describes the data and methodology. Section 4 reports the empirical results, and Section 5 concludes.

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[2] See Larsson (2014) which use geocoded data to study the density and wage relationship.

2. Theoretical background

Both NEG and UE theory are based on Dixit-Stiglitz monopolistic competition theory and provide a theoretical foundation for spatial wage inequality. However, different hypotheses can be derived from each with respect to the wage equation.

In typical urban economics (UE) theory, the density of productive activity has a positive effect on wages (Abdel Rahman and Fujita 1990; Ciccone and Hall 1996; Fujita and Thisse 2002; Fingleton 2003).

The core of UE theory is a Cobb-Douglas production function in which a monopolistically competitive (*M*) service sector is assumed to provide inputs to the final sector (competitive industry(*C*)). Following Fingleton and Longhi (2013), we can designate the production function of the final sector (assuming without loss of generality that the final sector comprises a single firm) as

$$Q = ((E^c)^\beta I^{1-\beta})^\alpha L^{1-\alpha},$$

where E^c is the number of C labor units, I represents the level of composite services and L is the amount of land, which, assuming that production is per unit area, yields $L = 1$. The presence of $\alpha < 1$ includes congestion effects (Ciccone and Hall 1996). Because I is only a function of the size of the labor force in the M sector, E^M, and because $E = E^C + E^M$, it has been shown that[3]

$$Q = ((E^c)^\beta I^{1-\beta})^\alpha = \phi E^\gamma$$

where ϕ is a constant and $\gamma = \alpha[1 + (1-\beta)(\mu - 1)]$. Thus, final sector production depends on the number of labor units, E. The overall level of returns to density is given by elasticity γ, which is larger than unity, as the production function of the intermediate good is characterized by nonzero fixed costs, which generate internal increasing returns to agglomeration.

[3] See, for example, Fujita and Thisse (2002) and Fingleton (2003).

As we wish to evaluate individual level data, taking the wage rate as the derivative, we use the following expression:

$$w = \frac{\partial Q}{\partial E^c} = \frac{\alpha\beta Q}{E^c} = \frac{\alpha Q}{E}$$

where $\beta = \frac{E^C}{E}$.

Taking the logs and adding a disturbance term ξ for unobserved random effects and k_1 to represent the constant yields the following wage equation:

$$\ln(w) = k_1 + (\gamma - 1)\ln(E) + \xi$$

Thus, the wage is a function of the total employees per square km (E). This method requires fewer assumptions than NEG theory, Fingleton (2011) and Fingleton and Longhi (2013) show that when working with panel data, we need only time varying wages (w) and the total employees per square km (E) to estimate this equation.

One of the most important equations deriving from NEG is a wage equation (Head and Mayer 2004) that links nominal wages to market access[4]. As Fujita et al. (1999) have shown, the short-run equation for the model requires simultaneous equation systems. However, the basic wage equation derived from NEG is

$$\ln(w) = \delta lnMA + \varepsilon$$

where wages (w) are increasing in market access (MA). The definition of MA makes the NEG wage equation more cumbersome than the wage equation used in UE theory.

In this study, we use a proxy for market potential or market access following Johansson and Klaesson (2011). Their approach accounts for the size, structure and spatial layouts of urban agglomerations. Market access in each area is defined in a manner that reflects the space-discounted value of economic activity in these markets. Two assumptions are made in this approach for the sake of simplicity. First, following Johansson et al. (2003), the supplier is

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[4] Only a summary of the UE and NEG theories is provided in this paper. For a detailed presentation of the two theoretical approaches, see Fingleton (2011).

assumed to have a random-choice preference function with the systematic component specified as $V_{rs} = \phi_{rs} - \lambda_{rs}t_{rs}$ and an extreme-value distributed random component.

Moreover, although it is likely in many markets that contact efforts are made by both customers and suppliers, the assumption is that suppliers make the main efforts to contact their potential customers.

Area *r*'s market access to customer demand or the demand potential of a supplier firm in an area is

$$\widetilde{MA_{rr}} = W_r exp\{\phi_{rs} - \lambda_{rs}t_{rs}\}$$

where W_r is the total sum of the wages in urban area *r*, which represents the total purchasing capacity in area *r* and reflects the size of the economic activity in that area; where t_{rs} is the time distance between areas r and s, which are connected to each other by a link, ϕ_{rs}, which represents the spatial preferences of individuals in area r regarding area s; and where λ_{rs} is a time-sensitivity coefficient.

The parameters $\phi_{rs}, \lambda_{rs}\, and\ t_{rs}$ were estimated in a previous study (Johansson et al. 2003) for all Swedish urban areas using a multi-constrained trip-making model based on detailed information on commuters and time-distances between areas. By using different spatial proximity values in estimating these parameters, we can calculate market access for different locations.

We consider market access on two different spatial scales. The first is intra-urban market access, which reflects access to the sum of wages inside area *r*, or consumer demand.

The second is the intra-region market accessibility to the wage sum, which is the accessibility to consumer demand in other neighboring local economies inside the functional region[5] to which area *r* belongs.

[5] Sweden has been divided into 72 functional regions.

To test the explanatory power of NEG theory and the UE model with respect to the regional spread of wages, this study employs an estimation method that allows us to distinguish the skill-based determinant of wage disparities from agglomeration effects.

3. Data and methodology

3.1. Data Description

The data used in this study come from a unique and rich matched employer-employee data set called FAD that was collected by Statistic Sweden. The merged data set contains information on the entire population of Sweden, and we use observations for the period from 2001 to 2008 (the panel contains data outside this time span, but the lack of data for certain variables limited our analysis to this period). The data provide information about workers in the private sector (their gender, age, education, occupation, earnings[6], place of birth, place of residence and place of work and whether they are entrepreneurs or employees) and indicate certain firm characteristics (industry, size, patenting, ownership structure and location). There were 290 municipalities in Sweden during this period. To only include full-time wage earners, we restrict the observations to individuals between 18 to 65 years of age with earnings greater than half the annual average.[7] Moreover, we limit the effects of outliers by excluding the top and bottom 1% of earners.

Workers' interactions in the workplace generate knowledge spillovers or higher productivity. Therefore, it is more important to consider the employment density of the place of work than to consider that of the place of residence. In the analysis, we construct a time-varying employment density variable by dividing the total number of employees in each municipality by its area[8] (in sq km). It is essential to use a time-varying measure because the mean value changes by nearly 3 units from the beginning of the period to the end, which means that municipalities are on average becoming denser over time.

[6] If a worker is registered with more than one firm in a given year, we connect him/her to the firm where he/she has the highest earnings for that year.
[7]The wages are reported as total annual earnings and that there is no information on total hours worked or part-time workers. Therefore, following Katz and Autor 2000, to find full-time employees, we drop those who earned less than the minimum wage, which can be defined in nominal terms as approximately 55 percent of the current average wage (Brown 1988) for men and women separately (the respective values are 120 and 90 thousand kronor per year). The alternative is to define full-time employees as those whose wage exceeds a minimum wage defined as 75 percent of the mean wage of janitors employed by local municipalities (Skans et al., 2009). This amounts to a wage of 121,575 Swedish kronor in nominal terms in 1997.
[8] Land area of each municipality (water area excluded).

We measure market accessibility based on place of work, but there are strong correlations between market access with respect to place of work and place of residence. As defined above, as a robustness check, we employ two different market accessibility measures that are based on two different spatial scales. The first is intra-urban market accessibility (MA1), and the second is intra-region market accessibility (MA2). Both relate to the place of work.

Tables 1 and 2 present separate detailed descriptive statistics for male and female employees. We pay special attention to the differences between male and female workers and wish to test the probable differences in the effect of density and market access on their wages based on other studies that identify different commuting patterns for men and women (e.g., Camstra (1996) claims that women work closer to home than men). Although their education levels are similar, the differences in the wage levels of men and women are evident. As the statistics show, approximately 9% of male workers are employed by firms with patent activities (the innovative firm dummy), whereas only 4% of females work for such companies. A somewhat larger share of males operate their own businesses compared to females (6% versus 3%).

Figures 1 to 4 in the appendix show the regional wage rates, intra-urban and intra-region market access and employment density measures, which are all presented relative to the average values from 2001 to 2008 for Swedish municipalities. It is clear from figure 1 that wages are substantially different across regions. Figure 2, which presents the intra-urban market access measure (MA1), shows the clear relationship between wages and market accessibility. Figure 3 also indicates the existence of similar relationships. Figure 4 demonstrates that employment density is concentrated in the main cities and nearby regions. The correlations between wages, market accessibility and employment density are apparent in these figures.

3.2. Methodology

Wage differences across regions can be due to differences in individual skills or to productivity differences across regions resulting from regional endowments (Combes et al. 2008). To separately capture the effects of individual and firm characteristics, in the first step, we estimate wages as a function of individual and firm time-varying and fixed covariates. Then, we add an area-year fixed effects dummy to capture the true productivity differences and use them as the dependent variable in the second step (Combes et al. (2008) and Fally et al. (2010) use a similar methodology). As Moulton (1990) highlights, single-stage estimation is not appropriate when one is using data at different aggregation levels due to large downward biases in the standard errors; a two-stage estimation method is used to address this issue.

In our econometric analysis, we combine municipal level data on employment density and market access measures with individual level data. We use a Mincerian wage equation, in which wages depend on experience and education. To capture the effect of experience, the age and age-squared of individuals are used. The first stage equation is as follows:

$$lnw_{ijt} = \lambda_i + \gamma_j + \eta_{rt} + x_{ijt}\beta_1 + y_{ijt}\beta_2 + \tau_{ijt} \quad (1)$$

where lnw_{ijt} is the logarithm of the nominal wage of individual *i* in firm *j* at time *t*, where x_{ijt} is a vector of observed worker characteristics and where y_{ijt} is a vector of observed firm covariates. The parameter η_{rt} is an area-year fixed effect[9], λ_i is an unobserved individual fixed effect, γ_j is a firm specific effect and τ_{ijt} is a zero-mean random error with constant variance.

In the second stage, instead of using wages as a dependent variable, we use the estimated area-year fixed effects from the first stage. The notion is that area-year fixed effects represent the wage differences across municipalities and years that are not explained by individual and firm characteristics such as education and industry. The second stage equation is as follows:

$$\hat{\eta}_{rt} = \theta_t + \alpha \ln(Density_{rt}) + \delta_1 \ln(MA1_{rt}) + \delta_2 \ln(MA2_{rt}) + u_{rt} \quad (2)$$

$$\hat{\eta}_{rt} = \theta_t + \alpha \ln(Density_{rt}) + \delta_1 \ln(MA1_{rt}) + \delta_2 \ln(MA2_{rt}) + \lambda M_r \hat{\eta}_{rt} + u_{rt} \quad (3)$$

$$u_{rt} = \rho W_r u_{rt} + \varepsilon_{rt} \quad (4)$$

Where $\ln(Density_{rt})$ is the logarithm of the employment density in region r at time *t*, $\ln(MA1_{rt})$ is the logarithm of intra-urban market accessibility in region r at time *t*, $\ln(MA2_{rt})$ is the logarithm of intra-regional market accessibility in region *r* at time t and u_{rt} is the disturbance term. We assume in equation (3) and (4) that the disturbance follows a first

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[9] Note that we have included 2320 (290 municipalities x 8 year) fixed effects.

order, spatial autoregressive process. The terms M_r and W_r are weighting matrices (contiguity weight matrices) that does not depend on t, ε_{rt} is the innovation term and λ and ρ are spatial autoregressive parameters. We first estimate equation 2 using pooled OLS and random effect models. Then, we estimate the second stage by equation 3 and 4 as a spatial-autoregressive model with spatial autoregressive disturbance (Kelejian and Prucha 1998).

After controlling for individual and firm-level covariates, we compare the explanatory power of market accessibility and employment density with respect to wage disparities. Wage disparities are proxied by the area-year fixed effects that are estimated in the first stage. By controlling for individual and firm characteristics in the first step, we attempt to minimize the bias induced by the differences in the composition of workers and firms across areas.

The impacts of other individual characteristics, x_{ijt}, and firm level characteristics, y_{ijt} , are considered in the following manner. We control for age, age squared, medium education level (equal to 2 years of university education) and higher education (at least 3 years of university education) and separately estimate the model for men and women. Standard Occupational Classification dummies and birthplace dummies are included. Moreover, we add a dummy to capture the difference between individuals working for a firm and those who own their own businesses or are co-owners. To control for firm characteristics, we use the size of the firm, its innovativeness (whether the firm has applied for patents) and 6 common OECD sector classifications[10]. To control for fixed effects, we include 2320 area-year dummies (290 municipality dummies*8 year dummies) in the first equation. Previous studies show that foreign owned firms pay higher average wages even after firm characteristics and labor force educational levels are controlled for (see, e.g., Lipsey and Sjöhom (2006); Doms and Jensen (1998); Griffith (1999)). To control for the impact of a firm being multinational, we include controls for firm ownership types in the analysis. In the data set, we can distinguish among 4 categories of firm ownership structure: domestic non-affiliated, member of a domestic group, member of a domestic multinational group and member of a foreign multinational group.

4. Results

[10] Two-digit sector dummies are used in a robustness check regression. No significant difference was observed with respect to the current regression. The results are available upon request.

In this section, we present the results for two different sets of data sources. The first contains individual wage data for nearly 4 million unique workers across 290 Swedish municipalities observed over the period from 2001 to 2008. The second contains average regional wage data. The results are reported separately for females and males. Table 3 estimates the Mincer wage equation; this is the first step in our two-step model. Tables 5 through 8 estimate wage differences across municipalities, regions and years. Tables 5 and 6 report results based on individual annual wages, while tables 7 and 8 are based on regional averages over an 8-year period. Three different estimators are employed: pooled OLS, a random-effects panel data estimator and a generalized spatial panel 2SLS model.

Figures 5 and 6 display regional wages after individual and firm characteristics are controlled for. The figures indicate considerable spatial wage disparities across municipalities for both men and women. We assume that these differentials reflect regional characteristics and externalities such as density and knowledge spillovers and market access.

4.1. Individual Wages

Table 3 reports the standard OLS estimates of the wage equation[11] for male and female employees. Individual level wages are regressed on education levels, experience, employment type, size of employer, innovation activities and firm ownership structure, with sector dummies, occupation dummies, place of birth and area-year dummies used to capture area-year-specific effects (equation 1). We split the sample into male workers and female workers because we expect different returns and commuting patterns with respect to sex. Columns 1 and 2 present the regression results for male and female workers, respectively. The results show that the return on education is higher for males, as expected. The returns on working in an innovative firm, interestingly, are higher for female workers (approximately 2.7%). Moreover, compared to individuals at non-affiliated firms, individuals working in other types of firms experience higher returns. The wage premium is highest at foreign owned multinational firms, as expected, but it is lower than those obtained in studies conducted at a more aggregate level (for a similar finding, see Heyman et al. 2007).

Before moving to the next step in the regressions, we should note the relationship between wage disparities and the aggregated wage rates for each region, density and market

[11] We tested both a fixed effects and a random effects model, and the Hausman test suggests the fixed effects model. However, due to the large number of observations (approximately 11 million), the fixed effects model is biased. See Cameron and Trivedi, 2010. Thus, we report the OLS results.

accessibility measure. Tables 4a and 4b present the correlation matrix for wage disparities, aggregated regional wages and the log of density and log of market accessibility measures. The results show that for both male and female workers, the wage disparities (area-year fixed effects) are highly correlated with aggregate regional wages, meaning that they are a good proxy for regional wages. The correlation between log density and the wage disparity is moderate at approximately 0.50. Thus, areas with high density also have rather high wages (after individual and firm effects are controlled for; when these effects are not controlled for, the correlation is approximately 0.70). Intra-urban market accessibility (MA1) is correlated with wage disparities, but this is true to a greater extent for female workers (0.40 vs. 0.31), indicating the importance of greater accessibility for women. Intra-region market accessibility has the same correlation for male and female workers (0.40).

Table 5 presents the coefficient obtained in the estimation of equation (2) for female workers. Column 1 reports the results for the OLS model where the only regressors are density and market accessibility, together with the year dummies. Column 2 shows the results for the same specification using a random effects panel data model. Glaeser and Gottlieb (2009) estimate that the elasticity of income with respect to city size in the U.S. is within the range of 0.04-0.08 for different model specifications. This finding is consistent with those of many other studies. As observed, our estimates suggest that the density premium is substantially lower. The elasticity is 1.4% in both the OLS and the RE model. Typically, previous studies have not accounted for both density and market accessibility; as a result, they have overestimated the density premium. However, rows 1 and 2 show that the density and market accessibility variables each have a separate positive effect on wages. The intra-urban market accessibility (MA1) is highly significant, although the size of the estimate is only approximately half that of the density coefficient.

To test for the presence of spatial autocorrelation in the residuals, we perform Moran's I test on the residuals of the estimations in Columns 1 and 2 separately for each year (the average of all years is reported). The results suggest the presence of spatial autocorrelation in the residuals.

Columns 3 and 4 use a spatial autoregressive model with a spatial-autoregressive disturbance term to control for spatial correlations, which is also known as a SARAR model. Due to computational limitations, we average the values for the 8-year period. We estimate the parameters using either maximum likelihood (ML) estimation, as in Column 3, or a generalized spatial two-stage least squares model (Kelejian, and Prucha, 1998), as in Column 4. When a contiguity weight matrix is used, the estimation results for these two models are similar. Moreover, the results are very similar to the OLS and RE estimates.

Table 6 reports the corresponding results for male workers. The first line suggests a slightly higher return to density than in Table 5. The coefficient estimate is 1.7% and is consistent across all models. However, the MA1 coefficients are not significantly different from zero in any of the estimated models. Thus, when density is controlled for, market accessibility has no effect on the individual wages of male employees.

To interpret the results more carefully, we employ the alternative market accessibility measure (intra-region market access rather than intra-municipality access). Using the second market accessibility measure, we obtained the opposite results with respect to male and female workers (Tables A1 and A2 in the Appendix). This finding implies that within municipality accessibility has a positive effect on female wages, whereas it has no effect on male wages. In contrast, within functional region accessibility has no effect on female wages and has a positive effect on male wages. Thus, it seems that males can travel further to maximize their wages, whereas females are likely to be more spatially constrained. Fingleton and Longi (2013) find that neither the NEG nor the UE theory has an effect on men's wage levels, whereas a higher employment density (as implied by UE theory) significantly increases female wages. These results are consistent with our findings with respect to female workers. They also indicate that women's preference for short commutes ties them to the local job market.

The two main conclusions here are as follows. First, density is more important to wage differences across regions than is market accessibility for both males and females. Thus, the urban economics model is more powerful than NEG in explaining wage dispersion. The results for the accessibility variable are mixed for females and males. Whereas intra-municipality access but not intra-region access correlates positively with wages for females, we find the opposite results for males.

4.2. Aggregate Wages

Tables 7 and 8 use aggregated regional wages as a dependent variable. This variable is constructed using individual level data to calculate the mean of log-wages. In the first column, no other control variables are included except the time dummies.

First, consider Table 7 and the results for females. Starting with Column 1, the table shows a 2.8% return to density and a 1.2% return to market accessibility. Column 2 controls for regional schooling[12] and regional technical knowledge[13]. These variables should capture the effect of skill in a region separate from the density and market accessibility effects. After controlling for regional skills, the effect of density decreases to 1.7%, and similar results are presented in Columns 2 (OLS) and 3 (FE). This result is also identical to the estimates in Table 5.

Considering the impact of accessibility, Row 2 presents a negative and significant result (0.007) for the OLS model and a non-significant result for the FE model. Moran's I, as reported in Columns 2 and 3 (averaged over the period under consideration), suggests that we should control for spatial autocorrelation. Using the SARAR model in the last two columns yields elasticity of 2.1% and 2.2% to density, respectively, and no significant effect for market accessibility.

Table 8 considers the aggregate wage equation for male workers. Column 1 does not control for regional skills. With this specification, doubling density will increase the wages of male workers by 3.2%. This figure is lower than the figure obtained by Ciccone and Hall (1996) because in that study, doubling the employment density in a county resulted in a 6% increase in average labor productivity. A close correlation between wages and labor productivity can be assumed. The effect of market accessibility is approximately 1% when regional skills and regional innovation are not controlled for. When these two controls are added, the sign of the MA variable becomes negative (-0.07) and highly significant. Moreover, the density coefficient deceases to 2.4% (Column 2).

It is noteworthy that in all four models, even once regional schooling and regional technical knowledge are controlled for (Columns 2 to 5), we find a nearly 3% elasticity for density, whereas using the individual level data and controlling for worker and firm characteristics yields an estimate of approximately half this size for male workers. The market accessibility coefficient is not significant (Tables A3 and A4 in the Appendix present the results of estimates made using MA2 measures, which yield similar, non-significant results for both male and female workers). These results suggest the superiority of individual level data and

[12] Calculated as the percentage of residents in each municipality with 3 years or more of university education.
[13] Calculated as the share of the workforce engaged in knowledge intensive services (SIC 72 and 73) relative to the national average for each municipality.

indicate that failing to consider worker and firm characteristics will lead to an overestimation of the effect of density of up to 100%.

5. Conclusion

The purpose of this paper was to shed more light on the growing wage gap that has characterized nearly all modern economies in recent decades. Our particular research interest is the importance of regional characteristics, and we distinguish between density and market accessibility.

As suggested by urban economic theory, wage dispersion is highly significantly associated with spatial proximity among both males and females within city proximity. Wage theories derived from the new economic geography predict that the accessibility of purchasing power, firms and people should also be important factors.

Our main results suggest that density is more important to wage differences across regions than is market accessibility for both males and females. This finding can be interpreted to mean that the urban economics model is more powerful than the NEG model in explaining wage dispersion using individual-level data. Moreover, our results provide mixed findings for the market access variable. Whereas intra-municipality access but not intra-region access is positively correlated with female wages, we find the opposite results for males. Thus, it seems that males can travel farther to maximize their wages, whereas females' preference for short commutes ties them to the local job market.

The paper also shows that individual and firm characteristics play an important role in wage disparities across regions and that failing to control for these effects will lead to the overestimation of agglomeration effects. Moreover, working for an innovative firm generates high returns for both male and female workers but particularly for female workers. For both women and men, higher education seems to count, though this is more true for men. Being an employee rather than a self- or co-owner is an important factor for both groups.

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TABLE SECTION

Table 1. Descriptive statistics for male employees. N= 10,742,513

Variables	Mean	Sd	Min	Max
Density (log)	3.35	2.19	-3.3	7.4
Market access (MA1), log	6.65	1.26	4.4	11.9
Market access (MA2), log	7.79	1.89	1.78	11.87
Wage (log)	12.50	0.35	11.7	13.6
Age	41.86	11.63	18.0	65.0
Medium education	0.12	0.32	0.0	1.0
Higher education	0.13	0.33	0.0	1.0
Innovative firm	0.09	0.29	0.0	1.0
Employee	0.94	0.24	0.0	1.0
Firm size (log)	4.97	2.62	0.0	10.9
Domestic non-affiliated	0.35	0.49	0.0	1.0
Domestic uni-national	0.19	0.47	0.0	1.0
Domestic multi-national	0.24	0.35	0.0	1.0
Foreign multi-national	0.22	0.34	0.0	1.0
High tech manufacturing	0.04	0.19	0.0	1.0
Medium high tech manufacturing	0.12	0.33	0.0	1.0
Medium low tech manufacturing	0.09	0.28	0.0	1.0
Low tech manufacturing	0.24	0.42	0.0	1.0
Knowledge intensive services	0.21	0.41	0.0	1.0
Other services	0.26	0.44	0.0	1.0
Military process	0.00	0.02	0.0	1.0
Managers	0.09	0.28	0.0	1.0
Technicians & professionals	0.12	0.33	0.0	1.0
Technicians & associate professionals	0.18	0.39	0.0	1.0
Office & customer service work	0.06	0.24	0.0	1.0
Service work & sales work	0.06	0.23	0.0	1.0
Skilled agricultural	0.01	0.10	0.0	1.0
Forestry & fisheries	0.21	0.41	0.0	1.0
Craft & related trade work & manufacturing	0.22	0.42	0.0	1.0
Elementary occupations	0.05	0.22	0.0	1.0
African	0.01	0.08	0.0	1.0
Asian	0.02	0.14	0.0	1.0
European	0.04	0.19	0.0	1.0
North American	0.00	0.05	0.0	1.0
Oceanian	0.00	0.02	0.0	1.0
Former Soviet Union	0.00	0.02	0.0	1.0
Swedish	0.90	0.30	0.0	1.0
South African	0.01	0.08	0.0	1.0
Other Nordic countries	0.03	0.16	0.0	1.0

Table 2. Descriptive statistics for female employees. N=5,106,431

Variables	Mean	Sd	Min	Max
Density (log)	3.61	2.27	-3.2	7.3
Market access (MA1), log	6.65	1.26	4.4	11.9
Market access (MA2), log	7.79	1.89	1.78	11.87
Wage (log)	12.23	0.38	11.4	13.2
Age	41.18	11.87	18.0	65.0
Medium education	0.12	0.33	0.0	1.0
Higher education	0.15	0.36	0.0	1.0
Innovative Firm	0.06	0.24	0.0	1.0
Employee	0.97	0.18	0.0	1.0
Firm size (log)	5.38	2.75	0.0	10.9
Domestic non-affiliated	0.38	0.43	0.0	1.0
Domestic uni-national	0.19	0.45	0.0	1.0
Domestic multi-national	0.21	0.39	0.0	1.0
Foreign multi-national	0.22	0.31	0.0	1.0
High tech manufacturing	0.04	0.20	0.0	1.0
Medium high tech manufacturing	0.06	0.24	0.0	1.0
Medium low tech manufacturing	0.04	0.20	0.0	1.0
Low tech manufacturing	0.12	0.32	0.0	1.0
Knowledge intensive services	0.32	0.47	0.0	1.0
Other services	0.36	0.48	0.0	1.0
Military process	0.00	0.02	0.0	1.0
Managers	0.04	0.18	0.0	1.0
Technicians & professionals	0.13	0.40	0.0	1.0
Technicians & associate professionals	0.21	0.41	0.0	1.0
Office & customer service work	0.22	0.34	0.0	1.0
Service work & sales work	0.19	0.46	0.0	1.0
Skilled agricultural	0.01	0.06	0.0	1.0
Forestry & fisheries	0.02	0.10	0.0	1.0
Craft & related trade work & manufacturing	0.09	0.19	0.0	1.0
Elementary occupations	0.10	0.24	0.0	1.0
African	0.00	0.07	0.0	1.0
Asian	0.02	0.14	0.0	1.0
European	0.04	0.19	0.0	1.0
North American	0.00	0.05	0.0	1.0
Oceanian	0.00	0.02	0.0	1.0
Former Soviet Union	0.00	0.03	0.0	1.0
Swedish	0.89	0.31	0.0	1.0
South African	0.01	0.08	0.0	1.0
Other Nordic countries	0.04	0.19	0.0	1.0

Table 3. Wages and individual and firm characteristics (equation 1)

VARIABLES	(1) OLS-male	(2) OLS-female
Medium education	0.049***	0.029***
	(0.000)	(0.000)
Higher education	0.123***	0.070***
	(0.001)	(0.001)
Age	0.037***	0.036***
	(0.000)	(0.000)
Age Square	-0.000***	-0.000***
	(0.000)	(0.000)
Employee	0.068***	0.054***
	(0.001)	(0.001)
Innovative firm	0.012***	0.039***
	(0.000)	(0.001)
Size	0.003***	0.000***
	(0.000)	(0.000)
Domestic groups	0.042***	0.044***
	(0.000)	(0.000)
Domestic multi-national	0.092***	0.074***
	(0.000)	(0.001)
Foreign multi-national	0.103***	0.080***
	(0.000)	(0.001)
Area*year dummies	Yes	Yes
Sector dummies	Yes	Yes
Occupation dummies	Yes	Yes
Place of birth dummies	Yes	Yes
Observations	10,742,513	5,106,431
Number of unique obs.	2,233,436	1,743,257
R-squared	0.412	0.333

Notes: *** Rejection of Ho at 1% level of significance; ** Rejection of Ho at 5% level of significance; *Rejection of Ho at 10% level of significance.

Table 4a. Correlations among home- and work-based wages, employment density and market accessibility by municipality for men.

	Wage disparity	Regional wage	log Density	lnMA1	lnMA2
Wage disparity	1.0000	0.85	0.51	0.31	0.40
Regional wage		1.00	0.74	0.55	0.44
log Density			1.00	0.68	0.64
lnMA1				1.00	0.24
lnMA2					1.00

Table 4b. Correlations among home- and work-based wages, employment density and market accessibility by municipality for women.

	Wage disparity	Regional wage	log Density	lnMA1	lnMA2
Wage disparity	1.0000	0.88	0.53	0.40	0.40
Regional wage		1.00	0.67	0.50	0.43
log Density			1.00	0.68	0.64
lnMA1				1.00	0.24
lnMA2					1.00

Table 5. Estimation results for equation 2 for female workers

VARIABLES Wage_disparity	(1) OLS	(2) RE	(3) Spatial ML	(4) Spatial GS2SLS
Density (log)	0.014***	0.014***	0.013***	0.013***
	(0.001)	(0.002)	(0.002)	(0.002)
MA1	0.007***	0.006***	0.005**	0.006***
	(0.001)	(0.002)	(0.002)	(0.002)
Year dummies	YES	YES	Average	Average
λ	----	----	0.098	0.090
			(0.109)	(0.100)
ρ	----	----	1.106***	1.080***
			(0.161)	(0.146)
σ^2	----	----	0.001***	----
			(0.000)	
Constant	-0.237***	-0.234***	-0.170***	-0.176***
	(0.005)	(0.012)	(0.010)	(0.010)
Moran's I	0.366	0.246		
p-value	0.00	0.00		
(H_0 = no spatial autocorrelation)				
Observations	2,318	2,318	290	290
R-squared	0.653	0.653	---	---

Notes: λ and ρ are the corresponding scalar parameters typically referred to as spatial-autoregressive parameters. σ^2 is the variance of error ε_{rt} in equation 3 $(\varepsilon_{rt} \sim N(0,\sigma^2 I))$; for a detailed discussion, please see Drukker et al. (2011)

*** Rejection of Ho at 1% level of significance; ** Rejection of Ho at 5% level of significance; *Rejection of Ho at 10% level of significance.

Table 6. Estimation results for equation 2 for male workers

VARIABLES Wage_disparity	(1) OLS	(2) RE	(3) Spatial ML	(4) Spatial GS2SLS
Density (log)	0.017***	0.018***	0.017***	0.017***
	(0.001)	(0.002)	(0.002)	(0.002)
MA1	-0.001	-0.001	-0.003*	-0.003
	(0.001)	(0.002)	(0.002)	(0.002)
Year dummies	YES	YES	Average	Average
λ	----	----	-0.051	-0.087
			(0.118)	(0.119)
ρ	----	----	1.042***	1.040***
			(0.166)	(0.156)
σ^2	----	----	0.001***	----
			(0.000)	
Constant	-0.173***	-0.169***	-0.108***	-0.115***
	(0.005)	(0.012)	(0.010)	(0.010)
Moran's I	0.265	0.229		
p-value	0.00	0.00		
(H_0=no spatial autocorrelation)				
Observations	2,318	2,318	290	290
R-squared	0.698	0.700		

Notes: λ and ρ are the corresponding scalar parameters typically referred to as spatial-autoregressive parameters. σ^2 is the variance of error ε_{rt} in equation 3 $(\varepsilon_{rt} \sim N(0,\sigma^2 I))$; for a detailed discussion, please see Drukker et al. (2011)

*** Rejection of Ho at 1% level of significance; ** Rejection of Ho at 5% level of significance; *Rejection of Ho at 10% level of significance.

Table 7. Estimation results with the aggregate regional wage rate as the dependent variable: female workers

VARIABLES Wage_rates	(1)	(2) OLS	(3) RE	(4) Spatial ML	(5) Spatial GS2SLS
Density (log)	0.028***	0.017***	0.017***	0.022***	0.021***
	(0.001)	(0.001)	(0.002)	(0.005)	(0.005)
MA1	0.012***	-0.007***	-0.004	-0.006	-0.006
	(0.001)	(0.001)	(0.003)	(0.007)	(0.007)
Regional schooling	NO	YES	YES	YES	YES
Regional tech. knowledge	NO	YES	YES	YES	YES
Year dummies	YES	YES	YES	Average	Average
λ	----	----	----	0.001	0.001
				(0.003)	(0.003)
ρ	----	----	----	0.085	0.070
				(0.225)	(0.285)
σ^2	----	----	----	0.008***	----
				(0.001)	
Constant	12.069***	12.116***	12.327***	12.108***	12.128***
	(0.007)	(0.006)	(0.015)	(0.015)	(0.035)
Moran's I		0.265	0.229		
p-value		0.00	0.00		
(H_0=no spatial autocorrelation)					
Observations	2,318	2,318	2,318	290	290
R-squared	0.674	0.796			

Notes: λ and ρ are the corresponding scalar parameters typically referred to as spatial-autoregressive parameters. σ^2 is the variance of error ε_{rt} in equation 3 $(\varepsilon_{rt} \sim N(0,\sigma^2 I))$; for a detailed discussion, please see Drukker et al. (2011)

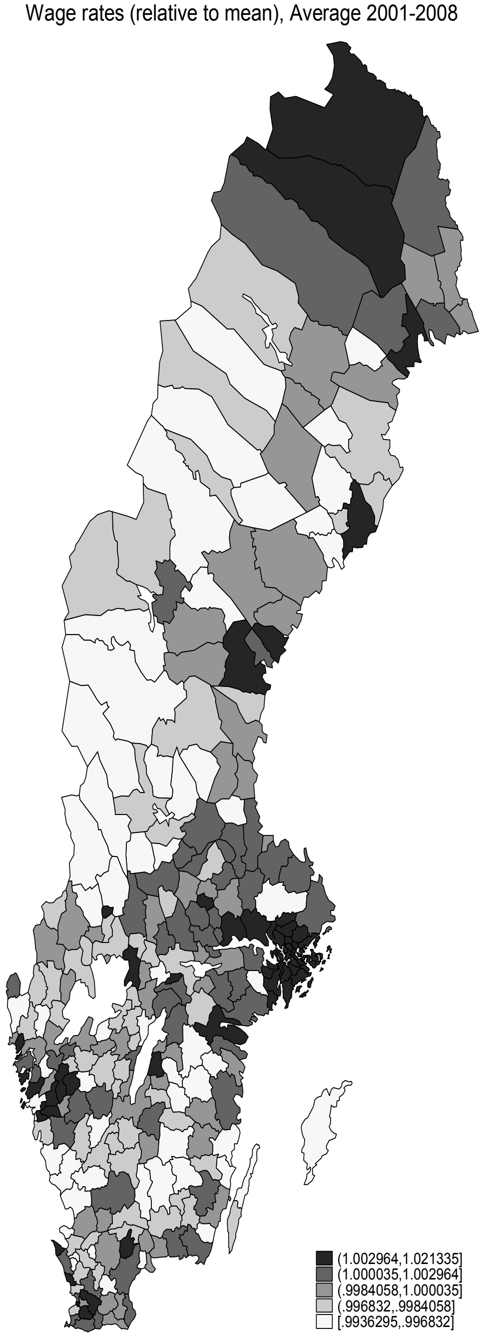
*** Rejection of Ho at 1% level of significance; ** Rejection of Ho at 5% level of significance; *Rejection of Ho at 10% level of significance.

Table 8. Estimation results with the aggregate regional wage rate as the dependent variable: male workers

VARIABLES Wage_rates	(1) OLS	(2) OLS	(3) RE	(4) Spatial ML	(5) Spatial GS2SLS
Density (log)	0.032***	0.024***	0.028***	0.029***	0.029***
	(0.001)	(0.001)	(0.002)	(0.005)	(0.005)
MA1	0.009***	-0.007***	-0.002	-0.009	-0.009
	(0.001)	(0.001)	(0.003)	(0.007)	(0.007)
Regional schooling	NO	YES	YES	YES	YES
Regional tech.	NO	YES	YES	YES	YES
Year dummies	YES	YES	YES	Average	Average
λ	----	----	----	0.003	0.003
				(0.003)	(0.003)
ρ	----	----	----	-0.102	-0.137
				(0.231)	(0.314)
σ^2	----	----	----	0.008***	----
				(0.001)	
Constant	12.296***	12.332***	12.327***	12.333***	12.333***
	(0.007)	(0.006)	(0.015)	(0.035)	(0.035)
Moran's I		0.265	0.229		
p-value (H_0=no spatial autocorrelation)		0.00	0.00		
Observations	2,318	2,318	2,318	290	290
R-squared	0.723	0.807			

Notes: λ and ρ are the corresponding scalar parameters typically referred to as spatial-autoregressive parameters. σ^2 is the variance of error ε_{rt} in equation 3 $(\varepsilon_{rt} \sim N(0,\sigma^2 I))$; for a detailed discussion, please see Drukker et al. (2011)

*** Rejection of Ho at 1% level of significance; ** Rejection of Ho at 5% level of significance; *Rejection of Ho at 10% level of significance.



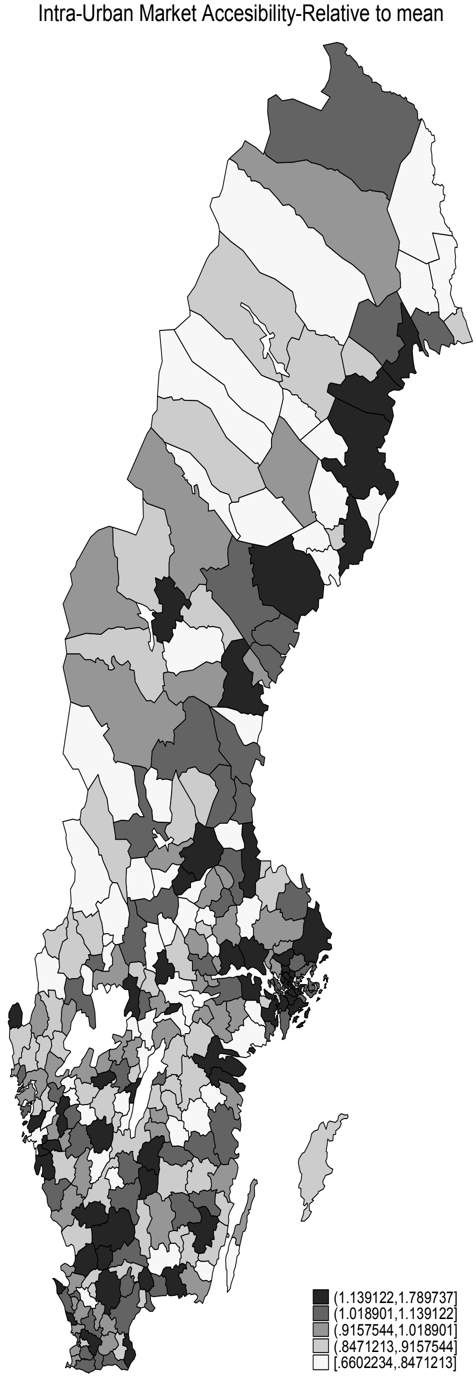
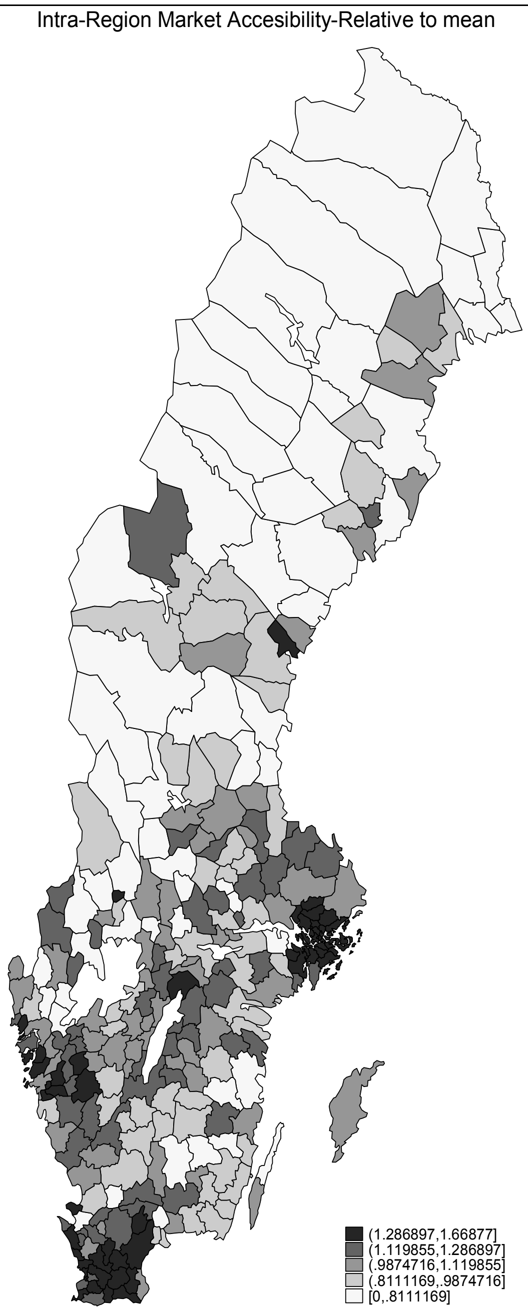


Figure 1. Aggregated individual level wage rates in Swedish municipalities. Black represents the highest wages, and white represents the lowest.

Figure 2. Intra-urban market accessibility in Swedish municipalities measured by total wage sum across 290 Swedish municipalities. Black represents the highest, and white represents the lowest.



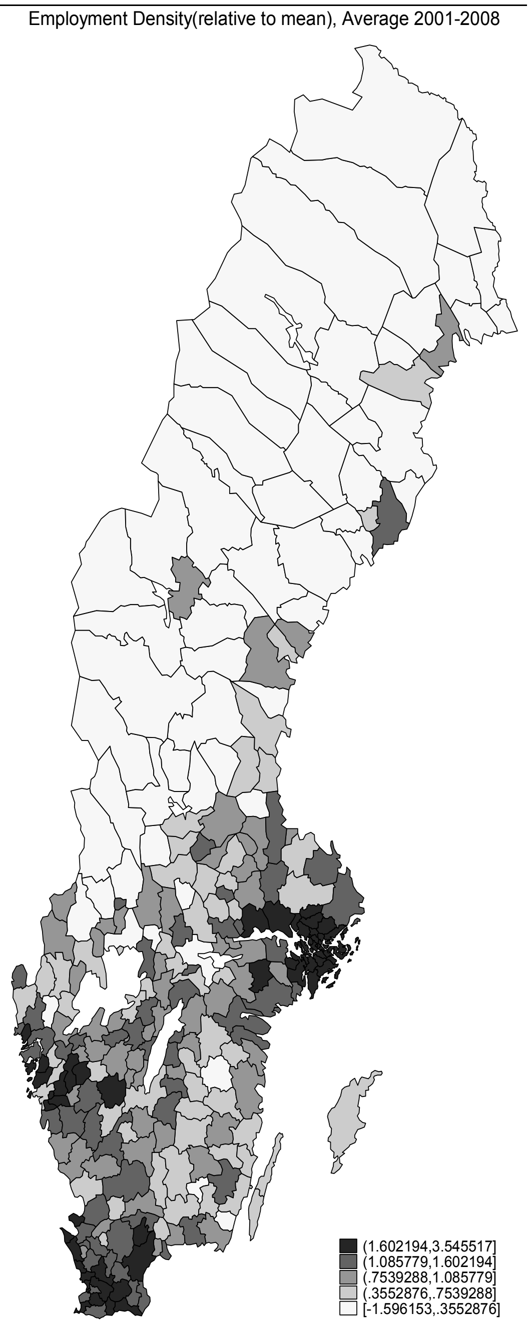
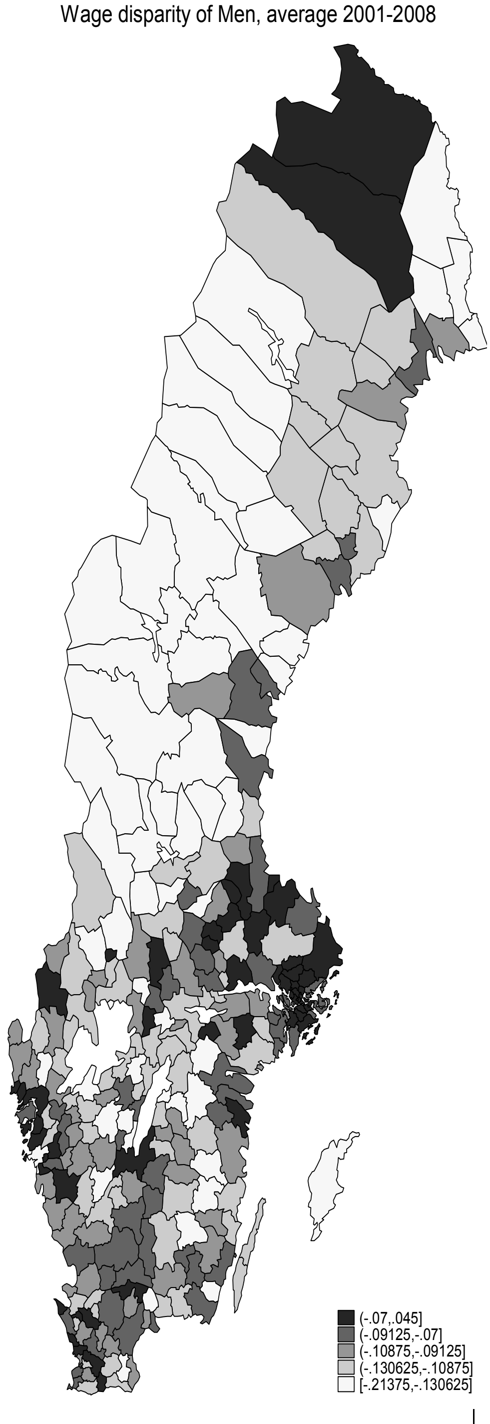


Figure 3. Intra-region market accessibility in Swedish municipalities as measured by total wage sum across 290 Swedish municipalities. Black represents the highest, and white represents the lowest.

Figure 4. Employment density, measured as the total number of employees divided by land area in (sq km), across 290 Swedish municipalities. Black represents the highest, and white represents the lowest.



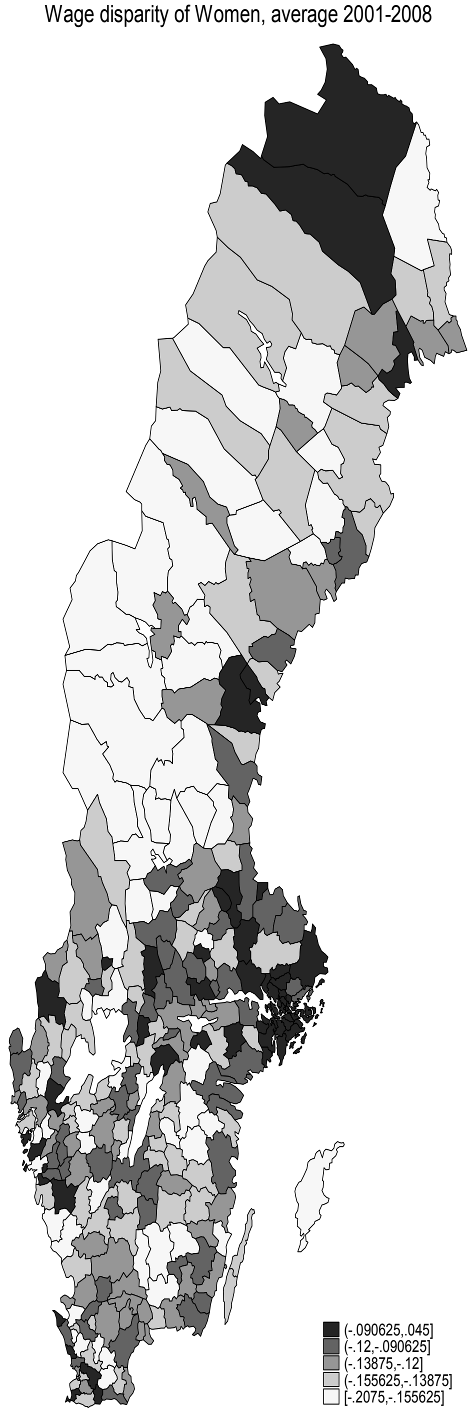


Figure 5. Wage disparity for men after individual and firm characteristics are controlled for across 290 Swedish municipalities. Black represents the highest wages, and white represents the lowest.

Figure 6. Wage disparity for women after individual and firm characteristics are controlled for across 290 Swedish municipalities. Black represents the highest, wages and white represents the lowest.

APPENDIX

Table A1. Estimation results for equation 2 for female workers with MA2

VARIABLES Dep: Wage_disparity	(1) OLS	(2) RE	(3) Spatial ML	(4) Spatial GS2SLS
Density (log)	0.017***	0.018***	0.016***	0.016***
	(0.001)	(0.002)	(0.001)	(0.001)
MA2	0.003***	0.003**	-0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Year dummies	YES	YES	Average	Average
λ	----	----	-0.046	0.018
			(0.103)	(0.103)
ρ	----	----	1.240***	1.174***
			(0.136)	(0.130)
σ^2	----	----	0.001***	----
			(0.000)	
Constant	-0.225***	-0.234***	-0.147***	-0.144***
	(0.009)	(0.012)	(0.008)	(0.009)
Observations	2,318	2,318	290	290
R-squared	0.671			

Notes: λ and ρ are the corresponding scalar parameters typically referred to as spatial-autoregressive parameters. σ^2 is the variance of error ε_{rt} in equation 3 $(\varepsilon_{rt} \sim N(0,\sigma^2 I))$; for a detailed discussion, please see Drukker et al. (2011)

*** Rejection of Ho at 1% level of significance; ** Rejection of Ho at 5% level of significance; *Rejection of Ho at 10% level of significance.

Table A2. Estimation results for equation 2 for male workers with MA2

VARIABLES Dep: Wage_disparity	(1) OLS	(2) RE	(3) Spatial ML	(4) Spatial GS2SLS
Density (log)	0.015***	0.016***	0.013***	0.013***
	(0.001)	(0.001)	(0.001)	(0.001)
MA2	0.004***	0.003***	0.003***	0.003***
	(0.000)	(0.001)	(0.001)	(0.001)
Year dummies	YES	YES	Average	Average
λ	----	----	-0.041	-0.015
			(0.102)	(0.115)
ρ	----	----	0.993***	0.965***
			(0.158)	(0.156)
σ^2	----	----	0.001***	----
			(0.000)	
Constant	-0.202***	-0.200***	-0.142***	-0.141***
	(0.003)	(0.007)	(0.008)	(0.008)
Observations	2,318	2,318	290	290
R-squared	0.725			

Notes: λ and ρ are the corresponding scalar parameters typically referred to as spatial-autoregressive parameters. σ^2 is the variance of error ε_{rt} in equation 3 $(\varepsilon_{rt} \sim N(0,\sigma^2 I))$; for a detailed discussion, please see Drukker et al. (2011)

*** Rejection of Ho at 1% level of significance; ** Rejection of Ho at 5% level of significance; *Rejection of Ho at 10% level of significance.

Table A3. Estimation results with the aggregate regional wage rate as the dependent variable: female workers with MA2

VARIABLES Dep: Aggregated Wage_rates	(1) OLS	(2) OLS	(3) RE	(4) Spatial ML	(5) Spatial GS2SLS
Density (log)	0.036***	0.016***	0.016***	0.023***	0.023***
	(0.001)	(0.001)	(0.003)	(0.006)	(0.006)
MA2	0.003***	0.003***	0.003*	-0.002	-0.002
	(0.001)	(0.001)	(0.002)	(0.003)	(0.003)
Regional schooling	NO	YES	YES	YES	YES
Regional tech.	NO	YES	YES	YES	YES
Year dummies	YES	YES	YES	Average	Average
λ	----	----		-0.000	0.000
				(0.003)	(0.003)
ρ	----	----		0.078	0.071
				(0.225)	(0.286)
σ^2	----	----		0.008***	----
				(0.001)	
Constant		12.060***	12.065***	12.116***	12.115***
		(0.006)	(0.013)	(0.027)	(0.027)
Observations	2,318	2,318	2,318	290	290
R-squared	0..687	0.797			
Number of AstkommunC	290	290	290		

Notes: λ and ρ are the corresponding scalar parameters typically referred to as spatial-autoregressive parameters. σ^2 is the variance of error ε_{rt} in equation 3 $(\varepsilon_{rt} \sim N(0,\sigma^2 I))$; for a detailed discussion, please see Drukker et al. (2011)

*** Rejection of Ho at 1% level of significance; ** Rejection of Ho at 5% level of significance; *Rejection of Ho at 10% level of significance.

Table A4. Estimation results using the aggregate regional wage rate as the dependent variable: male workers with MA2

VARIABLES Dep: Aggregated Wage_rates	(1) OLS	(2) OLS	(3) RE	(4) Spatial ML	(5) Spatial GS2SLS
log Density	0.040***	0.023***	0.030***	0.030***	0.030***
	(0.001)	(0.001)	(0.002)	(0.006)	(0.006)
MA2	-0.002***	0.000	-0.002	-0.002	-0.002
	(0.001)	(0.000)	(0.001)	(0.003)	(0.003)
Regional schooling	NO	YES	YES	YES	YES
Regional tech.	NO	YES	YES	YES	YES
Year dummies	YES	YES	YES	Average	Average
λ	----	----		0.002	0.002
				(0.003)	(0.003)
ρ	----	----		-0.098	-0.118
				(0.230)	(0.310)
σ^2	----	----		0.008***	----
				(0.001)	
Constant	12.354	12.296***	12.329***	12.308***	12.307***
	(0.005)	(0.004)	(0.010)	(0.027)	(0.027)
Observations	2,318	2,318	2,318	290	290
R-squared	0.729	0.797			

Notes: λ and ρ are the corresponding scalar parameters typically referred to as spatial-autoregressive parameters. σ^2 is the variance of error ε_{rt} in equation 3 $(\varepsilon_{rt} \sim N(0, \sigma^2 I))$. For a detailed discussion, please see Drukker et al. (2011)