WIDER Working Paper 2024/52

Economic geography determinants of spatial wage disparities in South Africa

Evidence from a firm-level panel

Sanduku Mulumba,[1,*] Lawrence Edwards,[1] and David Fadiran[1]

August 2024

Abstract: In this paper, we use the new economic geography (NEG) framework to estimate the extent to which spatial wage disparities in the South African manufacturing sector are an outcome of economic forces such as market access. To test the relationship, we use the anonymized tax data on employers and employees made available by the South African Revenue Service and National Treasury in collaboration with UNU-WIDER. We first document the key stylized facts that characterize the spatial distribution of wages across regions in South Africa using exploratory spatial data analysis (ESDA) techniques. We then test for the existence of a wage structure across South African local and metropolitan municipalities, controlling for individual and firm characteristics using a two-stage estimation method. Consistent with the NEG predictions, we find that wages are higher in municipalities that are closer to large markets, as measured by the Harris market potential index. However, much of the wage effect is driven by the income and employment density of the municipality's own market, and not that of surrounding areas. These results point to a combination of large spatial rigidities leading to highly localized effects of market potential, together with wage and productivity effects arising from urban agglomeration economies.

Key words: new economic geography, spatial wage disparities, firm characteristics, South Africa, exploratory spatial data analysis, two-stage estimation method, market access

JEL classification: R12, R23, O15

Acknowledgements: We thank Reza Daniels for the excellent comments on an earlier draft of the paper. We bear full responsibility for any mistakes in the results and the final presentation of the paper. Sanduku Mulumba would also like to express his gratitude to UNU-WIDER for its support.

---

[1] University of Cape Town, South Africa; * corresponding author: mlmsan005@myuct.ac.za

This study has been prepared within the UNU-WIDER project Southern Africa—Towards Inclusive Economic Development (SA-TIED).

Information and requests: publications@wider.unu.edu

ISSN 1798-7237 ISBN 978-92-9267-514-1

https://doi.org/10.35188/UNU-WIDER/2024/514-1

Typescript prepared by Joseph Laredo and Siméon Rapin.

United Nations University World Institute for Development Economics Research provides economic analysis and policy advice with the aim of promoting sustainable and equitable development. The Institute began operations in 1985 in Helsinki, Finland, as the first research and training centre of the United Nations University. Today it is a unique blend of think tank, research institute, and UN agency—providing a range of services from policy advice to governments as well as freely available original research.

The Institute is funded through income from an endowment fund with additional contributions to its work programme from Finland and Sweden, as well as earmarked contributions for specific projects from a variety of donors.

Katajanokanlaituri 6 B, 00160 Helsinki, Finland

1 Introduction

Economic disparities are a pervasive feature of the economic landscape. This certainly holds in South Africa (Turok et al. 2017). Despite the ending of the apartheid regime in 1994 and the increase in labour mobility that followed, wage disparities across South African regions (local and metropolitan municipalities) have persisted over time (Mudiriza and Edwards 2021). In 2017, the average monthly wage in the manufacturing sector in Johannesburg, a metropolitan city in the Gauteng province, was more than twice as high as the national average. On the other hand, the average wage in some of the lowest-paying local municipalities was more than 10 times lower than the national average.[1] Such disparities across regions have the potential to undermine social cohesion (Breinlich et al. 2014) and have attracted considerable research and public policy attention in countries all over the world (Head and Mayer 2004; Kim 2008: Redding 2010).

Yet, what drives these disparities is still an open question (for a review of the theoretical and empirical, see Proost and Thisse (2019) and Redding (2011)). Several strands emerge from the literature. In the traditional neoclassical economic approach, economic disparities across areas are the result of differences in their natural geographical features (Gallup et al. 1999; Henderson et al. 2018; Roback 1982; Rosen 1979; Sachs 2000). Although helping to explain the emergence of industrial agglomerations (Bosker and Buringh 2017), this approach falls short of providing convincing reasons as to why regions with similar underlying natural geographical features may take different economic development paths (Acemoglu and Robinson 2010).

The new economic geography (NEG) theory, on the other hand, provides explanations as to how and why regions that are otherwise homogeneous in their natural geographical features can take different agglomeration trajectories (Fujita and Krugman 2004; Fujita and Thisse 2009). The theory builds on the interaction between economies of scale at the firm level, transportation costs, and the consumer love of variety to explain disparities in the geographical concentration of economic activities across space (Head and Mayer 2004; Krugman 1991a; Krugman and Venables 1995). The idea can be traced back to Harris's (1954) market potential function and goes as follows: the closer a specific location is to consumer markets, the lower the transportation costs are and the stronger the demand linkages. This leads to higher economic activity and/or wage levels in locations with high market access (Head and Mayer 2004).

There are additional theories explaining wage differences across regions. Models involving technological spillovers and human capital externalities also suggest that wage levels can be linked to density of economic activity (Head and Mayer 2006). Urban agglomeration economies also arise from more efficient *sharing* of indivisible local infrastructure, risks, and a wider variety of inputs, better *matching* between buyers and suppliers and employers and employees, and better *learning* through knowledge generation, diffusion, and accumulation (Duranton and Puga 2004). These benefits from agglomeration can arise from the size of the overall local market (urbanization economies) or from the geographic concentration at the sector level (localization economies) (Combes et al. 2010).

This paper analyses the role that market access plays in driving spatial wage disparities in the manufacturing sector in South Africa. It extends the available literature by drawing on employer–

[1] Estimations based on own calculation using the anonymized South African Revenue Services (SARS) and National Treasury tax data. Table A1 in the Appendix A provides summary statistics of the average deflated manufacturing wage at the municipality level.

employee administrative tax data that allows for the control of firm and individual worker characteristics that may drive variations in wages. Controlling for individual and firm characteristics can be motivated on several fronts. High-skill workers tend to self-select in places that best remunerate their qualifications, such as cities (Diamond and Gaubert 2022). Combes et al. (2008), for example, find that differences in the skill composition of workers across space account for 40 to 50 per cent of aggregate spatial wage disparities. In addition, wages are not independent of firm characteristics such as productivity and size, which are often associated with higher wages (Abowd et al. 1999). Foster (2023), for example, finds that firm size, industry, profits, geographical location, and foreign ownership are important in driving firm wage premia in South Africa. Productivity-wage effects at the firm level may also be present in South Africa (Bhorat et al. 2017). High-productivity firms, however, are more likely to be located in larger cities, where competition allows only the most productive to survive (Okubo 2009; Combes et al. 2012). Failure to control for individual and firm selection, therefore, raises the risk of wrongly attributing spatial wage disparities to market access and new economic geography forces. This study controls for some of these factors to more precisely identify how market access affects wage disparities across local municipalities in South Africa.

To achieve this objective, we use the anonymized tax data on employers and employees made available by the South African Revenue Service and National Treasury (SARS-NT) in collaboration with UNU-WIDER (Pieterse et al. 2018; NT and UNU-WIDER 2020a, b). We first document the main features of the spatial distribution of wages across municipalities in South Africa over the period 2013 to 2017 using exploratory spatial data analysis (ESDA) techniques. ESDA serves as a preliminary assessment of the nature of spatial interdependence. Evidence of a positive spatial autocorrelation indicates that the economic forces suggested in the NEG theory, drive wage disparities across space (Khomiakova 2008; Mudiriza 2017), while negative spatial concentration patterns suggest the importance of region-specific factors, as postulated in human capital (Becker 1962; Willis 1986) or local amenities (Roback 1982, 1988) theories.

We then test for the existence of a wage structure across South African local and metropolitan municipalities, controlling for individual and firm characteristics. A key obstacle when attempting this is the large downward biases in the standard errors when using data at different aggregation levels, making single-stage estimation an inappropriate approach (Moulton 1990). Following Combes et al. (2008) and Groot et al. (2014), we use a two-stage estimation method to address this issue. We first estimate the Mincer (1974) equation relating individual wages to worker and firm characteristics, while including municipality–time dummy variables. The coefficients on the municipality–time dummy variables provide estimates of the conditional average wage and capture variations in wages across municipalities that cannot be accounted for by individual and firm characteristics. We subsequently relate these conditional average wage estimates to market access to capture the effects of economic geography forces on wage disparities across regions, following NEG theory.

Our analysis generates several interesting results. First, the ESDA provides evidence of wide variations in wages across municipalities in South Africa. Consistent with NEG predictions, regions with similar levels of wages per worker tend to cluster together, as is also found by Mudiriza (2017) using population census data. This result suggests that, in addition to NEG factors, other forces such as agglomeration effects and physical geographic features are at play in driving spatial wage disparities across municipalities in South Africa. Second, Mincerian wage regressions reveal the importance of firm characteristics such as productivity and trade participation in driving manufacturing wages in South Africa. Further, the Mincerian wage regressions reveal high and persistent wage disparities across regions even after controlling for firm and individual characteristics. Finally, in accordance with ESDA predictions, the second-stage estimation results confirm that market access is a key driver of wage disparities across municipalities in South Africa.

Manufacturing wages are higher in municipalities closer to larger markets, as measured by the Harris index, providing some support for the NEG model. However, we also find that much of the wage effect is driven by the income and employment density of the municipality's own market, and not that of surrounding areas. These results point to large spatial rigidities leading to highly localized effects of market potential, together with wage and productivity effects arising from urban agglomeration economies. Unpacking these relationships further requires additional research using tighter specifications of the NEG model, together with more disaggregated spatial data.

The rest of the paper is organized as follows. Section 2 outlines the analytical framework that is used as a benchmark for our empirical study. Section 3 provides a review of the relevant literature. Section 4 describes the data sources. Section 5 reports estimation results on the empirical relationship between wages and NEG market access. Section 6 concludes.

2 Theoretical framework

The theoretical framework underlying our empirical analysis is a reduced form of a standard Krugman-type multiregional model of the NEG developed by Fujita et al. (1999). Using firms' and workers' fundamental microeconomic decisions, the model shows how interactions between increasing returns to scale at the firm level, factor mobility, and transport costs can shape the uneven distribution of economic activity across space. In what follows, we briefly sketch the salient feature of the model to guide our discussion in the rest of the analysis. The detailed model is presented in chapter 4 and 5 of Fujita et al. (1999).

The economy is made up of R regions and two economic sectors. Regions are indexed by r , with $r = 1, \ \dots, \ R$ and the two economic sectors are agriculture and manufacturing. The agricultural sector, operating in a perfect competitive market structure, produces a homogeneous agricultural good at constant returns to scale. Trade in agriculture is free and wages are equal and normalized to 1 in all regions. The manufacturing sector is the sector where the agglomeration forces take effect. Firms in the manufacturing sector operate under increasing returns to scale and produce differentiated manufactured products in a monopolistic competitive market. In addition, firms in the manufacturing sector face transport costs T_{rj} in an iceberg form, i.e. only $1/T_{rj}$units arrive for any one unit of manufacturing good shipped from *r* to *j*. Because manufacturing goods are subject to transport costs, and because these goods are produced with increasing returns to scale technology, wages of manufacturing workers may differ both in nominal and in real terms between regions.

In the economy, the geographic distribution of resources is hybrid: one part is exogenous and another endogenous. The economy is endowed with L^A farmers. Each region is endowed with an exogenous share ϕ_r of this agricultural workforce. In the manufacturing sector the workforce is mobile over time and represents for a region r the share λ_r of the overall supply of manufacturing workers L^M. The general equilibrium solution of this model is obtained by solving the following system of equations:

$$Y_r = \mu \lambda_r w_r + (1 - \mu) \phi_r \quad (1)$$

$$G_r = [\textstyle\sum_{s=1}^{R} \lambda_s (w_s T_{sr})^{1-\sigma}]^{1/1-\sigma} \quad (2)$$

$$w_r = [\textstyle\sum_{s=1}^{R} Y_s \, T_{rs}^{1-\sigma} G_s^{\sigma-1}]^{1/\sigma} \quad (3)$$

$$\omega_r = w_r G_r^{-\mu} \tag{4}$$

$$\sum_{r=1}^{R} \lambda_r = L^M \tag{5}$$

where Y_r denotes the income for region r , μ the share of expenditure spent on the manufacturing good, $(1-\mu)$ the share of expenditure spent on the agricultural good, λ_r the share of manufacturing workers in region r, ϕ_r the share of agricultural labour force in region r , $w_s T_{sr}$the nominal wages paid by a representative firm in region r , T_{rs} iceberg trade costs between any two regions, G_r manufacturing good consumer price index, and σ the elasticity of substitution between any two varieties of good from the manufacturing sector.

Equation (1) is the income equation. It determines the equilibrium condition of income in region r . The income of a region in equilibrium is the sum of labour income from both the manufacturing and the agriculture sector. Equation (2) determines the consumer price index (CPI) for manufacturing goods in region r , given the regional level of manufacturing employment and wage rates. The CPI for manufacturing goods in region r will tend to be low, the higher the share of manufacturing goods in regions with low transport costs to region r . This will make the region more attractive to manufacturing workers. These forward linkages turn out to be one of the driving forces of disparities in economic activity across space.

Equation (3) is the so-called NEG nominal wage equation, i.e. the wage rate offered by a representative firm in the manufacturing sector given the level of income in other regions and the transport costs from region r . This equation shows that nominal wages are higher in region r , the higher the market access, i.e. the higher the incomes in other regions with low transport costs from region r . Firms in locations that have good access to large markets (high market access) will tend to pay their workers better salaries due to scale economies and their savings in transportation costs. These backward linkages reinforce the forward linkages from the price effect and contribute to widening disparities across space. This wage equation forms the foundation for our empirical analysis

Equation (4) is the no-migration condition; it requires that real wages be the same in all regions R. Any disparity in real wages is assumed to trigger the process of migration of workers in the manufacturing sector to regions where real wages are higher. As for Equation (5), it describes the equilibrium of the labour market. Together, Equations (4) and (5) determine the regional distribution of workers in the manufacturing sector.

From the above, the NEG model explains the emergence of heterogeneous economic space (Krugman 1991a; Krugman and Venables 1995). It is also worth noting that the NEG market access concept from Equation (3) is closely related to the intuitive Harris index of market potential (Harris 1954). Both express the idea that producers tend to locate in areas that ensure them easy accessibility to various markets, with the Harris index making strong assumptions regarding the freeness of trade and the price index (Combes et al. 2009). Wages are predicted to be higher when a particular location is closer to large consumer markets.

3 Literature review

The NEG focuses on disparities in the distribution of economic activities across space in a general equilibrium framework (Combes et al. 2009). It shows how spatial disparities arise from the microeconomic decisions of homogeneous workers and firms. But little attention has been given to how worker and firm heterogeneity, and their interactions, affect economic outcomes across space (Ottaviano 2011). Notable theoretical development exceptions include Baldwin and Okubo (2006, 2009), Okubo (2009), and Okubo et al. (2010). They include the Melitz (2003) firm heterogeneity in the NEG model to account for firm selection in the wage equation.

A growing number of works have empirically tested the market access effect on wage structure in both developed and developing countries. For developed countries, these empirical works include Mion (2004) for Italy, Brakman et al. (2004) and Kosfeld and Eckey (2010) for Germany, Hanson (2005) and Fallah et al. (2011) for the United States, and Pires (2006) for Spain. As for emerging economies, empirical works in NEG have covered economies such as China (Hering and Poncet 2010), Indonesia (Amiti and Cameron 2007), Brazil (Fally et al. 2010), Chile (Paredes 2015; Paredes and Iturra 2012), and, more recently, South Africa (Mudiriza and Edwards 2021). The general finding of the empirical literature is that market access has a positive effect on wages. As a result, wages are higher when a particular location is closer to consumer markets.

We extend this body of research in several ways. First, we use micro-level data to control for worker and firm characteristics. Most of the studies cited above use regional aggregate data to analyse spatial wage disparities in an economic geography framework. A key limitation of this approach is that it does not properly account for individual and firm selection and sorting effects. Combes et al. (2008), Fally et al. (2010), Hering and Poncet (2010), Mion and Naticchioni (2005), and Mudiriza and Edwards (2021) are notable exceptions, but they (like other studies) do not account for firm-specific characteristics, which are a major determinant of individual wages as well as a source of wage inequality (Pavcnik 2017).

Accounting for individual and firm characteristics is particularly important to the extent that it helps to shed light on how the interactions between the two levels of heterogeneity affect the existence and the intensity of agglomeration economies (Ottaviano 2011). In South Africa, for example, wages are higher among exporters, larger firms, and more productive firms (Bhorat et al. 2017; Matthee et al. 2018). By using matched employee–employer data, this study will be able to control for firm-specific characteristics that may play a role in driving spatial wage disparities. Such a study has not yet been conducted, internationally or nationally (as far as we are aware). Further, the use of employee-level data has the potential to reduce the endogeneity problem related to market access. This is due to the fact that a shock to an individual wage is less likely to result in a change in market access (Rokicki and Cieślik 2023). Finally, by controlling for firm productivity, we are able to control for some of the productivity-wage effects driven by urban agglomeration economies, helping us isolate the NEG forces influencing manufacturing wages.

Second, the study extends the growing international empirical literature in this field and brings new evidence of the spatial wage structure implied by NEG for South Africa. Several studies have drawn on NEG theory to explain regional economic disparities in South Africa (e.g. Krugell and Rankin 2012; Naudé and Krugell 2006; von Fintel 2018), but, with exception of Mudiriza and Edwards (2021), they use regional aggregate data to analyse spatial wage disparities and none of them accounts for how the combination of individual and firm characteristics may shape spatial wage outcomes.

Lastly, the study provides insight into the extent to which NEG forces contribute towards wage inequality in South Africa. South Africa is one of the most unequal economies in the world, with wage income a key driver of income inequality (Wittenberg 2017). A history of spatial segregation policies together with continued frictions impeding workers from moving across locations, shapes the unequal spatial distribution of wages and labour market impacts of economic shocks (Todes and Turok 2018; World Bank 2018). Erten et al. (2019), for example, find that workers in districts in South Africa facing larger tariff reductions experience a significant decline in both formal and informal employment in the tradable sector. This study contributes to this work by isolating how economic geography forces, which are inclusive of trade effects, may explain wage disparities in South Africa.

4 Empirical specification, data, and variable construction

4.1 Empirical specification

To evaluate the impact of the influence of market access on wage disparities between regions, we have opted for the two-stage estimation strategy suggested by Combes et al. (2008). In the first step, we derive the regional average wage by regressing a Mincer wage equation that relates workers' individual wages to their individual characteristics. We also control for firm characteristics given that they may have an impact on individual wages under the assumption that the labour market is imperfect. In addition, since workers choose the sector and location that match their skills and preferences, we also control for regions and sectors specific characteristics that do not change over time, but are likely to affect workers' productivity. The regression equation is formally denoted by:

$$\log\left(w_{ijrt}\right) = \alpha + x'_{ijt}\delta + y'_{jt}\beta + \lambda_{rt} + \lambda_s + \varepsilon_{ijrt} \qquad (6)$$

where x'_{ijt} are individual characteristics of an individual i in firm j at time t, and y'_{jt} are firm-level characteristics of firm j at time t. For individual characteristics we include age and age squared to serve as proxies for experience and its nonlinear effects. A dummy variable for gender is also included to control gender wage gaps. To control for firm-level characteristics that influence wages, we include the size of a firm, international trade status, and productivity (Bernard et al. 2006). In addition, to account for industry-specificity in wages, we include a fixed effect, λ_s, that varies with manufacturing industry s . The key variable of interest is λ_{rt} that denotes municipality by year fixed effects. These fixed effects capture the estimated annual municipality average wage after controlling for dissimilarities in worker, firm, and industry characteristics, and are used in the second stage of the regression analysis.

In the second stage we estimate the NEG wage equation represented by Equation (3). The relationship is specified as:

$$\log(\widehat{w_r}) = \theta + \sigma^{-1}\log[MA_r] + \sum_{n=1}^{N}\gamma_n X_r^n + \eta_r \qquad (7)$$

where $\widehat{w_r}$ is the mean over time of the estimated wage from the first stage, and MA_r denotes market access in region r. Our expectation is that the estimated coefficient on market access is positive.

Several considerations are required in estimating the NEG wage equation. Skills sorting (Combes et al. 2008) and natural geographical features (Henderson et al. 2018) can influence both market access and wages. Omitting controls for these effects will lead to biased estimates of the market access coefficient. Consequently, we include a vector of additional regional-level controls, including for skills and natural geography, denoted as X_r^n.

A second consideration is that market access in the NEG wage Equation (3) is non-linear and requires the use of location-specific price indexes (Head and Mayer 2006), which are rarely available. There are three different approaches to overcoming this challenge. A first possibility is to assume real wage equalization across space, and implement a non-linear least squares estimation to evaluate the NEG hypothesis on wages as in Brakman et al. (2004). A second approach, initiated by Redding and Venables (2004), makes use of the gravity equation to derive the regional market access index. This requires internal trade flow data between regions, which is not available for South Africa. The third approach, which we follow, is to assume equal price indexes across regions, and proxy the iceberg trade costs by bilateral distance (i.e. $T_{rs}^{1-\sigma} = \frac{1}{d_{rs}}$). In this approach, market access for a specific region is calculated as the distance weighted average of the market income across all regions:

$$MA_i = \sum_{j=1}^{R} \frac{Y_j}{d_{ij}} \tag{8}$$

where Y_j is the market income of j^{th} region and d_{ij} is the centroid distance between region i and j. This measure closely resembles the early Harris (1954) market potential concept. We estimate the linear relationship using ordinary least squares (OLS).

A third consideration is the potential endogeneity or simultaneity of market access. Wages in region i, for example, are included in the region's own market income. This induces correlation between the error (random wage shocks) and market access leading to biased estimates. To resolve this, we test the robustness of our findings using a two-stage-least squares (2SLS) estimator where we instrument market access using a measure of regional centrality (Head and Mayer 2006) and terrain ruggedness (Hanson 2005). A final consideration is the possibility that positive wage effects of market access could reflect other agglomeration economies that occur from proximity between firms, input suppliers and consumers, labour pooling, and spillover of ideas (Glaeser and Gottlied 2009; Ellison et al. 2010). We therefore test the robustness of our findings by including measures of employment density and industry specialization.

4.2 Data[2]

The data used is an unbalanced employer–employee panel dataset made available by SARS-NT and UNU-WIDER. Specifically, we use version 4 of the firm-level panel (NT and UNU-WIDER 2020a) to collect firm-level data, and the employer-issued employee tax certificates (IRP5 data) for individual characteristics (NT and UNU-WIDER 2020b).

The firm-level panel is an unbalanced panel dataset of firm-level characteristics. It is created by merging several sources of South African administrative tax data. The four data sources that constitute it are: (i) corporate income tax (CIT) data from CIT-registered firms that submit CIT forms; (ii) employee data from employee income tax certificates submitted by employers (i.e. IRP5 and IT3a); (iii) value-added tax (VAT) data from VAT-registered firms; and (iv) customs records from traders (Pieterse et al. 2018). The firm-level panel encompasses the full population of firms that submit corporate income tax forms to the South African Revenue Services. We restrict the sample to firms in the manufacturing sector. By its very nature (administrative data), this dataset excludes informal manufacturing sector firms and workers.

The firm-level panel does not contain individual wages and individual-level characteristics, which are needed for our analysis. These variables are found in the employer-issued employee tax certificates (IRP5 and IT3(a)) (NT and UNU-WIDER 2020b). We use the IRP5 data to create all

[2] See Appendix B for data access conditions and the software used to clean the data and to conduct the analysis.

the necessary individual-level variables, which we merge with the firm-level panel to obtain the employer–employee panel data. The individual identifier (IdNo), firm-level identifier (taxrefno), and time period identifier (taxyear) are used to merge the two datasets. We drop any worker observation with no ID number or passport number and restrict the sample to individuals between the ages of 15 and 65. Following this approach, we obtain an individual-level panel that includes matched firm data for the years 2013–17.

Table 1 reports the number of individuals and firms in the final constructed *main job sample* of working-age individuals in the manufacturing sector. The sample covers an average of 36,477 manufacturing firms and 1.57 million workers per year.

Table 1: Number of individuals and firms per year in the sample

Tax year	(1) Workers	(2) Firms
2013	1,483,759	35,757
2014	1,596,782	36,718
2015	1,592,988	36,913
2016	1,612,385	36,925
2017	1,550,075	36,072

Note: sample size per year. Column (1): number of workers in the manufacturing sector per year. Column (2): number of firms in the manufacturing sector per year.

Source: author's construction.

4.3 Variable construction

Dependent variable: individual wages

The IRP5 certificate data contains income reported for individuals from all jobs that require an IRP5 certificate to be issued. This includes both labour (earnings) and non-labour income. It is therefore important, when using IRP5 data for labour market research, to distinguish between what is labour income (earnings) and what is not (see Kerr 2020 for further discussion). We use the '*kerr_income*' variable in the IRP5 version 4 dataset for labour income (earnings) (NT and UNU-WIDER 2020b). This measure of individual labour income is calculated following the approach suggested by Kerr (2020), which improves the Pieterse et al. (2018) list of employment-related source codes by including allowances paid to employees (codes 3709, 3710, 3711, 3712, 3713) and removing directors' remuneration (code 3615), and independent contractors' income (code 3616).

However, the *kerr_income* variable that appears in the IRP5 version 4 dataset and the income on the IRP5 certificate are for the entire tax year. To calculate daily and monthly individual wages, we need to account for the fact that not all workers work for the full duration of the year. In addition, a single individual may have multiple contracts per year, often with different firms. By using the start and end date variables in accordance with the multiple-contracts-per-year decision rules (see Appendix B), we obtain the number of days an individual has worked for a particular firm in a specific year. Following the literature in this respect (Bhorat et al. 2017; Pieterse et al. 2018), we then weigh the labour income by the total number of days a particular individual has worked in a specific year. Finally, in cases where workers have multiple jobs, we only consider the longest contract or the highest paid job (should the job duration lengths be equal).

Individual and firm-level characteristics

The IRP5 form contains limited information about individual worker characteristics. It is only possible, for instance, to differentiate workers in our dataset on the basis of their gender and age.

The dataset does not, unfortunately, provide any information about workers' level of education or race (Ebrahim et al. 2017). Firm-level characteristics used include firm size, trade status, and firm productivity (measured as value added per worker). The Appendix B on data provides more information about these variables.

Location-specific aggregate variables

At the aggregate level, we use the local municipality as the unit of analysis. The geographical scale (the sub-regional administrative division) matters for the outcomes in spatial economic research. According to Briant et al. (2010), local labour market areas are the appropriate geographical scale for wage disparity analyses across space, since they are more in line with the level of aggregation at which spatial wage disparities are efficiently and effectively observed. Local municipalities are not, strictly speaking, equivalent to local labour market areas. However, given the limitations of the SARS-NT data, they are, in our view, the most practical geographical aggregation scale to understand the NEG forces driving spatial wage disparities in the South African context. We use the 2016 administrative classifications with 213 local and metropolitan municipalities.

Table 2 presents summary descriptive statistics for all the variables of interest.

Table 2: Summary statistics

Variables	(1) Observations	(2) Mean	(3) Min.	(4) Max.	(5) s.d.
1st-stage Mincerian regression					
Wages (log)	7,755,000	8.868	4.815	19.90	1.024
Firm size (Number employees)	8,146,000	1,784	1	28,664	3,796
Productivity (value added per worker in Rands)	8,000,000	12.24	-6.583	18.56	1.183
Age (Years)	8,151,000	38.23	15	65	11.06
Gender	8,151,000				
Male	5,446,000	66.82%			
Female	2,704,000	33.18%			
Trade status (Number of firms)					
Total	182,385				
Non-traders	135,506	74.29%			
Importers	9,923	5.44%			
Exporters	19,818	10.87%			
Exporter–importer	17,138	9.40%			
2nd stage (Municipality-level variables)					
Conditional wages (natural log)	190	-0.245	-0.793	0.659	0.238
Market access CIT data (natural log)	190	5.81	4.75	8.10	0.56
2011 Census-based variables					
Market access 2011 census (natural log)	190	19.75	18.67	21.62	0.49
Employment density (natural log)	190	10.42	6.74	15.50	1.55
Share mining in total employment	190	0.032	0	0.382	0.059
Unemployment rate	190	0.404	0.095	0.752	0.141
Male share of population	190	0.485	0.435	0.549	0.021

Note: the sample covers the period 2013 to 2017. The 1st stage Mincerian regression uses individual- and firm-level variables, notably wages, age, gender dummy, firm size, productivity, and trade status dummies. The 2nd stage uses municipality-level observations, including market access, density, specialization, and conditional regional wages estimated from the 1st stage. All monetary values are in Rands.

Source: author's construction.

Market access

Different studies have measured market income (Y_j) using values of regional gross domestic product (GDP), population, or retail sales. In this study we proxy Y_j using two different measures. Firstly, we use the real aggregate value of earnings of all workers within a municipality as reported in the administrative tax data. Secondly, we draw on individual incomes reported in the 2011 population census. The 2011 population census reports individual incomes in bands. Consequently, we use the mid-point income of each band, and 1.5 times the lower-bound of the top band when calculating aggregate individual income for each municipality. The 2011 population census measure of market capacity has the advantage in that it is more comprehensive in coverage (e.g., includes individuals without jobs, includes non-wage income, and covers all municipalities), and minimizes simultaneity problems in the estimation of the NEG wage equation.

Ideally, transport costs between municipalities should be used to measure proxy d_{ij}. However, calculating the cost of transport requires detailed information on the mode of transport, the type of merchandise, and the costs per mode of transport (Harris 1954). We therefore follow much of the literature and use geospatial data describing the geographical coordinates of the spatial units' boundaries to calculate the great-circle distance from the centre of region i to the centre of region j for i ≠ j. Following much of the literature (Head and Mayer 2004), internal distance (d_{ii}) is approximated as the average distance from the region centre to all other points in the region using the equation $d_{ii} = (2/3)\sqrt{A_i/\pi}$, where A_i represents the location's area in square kilometres.

5 Results

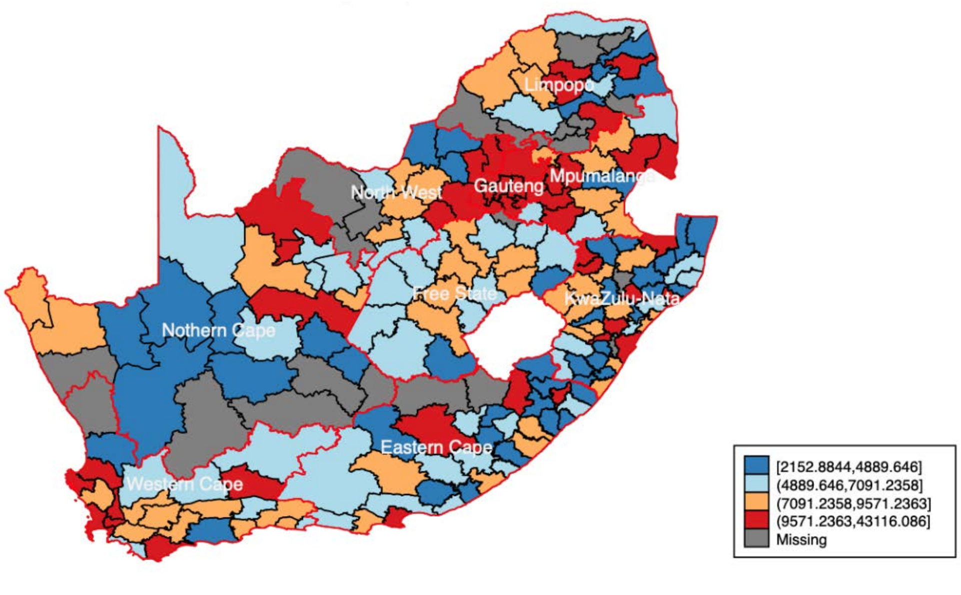
5.1 Exploratory spatial data analysis: a glimpse of the data

Exploratory spatial data analysis (ESDA) provides initial insights into the potential causes of wage disparities across regions. The technique is used to describe, visualize, and formally test the spatial dependence in a given variable across space, using box plots, choropleth maps, scatter plots, and spatial autocorrelation measures (Celebioglu and Dall'erba 2010; Patacchini and Rice 2007). Spatial autocorrelation (or concentration) plays a key role in ESDA. It is suggestive of the presence of a functional association between the occurrence of an event in an area and its occurrence in neighbouring areas (Anselin 1988). Evidence of a positive spatial concentration (clustering) of wages across regions is an indication of spatial economic forces working on wage distribution in line with NEG theory (Krugman 1991a), while a negative spatial concentration of wages across regions (spatial heterogeneity) suggests the importance of region-specific factors such as difference in human capital (Becker 1962; Willis 1986) or local amenities (Roback 1982, 1988) in the distribution of wages across regions.

Figure 1 illustrates the spatial distribution of the average monthly manufacturing wage between 2013 and 2017 across local and metropolitan municipalities in South Africa. Over time, wages may be influenced by business cycles and inflation. Consequently, we control for inflation by deflating wages using the consumer price index (CPI). To account for potential business cycle effects, we take the average of the real monthly wages of each municipality over the period of our analysis, i.e. from 2013 to 2017. On the maps, areas in red are municipalities with the highest average wage rate per worker while those in blue are municipalities with the lowest average wage rate per worker. The grey areas are municipalities for which there are no data, and the white area within the borders of South Africa denotes Lesotho.

Two stylized facts emerge from these choropleth maps. First, wages in the manufacturing sector are unevenly distributed across space in South Africa. Second, the map shows the formation of clusters based on municipalities' average wage level. Municipalities with similar levels of average wages per worker in the manufacturing sector tend to cluster near each other. The municipalities with high wages per worker are clustered in and around Gauteng province. Western Cape also has a cluster of high levels of average-wage-per-worker municipalities. Municipalities with lower levels of wage per worker are mainly clustered in the Northern Cape, and parts of the Free State and Limpopo. In the rest of the provinces, there is a mix of municipalities with high levels and low levels of average labour income per worker.[3]

Figure 1: Spatial map of average real monthly wage in the manufacturing sector from 2013 to 2017 (Rands)



Source: author's construction using anonymized tax data (NT and UNU-WIDER 2020a, b).

To formally test whether there is spatial dependence in the distribution of wages across local municipalities or not, we use the Moran's *I* spatial autocorrelation statistic. The Moran's *I* spatial autocorrelation statistic measures the correlation between a variable with itself across regions, i.e. the association between the standardized deviation of a variable at a given location and the standardized deviation in neighbouring geographic regions for the same variable. Mathematically, given the spatial weight matrix W, the Moran's *I* spatial autocorrelation statistic is calculated as follows:

$$I_w = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\overline{\mu_x})(x_j-\overline{\mu_x})}{\sum_{i=1}^{n}(x_i-\overline{\mu_x})^2} \quad (9)$$

where w_{ij} is the weight of W matrix, $\overline{\mu_x}$ is the sample mean, and x the variable of interest in region i and j, respectively.

As a measure of autocorrelation between statistical units across locations and their relative proximity, the Moran's *I* spatial autocorrelation statistic varies between -1 and 1. A positive value is an indication of spatial dependence (clustering of locations with similar characteristics), a

[3] Analysing choropleth maps for each year between 2013 and 2017 shows a stable spatial distribution of wages over time.

negative Moran's I statistic shows dispersion, while a zero value is indicative of a random spatial pattern (no spatial autocorrelation).

Table 3 provides the results of the Moran's I index test using the municipal average wage per worker in manufacturing including the five nearest neighbours in the spatial weight matrix. The test is conducted using wage data for 2013, 2017 and the average wage across all years from 2013 to 2017. The results reject the null hypothesis of no spatial dependence in favour of the alternative in all the years. This means that municipalities with similar levels of average wage per worker do not cluster in a random way. Rather, average wages per worker in a given municipality depend not only on the level of economic activities in that particular municipality, but also on wages and the level of economic activities in nearby municipalities, as postulated in the NEG model.

Table 3: Global Moran's *I* index (average wage per worker)

Variables	**2013**	**2017**	**201–17**
Moran's *I* index (*I*)	0.160	0.194	0.180
Moran's *I* index expected value – E(*I*)	-0.005	-0.005	-0.005
Standard deviation (*I*)	0.041	0.043	0.041
z-score	4.012	4.677	4.574
p-value*	0.000	0.000	0.000

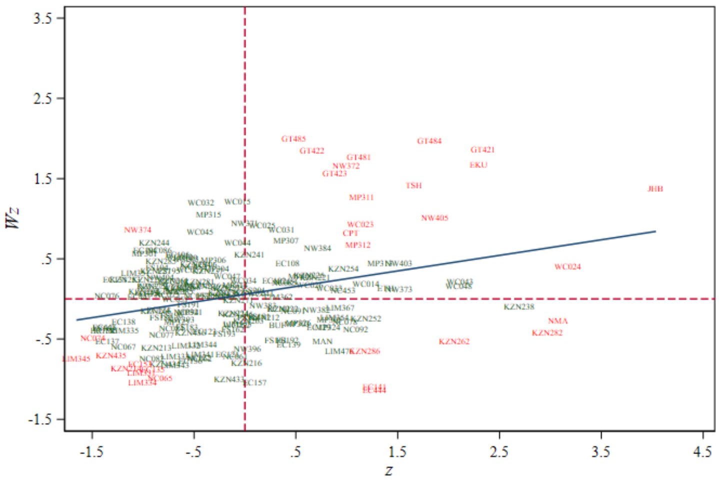
Note: the test bases the inference on the standardized z-value. The null hypothesis is spatial randomness ($I = 0$) and the alternative hypothesis is spatial autocorrelation ($I \neq 0$). The test compares the value of the Moran's *I* index with its expected value. We reject the null hypothesis in favour of the alternative if the Moran's *I* index calculated is greater than its expected value.

Source: author's construction.

However, the global Moran's I index displays only the general pattern. It remains silent on the respective contribution of the high average wage municipality clusters and low average wage municipality clusters to the positive and statistically significant global spatial autocorrelation. In addition, it does not say anything about municipalities that move away from the general pattern. The Local Indicator of Spatial Autocorrelation (LISA) analysis decomposes the global Moran's I index to evaluate the contribution of individual municipalities to its magnitude. To illustrate the results, we use Moran scatterplots, which graphically relate on the Cartesian plan the average wage per worker (z) of each municipality on the x-axis to the standardized spatial weighted average value of the average wages per worker (Wz) of all nearby municipalities on the y-axis.

Figure 2 displays the Moran scatterplot of the Moran's I index using average wage for 2017 reported in Column (2) of Table 3. Figures A1 and A2 in Appendix A provide the same information for the years 2013. The Moran scatterplot is made up of four quadrants, each of which represents a specific type of spatial association. The High z–High Wz quadrant (top right) defines the clustering across space of municipalities with a high monthly average wage per worker next to municipalities with a similar level of monthly average wage per worker. The Low z–High Wz quadrant (top left) specifies the clustering across space of municipalities with a low level of monthly average wage per worker next to municipalities with a high monthly average wage per worker. The Low z–Low Wz quadrant (lower left) is the clustering across space of municipalities with a low average monthly wage per worker next to municipalities that also have a low average monthly wage per worker. Finally, the High z–Low Wz quadrant (lower right) denotes the clustering across space of municipalities with a high average monthly wage per worker and municipalities with a low average monthly wage per worker. The red colour reflects municipalities with significant spatial associations in that specific quadrant. The green colour are municipalities with no significant spatial association.

Figure 2: Moran scatterplot for 2017 (Moran's *I* = 0.194)

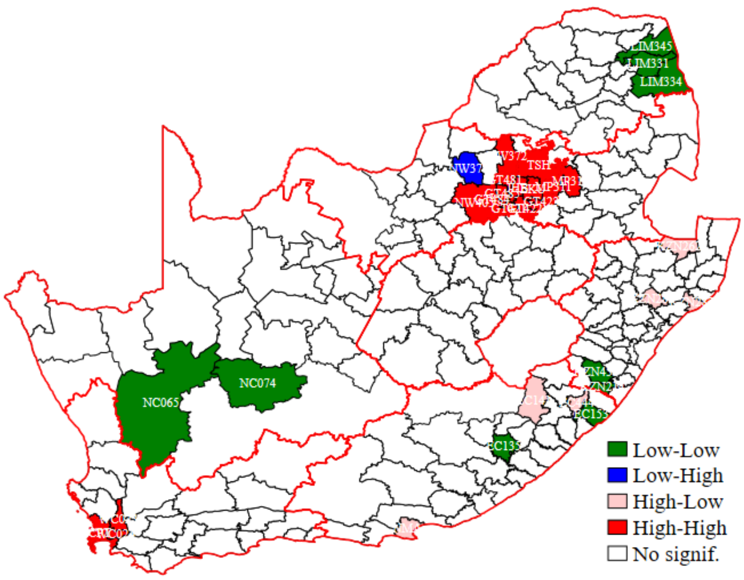


Note: the red colour reflects municipalities with significant spatial associations in that specific quadrant. The green colour are municipalities with no significant spatial association.

Source: author's construction using anonymized tax data (NT and UNU-WIDER 2020a, b).

The Moran scatterplot displays a positive slope, reflecting the positive global Moran's *I* index of 0.194 presented in Table 3. However, this overall positive spatial autocorrelation configuration hides significant spatial heterogeneity. The High–High quadrant contains essentially municipalities in the Gauteng and the Western Cape provinces, while the Low–Low quadrant is made up essentially of municipalities from Northern Cape and Limpopo. The Low–High and High–Low quadrants include mostly wealthy areas in Eastern Cape and KwaZulu-Natal.

Figure 3: Local spatial autocorrelation map for 2017



Source: author's construction using anonymized tax data (NT and UNU-WIDER 2020a, b).

Figure 3 presents the related local spatial autocorrelation map for 2017 that identifies municipalities with statistically significant positive or negative spatial associations. Regions in pink are the high-high regime, i.e. the positive concentration of municipalities with average wages above the national average. As for the green area, it indicates the low-low regime, that is, the positive concentration of municipalities with average wages below the national average. The blue regions are outliers, i.e. municipalities with average wages above the national average standing closer to municipalities with average wages below the national average in a statistically significant manner. The non-significant area, regions in white, indicates regions with statistically non-significant positive or negative concentration.

The LISA analysis thus reveals the presence of both a positive spatial clustering pattern and a negative spatial clustering pattern in the distribution of average wage per worker across municipalities in South Africa. This implies that the spatial distribution of average wage per worker across municipalities in South Africa is consistent with both the NEG and traditional neoclassical economic approach mechanisms. However, the net dominance of the positive spatial autocorrelation pattern (High–High and Low–Low quadrants) over the negative spatial autocorrelation pattern (Low–High and High–Low quadrants), as reflected in the positive and significant global Moran's *I*, suggests that NEG theory is a plausible explanation of the observed spatial wage disparities in South Africa. Yet, we must keep in mind the potential effects of traditional neoclassical economic approach mechanisms: the existence of a negative spatial autocorrelation pattern in the distribution of wages across space. This motivates us to take a deeper look at sources of wage disparities. In the next section we proceed with the estimation of the NEG model, controlling for individual- and firm-level characteristics to account for this fact.

5.2 The new economic geography model estimation

The exploratory spatial data analysis demonstrated the importance of human capital and amenities (or regional natural endowment) in addition to market access in explaining wage disparities in South Africa. To understand the drivers of spatial wage disparities in the country, we follow our two-step strategy to empirically estimate the NEG model, controlling for individual- and firm-level characteristics. In the first stage, we regress wages on firm and worker characteristics, controlling for municipality-year and industry fixed effects. We then use the predicted municipality-year fixed effect from the first stage to estimate the impact of market access on municipality average wages.

Estimation of the Mincer equation

Table 4 reports estimates of the Mincer wage relationship specified in Equation (6). Column (1) results include municipal-year fixed effects and controls for individual characteristics such as gender and age. This regression explains about 19.2 per cent of the overall variation in individual monthly labour income. Men earn on average more than women (approximately 34 per cent more), while experience, proxied by age, increases wages at a decreasing rate. Column (2) presents an alternative regression that only controls for firm and industry characteristics, as well as the municipality-year fixed effects. This estimate explains 26.4 per cent of the variation in manufacturing worker wages.

Productivity and firm size are positively related to wages, as is found in other studies on South Africa (Bhorat et al. 2017). The trade status of the firm also affects wages. Workers in firms that export but don't import earn around 7.2 per cent higher wages than workers in manufacturing firms that don't engage in international trade. Exporter wage premiums in South African manufacturing firms are also found by Matthee et al. (2018). Further, as found by Edwards et al. (2018), the wage premium is highest for workers in two-way trading firms that export and import. Workers in these firms earn a 14.2 per cent higher wage than workers in non-trading firms. Importing-only firms pay no wage premium.

Table 4: 1st stage Mincerian regression results (dependent variable: log wages)

	(1)	(2)	(3)
Variables	**Individual**	**Firm**	**Individual & firm**
Male	0.337***		0.214***
	(0.0312)		(0.0206)
Age (Log)	8.274***		7.002***
	(0.630)		(0.460)
c. Age(Log)#c. Age (Log)	-1.000***		-0.840***
	(0.0843)		(0.0606)
Productivity		0.302***	0.275***
		(0.0141)	(0.0140)
Firm size (Log)		0.0627***	0.0630***
		(0.00705)	(0.00590)
Import–export		0.142***	0.102***
		(0.0246)	(0.0203)
Import		-0.0169	0.0250
		(0.0394)	(0.0296)
Export		0.0721***	0.0575***
		(0.0184)	(0.0162)
Constant	-16.74***	-4.206***	-18.18***
	(1.160)	(0.140)	(0.942)
Municipality x time FE	YES	YES	YES
Industry FE	NO	YES	YES
R-squared	0.192	0.264	0.347
Observations	7,448,025	7,448,025	7,448,025

Note: robust standard errors in parentheses. Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Source: author's construction.

Column (3) reports estimates that include the combined effects of both the individual and firm characteristics. While the sizes of the coefficients change slightly, the significance is largely unaffected. Each variable therefore independently contributes towards wage differences across individuals. The predicted area–year-fixed effects from this model represent the average wage disparities across locations and periods that are not accounted for by controlling for individual- and firm-level characteristics. We use them as dependent variable in the second step of the empirical approach.

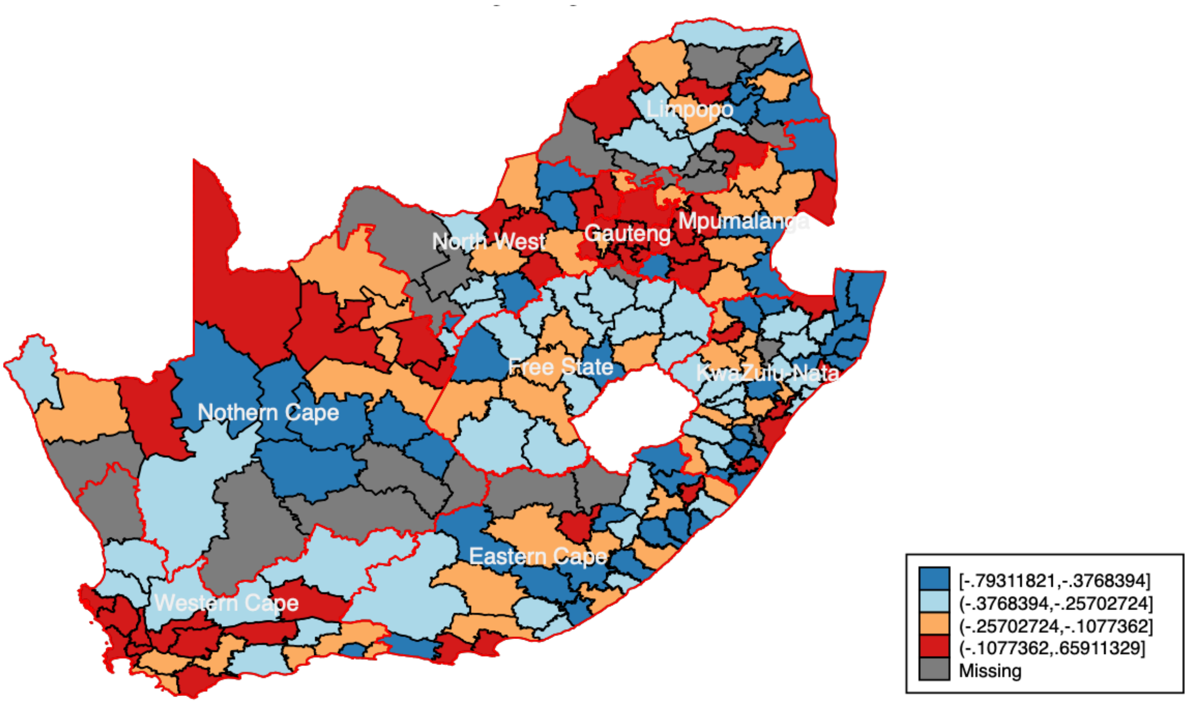
Wages and market access

The estimated values of the municipality-year fixed effects from the Mincer regressions represent the average wage disparities across locations and periods after accounting for individual- and firm-level characteristics. We use the conditional average wage for municipalities as the dependent variable in the second step of the empirical approach, where we estimate the NEG Equation (7).

Before estimating the NEG wage equation, we first visualize the relationship between market access and the conditional average wages calculated using the Mincer regression results presented in column (3) of Table 3. Figure 4 displays the spatial distribution of the conditional average wage for municipalities over the period 2013 to 2017. Red areas denote municipalities with relatively high manufacturing wages, while blue areas denote municipalities with relatively low manufacturing wages. We note that, even after controlling for individual and firm characteristics, spatial disparities in manufacturing wages across municipalities in South Africa remain considerable. In fact, Figure 4 clearly shows the concentration of municipalities with high manufacturing sector wages in and around the Gauteng province, as well as around the City of

Cape Town metropolitan municipality in the Western Cape province. In the rest of the provinces, municipalities with high average manufacturing sector wages emerge as islands alongside municipalities with low average manufacturing sector wages.

Figure 4: Map of conditional average manufacturing sector wages over the period 2013–17 by municipality.



Notes: the conditional average wage is calculated from the municipality-by-year fixed effects estimated in the Mincer regression presented in column (3) of Table 4. Based on average for years 2013 to 2017.Grey areas denote municipalities without data.

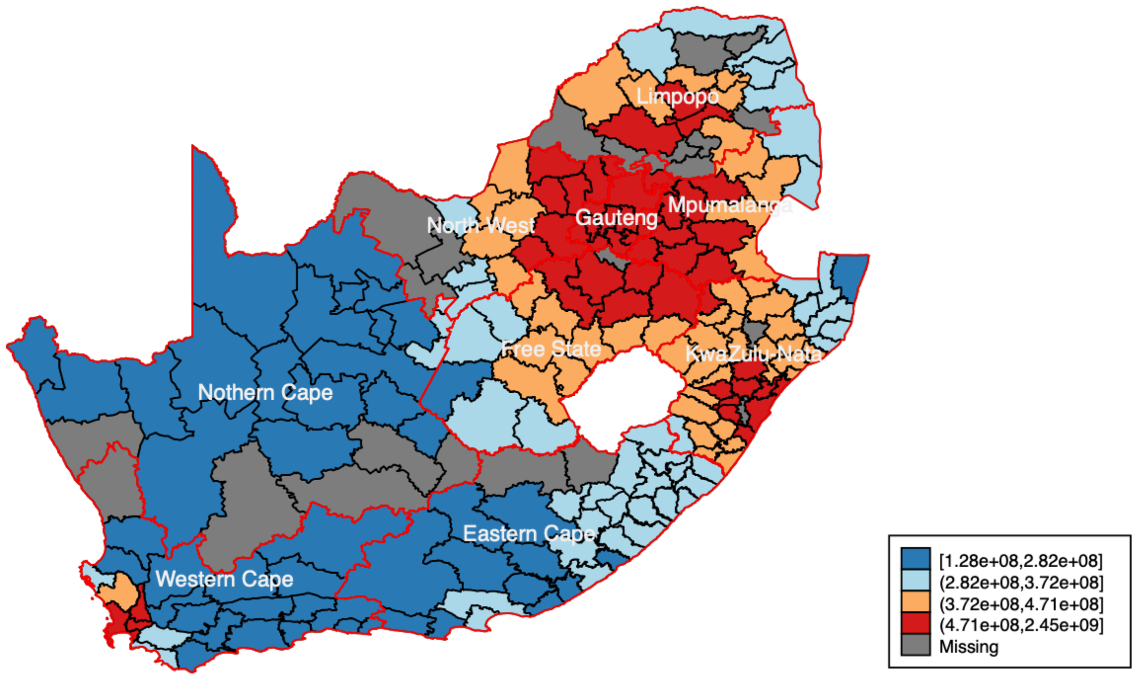
Source: author's construction using anonymized tax data (NT and UNU-WIDER 2020a, b).

The differences in average wages between municipalities even after controlling for individual worker and firm characteristics are indicative of the influence of factors specific to municipalities in driving spatial wage disparities in the manufacturing sector. One of these factors is market access, i.e. a region's ease of access to large market (Harris 1954; Krugman 1991a). Figure 5 represents the spatial distribution of the Harris index of market access based on individual income obtained from the 2011 population census. Figure A3 in Appendix A presents the equivalent figure using average labour earnings from 2013 to 2017 obtained from the administrative tax data. Municipalities coloured in red are those with high market access, whereas municipalities in blue are those with lower market access.

There is a clear three-pole core–periphery structure in terms of market access in South Africa. The largest and most important centre of concentration of economic activities in the country is the Gauteng province. The other centres are the metropolitan cities of City of Cape Town and eThekwini. High market access municipalities are clustered around these centres. As one moves away from these centres, the Harris market potential index decreases in intensity. Also shown in this figure are historic and geological specificities associated with market access. The former homeland area of Transkei in Eastern Cape, for example, is characterized by relatively low market access reflecting its remoteness from the economic centres of South Africa.

Comparing Figure 4 and Figure 5, we observe that market access and average wage at the municipality level are correlated. Municipalities in and around Gauteng province and some municipalities in the Western Cape, Eastern Cape, and KwaZulu-Natal, among others, have both the largest market access and the highest average wage per worker in the manufacturing sector, which is compatible with the NEG mechanisms and predictions. There are deviations. For example, several municipalities in Limpopo, North West, and Kwazulu-Natal have low manufacturing wages despite proximity to large economic centres. Many of these municipalities overlap with the former homelands suggesting persistence of spatial wage disparities despite the ending of Apartheid, as is found by Mudiriza and Edwards (2021) and World Bank (2018).

Figure 5: Map of the Harris index of market access calculated using individual income from the 2011 population census (Rands)



Note: values denote Rands in 2011 prices.

Source: author's construction using individual income obtained from the 2011 population census.

Table 4 presents the second-stage estimates of the conditional average wage on market access based on the administrative tax data (both in logs). The average values of each variable for the period 2013 to 2017 are used. Column (1) reports the results for conditional wages where the first step controlled only for individual characteristics. The estimated market access elasticity is significant and equals 0.251. Manufacturing workers in municipalities with high market access have significantly higher wages than workers in municipalities remote from markets. Column (2) presents estimates where the first-stage Mincer regression only controls for firm and industry characteristics. The market access coefficient remains statistically significant but falls in size to 0.138. In column (3), we use predicted municipality wages when controlling for both firm and individual characteristics. The market access relationship remains significant and of similar size to that of column (2). A 10 per cent rise in market access for a municipality is associated with a 1.19 per cent increase in average wages of manufacturing workers in that municipality.

Overall, the various estimates corroborate each other in highlighting the contribution of market access in driving spatial variation in manufacturing wages in South Africa. Further, accounting for firm and industry characteristics has a considerable downward impact on the estimated market access elasticity. This result is consistent with selection bias effects where relatively productive and large firms in regions locate in municipalities with high market access. This emphasizes the importance of controlling for firm characteristics when estimating wage effects of market access.

Table 4: Effects of market access on average manufacturing wage (dependent variable: conditional average wage)

Variables	(1) Individual	(2) Firm	(3) Individual & firm
Market access (log)	0.251**	0.138**	0.119**
	(0.035)	(0.029)	(0.030)
Constant	-1.923**	-1.058**	-0.941**
	(0.204)	(0.174)	(0.178)
Observations	190	190	190
R-squared	0.154	0.087	0.067
First-step controls include:			
Individual characteristics	YES	NO	YES
Firm and industry characteristics	NO	YES	YES
Municipality x time FE	YES	YES	YES

Note: estimates are based on the average wage and market access over the period 2013 to 2017. Market access is based on labour earnings obtained from the administrative tax data. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: author's construction.

The results line up with recent theoretical developments in NEG that call for finer micro-heterogeneity across workers and firms to shed light on how interactions between the two dimensions of heterogeneity affect economic outcomes across space (Ottaviano 2011). The results also line up with the new international trade theory that highlights the role of firm productivity in driving trade outcomes (Melitz 2003; Melitz and Ottaviano 2008). In terms of magnitude, the results correspond to those of Fally et al. (2010) for the Brazilian economy when the authors control for firm characteristics in their model.

Robustness checks: additional controls

The NEG wage equation with market access as the only explanatory variable as expressed in Equation (7) is a restricted explanation of wage disparities across regions. A number of additional explanatory variables might be important in order to explain differences in average wages across space (Head and Mayer 2004). These include among others local amenities, natural advantages, qualification of the work force, sectoral composition of the regional economy, or population density. Spatial self-selection of skilled workers in urban areas can also bias estimates (Mion and Naticchioni 2005; Combes et al. 2012). Failure to account for these additional explanatory factors, many of which may be related to market access, can give rise to omitted variable bias.

Table 5 reports results of the baseline model in column (3) of Table 4 extended to deal with some of these concerns. The market access variable is now based on individual earnings obtained from the 2011 population census. This should help ameliorate the simultaneity between wages and market access. Column (1) presents the baseline NEG wage regression including only the 2011 census-based market access. The coefficient is marginally higher (at 0.127) than the estimates using the market access variable based on the administrative tax data (0.111 in column (3) of Table 4). In column (2) the share of skilled workers in each municipality is included as a control for the spatial sorting of skills. Skilled workers cover managers, professionals, and technical occupations.[4] We observe that spatial sorting of skills does not play a meaningful role in driving spatial wage disparities. Its coefficient is not statistically significant. The estimated market access coefficient is statistically significant and valued at 0.13, which is slightly higher than that of Table 4. Column (3) adds the share of workers employed in mining to control for differences in natural endowment that may drive wage disparities. The estimated coefficient on the variable is positive and significant (at 5 per cent level) showing that resource endowments drive part of spatial wage disparities.[5] The market access coefficient falls slightly to 0.11 but remains statistically significant.

Table 5: Effects of market access on wages with additional control variables

	(1)	(2)	(3)	(4)	(5)	(6)
Market access, 2011 census (log)	0.127**	0.126**	0.109**	0.094**	0.239**	0.117**
	(0.034)	(0.034)	(0.034)	(0.032)	(0.033)	(0.031)
Share skilled workers		0.115	0.397	1.215**	1.766**	1.127**
		(0.281)	(0.272)	(0.298)	(0.453)	(0.297)
Share mining employed			0.891*	0.732+	0.660	0.731+
			(0.374)	(0.421)	(0.732)	(0.406)
Unemployment rate				-0.255	-0.313	-0.304
				(0.189)	(0.249)	(0.195)
Former homeland				-0.030	-0.008	-0.039
				(0.049)	(0.072)	(0.048)
Share male population				3.043*	4.129*	2.675*
				(1.245)	(1.886)	(1.317)
Constant	-2.745**	-2.766**	-2.520**	-3.745**	-7.450**	-3.984**
	(0.682)	(0.689)	(0.679)	(0.822)	(1.059)	(0.806)
Observations	190	190	190	190	190	190
R-squared	0.0632	0.0590	0.0967	0.223	0.276	0.231
First-step controls include:						
Individual characteristics	YES	YES	YES	YES	YES	NO
Firm and Industry characteristics	YES	YES	YES	YES	NO	YES
Municipality x time FE	YES	YES	YES	YES	YES	YES

Note: market access is based on aggregate individual income by municipality obtained from the 2011 population census. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: author's construction.

Historical factors, labour market conditions, and other socio-cultural conditions may also have an impact on the level of regional average wages. We control for these effects in the model estimates reported in column (4). All else constant, high unemployment rate depresses regional average wages, as is also found by Mudiriza and Edwards (2021). This points to the presence of a local wage curve, first shown by Kingdon and Knight (2006) for South Africa in the early 1990s. Column (4) also includes a dummy variable for municipalities where the share area covered by former homelands exceeds 30 per cent. Mudiriza and Edwards (2021) find a significant and persistent wage penalty for former homelands in their estimate of the NEG model. While the coefficient on the homeland variable is negative, it is not significantly different from zero. Further, to account for gender wage gaps, we include the male share of the population in the municipality. The coefficient on this variable is large, positive, and statistically significant. The inclusion of these controls results in a significant coefficient on the share of skilled worker providing evidence of

[4] The results are robust to alternative measures of skills, for example the share of workers with matric and above or tertiary and above education.

[5] We also include a ruggedness index obtained from Mudiriza and Edwards (2021) that reflects how jagged or flat the terrain of a municipality is, but this is not significant.

spatial sorting of skills. Lastly, the inclusion of these control variables reduces the size, but not significance, of the market access coefficient to 0.09.

So far, the extended estimates have jointly controlled for both worker and firm characteristics in the first step of the econometric approach we have adopted. The last two columns of Table 5 provide estimates where we separate worker (column 5) and firm (column 6) effects on wages in the Mincer equation. Results show that, though the market access elasticity remains positive and statistically significant in both cases, controlling for firm effects matters. Only controlling for worker effects results in a market access coefficient (0.24) that is double that when only controlling for firm effects (0.12). This suggests that productive firms tend to locate in regions with high market access and that not controlling for firm characteristics biases up market access effects.

Robustness checks: instrumentation and agglomeration economies

The ordinary least squares (OLS) method used to estimate the NEG wage equation results in Tables 4 and 5 assumes that the explanatory variables are not correlated with the random error term. This is unlikely to be the case when the market access variable contains the municipalities' own wages in its calculation. A positive shock to wages will, for example, raise regional income which is included in market access. This becomes increasingly problematic the larger the inter-regional transport costs are (Head and Mayer 2006).

An alternative approach to dealing with the potential endogeneity of market access is to use an instrumental variable estimation approach. The objective here is to find instruments which are correlated with the explanatory variable suspected of endogeneity but not with the shocks affecting the dependent variable. The challenge associated with this strategy is finding the right instruments. The first column of Table 6 presents a two-stage-least squares (2SLS) estimate where we follow the literature and use municipal centrality (Head and Mayer 2006) and terrain ruggedness (Hanson 2005) as instruments for market access calculated using the administrative tax data.[6] Municipality i 'centrality' is measured as $ln \sum_j (1/d_{ij})$ and is preferred to distance to main centre as it does not explicitly impose a centre (Head and Mayer 2006). The terrain ruggedness instrument is calculated using the Harris market potential Equation (8), but replacing regional income with an index of how jagged or flat the terrain of the region is. This is constructed using data from Nunn and Puga (2012).[7] Regions that have high ruggedness or are proximate to rugged regions have lower potential for new economic geography forces to drive agglomeration.

The first-stage equation is strongly identified, with the Cragg-Donald Wald F-statistic higher than the critical values proposed by Stock and Yogo (2005). The signs of the first-stage coefficient estimates are as expected with central distance positive and significant (at 1 per cent level) and ruggedness negative, although only significant at the 20 per cent level. The Hanson J-statistic test of overidentification cannot reject the null hypothesis that the instruments are valid. However, the consequence of instrumentation is that market access is no longer significantly different from zero.

Several explanations may underpin this result. Firstly, our spatial unit is the municipality, which may be too large an area to capture the influence of economic geography forces between regions.

[6] The results using the 2011 population census earnings data are very similar. Alternative instruments include distance to nearest central place (Redding and Venables 2004), prior population density (Moreno-Monroy 2011), and market access at a more aggregated administrative level, such as province (Mion 2004). The estimated market access coefficient is significant and positive when including the 2011 population density as one of the instruments, but according to the Hanson J-statistic, the validity of the instruments is rejected.

[7] Nunn and Puga (2012) provide terrain ruggedness data on their website (https://diegopuga.org/data/rugged/).

Briant et al. (2010), for example, find that market potential loses significance in explaining regional wages in France, once the country is divided into large areas. The results may also signify high trade costs across municipalities such that changes in market potential are highly localized. The size of the local municipal market in both these instances would be the primary driver of wages, and not incomes in surrounding areas. To assess this, we re-estimate the NEG wage equation but split the market access index into own municipality income and a market access index ('non-local market access index') that excludes own municipality income in its construction. The OLS results based on the 2011 census data are presented in column (2) of Table 6. Consistent with the above explanation, own municipality income is the primary driver of wages, with market access associated with incomes in other municipalities contributing no additional explanatory power.

Table 6: Instrumental variable estimation of effect of market access on wages

	(1)	**(2)**	**(3)**
Market access (log)	0.024		0.022
	(0.045)		(0.043)
Market access excl. own region (log)		0.020	
		(0.040)	
Own region income (log)		0.046**	
		(0.017)	
Employment density (log)			0.032*
			(0.015)
Specialization index			0.015
			(0.141)
Share skilled workers	1.208**	0.784*	0.925*
	(0.307)	(0.382)	(0.402)
Share mining employed	0.697+	0.522	0.639
	(0.388)	(0.416)	(0.410)
Unemployment rate	-0.199	-0.058	-0.107
	(0.191)	(0.211)	(0.208)
Former homeland	-0.029	-0.051	-0.055
	(0.049)	(0.049)	(0.052)
Share male population	3.413**	3.221**	3.261**
	(1.238)	(1.206)	(1.233)
Constant	-2.228**	-2.941**	-2.489*
	(0.624)	(0.642)	(0.995)
Observations	190	190	190
R-squared	0.183	0.220	0.211
First stage coefficients			
	1.853***		
	(0.302)		
	-0.305		
	(0.238)		
Cragg-Donald Wald F statistic	123.84		
Hansen J statistic, p value	0.79		

Note: instruments for market access calculated using the administrative tax data in column (1) are a measure of centrality of the municipality and ruggedness. Market access in columns (2) and (3) are based on the 2011 population census. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Source: author's construction.

This positive wage effect of market access index that we observed could also arise from agglomeration economies that occur from proximity between firms, input suppliers and consumers, labour pooling, and spillover of ideas (Glaeser and Gottlied 2009; Ellison et al. 2010). Traditionally, agglomeration economies are distinguished according to localization economies, which operate mainly within a specific sector; and urbanization economies, which are determined by the size of the local economy. We, therefore, follow Combes (2000) and include in the regression two measures of agglomeration: employment density (number of workers per area) to control for urbanization economies and Krugman's (1991b) specialization index to control for localization economies associated with the specialization of industries within a region. The Krugman Specialisation Index (KSI) is constructed as $KSI_i = \sum_s |se_{si} - \overline{se_s}|$ where se_{si} denotes the regional (*i*) share of employment in sector *s*, while $\overline{se_s}$ denotes the national share of employment in the sector. The Krugman Specialisation Index (KSI) takes value 0 if a municipality has an industry employment structure similar to the national structure, indicating that the municipality is not specialized, and takes a maximum value of 2 if a region has no sectors in common with the rest of South Africa, reflecting strong sectoral specialization. We construct the specialization index using employment data at the 3-digit level of the Standard Industrial Classification obtained from the 2011 population census. The OLS results reported in column (3) of Table 6 show that employment density is an important explanatory factor of wages, with market access becoming insignificant. The specialization index does not appear to be an important additional factor explaining regional wage variation. The result for employment density does not necessarily negate the finding that NEG forces have contributed towards the spatial wage disparities in South Africa. Rising employment density arise from both NEG forces and urban and external agglomeration economies. Given our spatial units, we are unable to properly distinguish across these influences. Nevertheless, what these results suggest is that agglomeration effects, in addition to NEG forces, can be a source of spatial wage disparities in South Africa.

Finally, the specification of the NEG wage regression we estimate is not tightly linked to theory. Our estimates, for example, do not consider the non-linearity of the market access relationship presented in Equation (8), nor do we control for regional prices. In contrast, Mudiriza and Edwards (2021) estimate a tightly specified NEG relationship using 354 magisterial districts in South Africa, and find significant, although still localized, effects of market access on wages even after instrumentation. Their results, for example, suggest a 10 per cent increase in market potential is associated with a 1.85 to 2.29 per cent increase in wages in that region over the period 2001 to 2011. This is consistent with Briant et al. (2010) who show, using French data, that specification, rather than size and shape of the spatial unit, is of first-order importance in economic geography estimations. This points to the need for further research that applies a more structural model of the NEG relationship to the administrative tax data, possibly at a more disaggregated spatial level.

6 Conclusion

This paper analyses the NEG determinants of spatial wage disparities in the manufacturing sector in South Africa. While the NEG wage equation has been widely tested in evaluating regional wage disparities in developed countries, we have only limited information about its explicative power in developing countries. Using firm-level data and employer-issued employee tax certificates (National Treasury and UNU-WIDER 2020a, b), we find evidence supporting market access as a key variable to explaining manufacturing sector wage disparities across municipalities in South Africa. Our analysis suggests that proximity to large markets (market access) is an important driver of wages disparities across municipalities in South Africa. Manufacturing workers in municipalities that are large or proximate to large markets have significantly higher wages than workers in remote municipalities. However, we also find that much of the wage effect is driven by the income and employment density of the municipality's own market, and not that of surrounding areas. These results point to potentially large spatial rigidities leading to localized effects of market access, together with wage and productivity effects arising from urban agglomeration economies. Further analysis using a tighter specification of the NEG relationship and more disaggregated spatial data, as in Mudiriza and Edwards (2021) for South Africa, may provide further insights.

In addition, the paper demonstrates that individual and firm characteristics play a significant role in explaining disparities in wages across municipalities in South Africa. Failure to control for individual and firm characteristics leads to an overestimate of the effects of market access on spatial wage disparities. Indeed, wages increase with age at a decreasing rate and male workers earn more than females. In addition, much of the variation in monthly wages comes from firm-level characteristics such as productivity and exporting activities.

With respect to the debates over spatial policy design, our empirical outcomes suggest that the effects of policy measures targeting a particular area will spread to other regions, not only the region they are aimed at, but this is dependent also on reducing internal trade costs. The results imply that it would require strong policy measures to change the existing spatial economic equilibrium. The reason is the existence of a breakpoint (a level of freeness of trade, for instance) in NEG models for a policy measure to become effective (van Marrewijk 2020). To avoid waste of resources, space-neutral or people-centred policies (see Todes and Torok (2018) for a discussion) are more likely to succeed than any attempt to rebalance the country's economic landscape through measures aimed at steering productive firms and workers from affluent to poorer areas.

References

Abowd, J.M., F. Kramarz, and D. Margolis (1999). 'High Wage Workers and High Wage Firms. *Econometrica*', 67: 251–333. https://doi.org/10.1111/1468-0262.00020

Acemoglu, D., and J. Robinson (2010). 'The Role of Institutions in Growth and Development'. *Review of Economics and Institutions*, 1(2). Available at: https://econpapers.repec.org/article/piareview/v_3a1_3ay_3a2010_3ai_3a2_3an_3a1.htm (accessed 16 January 2024).

Amiti, M., and L. Cameron (2007). 'Economic Geography and Wages'. *The Review of Economics and Statistics*, 89(1): 15–29. https://doi.org/10.1162/rest.89.1.15

Anselin, L. (1988). 'Lagrange Multiplier Test Diagnostics for Spatial Dependence and Spatial Heterogeneity'. *Geographical Analysis*, 20(1): 1–17. https://doi.org/10.1111/j.1538-4632.1988.tb00159.x

Baldwin, R.E., and T. Okubo (2006). 'Heterogeneous Firms, Agglomeration and Economic Geography: Spatial Selection and Sorting'. *Journal of Economic Geography*, 6(3): 323–46. https://doi.org/10.1093/jeg/lbi020

Baldwin, R., and T. Okubo (2009). 'Tax Reform, Delocation, and Heterogeneous Firms'. *The Scandinavian Journal of Economics*, 111(4): 741–64. https://doi.org/10.1111/j.1467-9442.2009.01582.x

Becker, G.S. (1962). 'Investment in Human Capital: a Theoretical Analysis'. *Journal of Political Economy*, 70(5, Part 2): 9–49. https://doi.org/10.1086/258724

Bernard, A.B., J.B. Jensen, and P.K. Schott (2006). 'Trade Costs, Firms and Productivity'. *Journal of Monetary Economics*, 53(5): 917–37. https://doi.org/10.1016/j.jmoneco.2006.05.001

Bhorat, H., M. Oosthuizen, K. Lilenstein, and F. Steenkamp (2017). 'Firm-level Determinants of Earnings in the Formal Sector of the South African Labour Market'. WIDER Working Paper 2017/25. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/2017/249-6

Bosker, M., and E. Buringh (2017). 'City Seeds: Geography and the Origins of the European City System'. *Journal of Urban Economics*, 98: 139–57. https://doi.org/10.1016/j.jue.2015.09.003

Briant, A., P. Combes, and M. Lafourcade (2010) 'Dots to Boxes: Do the Size and Shape of Spatial Units Jeopardize Economic Geography Estimations? *Journal of Urban Economics*, 67(3): 287–302. https://doi.org/10.1016/j.jue.2009.09.014

Brakman, S., H. Garretsen, and M. Schramm (2004). 'The Spatial Distribution of Wages: Estimating the Helpman-Hanson Model for Germany'. *Journal of Regional Science*, 44(3): 437–66. https://doi.org/10.1111/j.0022-4146.2004.00344.x

Breinlich, H., G.I. Ottaviano, and J.R. Temple (2014). 'Regional Growth and Regional Decline'. In *Handbook of Economic Growth*, Vol. 2, pp. 683–779. Amsterdam: Elsevier. https://doi.org/10.1016/B978-0-444-53540-5.00004-5

Briant, A., P.P. Combes, and M. Lafourcade (2010). 'Dots to Boxes: Do the Size and Shape of Spatial Units Jeopardize Economic Geography Estimations?'. *Journal of Urban Economics*, 67(3): 287–302. https://doi.org/10.1016/j.jue.2009.09.014

Cassim, A., and D. Casale (2018). 'How Large is the Wage Penalty in the Labour Broker Sector? Evidence for South Africa Using Administrative Data'. WIDER Working Paper 48/2018. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/2018/490-2

Celebioglu, F., and S. Dall'Erba (2010). 'Spatial Disparities across the Regions of Turkey: an Exploratory Spatial Data Analysis'. *The Annals of Regional Science*, 45: 379–400. https://doi.org/10.1007/s00168-009-0313-8

Combes, P. P. (2000). 'Economic Structure and Local Growth: France, 1984–1993'. *Journal of Urban Economics*, 47(3): 329–55. https://doi.org/10.1006/juec.1999.2143

Combes, P. P., G. Duranton, and L. Gobillon (2008). 'Spatial Wage Disparities: Sorting Matters!'. *Journal of Urban Economics*, 63(2): 723–42. https://doi.org/10.1016/j.jue.2007.04.004

Combes, P. P., G. Duranton, L. Gobillon, D. Puga, and S. Roux (2012). 'The Productivity Advantages of Large Cities: Distinguishing Agglomeration from Firm Selection'. *Econometrica*, 80(6): 2543–94. https://doi.org/10.3982/ECTA8442

Combes, P. P., G. Duranton, L. Gobillon, and S. Roux (2010). 'Estimating Agglomeration Economies with History, Geology, and Worker Effects'. In E. L. Glaeser (ed.), *Agglomeration Economics* (pp. 15–66). Chicago: University of Chicago Press. https://doi.org/10.7208/chicago/9780226297927.003.0002

Combes, P. P., T. Mayer, and J.F. Thisse (2009). *Economic Geography: the Integration of Regions and Nations*. Princeton, NJ: Princeton University Press. https://doi.org/10.1515/9781400842940

Correia, S. (2014). 'REGHDFE: Stata Module to Perform Linear or Instrumental-variable Regression Absorbing any Number of High-dimensional Fixed Effects'. Statistical Software Components S457874, Boston College Department of Economics. Available at: https://ideas.repec.org/c/boc/bocode/s457874.html (accessed 16 January 2024)

Duranton, G., and D. Puga (2004). 'Micro-Foundations of Urban Agglomeration Economies'. In J. V. Henderson and J-F. Thise (eds), *Handbook of Regional and Urban Economics*, Vol. 4, pp. 2063–117. Amsterdam: Elsevier. https://doi.org/10.1016/S1574-0080(04)80005-1

Diamond, R., and C. Gaubert (2022). 'Spatial Sorting and Inequality'. *Annual Review of Economics*, 14: 795–819. https://doi.org/10.1146/annurev-economics-051420-110839

Ebrahim, A., M. Leibbrandt, and V. Ranchhod (2017). 'The Effects of the Employment Tax Incentive on South African Employment. WIDER Working Paper 5/2017. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/2017/229-8

Edwards, L., M. Sanfilippo, and A. Sundaram (2018). 'Importing and Firm Export Performance: New Evidence from South Africa.' *South African Journal of Economics*, 86(S1): 79–95. https://doi.org/10.1111/saje.12154

Ellison, G., E. L. Glaeser, and W. Kerr (2010). 'What Causes Industry Agglomeration? Evidence from Coagglomeration Patterns'. *The American Economic Review*, 100(3): 1195–213. https://doi.org/10.1257/aer.100.3.1195

Erten, B., J. Leight, and F. Tregenna (2019). 'Trade Liberalization and Local Labor Market Adjustment in South Africa'. *Journal of International Economics*, 118: 448–67. https://doi.org/10.1016/j.jinteco.2019.02.006

Fallah, B.N., M.D. Partridge, and M.R. Olfert (2011). 'New Economic Geography and US Metropolitan Wage Inequality'. *Journal of Economic Geography*, 11(5): 865–95. https://doi.org/10.1093/jeg/lbq016

Fally, T., R. Paillacar, and C. Terra (2010). 'Economic Geography and Wages in Brazil: Evidence from Micro-data'. *Journal of Development Economics*, 91(1): 155–68. https://doi.org/10.1016/j.jdeveco.2009.07.005

Foster, S. (2023). 'Wage Inequality, Firm Characteristics, and Firm Wage Premia in South Africa'. WIDER Working Paper 131/2023. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/2023/439-7

Fujita, M., P. Krugman, and A.J. Venables (1999). *The Spatial Economy: Cities, Regions and International Trade*. Cambridge MA: MIT Press. https://doi.org/10.7551/mitpress/6389.001.0001

Fujita, M., and P. Krugman (2004). 'The New Economic Geography: Past, Present and the Future' [*sic*]. In R.J.G.M. Florax and D.A Plane (eds), *Fifty Years of Regional Science*, pp. 139–64. Springer. https://doi.org/10.1007/978-3-662-07223-3_6

Fujita, M., and J.F. Thisse (2009). 'New Economic Geography: an Appraisal on the Occasion of Paul Krugman's 2008 Nobel Prize in Economic Sciences'. *Regional Science and Urban Economics*, 39(2): 109–19. https://doi.org/10.1016/j.regsciurbeco.2008.11.003

Gallup, J.L., J.D. Sachs, and A.D. Mellinger (1999). 'Geography and Economic Development'. *International Regional Science Review*, 22(2): 179–232. https://doi.org/10.1177/016001799761012334

Glaeser, E.L., and J.D. Gottlieb (2009). 'The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States'. *Journal of Economic Literature*, 47(4): 983–1028. https://doi.org/10.1257/jel.47.4.983

Groot, S.P., H.L. de Groot, and M.J. Smit (2014). 'Regional Wage Differences in the Netherlands: Micro Evidence on Agglomeration Externalities'. *Journal of Regional Science*, 54(3): 503–23. https://doi.org/10.1111/jors.12070

Hanson, G.H. (2005). 'Market Potential, Increasing Returns and Geographic Concentration'. *Journal of International Economics*, 67(1): 1–24. https://doi.org/10.1016/j.jinteco.2004.09.008

Harris, C.D. (1954). 'The Market as a Factor in the Localization of Industry in the United States'. *Annals of the Association of American Geographers*, 44(4): 315–48. https://doi.org/10.1080/00045605409352140

Head, K., and T. Mayer (2004). 'The Empirics of Agglomeration and Trade'. In *Handbook of Regional and Urban Economics*, Vol. 4, pp. 2609–69. Amsterdam: Elsevier. https://doi.org/10.1016/S1574-0080(04)80016-6

Head, K., and T. Mayer (2006). 'Regional Wage and Employment Responses to Market Potential in the EU'. *Regional Science and Urban Economics*, 36(5): 573–94. https://doi.org/10.1016/j.regsciurbeco.2006.06.002

Helpman, E. (1998). 'The Size of Regions'. In D. Pines, E. Sadka, and I. Zilcha (eds), *Topics in Public Economics: Theoretical and Applied Analysis*. Cambridge: Cambridge University Press.

Henderson, J.V., T. Squires, A. Storeygard, and D. Weil (2018). 'The Global Distribution of Economic Activity: Nature, History, and the Role of Trade'. *The Quarterly Journal of Economics*, 133(1): 357–406. https://doi.org/10.1093/qje/qjx030

Hering, L., and S. Poncet (2010). 'Market Access and Individual Wages: Evidence from China'. *The Review of Economics and Statistics*, 92(1): 145–59. https://doi.org/10.1162/rest.2009.11418

Kerr, A. (2020). 'Earnings in the South African Revenue Service IRP5 data'. WIDER Working Paper 62/2020. Helsinki: UNU-WIDER. https://doi.org/10.35188/UNU-WIDER/2020/819-1

Khomiakova, T. (2008). 'Spatial Analysis of Regional Divergence in India: Income and Economic Structure Perspectives'. *International Journal of Economic Policy Studies*, 3: 137–61. https://doi.org/10.1007/BF03405710

Kingdon, G., and J. Knight (2006). 'How Flexible Are Wages in Response to local Unemployment in South Africa?' *Industrial and Labour Relations Review*, 59(3): 471–95. https://doi.org/10.1177/001979390605900308

Kim, S. (2008). 'Spatial Inequality and Economic Development: Theories, Facts, and Policies'. Working Paper 16. Washington, DC: World Bank Commission on Growth and Development. Available at: https://openknowledge.worldbank.org/server/api/core/bitstreams/bb0d9743-4d9d-594e-bf96-308989f7732c/content (accessed 16 January 2024).

Kosfeld, R., and H.F. Eckey (2010). 'Market Access, Regional Price Level and Wage Disparities: the German Case'. *Jahrbuch für Regionalwissenschaft*, 30: 105–28. https://doi.org/10.1007/s10037-010-0047-1

Krugell, W., and N. Rankin (2012). 'Agglomeration and Firm-level Efficiency in South Africa'. *Urban Forum*, 23: 299–318. https://doi.org/10.1007/s12132-012-9144-2

Krugman, P. (1991a). 'Increasing Returns and Economic Geography'. *Journal of Political Economy*, 99(3): 483–99. https://doi.org/10.1086/261763

Krugman, P. (1991b) *Geography and Trade*. Massachusetts: MIT Press.

Krugman, P.R., and A. Venables, A. (1995). 'The Seamless World: a Spatial Model of International Specialization'. NBER Working Paper 5220. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w5220

Matthee, M., N. Rankin, T. Webb, and C. Bezuidenhout (2018). 'Understanding Manufactured Exporters at the Firm-Level [*sic*]: New Insights from Using SARS Administrative Data'. *South African Journal of Economics*, 86: 96–119. https://doi.org/10.1111/saje.12158

Melitz, M.J. (2003). 'The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity'. *Econometrica*, 71(6): 1695–725. https://doi.org/10.1111/1468-0262.00467

Melitz, M.J., and G.I. Ottaviano (2008). 'Market Size, Trade, and Productivity'. *The Review of Economic Studies*, 75(1): 295–316. https://doi.org/10.1111/j.1467-937X.2007.00463.x

Mincer, J. (1974). 'Schooling, Experience and Earnings'. *Human Behavior and Social Institutions 2*. Cambridge, MA: National Bureau of Economic Research.

Mion, G. (2004). 'Spatial Externalities and Empirical Analysis: the Case of Italy'. *Journal of Urban Economics*, 56(1): 97–118. https://doi.org/10.1016/j.jue.2004.03.004

Mion, G., and P. Naticchioni (2005). 'Urbanization Externalities, Market Potential and Spatial Sorting of Skills and Firms'. CORE Discussion Paper 2006/99. https://doi.org/10.2139/ssrn.970299

Moulton, B.R. (1990). 'An Illustration of a Pitfall in Estimating the Effects of Aggregate Variables on Micro Units'. *The Review of Economics and Statistics*, 72(2): 334–38. https://doi.org/10.2307/2109724

Moreno-Monroy, A. (2011). 'Market Access and the Heterogeneous Effect of Shocks on Wages: Evidence from Chinese Cities'. *Papers in Regional Science*, 90(1): 9–25. https://doi.org/10.1111/j.1435-5957.2010.00319.x

Mudiriza, G. (2017). 'Regional Wage Disparities in Post-Apartheid South Africa: Spatial Patterns, Town Convergence Dynamics, and Causes'. Doctoral dissertation, University of Cape Town. Available at: https://open.uct.ac.za/server/api/core/bitstreams/87577bbc-d5b7-45a3-81b8-0169cbc3224d/content (accessed 16 January 2024).

Mudiriza, G., and L. Edwards (2021). 'The Persistence of Apartheid Regional Wage Disparities in South Africa'. *Journal of Economic Geography*, 21(6): 807–39. https://doi.org/10.1093/jeg/lbaa036

NT and UNU-WIDER (2020a). 'citirp5 2007-2017' [dataset]. Version 4.0. Pretoria: South African Revenue Service [producer of the original data]. Pretoria: National Treasury and UNU-WIDER [producer and distributor of the harmonized dataset].

NT and UNU-WIDER (2020b). 'IRP5 Worker-Level Data 2008–2018' [dataset]. Version 4.0. Pretoria: South African Revenue Service [producer of the original data], 2019. Pretoria: National Treasury and UNU-WIDER [producer and distributor of the harmonized dataset], 2020.

Naudé, W.A., and W.F. Krugell (2006). 'Sub-national Growth Rate Differentials in South Africa: an Econometric Analysis'. *Papers in Regional Science*, 85(3): 443–57. https://doi.org/10.1111/j.1435-5957.2006.00090.x

Nunn, N., and D. Puga (2012) 'Ruggedness: The Blessing of Bad Geography in Africa'. *Review of Economics and Statistics*, 94(1): 20–36. https://doi.org/10.1162/REST_a_00161

Okubo, T. (2009). 'Trade Liberalisation and Agglomeration with Firm Heterogeneity: Forward and Backward Linkages'. *Regional Science and Urban Economics*, 39(5): 530–41. https://doi.org/10.1016/j.regsciurbeco.2009.03.005

Okubo, T., P.M. Picard, and J.F. Thisse (2010). 'The Spatial Selection of Heterogeneous Firms'. *Journal of International Economics*, 82(2): 230–37. https://doi.org/10.1016/j.jinteco.2010.07.003

Ottaviano, G.I. (2011). '"New" New Economic Geography: Firm Heterogeneity and Agglomeration Economies'. *Journal of Economic Geography*, 11(2): 231–40. https://doi.org/10.1093/jeg/lbq041

Paredes, D. (2015). 'Can NEG Explain the Spatial Distribution of Wages of Chile?'. *Tijdschrift voor Economische en Sociale Geografie*, 106(1): 65–77. https://doi.org/10.1111/tesg.12088

Paredes, D., and V. Iturra (2012). 'Market Access and Wages: a Spatially Heterogeneous Approach'. *Economics Letters*, 116(3): 349–53. https://doi.org/10.1016/j.econlet.2012.03.022

Patacchini, E., and P. Rice (2007). 'Geography and Economic Performance: Exploratory Spatial Data Analysis for Great Britain'. *Regional Studies*, 41(4): 489–508. https://doi.org/10.1080/00343400600928384

Pavcnik, N. (2017). 'The Impact of Trade on Inequality in Developing Countries'. NBER Working Paper w23878. Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w23878

Pieterse, D., E. Gavin, and C.F. Kreuser (2018). 'Introduction to the South African Revenue Service and National Treasury Firm-level Panel'. *South African Journal of Economics*, 86: 6–39. https://doi.org/10.1111/saje.12156

Pires, A.J.G. (2006). 'Estimating Krugman's Economic Geography Model for the Spanish Regions'. *Spanish Economic Review*, 8(2): 83–112. https://doi.org/10.1007/s10108-006-9007-x

Pisati, M. (2012). 'Exploratory Spatial Data Analysis using Stata'. German Stata Users' Group Meetings 2012 07. Stata Users Group. Available at: https://www.stata.com/meeting/germany12/abstracts/desug12_pisati.pdf (accessed 16 January 2024).

Proost, S., and J.F. Thisse (2019). 'What Can Be Learned from Spatial Economics?'. *Journal of Economic Literature*, 57(3): 575–643. https://doi.org/10.1257/jel.20181414

Redding, S.J. (2010). 'The Empirics of New Economic Geography'. *Journal of Regional Science*, 50(1): 297–311. https://doi.org/10.1111/j.1467-9787.2009.00646.x

Redding, S.J. (2011). 'Economic Geography: a Review of the Theoretical and Empirical Literature'. In *Palgrave Handbook of International Trade*, pp. 497–531. https://doi.org/10.1007/978-0-230-30531-1_16

Redding, S., and A.J. Venables (2004). 'Economic Geography and International Inequality'. *Journal of International Economics*, 62(1): 53–82. https://doi.org/10.1016/j.jinteco.2003.07.001

Roback, J. (1982). 'Wages, Rents, and the Quality of Life'. *Journal of Political Economy*, 90(6): 1257–78. https://doi.org/10.1086/261120

Roback, J. (1988). 'Wages, Rents, and Amenities: Differences among Workers and Regions'. *Economic Inquiry*, 26(1): 23–41. https://doi.org/10.1111/j.1465-7295.1988.tb01667.x

Rokicki, B., and A. Cieślik (2023). 'Rethinking Regional Wage Determinants: Regional Market Potential versus Trade Partners' Potential'. *Spatial Economic Analysis*, 18(1). Available at: https://www.tandfonline.com/doi/full/10.1080/17421772.2022.2070657 (accessed 16 January 2024).

Rosen, S. (1979). 'Wage-based Indexes of Urban Quality of Life'. *Current Issues in Urban Economics*, 74–104.

Sachs, J.D. (2000). 'The Geography of Economic Development'. *Naval War College Review*, 92–105.

Stock, J. H., and M. Yogo (2005). 'Testing for Weak Instruments in Linear IV Regression'. In D. W. K. Andrews and J. H. Stock (eds), *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg* (pp. 80–108). Cambridge: Cambridge University Press.

Todes, A., and I. Turok (2018). 'Spatial Inequalities and Policies in South Africa: Place-based or People-centred?'. *Progress in Planning*, 123: 1–31. https://doi.org/10.1016/j.progress.2017.03.001

Turok, I., A. Scheba, and J. Visagie (2017). 'Reducing Spatial Inequalities through Better Regulation'. Report. Pretoria: Human Sciences Research Council. Available at: https://repository.hsrc.ac.za/bitstream/handle/20.500.11910/11097/9893.pdf?sequence=1 (accessed 16 January 2024).

van Marrewijk, J.G.M., H. Garretsen, S. Brakman, M. Fischer, and P. Nijkamp (2020). 'New Economic Geography after Thirty Years'. CESifo Working Paper 2658. Munich: CESifo. Available at: http://www2.econ.uu.nl/users/marrewijk/pdf/marrewijk/marrewijk%20cesifo%202009.pdf (accessed 16 January 2024).

von Fintel, D. (2018). 'Long-run Spatial Inequality in South Africa: Early Settlement Patterns and Separate Development'. *Studies in Economics and Econometrics*, 42(2): 81–102. https://doi.org/10.1080/10800379.2018.12097335

Willis, R.J. (1986). 'Wage Determinants: a Survey and Reinterpretation of Human Capital Earnings Functions'. *Handbook of Labor Economics*, 1: 525–602. https://doi.org/10.1016/S1573-4463(86)01013-1

Wittenberg, M. (2017). 'Wages and Wage Inequality in South Africa 1994–2011: Part 2–Inequality Measurement and Trends'. *South African Journal of Economics*, 85(2): 298–318. https://doi.org/10.1111/saje.12147

World Bank (2018). *Republic of South Africa-Systematic Country Diagnostic: An Incomplete Transition-Overcoming the Legacy of Exclusion in South Africa*. The World Bank, Washington DC. Available at: http://documents.worldbank.org/curated/en/815401525706928690/South-Africa-Systematic-country-diagnostic-an-incomplete-transition-overcoming-the-legacy-of-exclusion-in-South-Africa (accessed 22 May 2024).

Appendix A: Tables and Figures

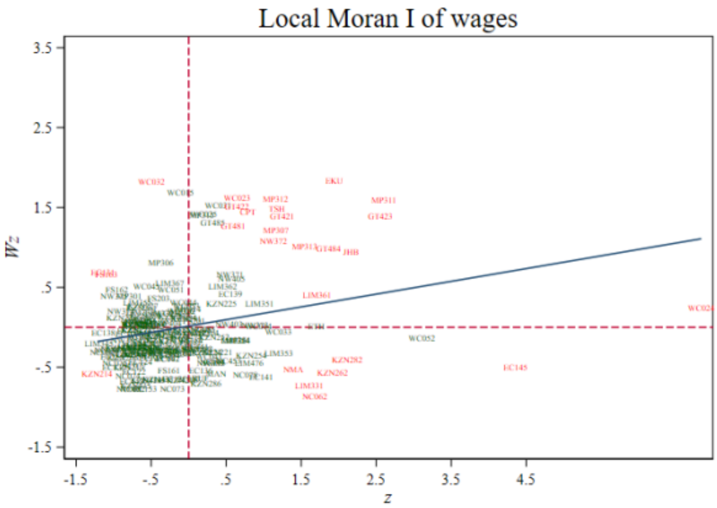
Table A1: Table of summary statistics of average deflated manufacturing wages at the municipality level

Tax year	No.	min.	p10	p25	mean	med.	p75	p90	max.
2013	194	2,042.385	3,818.040	4,806.801	8,001.292	6,727.077	9,644.31	13,734.00	42,029.77
2014	193	400.438	4,042.439	5,230.510	9,051.586	7,422.048	10,658.45	14,860.86	70,321.45
2015	190	1,312.325	4,378.312	5,860.136	9,497.698	8,061.193	11,199.79	15,399.10	64,278.50
2016	189	503.257	4,728.019	6,075.206	9,710.464	8,463.979	11,840.41	16,002.77	52,789.84
2017	191	1,646.803	5,077.843	6,584.763	10,413.150	9,488.859	13,298.40	16,776.26	32,000.42

Note: distribution of average monthly manufacturing wages deflated across local municipalities in South Africa.

Source: author's construction.

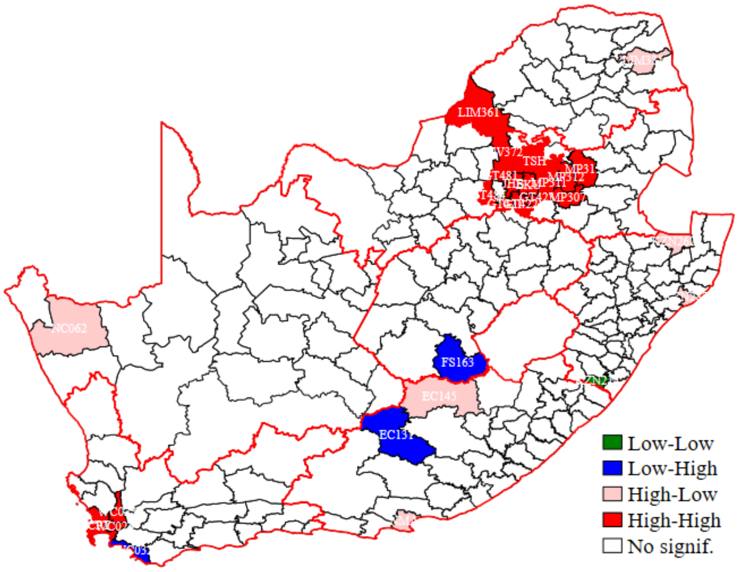
Figure A1: Moran scatterplots and corresponding local spatial autocorrelation maps for 2013



Note: the red colour reflects municipalities with significant spatial associations in that specific quadrant. The green colour are municipalities with no significant spatial association.

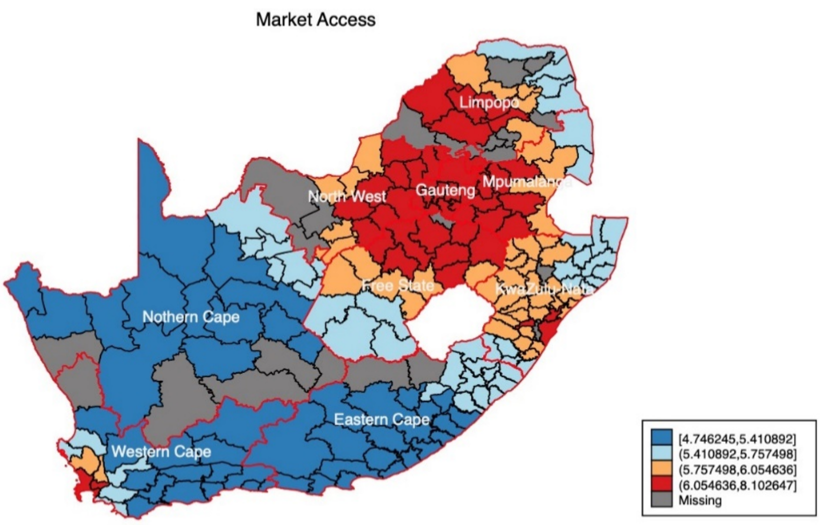
Source: author's construction using anonymized tax data (NT and UNU-WIDER 2020a, b).

Figure A2: Local spatial autocorrelation map for 2013



Source: author's construction using anonymized tax data (NT and UNU-WIDER 2020a, b).

Figure A3: Market access map based on wage earnings from the administrative tax data, 2013–17 average



Source: author's construction using anonymized tax data (NT and UNU-WIDER 2020a, b).

Appendix B: Data

This data appendix is created as per UNU-WIDER requirements for users of the National Treasury Secure Data Facility (NT-SDF). It reports on data directly used for the results presented in this paper.

Data access

The data used for this study was accessed from the NT-SDF, and is subject to a non-disclosure of private information agreement. Outputs were subject to strict control by qualified staff members assigned to this task to ensure anonymity of firms and individuals.

The data used for the study include the CIT-IRP5 Panel dataset (*citirp5_v4.0.dta*) and the version 4 of the IRP5 job-level data. Date of first access was January 2023, with final access provided in August 2023.

Software

The empirical analysis is conducted using Stata 17. The exploratory spatial data analysis was conducted using various user-written programmes including *spmap shp2dta spatwmat spwmatrix splagvar* and *genmsp* (see Pisati (2012) for details) and the first stage Mincerian estimation results were obtained using the user-written programme *reghdfe* (Correia 2014).

Variables

Variables used in the IRP5 data include: *UID PAYE_RefNo kerr_income tax_year taxrefno dateofbirth gender busprov_geo busdistmuni_geo buslocmuni_geo busmainplc_geo payereferenceno irp5_kerr_iweight_b*

Variables used in CIT-IRP5 include: *ITR14_c_CompDormant ITR14_c_compdormantthisyear IT14_companydormantind k_ppe c_type k_faother defl_gfcf_economywide defl_cpi_economywide comp_prof_sic5_1d vat_zroe vat_cgsimp vat_oimpgnc g_sales g_cos x_labcost x_wages g_grossprofit k_ppe_unadj*

Cleaning

To construct the database, firm-level information from the file *citirp5_v4.0.dta* are merged together with the worker-level data obtained from the IRP5 forms using the matching variable *taxrefno*. Only observations for which there is a mapping between the two datasets are used in the analysis.

Prior to merging the data, several cleaning processes were implemented for the firm-level and worker-level data. Dormant firms, as determined using variables *ITR14_c_CompDormant*, *ITR14_c_compdormantthisyear*, and *IT14_companydormantind*, are excluded from the analysis. The sample is also restricted to manufacturing firms using the industry classification variable *comp_prof_sic5_1d*. The sample of firms was further restricted to include firms reporting fixed capital stock (constructed using *k_ppe* and *k_faother*) and positive value added (calculated as *g_sales* - *g_cos*, with missing or negative values replaced by *x_labcost*+*g_grossprofit*).

For the worker-level data, we exclude all observations where earnings income (kerr_income) is missing. Workers who are not in the working-age group (workers below 15 years old and above 65 years old) are also dropped from the sample. The sample also excludes all individuals without a South African identification number as we are unable to determine the gender of the individual.

To deal with workers with multiple contracts within the same firm, or in different firms, we adopt the following process. If an individual has job contracts with more than one firm that overlap, we take the job with the highest wages as the 'main job' for that individual during that period. Where contracts at the same firm overlap, there are two possibilities: overlapping contracts with the same start and end date; and overlapping contracts with different start and end dates. In the first case, we take the contract offering the higher income as the individual's earning for that period. In the second case, we take the average earnings and average days worked for that individual. In cases where individuals have multiple non-overlapping job contracts at the same firm (e.g. one job contract from February to May and another from August to September), we add up the income and days worked for that person in that tax year. The variables *periodemployedfrom* and *periodemployedto* are used to calculate the duration of each job within the firm.

A firm's financial year may differ from the tax year (1 March–end Feb). We therefore update the start and/or end date of a worker's contract with a firm to match them to the correct tax year as follows: if the individual's contract with a firm starts before the corresponding tax year, we take back the individual's employment start date to align with the start of financial year; if the individual's contract with a firm ends after the end of the corresponding tax year, we bring forward the individual's employment end date to align with the end of financial year (see Bhorat et al. 2017; Pieterse et al. 2018). We drop any job contract with invalid start or end dates from the dataset.

Individual- and firm-level variables constructed

The following are constructed for use in the analysis.

Age: Age of a worker is calculated using the '*dateofbirth*' variable.

Gender: The gender of the individual is derived from the 7th digit of the South African identity number.

Size: Firm size is measured using the number of employees. To generate this variable, we use *irp5_kerr_weight_b* and *irp5_kerr_iweight_b* available in the dataset. These variables are obtained by summing the IRP5 forms linked to each firm in the CIT dataset weighted by the number of days worked by an individual in the firm in that year using the Kerr (2020) method.

Trade status: using '*vat_zroe*', '*vat_cgsimp*', and '*vat_oimpgnc*' available in CIT data, we re-construct the 'trade status' variable in terms of 'Non-Traders', 'Importer-Exporter', 'Importer', and 'Exporter'.

Labour productivity: Labour productivity is calculated by dividing value added calculated as *g_sales* - *g_cos*, with missing or negative values replaced by *x_labcost*+*g_grossprofit*, by firm employment.

Other data

The study also draws upon the 10% sample of the 2011 Population Census data, obtained from Statistics South Africa, for several variables in the wage-Market Access regressions. Market access at the municipality level is constructed using individual incomes reported in the 2011 population census. Because the 2011 population census reports individual incomes in bands, we use the mid-point income of each band, and 1.5 times the lower-bound of the top band when calculating aggregate individual income for each municipality. Distance between municipalities is calculated as the great-circle distance from the centre of region i to the centre of region j. The share skilled workers in a region cover *managers, professionals, and technical occupations* as a share of all workers. Homeland municipalities are defined as those municipalities where the share area covered by former homelands exceeds 30 per cent. Unemployment rate is calculated as the share of economically active workers that declare themselves to be unemployed.