Spatial Labor Market Power in Sub-Saharan Africa:

The Roles of Self-Employment and Migration*

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Abstract

I provide new evidence on the spatial distribution of labor market power in low-income countries, and quantify its effect on aggregate income and spatial income inequality. I develop a spatial general equilibrium model of monopsony that separates the effect of labor market power from that of migration costs and job search costs. Using a novel administrative dataset of Tanzanian firms, I map the complete spatial distribution of wage markdowns. Critically, I am able to identify the labor supply elasticity for each firm by leveraging Tanzania's first-ever minimum wage law, which specified different minimum wage levels across industries. I find that wage markdowns are substantial: on average, workers are paid only 70% of their marginal product. While rural labor markets are less competitive than their urban counterparts, the difference is modest. This is because self-employment plays an important role in mitigating the extent to which firms can markdown wages. In a competitive equilibrium counterfactual, total output increases by 4.8%. These gains are primarily driven by local reallocation of labor out of self-employment and into wage work. Surprisingly, because urban areas have a higher rate of wage employment, labor market power actually reduces spatial income inequality. JEL Codes: E24, J31, J23, J38, J42, O11, O15, R23.

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1 Introduction

A key distinction between rich and poor countries lies in their labor markets (Donovan et al., 2023). In low-income countries, there are significant income disparities between rural and urban areas, as well as between wage earners and the self-employed, and yet most workers live in rural areas and are self-employed. Existing literature largely attributes these patterns to differences in productivity and labor market frictions.[1] Yet one overlooked explanation is the scarcity of firms in rural labor markets. For example, in sub-Saharan Africa, a worker in a rural village may have very few firms nearby where she can look for work. This can be a source of labor market power, allowing firms to extract rents from workers and pay wages below the marginal product of labor. However, firms cannot suppress wages indefinitely, as workers have outside options. They could work in self-employment, though that is typically low productivity (Buera et al., 2015), or they could migrate to the city, though relocation is typically costly (Lagakos, 2020).

Strategic wage-setting is not the only source of labor market power. Indeed, a job is more than a wage; it is a location, an environment, tasks, and a part of the worker's identity. Because people value these things, even very small firms can extract rents from workers and pay wages below the marginal product of labor.[2] While imperfect labor market competition has been well-documented in high-income countries,[3] recent cross-country evidence suggests that labor markets are even less competitive in poorer countries (Armangué-Jubert et al., 2023). However, these effects are mitigated by high rates of self-employment (Amodio et al., 2024). A key unexplored question across all levels of development is how labor market power varies across space, and what role it plays in the spatial distribution of labor.

The contribution of this paper is to measure the spatial distribution of wage markdowns, and to then quantify the aggregate and distributional effects of labor market power in a low-income country context. I do so by constructing a new spatial general equilibrium model of monopsony,

[1] *e.g.* Restuccia et al. (2008); Lagakos and Waugh (2013); Herrendorf et al. (2014); Bryan and Morten (2019); Franklin et al. (2024) to name a few.

[2] This may not be the case if there are strong labor unions (Manning, 2004), minimum wages (Ashenfelter et al., 2010), wage indexing (Guillouzouic et al., 2024) or other labor market interventions.

[3] See Yeh et al. (2022) for the US; Manning (2003b) for the UK; Hirsch et al. (2022) for Germany.

which accounts for self-employment, job search costs and migration costs. The model features two sources of labor market power: monopsony, in which all firms can mark down wages because workers have heterogeneous preferences over firms, resulting in an upward sloping aggregate labor supply curve (Burdett and Mortensen, 1998; Manning, 2003a), and oligopsony, in which firms set wages strategically, internalizing how a change in their own wage will affect the wage offered by other firms (Berger et al., 2022). I quantify the complete spatial distribution of wage markdowns using a new administrative dataset of Tanzanian firms, the Employment and Earnings Survey (EES), which covers the entire country. Critically, I am able to identify the labor supply elasticity using Tanzania's first-ever minimum wage law, which specified different minimum wage levels across industries.

Wage markdowns are inherently unobservable, making it challenging to quantify how they vary across space. To address this, I develop a two-sector spatial general equilibrium model of monopsonistic competition. The model features a discrete set of locations, each varying in the number of firms and the productivity of self-employment. Workers are endowed with a birth location and have idiosyncratic preferences for firms and self-employment, which follows a nested Gumbel distribution as in Berger et al. (2022). Wage markdowns arise through firms observing the labor supply curve, and setting wages strategically via Bertrand competition. Workers choose where to work and live in a frictional environment similar to Monte et al. (2018), and face two types of frictions: search costs, which make it costly to access jobs in firms, and migration costs which may prevent them from optimally locating across space.[4] To the best of my knowledge, this paper is the first to construct a unified spatial general equilibrium framework of monopsonistic competition that incorporates self-employment.

In the model, self-employed workers earn the average product of labor, while wage workers earn a wage that is discounted from the marginal product of labor. This creates a wedge between labor productivity and labor income, but only in the firm sector, resulting in an undersupply of labor to

[4] Search costs aim to capture the present discounted value of searching for a job, as well as all of the unobservable frictions that prevent workers from engaging in wage work, *e.g.* information asymmetries between firms and workers (Abebe et al., 2020; Alfonsi et al., 2020), local commuting costs (Monte et al., 2018; Abebe et al., 2020), search frictions (Abebe et al., 2021), and demands for time in the household. The existence of high migration costs has been well established in the literature (Lagakos, 2020). Although these costs are unobservable, the returns to migration are large. Lagakos et al. (2020) find that migrants in Tanzania earn on average 11% more after migrating and those that migrate from rural to urban districts earn 21% more.

firms. The size of this wedge–the wage markdown–is determined by the labor supply elasticity (ε) and is calculated as $\varepsilon/(1+\varepsilon)$. In a model of perfect competition, labor supply is perfectly elastic and this term reduces to unity, meaning that workers are paid according to their marginal product. What differentiates models of monopsonistic competition is the functional form of the labor supply elasticity. Here, each firm faces its own labor supply curve which is a function of three elasticities: the between-firm elasticity (η), the sector elasticity, between wage-work and self-employment, (γ), and the migration elasticity (θ).

The model replicates the standard result that wages are more competitive in small firms, while making two new predictions. First, wages are more competitive in markets with more self-employment. Wage employment and self-employment are not disjoint labor markets: transitions between the two are high (Donovan et al., 2023). When either job search costs or self-employment earnings are high, firms must offer higher wages to attract workers away from self-employment. Second, wage competition has an inverse-U-shaped relationship with migration patterns. Low-emigration areas are characterized by high migration costs, which trap workers in these isolated labor markets. This allows firms to post lower wages because workers cannot emigrate to more competitive markets. In high-immigration areas, workers are arriving for other reasons (*e.g.* amenities, number of job opportunities), resulting in a surplus of labor, which allows firms to post lower wages. The most competitive labor markets are those in which migration flows are most tenuous, and firms must post higher wages to prevent migrants from redirecting. These features suggest some ambiguity as to whether urban or rural labor markets are more competitive. In practice, rural labor markets are less competitive because their workers are, on average, employed in larger firms. However, the higher rate of rural self-employment plays an important role in mitigating the gap in labor market competition between rural and urban areas.

I then turn to the data to estimate the parameters of the model, leveraging the full spatial distribution of wages and employment available in the EES. To the best of my knowledge, this is the first and only nationally representative survey of firms in sub-Saharan Africa. I combine this data with Tanzania's first ever minimum wage law to estimate the three key elasticities. The legislation set specific minimum wage level for 20 industries, as well as a national floor for all others. This created a heterogeneous effect across firms in two ways. First, within the same industry, firms experienced different levels of exposure to the minimum wage based on their pre-existing wage bills; firms with lower wages had to raise their wages more to comply with the law. Second, firms in different industries, with the same wage bill, needed to increase wages by different amounts to be compliant.[5] I identify the between-firm elasticity (η), using changes in wages and employment following the introduction of the minimum wage law. Following Card and Krueger (1994), I instrument for wages using the gap between the pre-policy wage bill and the minimum-wage-compliant wage bill. Because firms are setting wages strategically, these results will be biased.[6] The exception to this bias arises for very small firms who lack any oligopsony power, and face an isoelastic labor supply elasticity equal to η. I address this by interacting the gap instrument with the firm's share of local firm employment. I estimate a between-firm elasticity of 2.5 which is notably lower than Berger et al. (2022)'s estimate for the US (10.85) but is similar to Franklin et al. (2024)'s estimate for Ethiopia (3.36).

I estimate the sector elasticity (γ) using a model-generated moment that links the ratio of firm to self-employment with relative wages in each labor market. The market-level firm wage is modeled as a CES aggregator of individual firm wages, with the elasticity between firms being given by η. To identify γ, I instrument for the wage ratio using the hypothetical market-level firm wage that would occur if all firms were paying exactly the minimum wage. I estimate a sector elasticity of 1.5, slightly lower than Amodio et al. (2024)'s average estimate for Peru (2.8). Since the market-wage index is a function of η, I re-estimate the sector elasticity for different calibrated values of η. Across these alternative calibrations, the ratio of the sector elasticity to firm elasticity remains roughly constant at 0.6. This indicates that the way in which firms compete with each other for workers differs from

[5]A potential concern for identification is the well-documented lack of enforcement of minimum wage laws in developing countries (Basu et al., 2010). Indeed, while compliance with the law was imperfect, it improved over time. In 2007, the last observed pre-policy year, 19% of wage workers were paid below the minimum wage. In 2010, the year that the law was enacted, this share fell to 10%, representing a 47% rate of compliance, which is consistent with average compliance levels in sub-Saharan African countries (Bhorat et al., 2017). By 2013, non-compliance fell below 5%, likely reflecting both an adjustment period (Clemens and Strain, 2022) and changes in nominal wages caused by inflation (Kaur, 2019). For tractability, in the model I assume full compliance and do not consider how the level of the minimum wage is likely to affect compliance.

[6]The reduced form estimate is confounded by the Nash-equilibrium response of firms to wage changes in other firms; a change wages in any firm affects the wage of all other firms. However, this effect diminishes as the firm's share of employment decreases. The within-market elasticity is identified by the limiting case in which the firm is atomistic, and its wage-setting decision does not influence those of other firms.

the way in which they compete for workers with self-employment, and it implies that if a firm were to deviate from its equilibrium wage offer and post a higher wage, it would pull more workers from other firms in the local labor market than it would from self-employment.

I then use the spatial equilibrium framework to estimate the migration elasticity (θ). Migration flows between two locations are determined by the relative wages, amenities, and migration costs. To isolate the effect of relative wages on migration patterns, I again instrument for the market-wage index in each location using the hypothetical market wage index that I would observe if all firms were paying exactly the minimum wage. Critically, this instrument relies on the spatial variation in industrial composition, and hence applicable minimum wages, across labor markets. I estimate a migration elasticity of 1.4, which is higher than Berger et al. (2022)'s estimate for the US (0.42), but comparable to Tombe and Zhu (2019)'s estimate for China (1.5), and Bryan and Morten (2019)'s estimate for Indonesia (3.2). These estimates are consistent with the finding that migration elasticities are larger in developing than in developed countries (Bryan and Morten, 2019).

Having estimated the three key labor supply elasticities, I am able to estimate the wage markdown in each firm. Average wage markdowns vary between 66-71% of marginal product across labor markets, with rural labor markets being the least competitive. However, the gap would be much wider if not for the mitigating effects of self-employment. Because workers are relatively inelastic between wage- and self-employment, the higher rate of rural self-employment limits the extent to which rural firms can markdown wages.

I then use the model to quantify the aggregate and distributional effects of labor market power. To do this, I simulate the baseline equilibrium under labor market power to match the migration flows between districts, as well as the labor supply and wages in firms and self-employment in each district in the data. I compare these outcomes to the counterfactual in which firms are price takers and pay competitive wages.[7] In the counterfactual where firms pay competitive wages, total output rises by 4.8%, and wage employment increases from 13.9% to 18.3%, suggesting that labor market power

[7]The competitive equilibrium is less straightforward in Bertrand competition than in Cournot competition. The monopsony limit–in which all firms pay the same wage–is reached when firms do not internalize how a change in their wage affects the wage in other firms, leading to a uniform wage markdown. The competitive equilibrium is achieved by going one step further and assuming that firms do not internalize the labor supply curve. This precludes wage setting by firms, and necessitates that they demand quantities of labor, making it a more natural extension of Cournot competition.

significantly constrains both output and wage employment.

I then decompose the channels though which these gains occur by fixing various worker decisions at their baseline levels. First, when I hold fixed workers' baseline choice of wage- or self-employment fixed but allow them to spatially reallocate, total output falls. This happens because rural firms were paying workers a lower share of their marginal product and, as a result, rural wages rise more than urban wages, causing an exodus of labor from urban areas. Next, when I fix workers' baseline labor market decisions but allow them to reallocate between firms and self-employment, total output rises by 4%. This is 80% of the gain from fully flexible reallocation, indicating that the bulk of output gains in a competitive equilibrium stem from workers moving out of self-employment and into wage work for higher wages. Finally, when I fix both the labor market and sector decision, I isolate the oligopsony channel by only allowing workers to move between firms within a local labor market, and I find negligible gains in total output. This highlights the important role that self-employment plays in mitigating labor market power.

Turning to the impact of labor market power on the spatial distribution of income, I find that, because rural labor markets are less competitive than urban labor markets, the rural-urban income gap overstates the productivity gap for wage workers. However, in the competitive equilibrium counterfactual, the rural-urban income gap among all workers actually widens. This finding is driven by compositional differences between rural and urban areas: urban areas have a higher share of wage employment, meaning that urban workers disproportionately benefit from higher wages. Consequently, labor market power actually reduces cross-sectional income inequality by mitigating the extent to which urban workers capture the gains associated with wage employment.

A natural question that follows is: how important is labor market power in constraining total output relative to migration and job search costs? To answer this, I simulate a 10% reduction in each friction. When I reduce job search costs, wage employment rises to over 48%, leading to a 22% increase in total output. Since job search costs reduce the value of wage employment but not self-employment, the effect of this reduction is similar to the competitive equilibrium counterfactual. Unlike the competitive equilibrium counterfactual however, because the reduction is uniform across space, it reduces the rural-urban income gap.

Next, I simulate a reduction in migration costs and find that total output actually falls. This result arises because people choose where to live and work to maximize welfare, rather than output.[8] While preferences for non-wage aspects of jobs can create a wedge between the welfare-maximizing and output-maximizing labor allocations, labor market power exacerbates this distortion, particularly when workers face the low-productivity, non-discounted option of self-employment. This reasoning is highlighted by the finding that total output rises slightly when I reduce migration costs in the competitive equilibrium counterfactual.

This paper contributes to several strands of the literature, including the burgeoning literature on labor market power outside of high-income countries. I provide the first causally-identified wage markdown estimates in a low-income country context, finding that workers are paid between 64-71% of their marginal product in Tanzania. In a recent cross-country analysis, Armangué-Jubert et al. (2023) estimate wage markdowns as low as 55% in low-income countries. The authors do not account for the role of self-employment, which is not as relevant a margin in richer countries. While they are able to closely match other estimates for wage markdowns in high- and middle-income countries, their model does not account for the mitigating effects of self-employment, causing low-income country labor markets to appear less competitive.[9] Indeed, in recent work comparing rural labor markets in Peru, Amodio et al. (2024) find that labor markets with higher rates of self-employment are more competitive. The authors estimate that workers in very small firms, in which markdowns are driven entirely by the labor supply elasticity, are paid 70% of their marginal product, similar to other recent estimates for Latin America including: 70% in Colombia (Amodio and de Roux, 2021), and 50% in

[8]The idea that location amenities compensate for wage differentials was first proposed by Rosen (1974) and Roback (1982). More recently, Albouy (2008) showed that the rank-ordering of locations in the US is nonsensical when not accounting for variation in the cost-of-living. In Dar es Salaam, Tanzania's megacity, average wages are 11% higher than in rural areas, but these wage gains are insufficient to induce additional immigration when migration costs fall. Indeed, if I do not adjust for spatial variation in the cost-of-living, the output losses that I estimate are even larger.

[9]Causally identifying the labor supply elasticity, and hence wage markdowns, in a single country is hard, making Armangué-Jubert et al. (2023) consistency with the estimates in the literature for high- and middle-income countries all the more impressive. Here, I identify the labor supply elasticity using Tanzania's 2010 minimum wage law. A closely related literature studies the interaction between firms with labor market power and minimum wages (Manning, 2003a, 2004; Berger et al., 2025). The direct effect of the minimum wage is less clear in this context due to the well documented lack of enforcement in developing countries (Basu et al., 2010; Rani et al., 2013; Bhorat et al., 2017; Mansoor and O'Neill, 2021). In the development context, the employment effects of the minimum wage vary from no disemployment effects in Brazil (Almeida and Carneiro, 2012; Derenoncourt et al., 2021) to positive effects on formal employment in Indonesia (Magruder, 2013). To focus ideas, in this analysis, I abstract from the compliance decision of firms and use the minimum wage only as a means of identifying the labor supply elasticity.

Brazil (Felix, 2022).

Second, this paper makes a theoretical contribution by constructing a simple spatial general equilibrium framework of monopsony that accounts for self-employment. Typically, estimation of the labor supply elasticity requires data on firm hires or exits (Manning, 2003b). The general equilibrium framework developed by Berger et al. (2022) alleviated this constraint. To account for spatial frictions, I adapt their framework to the spatial general equilibrium model developed by Monte et al. (2018). These models have been used in the development context to study both migration (Bryan and Morten, 2019) and commuting frictions (Franklin et al., 2024). I add to this a sectoral choice between wage-work and self-employment in the spirit of Lewis (1954).

Third, this paper contributes to the literature on labor misallocation and development. Kuznets (1973) argued that development hinges on structural transformation: the reallocation of productive inputs out of agriculture and into manufacturing, and eventually to services. However, this transition remains incomplete in many countries, with a significant share of the workforce still in low-productivity agriculture (Gollin et al., 2014). To explain why this shift has not yet fully materialized, three distinct strands of literature have emerged, each focusing on different factors: spatial frictions[10], rural labor market frictions, and urban labor market frictions.[11] This paper introduces a unified framework to jointly assess the role of each of these frictions in labor misallocation.

I find that reducing job search costs increases total output. While this finding may seem intuitive, the underlying causes are more nuanced. Job search costs prevent workers from accessing the full range of jobs. A targeted reduction in search costs for a particular firm may reduce output if the firm is unproductive. Conversely, I find that lowering migration costs causes output to fall. This is possible because the labor allocation which maximizes welfare is not necessarily the same as that

[10]While some authors argue that workers are optimally located across space (Young, 2013; Hicks et al., 2021), the rural-urban income gap is often reconciled through high costs of migration (Lagakos et al., 2020). The literature has proposed several mechanisms through which monetary costs may preclude profitable migration including risk in finding employment and near subsistence levels of consumption at origin (Bryan et al., 2014) or village risk-sharing networks (Morten, 2019). However the main cost of migration is non-monetary (Lagakos et al., 2023; Imbert and Papp, 2020; Bryan et al., 2021). Indeed, reviewing the literature, Lagakos (2020) concludes that while early evidence pointed toward monetary costs as the primary constraint against migration, more recent evidence has determined that migration costs are largely non-monetary.

[11]For reviews of these literatures, see Lagakos (2020) for internal migration, Rosenzweig (1988) for rural labor markets, Caria and Orkin (2024) for urban labor markets, and Donovan and Schoellman (2023) for labor markets in general.

which maximizes total output. Indeed, even in the US, where labor misallocation is likely to be small, there are large gaps in productivity across both sectors and states (Herrendorf and Schoellman, 2015). This finding continues the trend of downward revisions in estimates of the gains from reducing migration costs (Bryan and Morten, 2019). While Bryan and Morten (2019) find modest gains in total output, their results reflect workers moving to locations where they are more productive, rather than to those which maximize welfare.

The decline in total output that I observe is tied to a net reduction in urban employment. This finding is not without precedent. Faber (2014) finds that construction of highways in China led to a decline in local rural output, while Imbert et al. (2022) find that an influx of immigrants in Chinese cities caused labor productivity in manufacturing firms to fall, attributing the decline to sticky capital allocation within firms. Applying the methodology of Au and Henderson (2006), I find that Dar es Salaam is not necessarily too large, but rather its economy is overly concentrated in services (Gollin et al., 2016; Henderson and Kriticos, 2018). From an amenity perspective, Lagakos et al. (2023) highlight the substantial disutility of poor urban housing when interpreting the experimental findings of Bryan et al. (2014) in a general equilibrium framework. They find that improving the quality of urban housing is equivalent to raising migrant wages by 21%.

2 Data

In this section, I describe the main source of data used for each piece of the model. I focus my data collection efforts around 2010, when Tanzania enacted its first minimum wage law. No single data source contains all of the information that I need, so I combine data from several sources including: the Tanzanian Employment and Earnings Survey (EES), the 2010 Tanzanian National Panel Survey (NPS), which is a part of the World Bank's Living Standards Measurement Study (LSMS) surveys, the 2002 and 2012 Censuses, Tanzania's 2014 Integrated Labor Force Survey (ILFS), and industry minimum wage levels from the Tanzanian gazette, a monthly bulletin that reports new laws.

Population Distribution I estimate the initial population distribution using the 2002 and 2012 census. I define the population in each district as the total prime-aged employment (inclusive of the self-employed). I do not directly observe the population in 2009. To estimate it, I use the value in 2012 and the growth rate (g_o) as implied from the 2002 and 2012 censuses

$$L_o^{2009} = L_o^{2012} \times (1 + g_o)^{-3}$$

To account for re-districting that occurred during this period, I use the time-consistent district boundaries from the Integrated Public Use Microdata Series-International (IPUMS) to define the set of districts used in this analysis. Because the EES does not cover the Zanzibar Archipelago, I exclude that region from the analysis, yielding a total of 119 distinct districts. To abstract from definitional issues of what constitutes an urban district, I define the set of urban districts as those that cover Tanzania's three largest cities and the capitol: Dar es Salaam (3 districts), Mwanza, Arusha, and Dodoma.

Firm Wages and Employment Data on firm employment and earnings is taken from the Tanzanian EES, an annual survey of firms. Marshall (2023) showed that the average wages and employment in this data is very similar to that in the Census, LSMS, and ILFS. I report the average wages and employment in Table 2. The dataset includes all firms with at least fifty employees and a representative sample of firms with fewer. In total, around 10,000 firms are surveyed each year. The survey covers all sectors of the economy, and is much larger than other manufacturing surveys. This coverage comes at the cost of information in the survey. For each firm, the survey reports employment by group, male, female, prime-aged, *etc.*, and total payments to each of those groups. However, I do not observe any single wage. For the main analysis, I calculate the wage for each firm as the total payments to prime-aged non-foreign-born workers over total employment in this group.

I am partially able to observe the distribution of wages in the firm through a series of questions that ask, "how many workers are paid between X and Y." In Section 6, I use this information to estimate the share of workers in each firm who are paid below the minimum wage. The survey was not run in

2008 or 2009, so I use the period 2005-2007 to estimate the firm's exposure to the minimum wage in the pre-policy period.

Self-Employment Earnings Self-employment income is notoriously difficult to calculate (Gollin et al., 2014). To this end, I estimate earnings relative to average firm wages in each market using household consumption per adult equivalent from the 2010 LSMS as

$$w_{sd} = w_{fd}^{\text{EES}} \times \frac{\text{consumption-equivalent}_d^{\text{self-employed}}}{\text{consumption-equivalent}_d^{\text{employed}}}$$

Where w_{fd}^{EES} is the average firm wage in district d in the EES, and the consumption equivalent values are the average among prime-aged individuals who report that their main occupation in the past year was either self-employment or wage-work.

Alternatively, I could directly use information on self-employment earnings from both the 2010 LSMS and 2014 ILFS. Both of these suffer from the aforementioned reporting issues. Those engaged in self-employment agriculture consume some of their output, and small household businesses may either under-report or not know their total earnings. Additionally, the 2014 ILFS, while quite large at 40,000 observations, occurred four years after the minimum-wage was implemented. Thus the deflated earnings from that year may not reflect the average income in 2010 if there was selection out of self-employment over that period. Self-employment income in the 2010 LSMS is not ideal because the the sample is much smaller at 12,000 observations, and the sampling scheme was not designed to be representative at the district level.

To calculate the total number of workers in self-employment, I first estimate the share of prime-aged workers in wage-work in each district in 2010 using the growth rate of employment between 2002 and 2012 from the census. I then calculate self-employment to be consistent with the observed number of workers in the EES

$$n_{sd} = (1 - s_d^{\text{Census}}) \times n_{fd}^{\text{EES}}$$

Where s_d is the share of employment in district d in wage-work, and n_{fd}^{EES} is total district employment in the EES.

Migration For the main analysis, I use the one-year migration flows from the 2012 Census. I limit my attention to the set of prime-aged individuals (15-65) to abstract from family moves (under 15) and return migration (over 65). Although these flows correspond to the year 2011, the coverage in the census is much larger than that in any of the surveys. However, given that the question is limited to moves during the past year, the matrix of migration between district pairs is still quite sparse. Hence, for the estimation of the migration elasticity in Section 7, I aggregate to the regional level (23 distinct units). When I estimate the structural migration costs, I use the implied ten-year flows between districts following the procedure outlined in Appendix B.2.

As a robustness exercise, I use data from the 2012, and 2014 LSMS and the 2014 ILFS to estimate migration flows between district pairs. These surveys ask about the year of migration, so I have a better idea of when the migration happened. With the 2014 surveys, the reported migration year may be inaccurate due to recall bias (Kirchberger, 2021). I address this concern by focusing on migration flows during the five-year period 2010-2014. As noted above, the ILFS was designed to be representative at the district level while the LSMS surveys were not. To account for differences in the sampling, I first weight the migration flows from the 2012 and 2014 LSMS surveys by the number of years since 2010. I then equally weight these shares with those from the ILFS.

Minimum Wages I get industry level minimum wages for the 2010 law from the Tanzania National Gazette, a monthly bulletin that includes all new national regulations. I assign to each two-digit ISIC code a corresponding minimum wage. I report the minimum wage-ISIC crosswalk in Appendix Table A.8. For industries with sub-sector levels (*e.g.* mining has three levels that are distinguished by the firm's license class) that cannot be discerned from standard ISIC codes, I assume that all firms in that sector are subject to the lowest minimum wage level.

3 Context & Motivating Facts

Labor markets in developing countries differ from those in developed countries along several dimensions that are relevant for labor market power. In this section, I document several empirical facts about labor markets in Tanzania to motivate the model. Of particular interest is new information on the size distribution of rural firms.

The Self-Employment Rate is High A key difference between labor markets in high- and low-income countries is the prevalence of self-employment. In Table 3, I report employment statistics from the 2012 Census. 70% of prime-aged individuals are engaged in some type of employment; of those, 86% are self-employed. To put this number in context, just 9% of workers in the US are self-employed. Self-employment here should not be conflated with informal employment. In Brazil where informality is a primary concern, the rate of self-employment is 25%.[12] Self-employment is a much larger share of the economy in Tanzania than in India (49%) or the USA in 1910 (28%), and it is driven by rural areas, where most of this work is in agriculture. However, the high rate of self-employment is not unusual in sub-Saharan Africa. In Figure 1, I plot the self-employment share against GDP per capita across countries .The self-employment rate is highest in countries in sub-Saharan Africa, shown in red. Across countries, self-employment is negatively correlated with income. Indeed, those countries in sub-Saharan Africa with lower rates of self-employment are those with higher average incomes.

Average Wage > Average Self-Employment Earnings One may expect that a high rate of self-employment reflects an earnings premium relative to wage work. However, this is not typically the case. In Figure 2, I plot the average income of wage workers against the self-employed across districts. I calculate earnings as the district-mean household consumption per adult equivalent to reduce downward-biased measurement error in agriculture (Gollin et al., 2014). The black line indicates parity between wage and self-employment income. While most districts lie to the left of the line–indicating that wage income exceeds self-employment earnings–that is not uniformly true. Average consumption is typically higher in urban districts, and the income gap between wage work and self-employment is highest in rural districts.

[12] See (Ulyssea, 2018, 2020; Derenoncourt et al., 2021). There is little evidence that informal work arrangements, in which some workers in a firm are under contract and others are not, is common in this context. While there is some reported piecemeal casual labor, it is not common. In this analysis, I do not distinguish between formal and informal employment within the firm.

Rural Employment is Concentrated in Large Firms I report the distribution of firms and employment by firm size in Table 4. The missing missing-middle firm size distribution that Hsieh and Olken (2014) document in middle-income countries is, if anything, more pronounced here. In both rural and urban areas, approximately 60% of firms have fewer than ten employees. Differences in the firm size distribution arise when considering firms with at least fifty employees. These firms account for 8.3% of all firms in rural areas, versus just 5.7% in urban areas.

The distribution of employment across firms shows more differences between rural and urban areas, and is most pronounced in large firms. In rural areas, 65.5% of workers are employed in firms with at least fifty employees versus 50.4% in urban areas. To the best of my knowledge, these differences in the employment distribution between rural and urban areas have not been documented elsewhere in sub-Saharan Africa. However, these findings are likely typical for two reasons. First, the preponderance of large firms in rural areas likely reflects production economies of scale in extractive activities such as farming or mining that cannot be attained by growing small businesses (Foster and Rosenzweig, 2022). Second, as shown in Table 3, most rural self-employment is in agriculture for which the shift into a small-scale business may be less conducive than for manufacturing (Bassi et al., 2024).

Migration is Costly In many developing countries, 20-25% of individuals migrate out of rural areas as young adults (Young, 2013). While the literature has largely focused on rural to urban moves, a substantial share of all migration is urban-to-urban or rural-to-rural (Bryan and Morten, 2019). In columns 1-4 of Table 5, I report the five-year migration rates in a number of surveys. Across all surveys, the migration rate between rural and between urban areas is higher than that between rural and urban areas. In columns 5-8, I report the migration rate in 2010 only–the year that the minimum wage was enacted. For all but the 2014 LSMS, the one year migration rate exceeds what would be expected from the five-year migration rate (20%), suggesting that the minimum wage may have had an effect on migration patterns.

In Figure 3, I plot the one-year emigration rate in the 2012 Census. Emigration rates are highest near the four main cities and as low as 3% in the hinterlands. This spatial depiction of emigration is consistent with a gravity model of migration–migration to the city is decreasing with distance. Overall, 6.8% of prime-aged individuals migrated in the previous year. To put this number in context, in 2005 almost 12% of the US population had moved residence in the previous year (Molloy et al., 2011).

More Concentrated Labor Markets have Lower Wages One source of labor market power is labor market oligopsony, in which non-atomistic firms set wages strategically. This implies that wages will be marked down more in labor markets with higher employment concentration (Berger et al., 2022). I plot the relationship between average incomes and employment concentration in Figure 4. There is a negative relationship between employment concentration and income, suggesting that there is labor market oligopsony. However, the relationship is not very strong. This is because larger firms are also more productive and hence pay higher wages. Hence, if there were no labor market oligopsony, more concentrated labor markets would be expected to pay higher wages.

4 Economic Framework

The aim of this section is to develop a spatial general equilibrium framework to disentangle the role of labor market power from search costs and migration costs on labor misallocation. The model combines elements from Berger et al. (2022)'s monopsony framework with the spatial general equilibrium model employed by Bryan and Morten (2019).[13] New here is the addition of self-employment as a job choice, and search costs that make it costly for workers to obtain wage work.[14]

The economy is composed of a unit measure of workers indexed by $\omega \in [0, 1]$, and a discrete set of locations indexed by o or $d \in D$. In each location there are $(M_d - 1)$ firms indexed by (f) and a self-employment sector indexed by (s). I use the word job and index (i) to refer to the set of firms and the self-employment option. Locations are characterized by a non-rival amenity value (B_d), a labor market friction (δ_d), and an initial population $L_o \sim F(L)$.

[13] I make two key distinctions from Berger et al. (2022). First, I model firm competition as Bertrand rather than Cournot. Second, I model a labor market as a location rather than a commuting zone crossed with an industry. This allows me to distinguish between job search costs and migration costs.

[14] Search costs capture the present discounted value of obtaining a wage job. This friction encompasses all of the reasons that could make it costly to get a job in a firm, including the opportunity cost of searching, commuting costs, information asymmetries, familial constraints, land tenure rights, *etc.*.

4.1 Technology

Both firms and the self-employed produce a homogeneous final good which is traded in a perfectly competitive national market at a price P which is normalized to one.

Firms Each firm is endowed with productivity $A_{f(d)} \sim F(A^d)$ and produces output (y_f), measured in value-added, using labor (n_f) as its sole input according to the production function:

$$y_f = A_f n_f^{\alpha} \tag{1}$$

Where $\alpha \in (0, 1)$, implying that production in each firm exhibits decreasing returns to scale. I also implicitly assume that expected firm productivity is independent across locations.

Self-Employment In each location there is a self-employment productivity $A_{sd} \sim F(A^s)$ that is common to all workers. Output is produced using the same technology as firms as if the self-employment sector were operating as a single firm:

$$y_{sd} = A_{sd} n_{sd}^{\alpha}$$

Each worker in self-employment earns the average product of labor $w_{sd} = A_{sd} n_{sd}^{\alpha-1}$.

Total output in each location and aggregate output are defined as

$$y_d = y_{sd} + \sum_{f \in d} y_f \quad ; \quad Y = \sum_d y_d$$

4.2 Preferences and Choices

In this section, I develop a discrete choice migration model and derive the labor supply curve to each firm from each origin. In what follows, I use the term job to refer to the set of firms in each location and the option of self-employment.

Individuals are heterogeneous in two dimensions: their place of birth (o), which determines the migration cost to all other locations, and their idiosyncratic tastes over jobs. These tastes are described by a vector of preferences (idiosyncratic amenities) for each firm and self-employment in each location $\zeta(\omega)$, which is distributed according to the multivariate Gumbel distribution

$$F(\zeta_{11}, \ldots, \zeta_{id}, \ldots, \zeta_{(M_D+1)D}) = \exp\left[-\sum_{d}\left(\left(\sum_{f\in d} e^{-\eta\,\zeta_{f(d)}}\right)^{\frac{\gamma}{\eta}} + e^{-\gamma\,\zeta_{sd}}\right)^{\frac{\theta}{\gamma}}\right]$$

The parameter η captures the elasticity between firms in a given labor market. When $\eta \to \infty$, workers are indifferent between firms, and all labor will go to the firm with the highest wage. γ captures the elasticity between wage work and self-employment, and θ captures the elasticity between locations. I make two assumptions on the elasticities which I later verify empirically in the data. First $\eta > \gamma$. This implies that if a firm were to raise its wage, it would pull more workers from other firms in the local labor market than from self-employment. Second, $\gamma > \theta$. This implies that if the wage in any firm or in self-employment were to go up, more labor would reallocate to that job from within the market than from other markets. In practice, the distributional assumptions capture the fact that people have personal preferences over both locations and firms. One's preferences over firms within a market are correlated because they share a location, *e.g.* an individual with a family network in a certain location will have a higher amenity value for all firms in that location.

Workers choose a job (i) from the set of firms (f) or self-employment (s), in a market (d) to maximize their indirect utility

$$v(\omega|o(\omega)) = \max_{d}\Big\{B_d\tau_{od}\ \max\big\{\delta_d \max_{f\in d}\left\{e^{\zeta_{fd}(\omega)}b_f w_f\right\},\ e^{\zeta_{sd}(\omega)}w_{sd}\big\}\Big\} + \Pi\partial\omega$$

The job choice is made in three steps. First, in each market (d), the worker chooses the firm that delivers the highest utility based on the wage (w_f), the firm's non-rival amenity value (b_f), and their idiosyncratic amenity draw (ζ_f).[15] Second, the worker chooses between working in self-employment, where they earn (w_{sd}), and have idiosyncratic value (ζ_{sd}) or working in their most preferred firm,

[15]While I use the term amenity here, b_f captures both positive and negative aspects of the firm, *e.g.* flexible hours, and hazardous work. Equivalently, b_f can be modeled as the location parameter for ζ_f in the amenity vector.

discounted by the cost of search (δ_d). I assume that $\delta_d \in (0,1]$ is common to all workers but may vary across markets. The lower bound ensures that in each market a non-zero measure of workers will supply labor to firms. Third, the worker chooses the market (d) based on the value of their most preferred job, the non-rival amenity in d, (B_d), and the cost of migrating from their birth location o to d, (τ_{od}).[16] I assume that $\tau_{od} \in [0,1]$ and $\tau_{oo} = 1$. The latter assumption states that there is no cost for not migrating, while the former implies that a percentage of utility is lost for migrating to any other district. The special case where $\tau_{od} = 0 \,\forall\, d$ corresponds to infinite costs of migration. I make the additional assumption that migration costs are symmetric; that is $\tau_{od} = \tau_{do}$.

Firm profits (Π) are redistributed lump-sum across all workers (including the self-employed). This has no effect on choices, but does affect welfare.

5 Equilibrium

In this section, I present the equilibrium of the model and show how wage markdowns are affected by self-employment and migration.

Labor Supply Under the distributional assumptions on the amenities, total labor supply from o to firm f or self-employment s in market d, can be expressed as

$$n_{fdo} = \left(\frac{b_f w_f}{W_{fd}}\right)^{\eta} \left(\frac{\delta_d W_{fd}}{W_d}\right)^{\gamma} \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^{\theta} L_o \tag{2a}$$

$$n_{sdo} = \left(\frac{w_{sd}}{W_d}\right)^{\gamma} \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^{\theta} L_o \tag{2b}$$

Where the wage indices are given by

$$W_{fd} := \left[\sum_{f\in d} (b_f w_f)^{\eta}\right]^{\frac{1}{\eta}} \quad , \quad W_d := [w_{sd}^{\gamma} + (\delta_d W_{fd})^{\gamma}]^{\frac{1}{\gamma}} \quad , \quad \mathbf{W_o} := \left[\sum_{d} (\tau_{od} B_d W_d)^{\theta}\right]^{\frac{1}{\theta}}$$

[16] As with firm amenities, B_d captures both positive aspects of the location, *e.g.* clean air, markets, natural beauty, as well as negative aspects, *e.g.* pollution, crime.

The first term in (2a) is the probability of choosing firm f conditional upon choosing firm employment in market d. Among firms, the labor share to firm f is increasing in the own wage and amenity at the rate η. When $\eta \rightarrow \infty$, markets are perfectly competitive, and the wage-amenity value in each firm will equate. This implies that even under perfectly competitive markets, wage dispersion can be explained by firm amenities.

When $\eta < \infty$, workers have tastes over firms within the market and do not supply all of their labor to the firm with the highest value. The elasticity between firms is one source of market power within a market. This term is independent of the worker's origin and implies that workers from all origins will supply labor in equal proportion across firms.[17]

The second term in (2a) is the probability of choosing wage-work in market d. When $\gamma \rightarrow \infty$, some labor will still be misallocated into self-employment because of search costs (δ_d). For $\gamma < \infty$, workers are elastic between wage-work and self-employment, meaning that, in the absence of labor market frictions, if all firms in the market lower their wages uniformly, not all labor will reallocate to self-employment.

The third term in (2a) is the probability of choosing market d. This expression says that first, locations with higher amenities (B_d) have more migrants from all origins. Second, there will be more migrants from o in places with lower costs of migration (τ_{od} closer to one).[18] Third, migration into any location is increasing in the market wage index, (W_d). That is, migration is increasing in both the average wage and the total number of wage offers. When $\theta \rightarrow \infty$, the wage-amenity value will not necessarily equate across markets due to variation in the supply of labor across locations and the costs of migration (τ_{od}).

[17]In practice, this means that a change in total labor supply in market d will only affect the distribution of workers across firms through the distortionary effect on relative wages of self-employment. When labor supply rises, wages in self-employment decline more slowly than those in firms, increasing the relative share of labor engaged in self-employment.

[18]However, for any two origins o and o' with $\tau_{od} > \tau_{o'd}$ does not imply that there will be more migration form o. This is because the cost of migration relative to other locations matters. For example, two rural villages with high costs of migration to Dar es Salaam may differ in their migration there because one is closer to a smaller city.

Welfare Following Small and Rosen (1981), the welfare value for workers born in o can be expressed by the expected utility

$$E[v_o] = \log\left(\sum_d (B_d\tau_{od})^\theta \left(w_{sd}^\gamma + \left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}}\right)^{\frac{\theta}{\gamma}}\right) + \psi \tag{3}$$

Where ψ is the Euler-Mascheroni constant $(\sim\ 0.577)$. Because workers are infinitesimal, transfers have no effect on individual welfare. However, they do matter for aggregate welfare which is given by

$$W = \sum_o \log\left(\sum_d (B_d\tau_{od})^\theta \left(w_{sd}^\gamma + \left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}}\right)^{\frac{\theta}{\gamma}}\right) L_o + \psi + \Pi$$

Aggregate Labor Supply Curve Because the measure of workers in the total economy is unitary, the labor supply to each firm can be be expressed as the share of workers in market d that are employed in firm f, multiplied by the share of workers in market d from o. Summing over origins, the aggregate labor supply curve to firm f can be expressed as

$$n_f = \left(\frac{b_f w_f}{W_{fd}}\right)^\eta \left(\frac{\delta_d W_{fd}}{W_d}\right)^\gamma \left[\sum_o \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^\theta L_o\right] \tag{4}$$

Firm Problem Labor market competition is Bertrand, so firm f in market d takes as given local competitor's wages $\{w_{-f(d)}\}$, the local self-employment wage w_{sd}, the wage level in all other markets $\{W_{-d}\}$, and the aggregate distribution of labor $\{L_o\}$, and chooses its wage (w_f) to maximize profits

$$\max_{w_f} \quad A_f n_f^\alpha - w_f n_f \tag{5}$$

Subject to

$$n_f = \sum_o n_{fdo}(w) \quad , \quad n_{fdo}(w) = \left(\frac{b_f w_f}{W_{fd}}\right)^\eta \left(\frac{\delta_d W_{fd}}{W_d}\right)^\gamma \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^\theta L_o \quad , \quad o = 1,\ldots,D$$

Under the assumption of Bertrand competition, the firm understands that $\partial n(w_f, W_{fd}, W_d, \mathbf{W_o})/\partial w_f \neq 0$, $\partial W_{fd}/\partial w_f \neq 0$ and $\partial W_d/\partial w_f \neq 0$. That is, firm wages affect hiring both directly and indirectly through the market level wage index W_d.

Self-Employment operates like a firm in this context. However, it differs from firms in that it does not compete in Bertrand competition. It pays each worker the average revenue product of labor. This implies that all profits from self-employment are paid to the worker.

Equilibrium Definition Given an initial population distribution $\{L_o\}_{o=1}^{D}$, market amenities $\{B_d\}_{d=1}^{D}$, firm amenities $\{b_f\}$, search costs $\{\delta_d\}$, and origin-destination migration costs $\{\tau_{od}\}$, a *spatial oligopsonistic Nash-Bertrand* equilibrium is: (1) a household labor supply curve for each origin $n(w_f, W_{fd}, W_d, \mathbf{W_o})$, (2) firm wages $\{w_f\}$, (3) self-employment wages $\{w_{sd}\}$, (4) quantities of labor $\{n_f\}$, $\{n_{sd}\}$ and $\{n_{fdo}\}$, (5) profits (Π), and (6) aggregate wage indices for each origin $\{\mathbf{W_o}\}$ and market level wage indices $\{W_{fd}\}$ and $\{W_d\}$ for each destination that satisfy the following conditions:

1. Given wages $\{w_f\}$ and $\{w_{sd}\}$, search costs $\{\delta_d\}$, migration costs $\{\tau_{od}\}$, amenities $\{B_d\}$ and $\{b_f\}$ and profits (Π), household optimization implies the labor supply curve $n(w_f, W_{fd}, W_d, \mathbf{W_o})$ for each origin o.

2. For every firm f in location d: given competitor wages $\{w_{-f(d)}\}$, the self-employment wage w_{sd}, the aggregate wage indices $\{\mathbf{W_o}\}$ from each origin and the labor supply curve from each origin $n(w_f, W_{fd}, W_d, \mathbf{W_o})$, firm f's optimization yields wage w_f and employment n_f.

3. Firm wage decisions are consistent with the market $\{W_{fd}\}$, $\{W_d\}$ and aggregate $\{\mathbf{W_o}\}$ wage indices for each origin, as well as profits (Π)

4. Markets clear $n_f = \sum_o n_{fdo} \, \forall f, d$, $n_{sd} = \sum_o n_{sdo} \, \forall d$, and $\sum_d \left(n_{sd} + \sum_f n_{f(d)}\right) = \sum_o L_o$.

5.1 Markdowns in the Model

The labor supply elasticity to firm f in market d is given by

$$\varepsilon_f = \eta + s_f(\gamma - \eta) + s_f s_d(\theta - \gamma) - s_f s_d \left(\frac{\sum_o s_{od}^2 L_o}{s_m(d)}\right)\theta \tag{6}$$

Where s_f is firm f's share of firm-employment its local market, d, s_d is the share of workers in d who are employed in a firm, s_{od} is the share of workers from o who migrate to d, and $s_m(d)$ is market d's share of total employment. These shares can be expressed as

$$s_f = \left(\frac{b_f w_f}{W_{fd}}\right)^\eta \quad ; \quad s_d = \left(\frac{\delta_d W_{fd}}{W_d}\right)^\gamma \quad ; \quad s_{od} = \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^\theta \quad ; \quad s_m(d) = \sum_o s_{od} L_o$$

The labor supply elasticity in (6) affects wages through the markdown (μ_f) that firms pay on workers' marginal product

$$w_f = \mu_f \, mrpl_f \qquad ; \qquad \mu_f = \frac{\varepsilon_f}{1+\varepsilon_f} \tag{7}$$

Where $mrpl_f = \alpha A_f n_f^{\alpha-1}$ is the marginal revenue product of labor. In the case of perfect competition, $\varepsilon = \infty$, the markdown is one, and workers are paid their marginal product. When firms have market power, $\varepsilon < \infty$, and workers are paid a fraction of their marginal product. Thus, lower values of ε_f imply that a firm will pay its workers a lower share of their marginal product.

The first term in (6) captures the preferences channel of markdowns. For atomistic firm $(s_f \to 0)$, the only source of labor market power is through preferences, and (6) reduces to η–the monopsony limit. Under the assumption that $\eta > \gamma > \theta$, only the first term in (6) will be positive, and the rest of the expression, which captures the oligopsony channel of labor market power, will be negative. The second term in (6) captures strategic wage-setting between firms. This term states that firms with a higher share of local wage employment will pay less competitive wages, and that the rate at which wages are falling is increasing in the gap between the firm and sector elasticity. The third term in (6) captures the role of self-employment. It states that the extent to which firms can mark down wages is decreasing the self-employment's share of local employment.

The final term in (6) captures the role of migration in wage markdowns. In a world with no migration costs, it reduces to $\theta s_f s_d s_m$, implying that larger markets will be less competitive than smaller ones.[19] When τ_{od} varies across markets, the final term in (6) is a kin to a Herfindahl-Hirschman index of immigration concentration. Here, immigration concentration is a bit of a misnomer because it includes non-migration. That is, labor market competition will be lowest in both high immigration and low emigration labor markets. Intuitively, firms in isolated rural labor markets will be able to mark down wages more because it is very costly to emigrate, while firms in major immigration destinations will also be able to mark down wages more because workers are attracted to that area. The most competitive labor markets are those in which migration flows are most tenuous. Firms in those labor markets need to pay more competitive wages to prevent migrants from redirecting elsewhere.

Comparative Statics Under the assumption that $\eta > \gamma > \theta$, the implications of equation (6) can be summarized as follows

1. For any two firms f' and f'' in the same market d such that $s'_f > s''_f$, then $\mu_{f''} > \mu_{f'}$. That is wages are less competitive in the larger firm.

2. For any market d, holding fixed the firm shares $\{s_f\}$ and immigration shares $\{s_{od}\}$ and comparing two equilibria with $s'_d > s''_d$, then $\mu_{f(d')} \leq \mu_{f(d'')}$, with strict inequality whenever $s_f > 0$. That is, wages are less competitive in markets with less self-employment.

3. For any two firm in different markets $f(d')$ and $f(d'')$ such that $s_{f(d')} = s_{f(d'')}$ and $s_{d'} = s_{d''}$ and $\sum_o s^2_{od'} L_o / s_m(d') > \sum_o s^2_{od''} L_o / s_m(d'')$, $\mu_{f(d')} \leq \mu_{f(d'')}$, with strict inequality whenever $s_{f(d')} > 0$ and $s_{d'} > 0$. That is, wages are less competitive in markets with a higher concentration of immigration.

Comparison with Berger et al. (2022) This model differs from that in Berger et al. (2022) on two key dimensions: there is self-employment and there is a discrete number of markets. These modelling choices reflect differences in context. As shown in Table 3, 85% of prime-aged workers in Tanzania

[19] Technically, this logic holds under any case of homogeneous migration costs ($\tau_{od} = \tau \,\forall\, o, d$). Under the realistic assumption that $\tau_{oo} = 1$, the only case of homogeneous migration costs is no migration costs.

are engaged in self-employment versus just 10% in the US. Here, a labor market is a district whereas in their context it is a commuting zone crossed with an industry. I define a labor market as a district for two reasons. The first is due to data limitations: districts are the most disaggregated level of geography that is available. The second is due to context. It is not obvious that firms in different industries are not competing for the same workers. Moreover, self-employment competes with all industries. If I were to ignore self-employment and assume a continuum of markets, equation (6) would reduce to $\varepsilon_f = \eta\left(1 - s_f\right) + \theta s_f$. This still differs from their formulation, $\varepsilon_f^{BHM} = (\eta^{-1}(1-s_f^{WB}) + \theta^{-1}s_f^{WB})^{-1}$, slightly because I have assumed Bertrand rather than Cournot competition. In their formulation, oligopsonistic labor market power is derived through the firm's wage-bill market share (s_f^{WB}), rather than the employment market share. However, these two formulations yield quantitatively similar predictions for wage markdowns.

5.2 Misallocation

I now turn to each of the three sources of labor misallocation in the model–wage markdowns, search costs, and migration costs–to quantify their role in both welfare and output.

Wage Markdowns The estimated wage markdown depends upon the type of competition that the researcher assumes. These are summarized as follows

$$\varepsilon_f = \begin{cases} \infty & \text{Perfect Competition} \\ \eta & \text{Monopsonistic Competition} \\ \eta + s_f\left(\gamma - \eta\right) + s_f s_d\left(\theta - \gamma\right) & \text{Local Oligopoly} \\ \eta + s_f\left(\gamma - \eta\right) + s_f s_d\left(\theta - \gamma\right) - s_f s_d\left(\frac{\sum_o s_{od}^2 L_o}{s_m(d)}\right)\theta & \text{Spatial Oligopoly} \end{cases}$$

Under perfect competition, the firm is a price taker, and markdowns are zero. Non-uniform wages across firms arise through variation in the labor supply elasticity to each firm. Under monopsonistic competition, the firm internalizes how a change in their wage affects their own labor supply, but they do not internalize how a change in their wage affects other wages in the market, *i.e.* $\partial W_{fd}/\partial w_f = 0$, implying a uniform markdown across firms.

Under local oligopoly, the firm additionally internalizes how a change in their own wage affects the labor supply in the rest of the local market, but does not internalize how it affects migration decisions, *i.e.* $\partial \mathbf{W_o}/\partial w_f = 0$. As discussed in Section 5.1, markdowns will be larger in bigger firms and in markets with less self-employment. Under spatial oligopoly, the firm internalizes how a change in their wages affects migration decisions, leading to less competitive wages in high immigration and low emigration labor markets.

Search Costs Individuals are misallocated into self-employment whenever

$$1 > \frac{e^{\zeta_{sd}(\omega)} w_{sd}}{\max\limits_{f \in d} \left\{ e^{\zeta_{fd}(\omega)} b_f w_f \right\}} > \delta_d$$

This inequality states that the share of self-employment that is misallocated is higher in markets with larger labor market frictions. As the friction decreases ($\delta_d \rightarrow 1$), the share of workers in self-employment will decline. This causes the average productivity of those workers who remain in self-employment to increase. Thus, a uniform reduction in search costs will raise output by increasing the share of labor in firms and by increasing the productivity of the self-employed. Moreover, because wages are a fraction of productivity, a 1% reduction in search costs will increase output by more than 1%. From equation (3), it follows that reducing this friction will have an unambiguous positive effect on welfare.

Migration Costs This friction is a tax on welfare; it does not imply that workers are misallocated across space. If the initial distribution of labor were that which maximizes welfare, reducing migration costs would have no effect on output.[20] Taking this idea one step further, reducing migration costs may actually reduce total output. This is because labor market power creates a wedge between the welfare maximizing and output maximizing labor allocations. This wedge is sourced from both firms and workers. Because firms pay a non-uniform markdown on wages, workers supply too little labor to the

[20]The distributional assumptions on amenities together with a measure of workers imply that there would be migration, but no net change in population.

most productive firms. This distortion is exacerbated by self-employment in which earnings are not distorted. However, even in the absence of labor market power, because workers value non-wage job amenities, the labor allocation which maximizes welfare may not be equal to that which maximizes output.

6 Minimum Wage Compliance

The Labour Institutions Order of 2010 created Tanzania's first minimum wage law. The law set forth specific levels for 20 industries and a national minimum wage for all others.[21] The law had a heterogeneous effect across firms in two ways. First, firms in the same industry were exposed differently to the law based on their pre-existing wages. Second, firms with equivalent wage structures in industries with different minimum wages had to raise their wages by different amounts to comply with the law.

The aim of this section is to show that the minimum wage law had an effect on wages. I consider two measures of non-compliance: the share of workers paid below the minimum wage and the gap between the minimum wage compliant wage-bill and the firm's wage bill. Following Marshall (2023), I define the rate of Employment Non-Compliance (ENC) for firm f in industry i in district d in year t to the minimum wage law as

$$ENC_{fidt} = \frac{\sum_{r \in R_t} n_{rfidt}\, \mathbf{1}\left[\underline{w}_i - w_r > 0\right]}{\sum_{r \in R_t} n_{rfidt}}$$

Where $r \in R_t$ are the set of wage ranges, which vary across years, where $R_t = [o, \infty)\, \forall t$; n_{rfidt} is the number of workers with wages in range r; $\underline{w}_i$ is the industry minimum-wage that applies to firm f and w_r is the average wage of workers in wage range r.[22] The term ENC_{fidt} can be interpreted as the share of workers paid below the minimum wage level. An alternative measure is the gap between the

[21] See Appendix C for details of the Wage Order. The interested reader is directed to Marshall (2023) for a more detailed discussion of the effects of the law.

[22] Assuming a uniform distribution between each range r's lower-bound wage ($\underline{w}_r$) and upper-bound wage ($\bar{w}_r$). Under this distributional assumption, $w_r = (\underline{w}_r + \bar{w}_r)/2$. When the minimum wage falls between these two numbers, the number of workers in range r who are paid below the minimum wage is unknown. The interested reader is directed to Marshall (2023) who considers several methods for counting these workers.

firm's current wage-bill and the minimum wage compliant wage-bill defined as[23]

$$GAP_{fidt} = \frac{\sum_{r \in R_t} n_{rfidt} \min\{0, \underline{w}_i - w_r\}}{\sum_{r \in R_t} n_{rfidt} w_r} \tag{8}$$

When multiplied by 100, GAP_{fidt} can be interpreted as the percent by which a firm would need to raise its wages to be fully compliant with the minimum wage law. These measures are typically used to assess the bite of the minimum wage in the pre-policy period. Here, I use them to assess the degree of compliance once the minimum wage law was enacted. I estimate the rate of non-compliance as an event study, limiting my attention to the period 2005-2013 to avoid changes caused by the 2014 minimum wage law reform.

$$Y_{fidt} = \sum_t \delta_t + \boldsymbol{\mu}_i + \boldsymbol{\lambda}_d + \varepsilon_{fidt} \tag{9}$$

Where $\boldsymbol{\mu}_i$ are industry fixed effects and $\boldsymbol{\lambda}_d$ are district fixed effects. I exclude an intercept term so that the δ_t coefficients can be interpreted as the share of employment below the minimum wage level in each year. I plot the ENC and GAP coefficient estimates in Figure 5. In 2007, roughly 19% of workers earned a wage below the proposed minimum wage levels. When the law was enacted in 2010, the share fell to 10%, representing a 47% rate of compliance, consistent with the findings of Bhorat et al. (2017) for sub-Saharan African countries. I find a similar pattern when using the GAP measure. By 2013, the share of workers paid below the minimum wage fell below 5%. The decline in non-compliance over this period was likely caused by inflation reducing the real cost of employing workers at the minimum wage (Kaur, 2019). However, even in developed countries, where enforcement is strongest, firms are not fully compliant with unforeseen increases in the minimum wage (Clemens and Strain, 2022). Taken together, this evidence suggests that firms were adjusting wages in response to the legislation.

[23] Card and Krueger (1994) first used this measure to estimate the positive employment effects of New Jersey's minimum wage law on fast food workers. It remains a useful measure for analysis at the firm level and has been taken up more recently in minimum wages studies in the UK (Draca et al., 2011) and Germany (Dustmann et al., 2020).

7 Estimation of the Structural Parameters

In this section I estimate the full set of parameters that govern firm and worker behavior in the model: the three elasticities (η, γ, θ), firm and market amenities $\{b_f\}$, $\{B_d\}$, search costs $\{\delta_d\}$ and migration costs $\{\tau_{od}\}$, and firm and self-employment productivity $\{A_f\}$ and $\{A_{sd}\}$. I begin with the interactions between firms and build outwards.

Between-Firm Elasticity (η) I estimate η via the reduced form labor supply elasticity. As shown by Berger et al. (2022), these estimates do not account for the strategic interaction between firms, making markets appear less competitive than they are. However, the strategic response to a marginal change in the wage offer of another firm is decreasing in the size of the firm making the change. In particular $\lim_{s_f \to 0} \varepsilon_f = \eta$. Put differently, for very small firms, only the monopsony channel is relevant; they have no local wage setting power. Hence, the structural and reduced form estimates will align for very small firms.

Since I cannot match firms across years, I predict the exposure to the minimum wage, $\widehat{\text{GAP}}_{fidt}$, in the pre-policy period, 2005-2007, for firm (f) in industry (i) in district (d) in year (t) via a random forest regression algorithm. GAP_{fidt} is the GAP measure (8) defined in Section 6, and represents the fraction by which a firm would need to raise its wages to be fully compliant. A value of zero indicates that the firm was already paying each of its workers a wage greater than the minimum wage. The set of independent variables include s_f, $s_f s_m$, $s_f s_d s_m$, an indicator for each sector, district, and region, the log Herfindahl-Hirschman Index, the log number of firms, the log employment share in the largest industry, log total employment in the district, log firm employment in the district, an indicator for whether the firm is privately owned, in a tradeable industry, in a non-agricultural industry, and the year. The inclusion of the year allows me to predict the exposure of each firm in 2009. I then follow the same procedure to predict the employment weighted exposure to the minimum wage, the ENC.

I then estimate the within-market elasticity via Instrumental Variables (IV), using information from both the GAP and ENC.

$$\log n_{fd} = \beta_0 + \beta_1 \log w_{fd} + \beta_2 \log w_{fd} \times s_f + \beta_3\, s_f s_d \times \log w_{fd} + \Gamma X_{fd} + \epsilon_{fd} \tag{10}$$

Where the endogenous variables are $\log w_{fd}$, $s_f\ \log w_{fd}$, and $s_f s_d\ \log w_{fd}$. X_{fd} includes controls for the firm's employment share, s_f, the firm's share of market employment, $s_f s_d$, log total employment, inclusive of self-employment, in district d, the log Herfindahl-Hirschman Index, and dummy variables for each region. I report the estimation results of (10) in Table 6. η can be interpreted as the coefficient on log wage. Column 1 reports the OLS estimates. In columns 2-4, I vary the set of included instruments. Column 2 restricts the set of instruments to the interactions of $\widehat{GAP}$ with s_f and $s_f s_d$. The estimated elasticity is 3.9, but the F-stat is low. Column 3 restricts the set of instruments to the interactions of $\widehat{ENC}$ with s_f and $s_f s_d$. The estimated elasticity is lower at 2.5 and the F-stat is sufficiently high at 22. In column 4, I include both sets of instruments and the estimated elasticity falls to 2.1. The first-stage F-stat is lower with the inclusion of the additional instruments. I calibrate $\eta = 2.5$ to estimate the rest of the parameters and use $\eta = 3.9$ as a robustness.

Firm Amenities (b_f) To estimate the employment elasticity, I first need to calculate W_{fd}, which is a function of $\{b_f\}$. I calibrate $\eta = 2.5$ using an intermediate value from the estimates in Table 6. I then estimate b_f for each firm via the following procedure. I begin with the initial guess of $b_f^0 = 1\, \forall\, f$. I then iterate on the following loop until $b_f^0 - b_f^1 < \varepsilon$, where ε is the tolerance threshold.

1. $W_{fd} = \left[\sum_{f\in d} \left(b_f^0 w_f\right)^\eta\right]^{\frac{1}{\eta}}$
2. $b_f^1 = (s_f^{\text{data}})^{1/\eta} \frac{W_{fd}}{w_f}$
3. $b_f^1 = \frac{b_f^1}{\sum_{f\in d} b_f^1}$
4. $b_f^0 = b_f^1$

Step 3 ensures that the value of W_{fd} is normalized across markets and that the b_f do not capture anything related to the aggregate market amenities.

Sector Elasticity (γ) The ratio of firm to self-employment in each market can be related as $\log(s_d) - \log(1 - s_d) = \gamma \log(W_{fd}/w_{sd}) + \gamma \log \delta_d$, which I use to estimate γ, instrumenting for log W_{fd}/w_{sd} using the firm-wage index evaluated at the minimum wage, $W_{fd}(\underline{w})$.

$$\log\left(\frac{s_d}{1 - s_d}\right) = \beta_0^d + \beta_1^d \log\left(\frac{W_{fd}}{w_{sd}}\right) + \Gamma^d X_d + \epsilon_d \tag{11}$$

Where W_{fd} is calculated using the firm amenities estimated above with η =2.5. Γ^d includes controls for the district's log share of total employment, (s_m), and an indicator for whether the district is urban. I report the estimation results of (11) in Table 7. γ can be interpreted as the coefficient on log W_{fd}/w_{sd}. Column 1 reports the OLS estimates. In columns 2-7 I report the IV estimates under various values of η. For each iteration, I re-estimate the implied firm amenities for the calibrated between-firm elasticity. In Column 2, using the preferred calibration of η, I estimate a sector elasticity of 1.5. Across the range of calibrated values for η, the ratio of elasticities, γ/η, is roughly constant between 0.46 - 0.6, implying that the way in which firms compete with one another is different from the way in which they compete with self-employment. Quantitatively, this means that as the value of η varies, the point estimate of markdowns in small firms will vary, but the rage of markdowns will not be affected.

The F-stat in the preferred specification is 14, but it ranges from 118 for $\eta = 1$ to 4 for $\eta = 5$. This is because when $\eta = 1$, workers are very inelastic, so the b_f need to vary more to match the observed labor shares than when $\eta = 5$. Hence, for lower values of η, the b_f will explain more of the variation in W_{fd}, and the minimum wage instrument will be more correlated with the wage index. For the remaining estimation, I calibrate $\gamma = 1.5$.

Search Costs (δ_d) To calculate each market wage index, W_d, I need to calculate δ_d. Having estimated η and γ, this can be solved for explicitly by inverting the market's firm-employment share, s_d.

$$\delta_d = \left(\frac{s_d}{1 - s_d}\right)^{\frac{1}{\gamma}} \frac{w_{sd}}{W_{fd}}$$

Between-Market Elasticity (θ) I estimate θ via Poisson using migration flows between regions.[24] The model-based relationship between migrants and non-migrants for any origin, o, can be expressed as:

$$\log\left(\frac{n_{od}}{n_{oo}}\right) = \theta\log\left(\frac{W_d}{W_o}\right) + \theta\log\left(\frac{B_d}{B_o}\right) + \theta\log\tau_{od}$$

The main estimating equation is then the empirical equivalent:

$$n_{od} = n_{oo}\exp\left[\theta\log\left(\frac{W_d}{W_o}\right) + \alpha_1\log\tau_{od} + \mu_o\right] + \varepsilon_{od} \tag{12}$$

Where n_{od} and n_{oo} are the annualized number of migrants from o to d and non-migrants, respectively in the 2012 census. W_d and W_o are the market wage indices for the destination and origin, respectively, as calculated in 2010. I calculate region-level indices as an employment-weighted average of the values for each district in the region. The theoretical migration costs can be calculated up to a constant by multiplying $n_{od}/n_{oo} \times n_{do}/n_{dd}$. I calculate these ratios using the flows between regions since birth to limit any contamination with the left hand side variable. μ_o are origin fixed effects. I instrument for W_d in (12) using the equivalent CES aggregator of the applicable minimum wages for each firm defined as

$$\log\left(\frac{W_d(\underline{w})}{W_o(\underline{w})}\right) = \log\left(\frac{\delta_d W_{fd}(\underline{w})}{\delta_o W_{fo}(\underline{w})}\right)$$

Where the expression simplifies because there is no minimum wage in self-employment.

To control for variation in prices across locations, I spatially deflate wages using the LSMS price index. I report the estimation results for (12) Table 8. θ can be interpreted as the coefficient on W_d/W_o. Columns 1-3 report the estimates using nominal wages, while columns 4-6 use spatially deflated wages. The reduced form estimate for the minimum wage in columns 1 and 4 is around 0.35, suggesting the migrants are aware of the minimum wage policy, and respond to it when making

[24] This is a higher level of aggregation than that used in the rest of the analysis. I use regional rather than district migration flows because the latter is more sparse and susceptible to over-fitting (Dingel and Tintelnot, 2021). An observation of zero migrants between a district pair may be caused by sample size limitations. That is, there may be some migrants between the pair, but none that were in the sampling frame. As a robustness exercise, I estimate θ using district migration flows in Section 7.1.

migration decisions. The preferred estimate for the migration elasticity in column 6 is 1.4. This value is larger than the Poisson estimate in column 5, 1.1. The larger coefficient in column 6 implies that wages are negatively correlated with amenities: locations with higher amenities can offer lower wages. This finding is consistent with Rosen (1974), but conflicts with recent findings in Africa (Gollin et al., 2021).

Migration Costs (τ_{od}) Following a similar procedure to Bryan and Morten (2019), I use the assumption of symmetric migration costs to express τ_{od} in terms of the migration shares as[25]

$$\tau_{od} = \left(\frac{s_{od}}{s_{oo}} \times \frac{s_{do}}{s_{dd}} \right)^{\frac{1}{2\theta}}$$

This implies two principle assumptions on migration costs: $\tau_{oo} = 1$ is true for all θ, and no migration between any pair of markets implies that the migration cost is infinite.

I estimate s_{od} using migration flows between districts in the 2012 census. I observe two types of migration flows in the census, those in the past year and those since birth. Neither reflect the lifetime decision to migrate which is what I aim to capture with the migration costs. To close this gap, I calculate the implied migration shares that I would have observed over a ten-year period following the procedure outlined in Appendix B.2.

Market Amenities (B_d) The amenity in each market can be solved for as an implicit function by rearranging $s_m(d)$:

$$B_d = \frac{s_m^{\text{data}}(d)^{\frac{1}{\theta}}}{W_d} \left[\sum_o L_o \left(\frac{\tau_{od}}{\mathbf{W_o}} \right)^{\theta} \right]^{\frac{-1}{\theta}}$$

I estimate B_d following an iterative procedure similar to that used to estimate b_f. I begin with an initial guess of $B_d^0 = 1 \, \forall \, d$. I then iterate on the following loop until $abs(B_d^0 - B_d^1) < \varepsilon^B$

1. $\mathbf{W_o} = \left[\sum_d \left(\tau_{od} B_d^0 W_d \right)^{\theta} \right]^{\frac{1}{\theta}}$

[25] I derive this expression explicitly in Appendix B.2. Bryan and Morten (2019) express the migration costs as $\log \pi_{od} - \log \pi_{oo} + \log \pi_{do} - \log \pi_{dd} = 2\theta \tau_{od}$. This expression is equivalent to that but is well-defined for the case when $\pi_{od} = 0$.

Table 1: Model Calibration and Estimation

Parameter	Value	Parameter	Mean	Range
α	0.65	b_f	1.00	[0.046, 19.462]
η	2.50	B_d	1.42	[0.08, 13.373]
γ	1.50	A_f	0.02	[0.002, 0.769]
θ	1.40	A_{sd}	0.17	[0.028, 0.565]
		δ_d	0.03	[0.004, 0.116]
		τ_{od}	0.03	[0, 1]

2. $s_m^{\text{model}} = \left(\frac{\tau_{od} B_d^0 W_d}{\mathbf{W_o}}\right)^{\theta}$

3. $B_d^1 = \frac{s_m^{\text{data}}(d)^{\frac{1}{\theta}}}{W_d} \left[\sum_o L_o \left(\frac{\tau_{od}}{\mathbf{W_o}}\right)^{\theta}\right]^{\frac{-1}{\theta}}$

4. $B_d^0 = B_d^1 \left(\frac{s_m^{\text{data}}(d)}{s_m^{\text{model}}(d)}\right)^{\rho}$

Where $\rho \in (0,1)$ in the final step dampens the updating procedure to improve the rate of convergence.

Firm and Self-Employment Productivity $\{A_f, A_{sd}\}$ The productivity in each firm can be solved for by rearranging the equilibrium expression for wages in each firm

$$A_f = \left(\frac{w_f}{\alpha \mu_f}\right) n_f^{1-\alpha}$$

I calibrate $\alpha = 0.65$ from Gollin (2002). Notice that the estimated value of A_f depends upon μ_f, which itself depends upon the assumed form of labor market competition. Hence, when I assume other forms of competition between firms, I update my estimate of A_f.

The value of self-employment productivity is invariant to the assumption on firm competition and is given by

$$A_{sd} = w_{sd} n_{sd}^{1-\alpha}$$

Model Fit Table 1 summarizes the estimation results from the above procedure. I report the key moments in the data and the simulated model in Table 9. With firm and location amenities, the model is able to match the labor share in each firm and in self-employment in each location precisely.

7.1 Robustness

Alternative η Estimation To assess whether my estimate of the between-firm elasticity is dependent upon the estimation method, I follow the two-step procedure in Berger et al. (2022) to estimate η. In the first step, I use the predicted instruments, $\widehat{GAP}$ and $\widehat{ENC}$, denoted by $\hat{Z}$, to estimate log-wages and log-employment in 2010 as a function of the firm's market share interacted with the instrument

$$y_{fd} = \beta_0^y + \beta_1^y s_f + \beta_2^y \hat{Z}_f + \beta_3^y s_f \times \hat{Z}_f + \beta_4^y s_f s_d \times \hat{Z}_f + \beta_4^y s_f s_d + \Gamma^y X_{fd} + e_{fd}^y \tag{13}$$

Where the dependent variable y_{fd} takes log-average-wage in the firm and log-employment. To be consistent with the estimation in Section 7, in X_{fd} I include region fixed effects, the log district employment and the log Herfindahl-Hirschman Index. The reduced form labor supply elasticity is calculated by differentiating (13) with respect to the instrument $\hat{Z}_f$

$$\hat{\varepsilon}(s_f) = \frac{\partial \log n_{f(d)} / \partial \hat{Z}_f}{\partial \log w_{f(d)} / \partial \hat{Z}_f} = \frac{\hat{\beta}_2^n + \beta_3^n s_f + \beta_4^n s_f s_d}{\hat{\beta}_2^w + \beta_3^w s_f + \beta_4^w s_f s_d} \tag{14}$$

The between-firm labor supply elasticity is then estimated by taking the limit of (14).

$$\hat{\eta} = \lim_{s_f \to 0} \hat{\varepsilon}(s_f) = \frac{\hat{\beta}_2^n}{\hat{\beta}_2^w}$$

Table A.2 presents the estimation results for (13). Columns 1 and 2 use $\widehat{ENC}$ as the instrument. The estimated elasticity is 2.7, slightly higher than the value estimated via instrumental variables, but not statistically different. In columns 3 and 4, I use $\widehat{GAP}$ as the instrument, and estimate an elasticity of 4.9, similar to that estimated earlier. The standard errors are tighter when using the ENC versus the GAP instrument, consistent with the significantly higher first-stage F-statistic found when using the ENC in the instrumental variables estimation. This confirms that the within-market elasticity estimate is robust to alternative empirical specifications.

Alternative θ Estimation Estimation of the migration elasticity relies upon two key assumptions: that the census migration flows accurately reflect the true migration flows and that the migration cost is symmetric. A particular concern is whether the model may be biased due to zero observed flows between district pairs due to sampling when the true flow is positive. I test these assumptions in Table A.3. For expositional convenience, in Column 1 reports the IV-Poisson estimation results from Table 8. Column 2 limits the sample to only pairs with non-zero migration flows. Almost all pairs have non-zero observed flows in the census, and the results are unchanged. In column 3, I estimate migration costs with log distance between districts, the log stock of migrants in d from o and the log employment ratio. The estimated migration elasticity is slightly lower at 0.9. In columns 4-6, I repeat the same set of exercises using migration flows from the LSMS and ILFS. In the full sample, I estimate an elasticity of 2.2. More than 200 of the 552 region pairs have non-zero migration flows, and when I limit the sample to migrating pairs, the elasticity estimate falls to 2.0. Finally, when I use the asymmetric migration costs, the elasticity is 1.3, nearly identical to the baseline estimation.

To assess the sensitivity of the estimation to the level of aggregation, I report the estimation results at the district level in Table A.4. Under the assumption of symmetric migration costs, the instrumented migration elasticity estimate in Column 3 is 0.8. When I use asymmetric migration costs in Column 6, the estimate falls to 0.2. These results likely reflect a lower bound on the true migration elasticity as the level of aggregation may be too granular (Dingel and Tintelnot, 2021). Moreover, migrants may not have perfect information about the wages in a specific location (Baseler, 2023), but may have a general idea. Hence their exact choice of location may not accurately reflect their sensitivity to the differences in wages between the origin and destination.

7.2 Discussion

Markdowns Across Space I plot the spatial distribution of wage markdowns in Figure 6. Average wage markdowns are substantial, ranging between 0.66 in some rural districts to 0.71 in Dar es Salaam. This implies that urban labor markets are more competitive than rural labor markets. The relationship between urbanization and labor market competition is made more stark in Figure 7 where I plot the average wage markdown against population density. This finding is intuitive: as show in Table 3, firm employment is more concentrated in rural labor markets. However, the gap between rural and urban labor markets is small. This is not due to differences in migration patterns as those reduce labor market competition in both rural and urban areas. This is because, as noted in Section 3, urban labor markets have less self-employment. To illustrate this point, in Figure 8, I plot the markdown curve for the average rural and urban district. The curve relates the firm's share of firm employment (s_f) to its equilibrium wage markdown. The urban curve lies below the rural curve, implying that for two firms of equal employment share, the firm in the urban market will pay workers a lower share of marginal product. In the figure, I show where the mean worker is located on the curve in a rural and urban market. The average worker in a rural labor market is employed in a larger (by employment share) firm the average urban worker. This implies that reducing the rate of rural self-employment will actually increase the gap in labor market competition between rural and urban areas.

Rural-Urban Productivity Gap The persistently high share of workers engaged in low-productivity agriculture is a puzzle (Gollin et al., 2014). This type of work is primarily done in rural areas, and since Kuznets (1973), the agricultural productivity gap has often been conflated with the rural-urban productivity gap.[26] However, when firms markdown wages, the income and productivity gaps are not the same. In Table 10, I report both the rural-urban and agricultural productivity gaps by worker type. In Panel A, I compare the earnings of the rural self-employed with those in several definitions of urban markets. For the self-employed, there is no markdown, so the earnings and productivity gap are the same. Self-employed workers in Dar es Salaam are 47% more productive than those in rural areas. Looking further down the table, the gap between rural wage-workers and those in Dar es Salaam is tighter; workers in Dar es Salaam are 8.7% more productive but earn 10.8% more. The income gap exceeds the productivity gap because rural labor markets are less competitive. However, because the difference in labor market power between rural and urban areas is small, it does little to explain the

[26] Henderson and Kriticos (2018) documents that there is more agriculture happening in African cities than in other developing countries. However, this urban agriculture appears to primarily be an artifact of the data: smaller cities have rural areas within their administrative boundaries. Indeed there is very little agriculture in primary cities. Their findings do highlight two important features of cities in Africa though: they are small and have not induced a transition out of agriculture in the surrounding areas.

income gap between rural and urban wage workers. The often cited rural-urban income gap arises once we look at all workers together. The average urban worker earns 53% more than a rural worker, but is more than twice as productive. This implies that the rural-urban income gap actually understates the productivity gap. The reason for this is that there are more workers in self-employment in rural areas where they are much less productive than those in cities.

In Panel B, I instead consider the agricultural productivity gap. Non-agricultural wage workers earn 24% more than those in agriculture, and the productivity gap is nearly identical. This suggests that the rural-urban income gap understates the agricultural productivity gap. However, when I look at all workers, the earnings and productivity gaps are nearly identical to those in Panel A.

Together, these findings highlight two important features of labor markets. First, because the rural-urban income gap understates the productivity gap, labor market power actually reduces income inequality. Second, the well-documented rural-urban and agricultural productivity gaps arise because of compositional differences. As shown in Table 3, rural labor markets have higher rates of self-employment and a larger share of that employment is in agriculture.

Migration Costs I plot the model generated average migration cost in each district against the prime aged emigration rate in Figure 9. The two series are positively correlated. The correlation is weakest in urban areas where emigration is low and migration costs are also low. This is because urban areas are well connected, but they also offer higher earnings potential, making it less profitable to move away. The average migration costs reported in Table 1 are higher than recent estimates for Indonesia (Bryan and Morten, 2019) or China (Tombe and Zhu, 2019). While this may reflect differences in context, it is necessarily lower because the data here is more disaggregated. As the number of potential destinations rises, the share of migrants going to each must fall, causing the estimated average cost of migration to rise.

Search Costs A firm can post a vacancy for two reasons: it is expanding, and creating new positions, or an employee has left and they have not yet filled the position. To abstract from the first type of vacancy, I plot the number of unfilled positions per employee against the estimated search costs in the top panel of Figure 10. The relationship is negative, implying that labor markets with higher job search costs have more unfilled job vacancies (recall that higher values of δ_d imply lower frictions). This makes intuitive sense; if the cost of finding a job is higher, there will be more unfilled positions.

In the bottom panel of Figure 10, I plot the number of hires per vacancy. Here the relationship is positive, implying that labor markets with lower search costs hire more workers per posted vacancy. This relationship also makes sense; labor markets with low job search costs are able to fill more of their vacancies. It is worth noting that the data on hires and vacancies were not used to estimate search costs in the model, hence these patterns provide empirical support that the estimated job search costs accurately reflect conditions in the labor market.

8 Quantifying Labor Misallocation

In this section, I first quantify the effects of labor market power on welfare, output, and the distribution of labor by comparing the equilibrium with one in which firms pay competitive wages. I then contextualize these gains by comparing them with those obtained by reducing the other frictions in the model, namely search and migration costs.

8.1 Competitive Equilibrium

There are two ways in which firms could pay competitive wages in the model. One way is to change worker preferences so that they are perfectly elastic with respect to wages, *i.e.* $\eta \to \infty$. From a technical standpoint, this is undesirable because it is unclear how to quantify changes in welfare. Moreover, from a policy perspective this is undesirable: there is little to be learned from a counterfactual that does not reflect how individuals are observed to behave. An alternative approach, which I use here, is to change the way in which firms compete for workers. I do so by modeling firms as price takers who demand quantities of labor to maximize profits.[27]

[27] The logic of this approach is as follows. First, when firms do not internalize how a change in their own wage affects the wages in other firms, *i.e.* there is no strategic component to wage setting, all firms will pay a uniform markdown, eliminating the oligopsony channel of labor market power. A competitive equilibrium is reached by eliminating the monopsony channel of labor market power by having firms not internalize how a change in their own wage affects labor

I compare the labor market power equilibrium (column 1) with the competitive equilibrium (column 2) in Table 11. Total output is 4.8% higher when firms pay competitive wages. This gain is primarily driven by an increase in firm employment from 13.9% to 18.3%. Average income rises by 9%, while welfare rises by 5.1%. The reason that welfare rises by less than wages is because workers who move across space and into wage employment still must pay the search and migration costs associated with those transitions.

In the remainder of Table 11, I quantify the channels through which these gains occur. In column 3, I quantify spatial misallocation by allowing workers to reallocate across space, but hold fixed their sector decision in the baseline labor market power equilibrium. Total welfare rises by 7.4% while output falls by 2.1%. The reason that output falls is that because rural labor markets were less competitive, rural wages rose by more than those in urban areas, making them more attractive. This is confirmed by the net decline in the urban share of total employment from 14.2% to 11.9%.

In column 4, I quantify local misallocation into self-employment by holding fixed the baseline labor market choice, but allowing workers to locally reallocate between jobs. Total output rises by 4%, representing eighty percent of the gains from the full adjustment in column 2. Welfare is slightly higher than in the competitive equilibrium because those who would have migrated are not incurring those costs. This implies that labor market power primarily reduces aggregate output through local misallocation into self-employment. Given the small difference in labor market power between rural and urban areas, this makes sense. However, some of the gains from local reallocation could be driven by misallocation across firms on account of heterogeneity in wage markdowns. In column 5, I isolate the oligopsony channel of labor market power by holding fixed both the baseline location and sector decision, only allowing workers to reallocate between firms within a market. Here, the welfare and income gains are more closely aligned, as no additional workers are incurring job search or migration costs. The gains in output in this counterfactual are quantitatively insignificant. This finding is explained by the mitigating effects of self-employment which prevent any single firm from having substantial labor market power.

supply. This switch requires that firms instead choose quantities of labor rather than wages to maximize profits, making it a more natural transition under Cournot competition.

Congestion and Agglomeration A potential concern with the findings in Table 11 is that the model does not account for congestion or agglomeration forces. The model may over predict urbanization if congestion reduces the value of moving to an urban location. Alternatively, it may under predict urbanization if agglomeration makes firms more productive. Following Bryan and Morten (2019), I model endogenous amenities and productivity as

$$B_d = \bar{B}_d L_d^{\lambda} \quad ; \quad A_i = \bar{A}_i L_d^{\phi}$$

Congestion forces are present whenever $\lambda < 0$. This implies that more people reduce each person's ability to enjoy public goods. Similarly, agglomeration forces are present whenever $\phi > 0$. This implies that firms are more productive when there are more people in a location. This captures, for example, knowledge spillovers from chance encounters of workers in different firms. This is a slight deviation from Bryan and Morten (2019), who use total human capital to measure agglomeration, but is consistent with Au and Henderson (2006).

In Table A.5, I report the competitive equilibrium counterfactual under various calibrations of λ and ϕ. For reference, column 1 reports the equilibrium with no congestion or agglomeration forces. In column 2, I add congestion only, by making amenities endogenous. I follow Bryan and Morten (2019) and calibrate $\lambda = -0.04$. Urbanization is unchanged, suggesting that this level of congestion is not enough to reduce immigration into cities. In column 3, I add agglomeration only, by making productivity endogenous. I calibrate $\phi = 0.05$, the high end of values considered by Bryan and Morten (2019). Both firm and urban employment rise by 0.1 percentage points relative to baseline, causing total output to rise by 0.1%. In column 4, I turn on both congestion and agglomeration forces. The agglomeration effect slightly wins out, and the overall effect on output is an addition 0.1% relative to baseline. Given the null result for congestion in column 2, in column 5, I ask whether an impossibly high value of congestion could possibly undo the gains from a competitive equilibrium. To do so, I calibrate $\phi = 0$ and $\lambda = -0.5$. The urban share of employment falls by 0.3 percentage points relative to the baseline competitive equilibrium counterfactual, while the gain in total output is a slightly lower 4.6%. This suggests that the findings are robust to congestion and agglomeration forces.

Increasing Firm Competition There is no policy that can change the way in which firms compete for workers *per se*, but one may think of other policies that increase firm competition. One potential avenue is to increase the number of firms in rural areas where wages are less competitive. In Table A.6, I simulate counterfactuals that increase the number of firms without changing the productivity distribution. To put these results in context, in column 2, I simulate the monopsony limit, in which firms do not set wages strategically, and pay a uniform markdown on wages. This yields negligible gains in employment, output, and welfare, consistent with the findings discussed above. In column 3, I double the number of rural firms only. While wages become more competitive, their real value along with total output and firm employment all fall. This is because, when firms become smaller, they have less market power but the marginal product of labor also falls. This finding is even more pronounced when I additionally double the number of urban firms in column 4. Because urban workers are, on average, employed in small firms, this has no effect on urban wage markdowns.

8.2 Decomposing Labor Misallocation

Two separate literatures have evolved in development that study labor market frictions. One studies the role of migration costs in preventing profitable migration (Lagakos, 2020), while the other studies the role of local labor market frictions in limiting wage employment (Caria and Orkin, 2024). Yet little is known about the relative importance of these two types of frictions on labor misallocation. This model allows me to quantify the relative importance of these two types of frictions in a unified framework, and to understand how they interact with labor market power. In Table 12, I report the new equilibrium under a reduction in each friction with and without labor market power. For comparison, in columns 1 and 2, I report the equilibrium under labor market power and the competitive equilibrium counterfactual, respectively. In column 3, I simulate a 10% reduction in search costs.[28] Total output rises by 21.7% because firm employment rises to nearly 50%. Firm wages fall by 30% relative to baseline, while average incomes rise slightly. Unlike the competitive equilibrium, the rural-urban income gap falls in this counterfactual. That is because the urban labor markets benefit more from

[28] The estimated search cost may be too high if there is an aggregate preference for self-employment because of poor working conditions in firm jobs (Blattman and Dercon, 2018). Hence, I consider only a partial reduction in each friction.

firms paying higher wages on account of having more firms, whereas a reduction in search costs makes it easier to access firm jobs equally across space. Indeed, the share of workers who choose wage work is so high that self-employment earnings actually exceed those in wage employment. However, when I simulate a reduction in search costs in the competitive equilibrium counterfactual in column 4, the self-employment income gap reaches parity.

In column 5, I simulate a 10% reduction in migration costs, and total output actually falls, mirroring the finding in 11. The reason output falls is that reducing job search costs does nothing to ease the transition to wage employment. It does, however, make it feasible for workers to move to other locations that are more preferable, but may be less productive. While per-capita income may be a good measure of welfare in the long-run, in any particular country or in the short-run, there may be substantial variation between the two (Jones and Klenow, 2016). Without labor market power, heterogeneous preferences over jobs create a wedge between the output maximizing and welfare maximizing labor allocations. With labor market power, the wedge is even larger because the wage that a worker receives is a share of their marginal product. The wedge created by labor market power is exacerbated when self-employment is a less productive and yet viable option. When I simulate a reduction in migration costs in the competitive equilibrium counterfactual in column 6, welfare and output are more closely aligned and total output rises. Together, these findings suggest that local labor market frictions are quantitatively more important for labor misallocation than spatial frictions.

Comparison with Bryan et al. (2014) The finding that reducing migration costs reduces total output may seem to conflict with the experimental results of Bryan et al. (2014), who show that rural workers in Bangladesh were induced to migrate when given bus tickets to seasonally migrate to Dhaka. In Table A.7, I simulate this policy counterfactual by reducing migration costs in the direction of the urban districts (cities) only. Relative to a decline in total output under a symmetric reduction in migration costs of 4.2% in column 2, when I reduce migration costs only in the direction of the city, total output rises by 3.8%, implying that this finding does not contradict the experimental results. Indeed, the urban share of total employment rises from 14.2% to 25.7%. Reflecting the higher number of job opportunities in urban areas, firm employment rises as well. To understand which migration costs are responsible for the observed decline in total output, in columns 4 and 5, I simulate alternative reductions in migration costs. In column 4, I simulate a reduction in migration costs away from the city only. While both output and the urban employment share fall relative to baseline, they do so by less than under the symmetric reduction in migration costs. Finally, in column 5, I simulate a reduction in migration costs between rural markets only, and total output falls by 5%. Interestingly, the urban share of total employment falls by more than under a symmetric reduction in migration costs. Together, this suggests that reducing rural to rural migration costs is causing workers to redirect away from urban areas to other rural areas.

8.3 Urbanization without Growth

Over the past 60 years, the urban population in sub-Saharan Africa has grown at a faster rate than any other region in the world. At the same time, the region has seen the lowest growth in income per-capita. I plot these trends in Figure 11. Urbanization without economic growth is atypical; East Asia, which had nearly as much urban growth as sub-Saharan Africa, experience the fastest rate of growth over the period.

The anomalous relationship between urbanization and economic growth in Africa is a puzzle. However, it is consistent with two findings from this analysis, namely that output falls under both spatial reallocation in the competitive equilibrium counterfactual as well as under lower migration costs. These findings arise because wage markdowns, which are not present in self-employment, create a wedge between what is welfare enhancing and what is output enhancing. This idea is consistent with evidence that, at the country level, income per-capita may not accurately reflect welfare (Jones and Klenow, 2016).

An obvious question then is whether this model does better than one without labor market power in predicting the observed patterns of urbanization without growth in sub-Saharan Africa.[29] To do this, I use Census data to calculate the population distribution as it was in 2000. I then simulate the model

[29]The aim here is to compare a standard model in macro development in which there is no tension between what is welfare improving and what is output improving. Specifically, I compare the predictions of this model from those in a competitive equilibrium framework with no amenities, implying that there is no gap between the welfare and output maximizing labor allocations.

with infinite migration costs to find the baseline level of output in that year, before slowly reduce migration costs towards their level in 2010 and beyond. I compare these changes in urbanization and output to those in a 'standard model' that assumes competitive labor markets and no amenities, so that there is no wedge between welfare and output. I plot these results in Figure 12. Urbanization increases from 9.5% in 2000 in both models. However, it flattens around 14% in the spatial labor market power model, while it continues to rise in the standard model. Output on the other hand, initially rises in the spatial labor market power model, reaching a peak of 6%, before falling. In the standard model, output continues to rise, reaching 17% when migration costs reach their 2010 level.

These results should be interpreted as suggestive evidence that this framework is better able to match the observed patterns of growth and urbanization in the data. Of course, the spatial distribution of both firms and productivity has changed over this period, and that is not accounted for here. Moreover, it is likely that urbanization will continue to rise in the data as the number of firms in mega cities, such as Dar es Salaam, increase.

Is Dar es Salaam too big? Au and Henderson (2006) proposed that the optimal city employment follows an inverted u-shape, with the peak being determined by the ratio of value-added in manufacturing to services. While the authors were interested in whether Chinese cities were too small, the hypothesized that cities in other regions may be too big. In Table 13, I follow their logic to assess whether Dar es Salaam is too large. In 2012, Dar es Salaam had 1.7 million employed persons and a value-added ratio of 0.16. To put this in context, in Au and Henderson (2006) the typical Chinese city had a ratio of 1.4, with the most services-intensive cities having a value of 0.6. Their model would suggest that employment is approximately half of the optimal level as reported in column (5).

The value-added ratio may be confounded if self-employment is more heavily engaged in manufacturing. In column (7), I report the optimal city size under the assumption that all self-employment is in services and the optimal city size is slightly higher. When I assume that all self-employment is manufacturing in column (9), Dar es Salaam is too big. However, Tanzania's three other cities are still far too small. In column (3), I report the ratio of employment in services and manufacturing among the self-employed. The value is comparable to the value-added ratio among firms, suggesting that the estimates based on firm-employment are reasonable.

Taken together, these results suggest that it is not that Dar es Salaam is too large *per se*, but rather that the city's economy is overly concentrated in services (Gollin et al., 2016; Henderson and Kriticos, 2018). Au and Henderson (2006) do not directly address the reverse question of what is the optimal ratio of value-added between services and manufacturing given a city's size, however we can infer that a number closer to 0.6, that of China's most services intensive cities would be optimal.

9 Conclusion

Economic development requires the shift of productive inputs out of agriculture and into manufacturing and services. In low-income countries, these transitions have been happening slowly, and most workers remain in low paying rural self-employment. This slow rate of transition has been attributed to frictions that prevent workers from moving into more productive work. Yet one overlooked explanation is that firms may have labor market power, allowing them to extract rents from workers, and pay wages below the marginal product of labor. When firms markdown wages, it creates a wedge between earnings and productivity that is not present in self-employment, making self-employment more attractive. In this paper, I construct a spatial general equilibrium model of monopsony to measure the spatial distribution of wage markdowns in a low-income country context. To quantify the model, I use a novel administrative dataset of Tanzanian firms that has complete geographic coverage, and I use Tanzania's first ever minimum wage law to identify the labor supply elasticity to each firm. I find that wage markdowns are substantial: most workers are paid between 66-71% of their marginal product. While rural labor markets are less competitive than their urban counterparts, the gap would be wider if not for the mitigating effects of self-employment.

I then use the model to quantify that aggregate and distributional effects of labor market power. Because rural labor markets are less competitive than their urban counterparts, the income gap between rural and urban wage workers overstates the productivity gap. However, because a higher share of urban workers are engaged in wage work, labor market power actually reduces spatial income inequality. In the counterfactual in which firms pay competitive wages, total output rises by 4.8%.

These gains are largely due to local reallocation of workers out of self-employment and into wage work, implying that labor market power substantially hinders the productive allocation of labor in low-income countries. This suggests that policies aimed at increasing firm competition could aid in the transition out of self-employment, and ultimately raise incomes.

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References

Abebe, G., A. S. Caria, M. Fafchamps, P. Falco, S. Franklin, and S. Quinn (2020). Anonymity or Distance? Job Search and Labour Market Exclusion in a Growing African City. *The Review of Economic Studies* (September), 1–32.

Abebe, G., S. Caria, and E. Ortiz-ospina (2021). The Selection of Talent Experimental and Structural Evidence from Ethiopia. *American Economic Review 111*(6), 1757–1806.

Albouy, D. (2008). Are Big Cities Bad Places to Live? Estimating Quality of Life across Metropolitan Areas. Technical Report No. 14472, NBER.

Alfonsi, L., O. Bandiera, V. Bassi, R. Burgess, I. Rasul, M. Sulaiman, and A. Vitali (2020). Tackling Youth Unemployment: Evidence From a Labor Market Experiment in Uganda. *Econometrica 88*(6), 2369–2414.

Almeida, R. and P. Carneiro (2012). Enforcement of labor regulation and informality. *American Economic Journal: Applied Economics 4*(3), 64–89.

Amodio, F. and N. de Roux (2021). Labor Market Power in Developing Countries: Evidence from Colombian Plants.

Amodio, F., P. Medina, and M. Morlacco (2024). Labor Market Power, Self-Employment, and Development. Mimeo.

Armangué-Jubert, T., N. Guner, and A. Ruggieri (2023). Labor Market Power and Development. Mimeo.

Ashenfelter, O. C., H. Farber, and M. R. Ransom (2010). Labor Market Monopsony. *Journal of Labor Economics 28*(2), 203–210.

Au, C. C. and J. V. Henderson (2006). Are Chinese cities too small? *Review of Economic Studies 73*(3), 549–576.

Baseler, T. (2023). Hidden Income and the Perceived Returns to Migration. *American Economic Journal: Applied Economics 15*(4), 321–352.

Bassi, V., J. H. Lee, A. Peter, T. Porzio, R. Sen, and E. Tugume (2024). Self-employment within the Firm. Mimeo.

Basu, A. K., N. H. Chau, and R. Kanbur (2010). Turning a blind eye: Costly enforcement, credible commitment and minimum wage laws. *Economic Journal 120*(543), 244–269.

Berger, D. W., K. Herkenhoff, and S. Mongey (2025). Minimum Wages, Efficiency and Welfare. *Econometrica 93*(1), 265–301.

Berger, D. W., K. F. Herkenhoff, and S. Mongey (2022). Labor Market Power. *American Economic Review 112*(4), 1147–1193.

Bhorat, H., R. Kanbur, and B. Stanwix (2017). Minimum wages in sub-saharan Africa: A primer. *World Bank Research Observer 32*(1), 21–74.

Blattman, C. and S. Dercon (2018). The Impacts of Industrial and Entrepreneurial Work on Income and Health. *American Economic Journal: Applied Economics 10*(3), 1–38.

Bryan, G., S. Chowdhury, and A. M. Mobarak (2014). Under-investment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh. *Econometrica 82*(5), 1671–1748.

Bryan, G., S. Chowdhury, A. M. Mobarak, M. Morten, and J. Smits (2021). Encouragement and distortionary effects of conditional cash transfers. Discussion Papers 1085, Economic Growth Center at EliScholar – A Digital Platform for Scholarly Publishing at Yale.

Bryan, G. and M. Morten (2019). The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia. *Journal of Political Economy 127*(5), 2229–2268.

Buera, F. J., J. P. Kaboski, and Y. Shin (2015). Entrepreneurship and Financial Frictions: A Macrodevelopment Perspective. *Annual Review of Economics 7*(1), 409–436.

Burdett, K. and D. T. Mortensen (1998). Wage Differentials, Employer Size, and Unemployment. *International Economic Review 39*(2), 257–273.

Card, D. and A. Krueger (1994). Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania. *American Economic Review 84*, 772–784.

Caria, S. and K. Orkin (2024). Barriers to Search and Hiring in Urban Labour Markets. *VoxDevLit 10*(1), 1–46.

Clemens, J. and M. R. Strain (2022). Understanding "Wage Theft": Evasion and avoidance responses to minimum wage increases. *Labour Economics 79*(March), 102285.

Derenoncourt, E., C. Noelke, D. Weil, and B. Taska (2021). Spillover Effects from Voluntary Employer Minimum Wages. Technical Report No. 29425, NBER.

Dingel, J. I. and F. Tintelnot (2021). Spatial Economics for Granular Settings. Technical Report No. 27287, NBER.

Donovan, K., W. J. Lu, and T. Schoellman (2023, 05). Labor Market Dynamics and Development. *The Quarterly Journal of Economics 138*(4), 2287–2325.

Donovan, K. and T. Schoellman (2023). The role of labor market frictions in structural transformation. *Oxford Development Studies 51*(4), 362–374.

Draca, M., S. Machin, and J. Van Reenen (2011). Minimum Wages and Firm Profitability. *American Economic Journal: Applied Economics 3*(1), 129–151.

Dustmann, C., A. Lindner, U. Schönberg, M. Umkehrer, and P. vom Berge (2020). Reallocation Effects of the Minimum Wage. Discussion Paper CDP 07/20, Centre for Research and Analysis of Migration.

Employment and Labour Relations Act (2004). United Republic of Tanzania.

Faber, B. (2014). Trade integration, market size, and industrialization: Evidence from China's national trunk highway system. *Review of Economic Studies 81*(3), 1046–1070.

Felix, M. (2022). Trade, Labor Market Concentration, and Wages.

Foster, A. D. and M. R. Rosenzweig (2022). Are There Too Many Farms in the World? Labor Market Transaction Costs, Machine Capacities, and Optimal Farm Size. *Journal of Political Economy 130*(3), 636–680.

Franklin, S., C. Imbert, G. Abebe, and C. Mejia-Mantilla (2024, May). Urban Public Works in Spatial Equilibrium: Experimental Evidence from Ethiopia. *American Economic Review 114*(5), 1382–1414.

Gollin, D. (2002). Getting Income Shares Right. *Journal of Political Economy 110*(2), 458–474.

Gollin, D., R. Jedwab, and D. Vollrath (2016). Urbanization with and without industrialization. *Journal of Economic Growth 21*(1), 35–70.

Gollin, D., M. Kirchberger, and D. Lagakos (2021). Do urban wage premia reflect lower amenities? Evidence from Africa. *Journal of Urban Economics 121*.

Gollin, D., D. Lagakos, and M. E. Waugh (2014). The Agricultural Productivity Gap. *Quarterly Journal of Economics 129*(2), 939–993.

Guillouzouic, A., E. Henry, and J. Monras (2024). Public Sector Pay in Spatial Equilibrium. Discussion Paper No. 19014, CEPR.

Henderson, J. V. and S. Kriticos (2018). The Development of the African System of Cities. *Annual Review of Economics 10*, 287–314.

Herrendorf, B., R. Rogerson, and Á. Valentinyi (2014). Growth and Structural Transformation. In *Handbook of Economic Growth*, Volume 2, pp. 855–941. Elsevier B.V.

Herrendorf, B. and T. Schoellman (2015). Why is measured productivity so low in agriculture? *Review of Economic Dynamics 18*(4), 1003–1022.

Hicks, J. H., M. Kleemans, N. Y. Li, and E. Miguel (2021). Reevaluating Agricultural Productivity Gaps with Longitudinal Microdata. *Journal of the European Economic Association 19*(3), 1522–1555.

Hirsch, B., E. J. Jahn, A. Manning, and M. Oberfichtner (2022). The Urban Wage Premium in Imperfect Labor Markets. *Journal of Human Resources 57*(Special Issue Monopsony in the Labor Market), S111–S136.

Hsieh, C.-t. and B. A. Olken (2014). The Missing "Missing Middle". *Journal of Economic Perspectives 28*(3), 89–108.

Imbert, C. and J. Papp (2020). Costs and Benefits of Rural-Urban Migration: Evidence from India. *Journal of Development Economics 146*, 1–17.

Imbert, C., M. Seror, Y. Zhang, and Y. Zylberberg (2022). Migrants and Firms: Evidence from China. *American Economic Review 112*(6), 1885–1914.

Jones, C. I. and P. J. Klenow (2016). Beyond GDP? Welfare across countries and time. *American Economic Review 106*(9), 2426–2457.

Kaur, S. (2019). Nominal wage rigidity in village labor markets. *American Economic Review 109*(10), 3585–3616.

Kirchberger, M. (2021). Measuring internal migration. *Regional Science and Urban Economics*.

Kleibergen, F. and R. Paap (2006). Generalized reduced rank tests using the singular value decomposition. *Journal of Econometrics 133*(1), 97–126.

Kuznets, S. (1973). Modern Economic Growth: Findings and Reflections. *The American Economic Review 63*(3), 247–258.

Lagakos, D. (2020). Urban-Rural Gaps in the Developing World: Does Internal Migration Offer Opportunities? *Journal of Economic Perspectives 34*(3), 174–192.

Lagakos, D., S. Marshall, A. M. Mobarak, C. Vernot, and M. E. Waugh (2020). Migration costs and observational returns to migration in the developing world. *Journal of Monetary Economics 113*, 138–154.

Lagakos, D., A. M. Mobarak, and M. Waugh (2023, May). The Welfare Effects of Encouraging Rural-Urban Migration. *Econometrica 91*(3), 803–837.

Lagakos, D. and M. E. Waugh (2013). Selection, Agriculture, and Cross-Country Productivity Differences. *American Economic Review 103*(2), 948–980.

Lewis, W. (1954). Economic Development with Unlimited Supplies of Labour.

Magruder, J. R. (2013). Can minimum wages cause a big push? Evidence from Indonesia. *Journal of Development Economics 100*(1), 48–62.

Manning, A. (2003a). *Monopsony in Motion: Imperfect Competition in Labor Markets*. Princeton, NJ: Princeton University Press.

Manning, A. (2003b). The real thin theory: Monopsony in modern labour markets. *Labour Economics 10*(2), 105–131.

Manning, A. (2004). Monopsony and the efficiency of labour market interventions. *Labour Economics 11*(2), 145–163.

Mansoor, K. and D. O'Neill (2021). Minimum wage compliance and household welfare: An analysis of over 1500 minimum wages in India. *World Development 147*, 1–19.

Marshall, S. (2023, April). Minimum Wage Compliance and Migration: The Labor Market Effects of Tanzania's Sectoral Minimum Wage Bill. Mimeo.

Molloy, R., C. L. Smith, and A. Wozniak (2011). Internal migration in the United States. *Journal of Economic Perspectives 25*(3), 173–196.

Monte, F., S. J. Redding, and E. Rossi-Hansberg (2018). Commuting, migration, and local employment elasticities. *American Economic Review 108*(12), 3855–3890.

Morten, M. (2019). Temporary migration and endogenous risk sharing in village India. *Journal of Political Economy 127*(1), 1–46.

Rani, U., P. Belser, and M. Oelz (2013). Minimum wage coverage and compliance in developing countries. *International Labour Review 152*(3), 381–410.

Restuccia, D., D. T. Yang, and X. Zhu (2008). Agriculture and aggregate productivity: A quantitative cross-country analysis. *Journal of Monetary Economics 55*, 234–250.

Roback, J. (1982). Wages, Rents, and the Quality of Life. *Journal of Political Economy 90*(6), 1257–1278.

Rosen, S. (1974). Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition. *Journal of Political Economy 82*(1), 34–55.

Rosenzweig, M. R. (1988). Labor markets in low-income countries. In *Handbook of Development Economics*, Volume 1, Chapter 15, pp. 713–762. Elsevier.

Small, K. A. and H. S. Rosen (1981). Applied Welfare Economics with Discrete Choice Models. *Econometrica 49*(1), 105.

Tombe, T. and X. Zhu (2019). Trade, migration, and productivity: A quantitative analysis of China. *American Economic Review 109*(5), 1843–1872.

Ulyssea, G. (2018). Firms, informality, and development: Theory and evidence from Brazil. *American Economic Review 108*(8), 2015–2047.

Ulyssea, G. (2020). Informality: Causes and consequences for development. *Annual Review of Economics 12*, 525–546.

Yeh, C., C. Macaluso, and B. Hershbein (2022). Monopsony in the US Labor Market. *American Economic Review 112*(7), 2099–2138.

Young, A. (2013). Inequality, the Urban-Rural Gap, and Migration. *Quarterly Journal of Economics 128*(4), 1727–1785.

Figures & Tables

Table 2: Firm Monthly Wage and Employment Summary Statistics

Year	Firms	Minimum Wage	Wage	Wage + Inkind	Employees
		(2)	(3)	(4)	(5)
2005	9035	0	258.1	302.6	19.8
		[0]	[244.8]	[311.3]	[155.2]
2006	11948	0	288.1	339.3	16.3
		[0]	[259.8]	[338]	[76.3]
2007	11056	0	259.8	310.9	19.9
		[0]	[241.2]	[315.2]	[205.5]
2010	8112	86.4	343.4	388.7	24.6
		[28.5]	[248]	[308.6]	[128.6]
2011	8648	75.9	332.9	377.4	24.9
		[24.3]	[250.5]	[301.1]	[132.5]
2012	9417	66.1	349.3	394.6	25.1
		[22.6]	[271.6]	[326.2]	[115.8]
2013	8802	61.3	357.2	391.9	26.4
		[20.3]	[253.5]	[296.9]	[129.1]

Notes: Reporting real average monthly wages in thousands of Tanzanian Shillings (TSH) in the EES. Standard deviation in brackets. Wages are deflated using the Tanzanian CPI but are not adjusted for spatial variation in the price level. Wages are weighted by firm weight and the number of employees at the firm and employment is weighted by the firm sampling weight.

Table 3: Employment by Type

	Employed (%)	*Employment Share (%)*		
		Wage Worker	Self-Employed	
			Total	Agriculture
	(1)	(2)	(3)	(4)
Panel A: *Tanzania*				
Rural	76.5	5.2	94.8	77.9
Urban	61.2	30.0	70.0	28.2
Panel B: *Countries*				
Tanzania	70.2	14.1	85.9	60.1
USA	65.6	90.6	9.4	0.4
Brazil	60.9	74.8	25.2	5.1
India	53.7	51.5	48.5	29.0
USA (1910)	60.8	72.2	27.8	16.2

Notes: Source: IPUMS International. Reporting the shares of employment by geographic designation in the 2012 Tanzania census (Panel A) and national aggregates in Panel B. The sample includes all individuals aged (15-65). Column (1) reports the share of individuals who are employed. Columns (2) and (3) report the employment share in wage-work and self-employment, respectively. Column (4) reports the share of all workers who are engaged in self-employment agriculture. The samples in Panel B are the 2012 Tanzania, 2010 USA, 2010 Brazil, 1910 USA censuses and a 2010 India employment survey.

Table 4: The Firm Size Distribution in Rural and Urban Markets

	Employment Share			Firm Share		
	Rural	Urban	p value	Rural	Urban	p value
Firm Size	(1)	(2)	(3)	(4)	(5)	(6)
1-9	11.6	15.4	0.136	61.8	62.0	0.962
10-49	24.0	34.2	0.120	30.1	32.3	0.617
50+	65.5	50.4	0.034	8.3	5.7	0.030

Notes: The table reports the average share of employment and firms by firm size in 2010 across districts by type. Reporting the p-value for the two-sided t-test that $\mu_{urban} = \mu_{rural}$. *Source:* EES.

Table 5: Migration Rates by Type

Sample	Year	Last 5 Years				2010 Only			
		Rural to		Urban to		Rural to		Urban to	
		Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
LSMS	2010	5.15	2.90	3.86	6.15	5.23	2.42	1.30	3.10
LSMS	2012	6.78	2.99	5.34	7.10	3.17	1.17	0.74	2.55
LSMS	2014	6.74	4.00	6.37	11.01	2.25	0.72	0.46	1.50
ILFS	2014	4.06	3.25	2.24	5.45	3.72	3.25	0.61	2.51

Notes: Reporting five-year migration rates in percent for each sample in columns (1)-(4) and the reported 2010 migration rate in columns (5)-(8). Rural-rural and urban-urban migration episodes exclude migration within the district. All values are weighted by the respective sample's survey weights. Urban districts are defined as those for which at least half of the population was living in an urban area.

Table 6: Between-Firm Elasticity IV Estimation Results

	Dependent Variable: log employment			
	(1)	(2)	(3)	(4)
log wage	0.405***	3.919***	2.474***	2.099***
	(0.082)	(0.683)	(0.381)	(0.406)
log wage $\times$ s_f	-0.058	-39.142***	-20.016**	-11.042*
	(2.539)	(13.337)	(8.428)	(5.974)
log wage $\times$ $s_f\, s_d$	12.598**	13.297***	11.479***	12.887***
	(5.419)	(4.390)	(4.426)	(4.427)
F-statistic		7.958	22.135	15.450
Firms	3880	3880	3880	3880
Controls	Y	Y	Y	Y
Instruments		$\widehat{\text{GAP}}$	$\widehat{\text{ENC}}$	$\widehat{\text{GAP}}$ & $\widehat{\text{ENC}}$
Estimation	OLS	IV	IV	IV

Notes: The table presents OLS and IV estimation results for the reduced form estimation of the between-firm elasticity η. s_f is the firm's share of firm-employment in the local market, s_d is the share of employment in the local market that is engaged in wage-work. Columns (1) reports the OLS estimates. Columns (2)-(4) vary the set of instruments. The $\widehat{GAP}$ instruments are $\{\widehat{GAP}, \widehat{GAP} \times s_f, \widehat{GAP} \times s_f s_d\}$ and the $\widehat{ENC}$ instruments are $\{\widehat{ENC}, \widehat{ENC} \times s_f, \widehat{ENC} \times s_f s_d\}$. Controls include s_f, $s_f s_d$, log total employment in district d (inclusive of self-employment), the log HHI, and region fixed effects. Robust standard errors clustered by district in parenthesis. Reporting the Kleibergen and Paap (2006) cluster robust F-statistic. $^{*}p < .1,^{**} p < .05,^{***} p < .01$

Table 7: Sector Elasticity IV Estimation Results

	Dependent Variable: $s_d/(1-s_d)$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\log W_{fd}/\log w_{sd}$	0.225**	1.537***	0.455***	1.157***	1.897***	2.521**	3.026*
	(0.087)	(0.494)	(0.099)	(0.337)	(0.679)	(1.130)	(1.688)
log s_m	-0.349**	-0.767***	-0.486***	-0.690***	-0.831***	-0.925**	-0.990**
	(0.142)	(0.221)	(0.101)	(0.176)	(0.269)	(0.368)	(0.468)
urban	2.312***	2.128***	1.393***	1.847***	2.431***	3.030***	3.571***
	(0.273)	(0.359)	(0.304)	(0.340)	(0.398)	(0.557)	(0.826)
F-statistic		14.560	117.856	22.399	10.434	6.157	3.855
Districts	103	103	103	103	103	103	103
η	2.5	2.5	1	2	3	4	5
Estimation	OLS	IV	IV	IV	IV	IV	IV

Notes: The table presents OLS and IV estimation results for the sector elasticity. γ can be interpreted as the coefficient on $\log W_{fd}/\log w_{sd}$. s_d and $s_m(d)$ are as defined in the main text. Columns (2)-(7) change the calibrated value of η. Firm amenities are re-estimated for each iteration. Robust standard errors clustered by region in parenthesis. Results are weighted by total district employment. Reporting the Kleibergen and Paap (2006) weak identification F-statistic. $^{*}p < .1,^{**} p < .05,^{***} p < .01$

Table 8: Migration Elasticity GMM Estimation Results

	Dependent Variables: n_{od}					
	Nominal			Spatially Deflated		
	(1)	(2)	(3)	(4)	(5)	(6)
$W_d(\underline{w})/W_o(\underline{w})$	0.337***			0.360***		
	(0.026)			(0.028)		
W_d/W_o		0.997***	1.082***		1.139***	1.398***
		(0.073)	(0.082)		(0.099)	(0.116)
$\log \tau_{od}$	0.424***	0.426***	0.422***	0.424***	0.433***	0.422***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
F-statistic			1879.844			1345.804
Region Pairs	552	552	552	552	552	552
Origin FE	Y	Y	Y	Y	Y	Y
η	2.5	2.5	2.5	2.5	2.5	2.5
γ	1.5	1.5	1.5	1.5	1.5	1.5
Estimation	Poisson	Poisson	IV-Poisson	Poisson	Poisson	IV-Poisson

Notes: The table presents Poisson and IV-Poisson estimation results for the migration elasticity θ at the regional level. τ_{od} is calculated using the Census migrants since birth. The exposure variable is the number of non-migrants. Results are weighted by destination population. Migrants are counted as the number of prime-aged individuals who moved in the past year in the 2012 census. $W_d(\underline{w})$ and $W_o(\underline{w})$ are the market wage indices calculated using the minimum wage and is the instrument for the wage ratio, W_d/W_o. Columns (1)-(3) use nominal wages, while columns (3)-(6) spatially deflate wages in each region. Robust standard errors in parenthesis. Reporting the Kleibergen and Paap (2006) weak identification F-statistic. $^{*}p < .1, ^{**} p < .05, ^{***} p < .01$

Table 9: Baseline Calibrated Model Fit

	Rural		Urban	
	Data	Model	Data	Model
	(1)	(2)	(3)	(4)
Wages				
Firms	1.458	1.458	1.325	1.325
Self-Employment	0.916	0.916	1.112	1.112
All Workers	0.967	0.967	1.199	1.199
Markdowns				
Firms	0.705	0.704	0.714	0.714
Self-Employment	1.000	1.000	1.000	1.000
All Workers	0.972	0.972	0.883	0.883
Employment Share				
firm	0.095	0.095	0.407	0.407
self-emp	0.905	0.905	0.593	0.593
All	0.858	0.858	0.142	0.142
Output				
Firms	0.260	0.260	0.165	0.165
Self-Employment	0.711	0.711	0.094	0.094
All Workers	0.971	0.971	0.259	0.259
Output per Worker				
Firms	3.187	3.192	2.857	2.857
Self-Employment	0.916	0.916	1.112	1.112
All Workers	1.131	1.132	1.823	1.823

Notes: Reporting the simulated and data moment averages weighted by number of workers.

Table 10: The Earnings and Output Gap

	Earnings		Output per Worker	
	Value	Gap	Value	Gap
	(1)	(2)	(3)	(4)
Panel A: *Rural-Urban Productivity Gap*				
Self-Employment				
Rural	1.000		1.000	
All Urban	1.314	1.314	1.314	1.314
Tier 2 Cities	1.252	1.252	1.252	1.252
Dar es Salaam	1.470	1.470	1.470	1.470
Wage-Employment				
Rural	1.596		3.508	
All Urban	1.715	1.075	3.702	1.055
Tier 2 Cities	1.431	0.897	3.088	0.880
Dar es Salaam	1.769	1.108	3.812	1.087
All Employment				
Rural	1.043		1.181	
All Urban	1.456	1.396	2.158	1.828
Tier 2 Cities	1.311	1.257	1.861	1.576
Dar es Salaam	1.600	1.534	2.487	2.106
Panel B: *Agricultural Productivity Gap*				
Self-Employment				
Agriculture	1.000		1.000	
Non-Ag.	1.580	1.580	1.580	1.580
Wage-Employment				
Agriculture	1.247		2.723	
Non-Ag.	1.552	1.244	3.371	1.238
All Employment				
Agriculture	1.003		1.021	
Non-Ag.	1.570	1.565	2.220	2.175

Notes: Panel A reports the earnings by rural-urban status. Gaps are calculated relative to the value for rural by employment type. Panel B reports the gaps between agricultural and non-agricultural employment. Earnings and output per worker in rural self-employment are normalized to one.

Table 11: Reallocation under Competitive Equilibrium

	Labor Market Power (1)	Competitive Equilibrium (2)	Spatial Reallocation Only (3)	Sector Reallocation Only (4)	Local Reallocation Only (5)
Total Output	1.000	1.048	0.979	1.040	1.000
Output per Worker					
Rural	0.894	0.892	0.914	0.892	0.894
Urban	1.643	1.601	1.632	1.652	1.642
Firm	3.105	2.821	2.917	2.850	3.106
Welfare	1.000	1.051	1.074	1.052	1.055
Average Firm Wage	1.429	1.834	1.896	1.852	2.019
Average Income	0.978	1.088	1.043	1.083	1.060
Markdown					
Rural	0.705	1.000	1.000	1.000	1.000
Urban	0.714	1.000	1.000	1.000	1.000
Employment Share					
Firm	0.139	0.183	0.139	0.178	0.139
Urban	0.142	0.152	0.119	0.142	0.142

Notes: Column 1 reports the baseline equilibrium under labor market power. Column 2 reports the equilibrium under the competitive wages counterfactual. Column 3 holds the baseline sector choice fixed but allows workers to spatially reallocate. Column 4 holds the baseline location choice fixed but allows workers to move between wage and self-employment. Column 5 holds fixed the baseline sector and location but allows workers to reallocate between firms in the local market. Welfare and total output are normalized to one at baseline.

Table 12: Quantifying Labor Misallocation

	Baseline		10% Reduction in Search Costs		10% Reduction in Migration Costs	
	Labor Market Power (1)	Competitive Equilibrium (2)	Labor Market Power (3)	Competitive Equilibrium (4)	Labor Market Power (5)	Competitive Equilibrium (6)
Total Output	1.000	1.048	1.217	1.249	0.958	1.005
Output per Worker						
Rural	0.894	0.892	0.909	0.911	0.894	0.890
Urban	1.643	1.601	1.482	1.448	1.916	1.854
Welfare	1.000	1.051	1.492	1.664	2.002	2.049
Average Firm Wage	1.429	1.834	0.861	1.154	1.461	1.866
Average Income	0.978	1.088	0.981	1.159	0.945	1.050
Urban-Rural Income Gap	1.414	1.532	1.346	1.438	1.646	1.775
Urban-Rural Wage Gap	1.030	1.026	1.501	1.490	1.182	1.175
Self-Emp Income Gap	1.579	1.992	0.787	0.990	1.677	2.106
Markdown						
Rural	0.705	1.000	0.701	1.000	0.704	1.000
Urban	0.714	1.000	0.714	1.000	0.714	1.000
Employment Share						
Firm	0.139	0.183	0.484	0.568	0.125	0.167
Urban	0.142	0.152	0.158	0.165	0.104	0.114

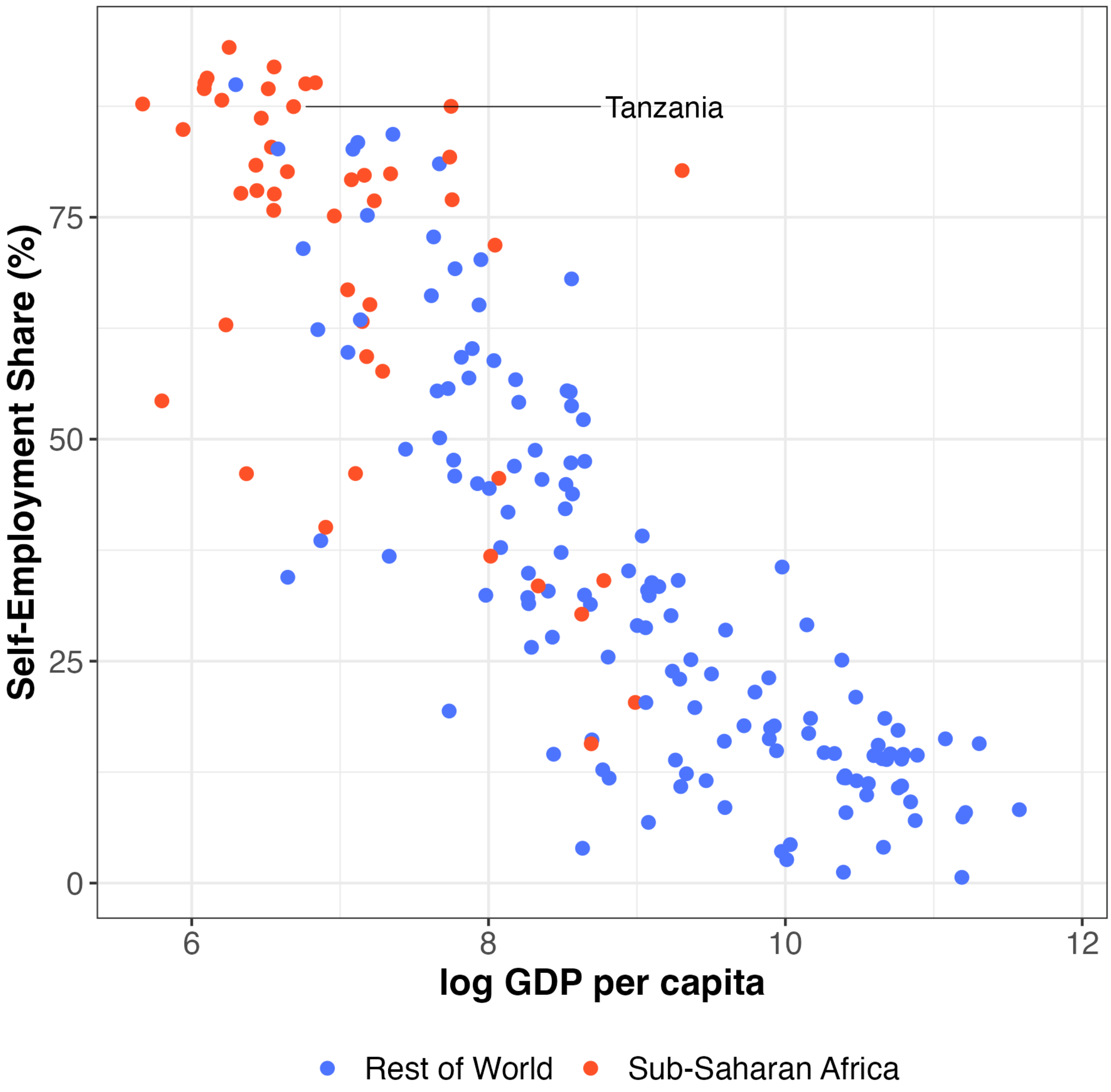
Notes: Odd numbered columns report the results under spatial labor market power. Even numbered columns report the results when moving to competitive equilibrium. Columns (3) and (4) reduce job search costs by 10%, *i.e.* $\delta_d = 0.9 * \delta_d^{data} + 0.1 * 1$ for all d. Columns (5) and (6) reduce migration costs by 10%, *i.e.* $\tau_{od} = 0.9 * \tau_{od}^{data} + 0.1 * 1$ for all o, d. Welfare and total output are normalized to one at baseline.

Table 13: Optimal City Size

			Self-Emp	Firms		Lower Bound		Upper Bound	
City	Pop.	Empl.	Ratio	MS	N^*	MS	N^*	MS	N^*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dodoma	394	160	0.176	0.013	3517	0.006	3543	1.252	980
Arusha	291	114	0.184	0.213	2862	0.130	3116	0.847	1487
Dar es Salaam	4288	1731	0.202	0.164	3009	0.103	3204	0.751	1642
Mwanza	612	196	0.176	0.145	3068	0.071	3313	1.197	1036

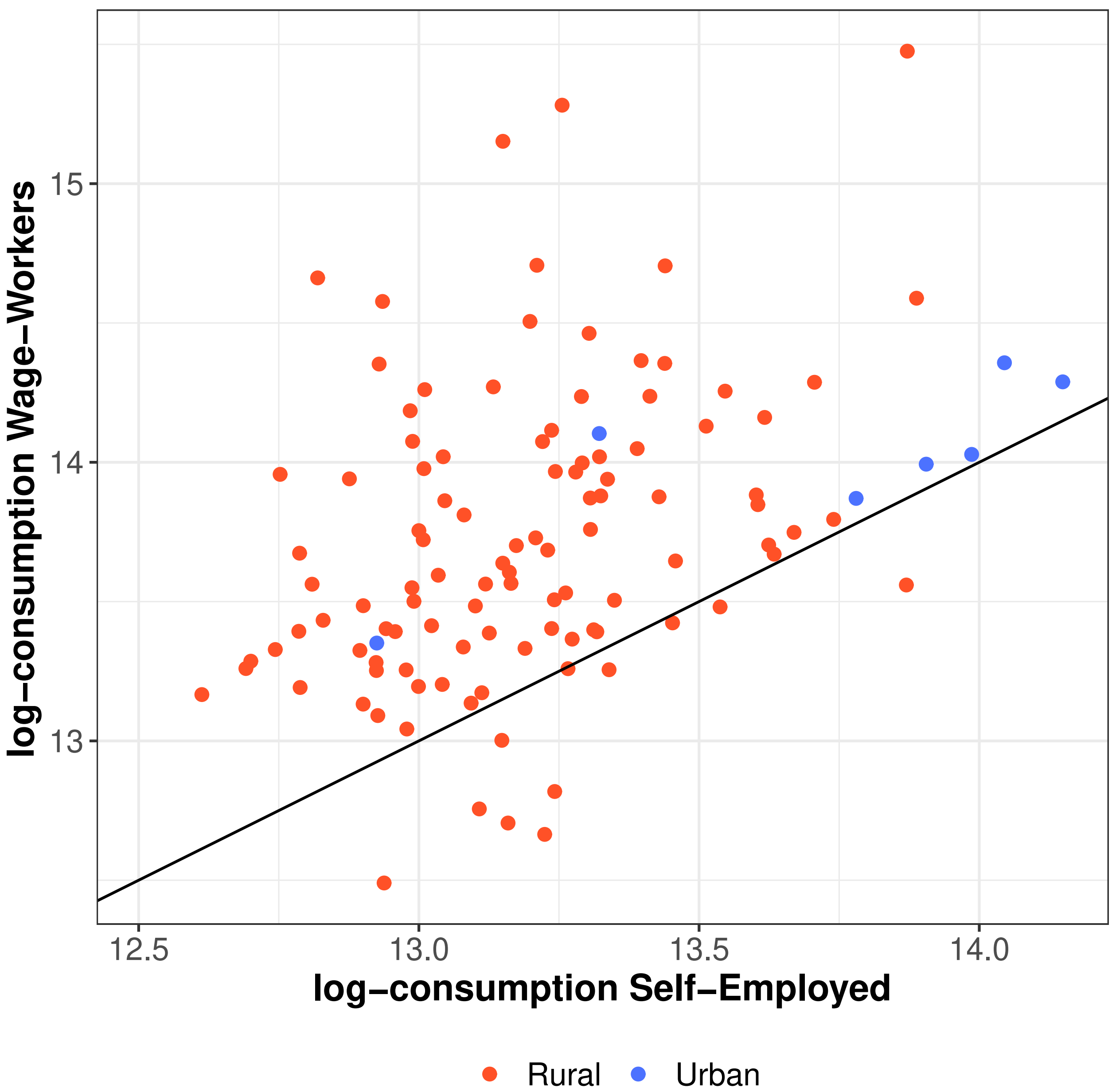
Notes: Population, employment ant N^* are in thousands. The self-employment ratio is the ratio of manufacturing to services in the 2012 census. Population and employment are totals from the 2012 census. MS is the manufacturing to services value-added ratio. N^* is the optimal city employment for that ratio using the values from Au and Henderson (2006).

Figure 1: Self-Employment and Income



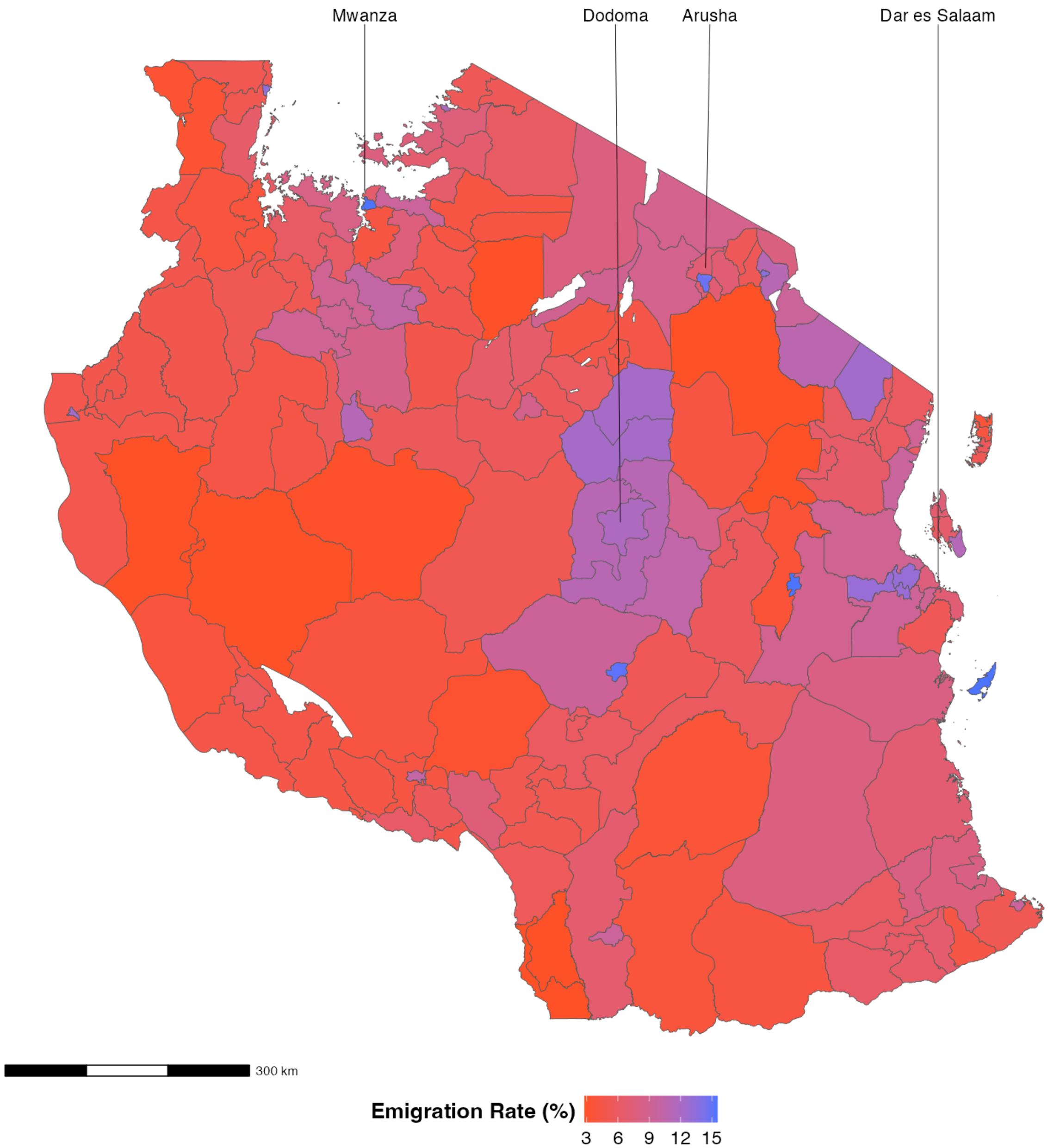
Source: World Bank Development Indicators 2010.

Figure 2: Average Consumption by Main Occupation



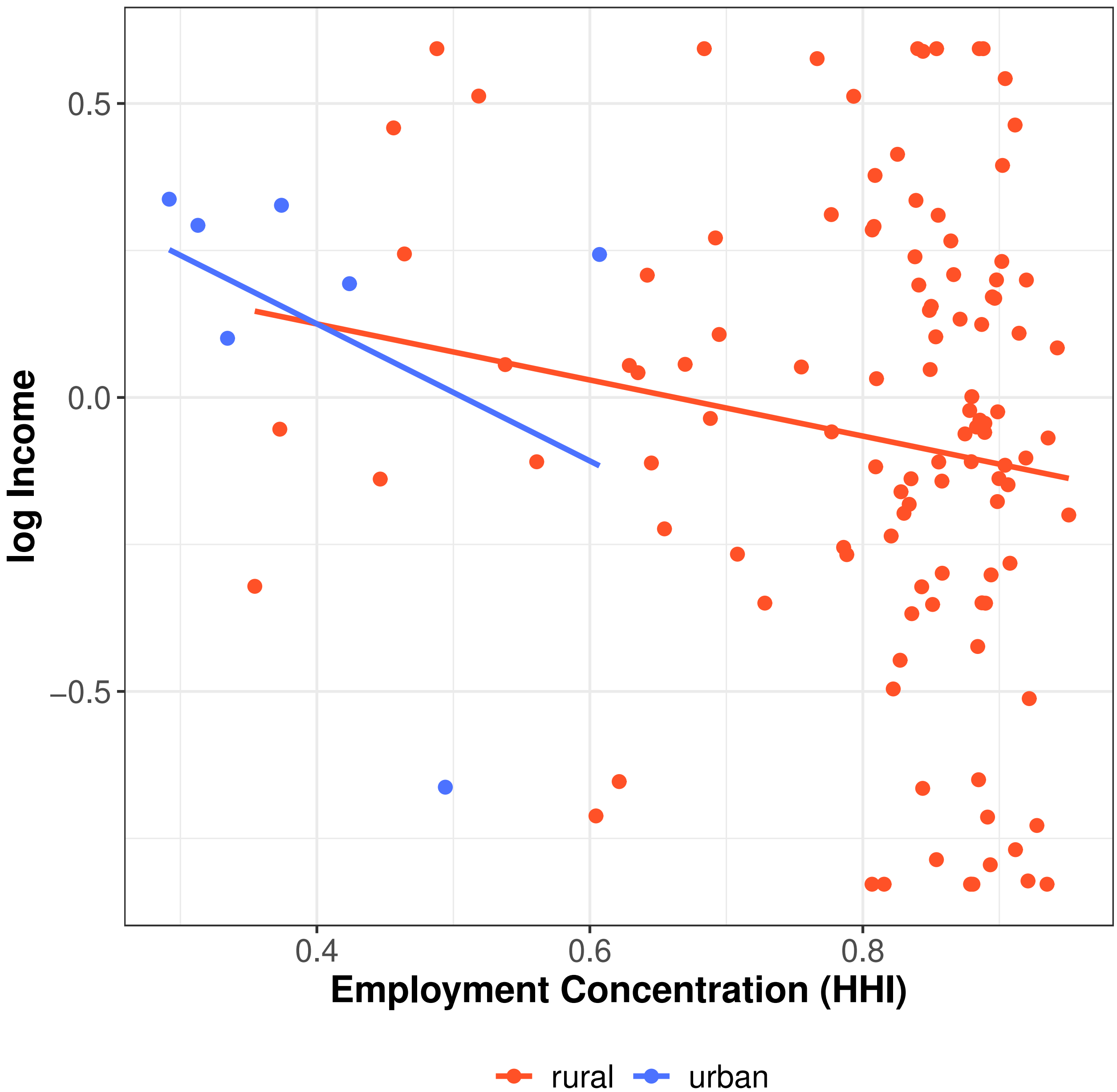
Notes: The figure plots the district average log-consumption-per-adult-equivalent by main occupation in the 2010 LSMS. The sample is limited to prime-aged individuals whose main occupation in the last twelve months was either self-employment or work for a wage.

Figure 3: Prime-Aged Emigration



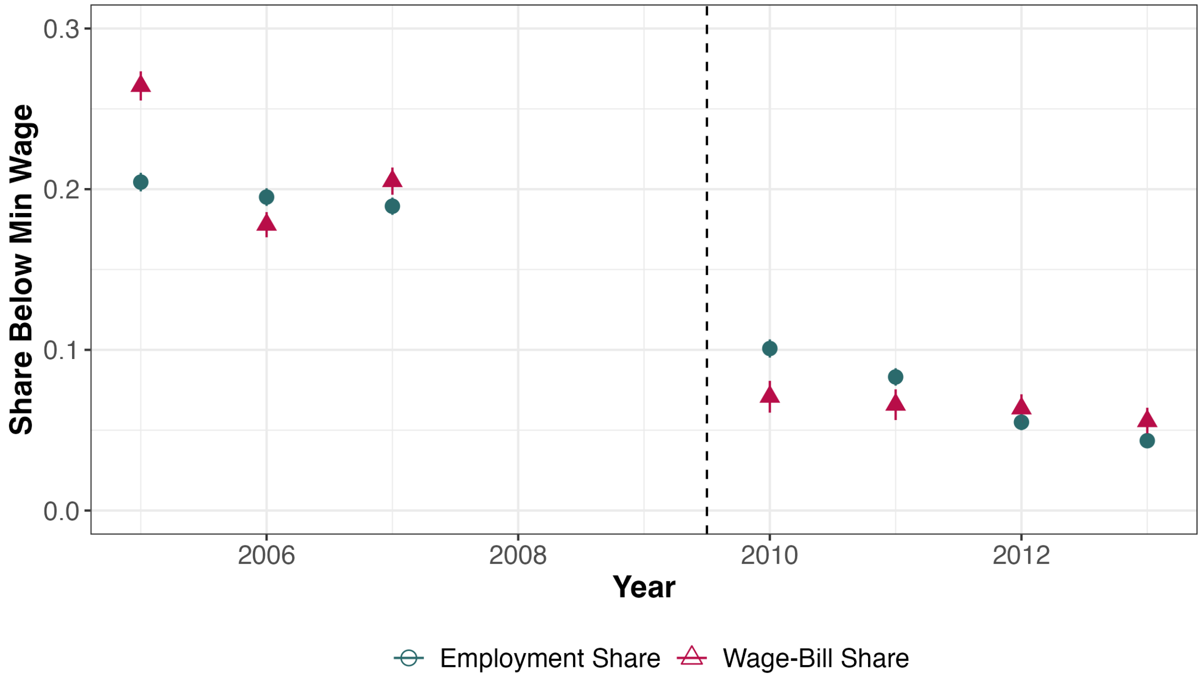
Notes: Displaying one-year emigration rate among individuals aged 15-65 in the 2012 census. Emigration Rates are winsorized at the 2nd and 98th percentiles.

Figure 4: Wages and Employment Concentration in Rural and Urban Districts



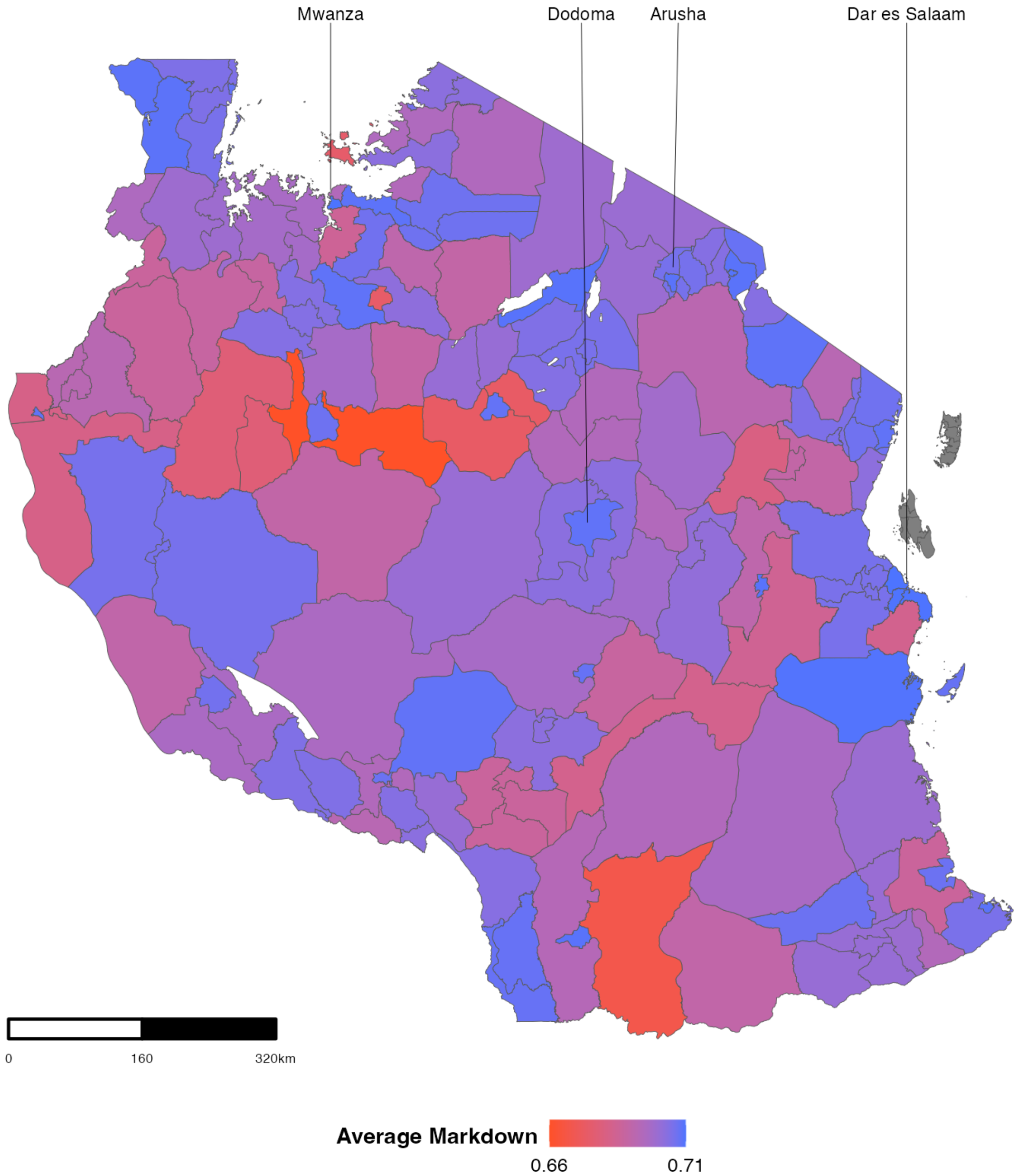
Notes: Plotting the log average district income, inclusive of self-employment, against the employment HHI. Incomes are winsorized at the 2nd nd 98th percentiles, and are normalized such that total income in the economy is one.

Figure 5: Non-Compliance Rate Event Study



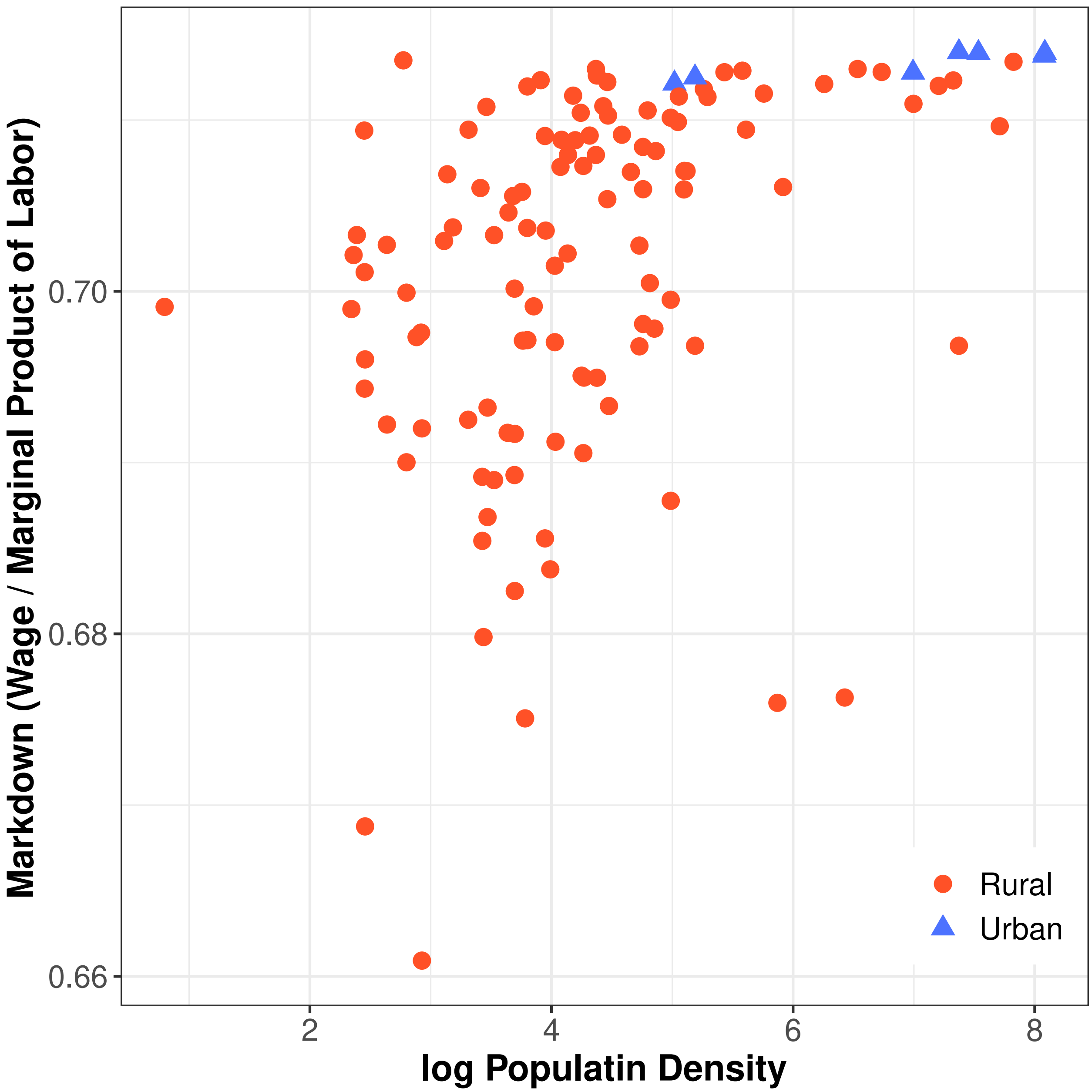
Notes: Plotting the coefficient estimates and 95% confidence interval from equation (9) for the employment non-compliance rate (ENC) and GAP measure. The dashed line indicates the date when the minimum wage law was implemented.

Figure 6: Spatial Distribution of Markdowns



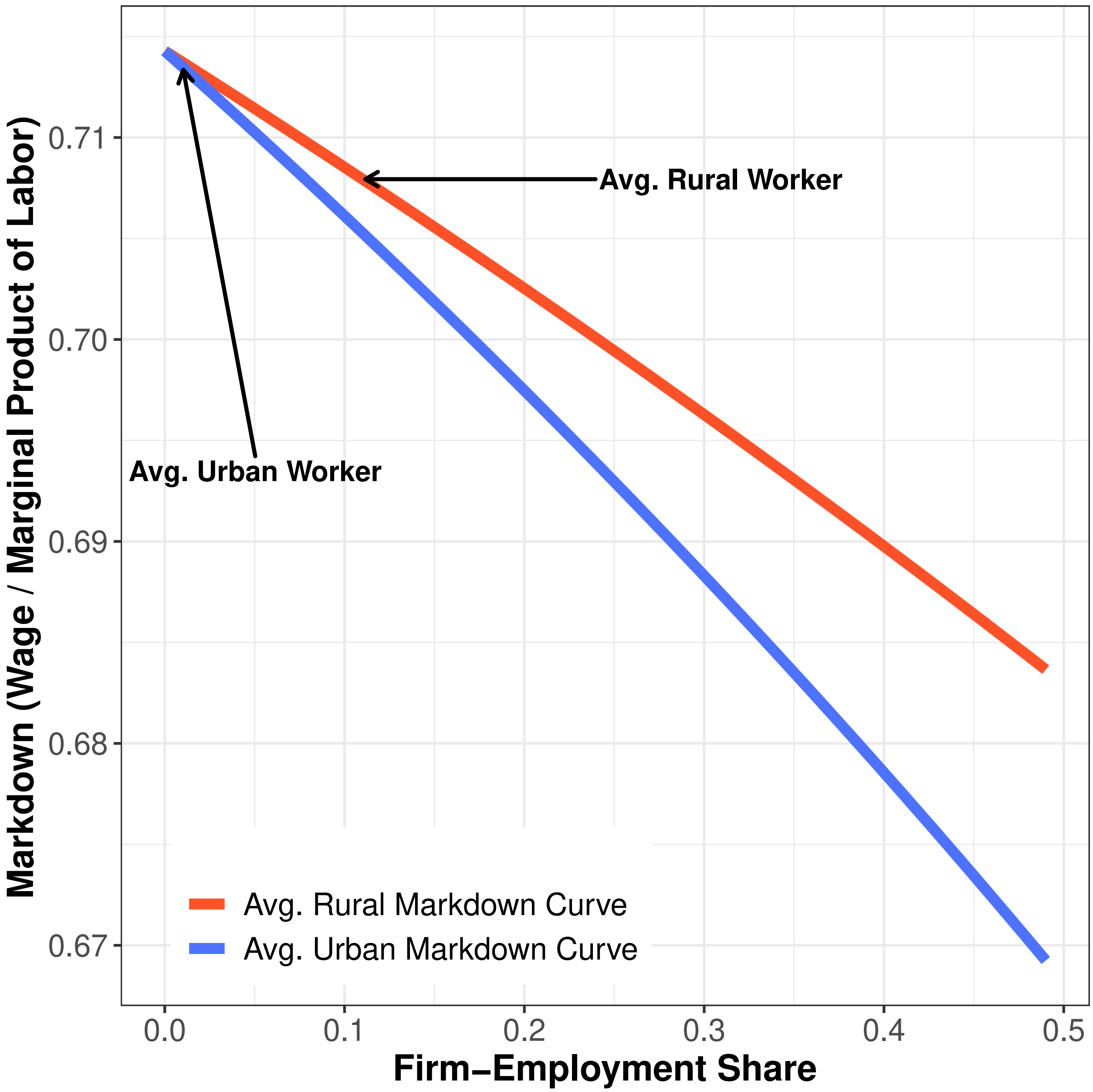
Notes: Displaying the estimated average wage markdown faced by a firm worker in each district.

Figure 7: Wage Markdowns by Population Density



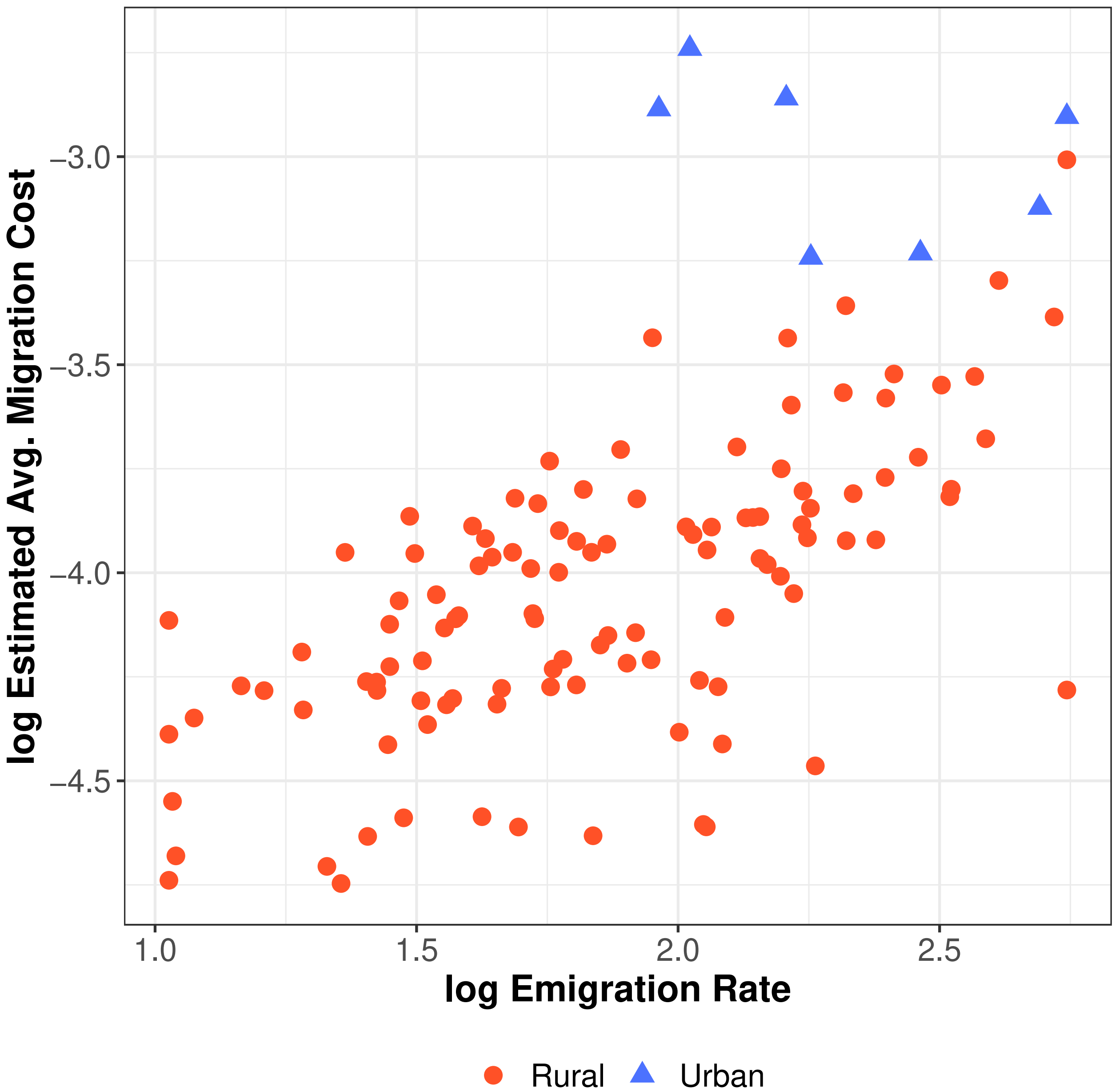
Notes: The figure plots the estimated average wage markdown among firm employees by district against the reported population density in the Census.

Figure 8: Equilibrium Markdown Curve in Urban and Rural Districts



Notes: The figure plots the equilibrium wage markdown (μ) as a function of firm employment share (s_f). The markdown curves are calibrated with the average values of s_d and s_m in urban and rural markets. The two highlighted points represent the average values for s_f in urban and rural markets.

Figure 9: Estimated Average District Migration Cost Against Emigration Rates

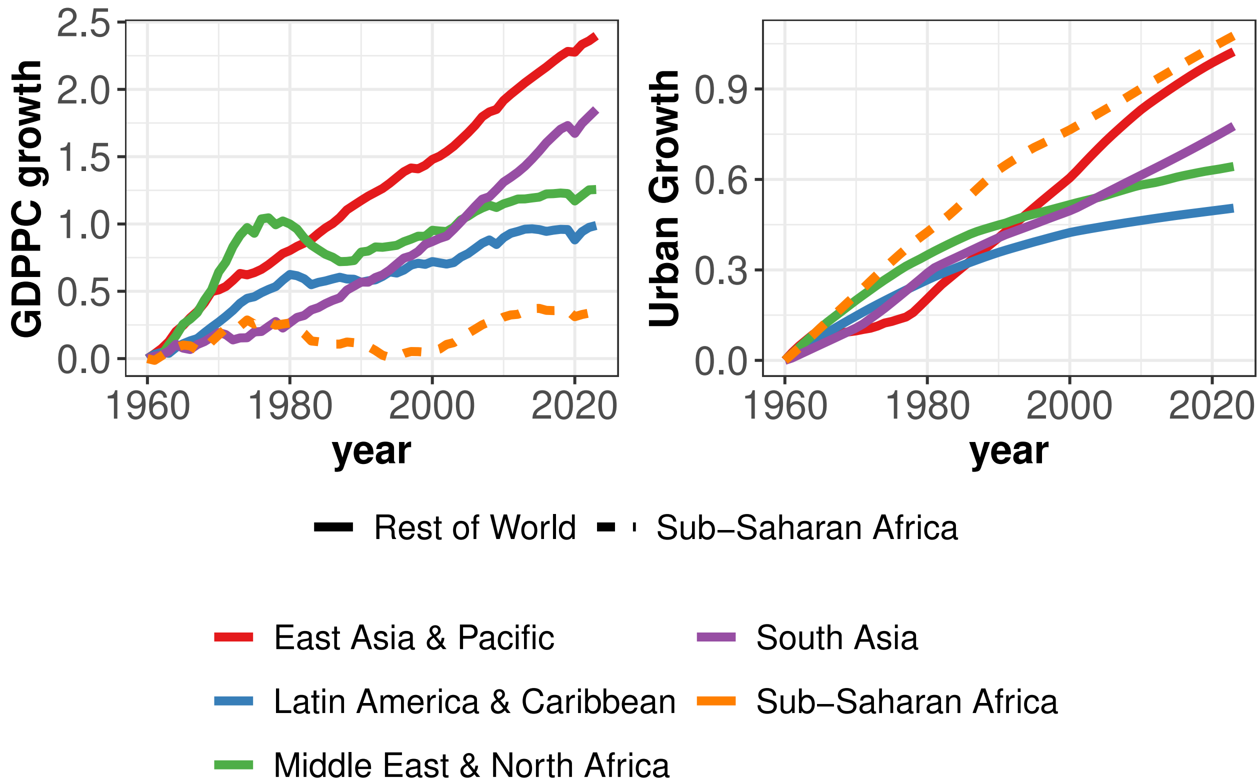


Notes: Plotting the model generated average cost of migration in each district against the one-year prime aged emigration rate shown in Figure 3.

Figure 10: The Correlation between Search Costs and Hires and Vacancies

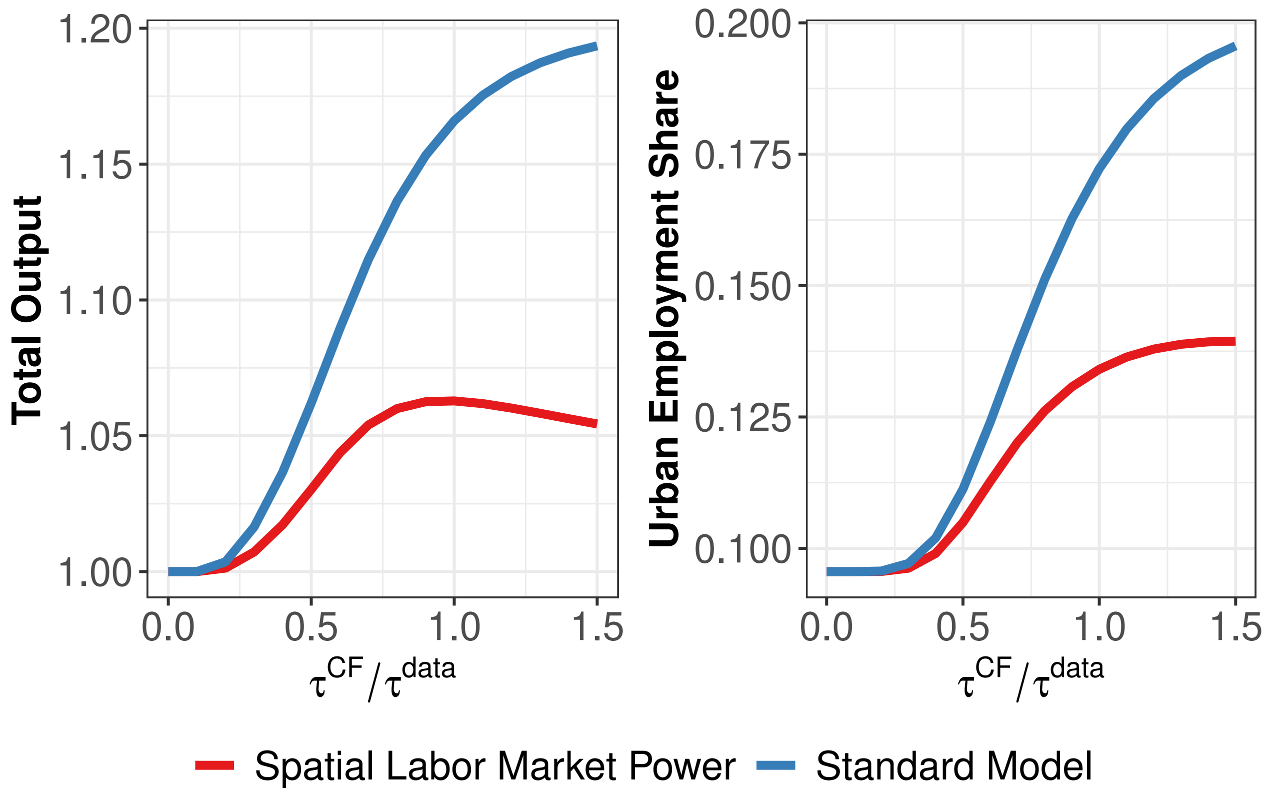
Notes: Displaying the average number of vacancies per worker by district (top) and the number of hires per posted vacancy (bottom) against the estimated search cost δ. Vacancy and hires are averaged over the period 2010-2017 and are winsorized at the 5th and 95th percentile.

Figure 11: Urbanization and Growth Across Regions



Notes: The figure plots the log change in real GDP per capita relative to the base year (left) and the log change in the urban population share (right). North-America and Europe are not pictured. *Source:* World Bank Development Indicators.

Figure 12: Urbanization and Growth in Two Models



Notes: The figure plots total output per worker relative to the baseline case with infinite migration costs (left) and the share of the population living in Dar es Salaam (right). The initial labor distribution corresponds to the labor shares in each district in 2000. In the standard model firms pay workers their marginal product, and has location amenities normalized to one across locations.

A Additional Figures and Tables

Table A.1: First Stage Estimation Results for the Between-Firm Elasticity

	log wage			log wage $\times s_f$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\widehat{GAP}$	-0.215***		0.201***	0.002		-0.004
	(0.046)		(0.049)	(0.001)		(0.002)
$s_f \times \widehat{GAP}$	-0.698		-1.530	-0.427*		-0.133
	(1.758)		(2.209)	(0.252)		(0.461)
$s_f\, s_d \times \widehat{GAP}$	0.566		32.843	-3.659*		6.513*
	(18.520)		(28.162)	(2.033)		(3.847)
s_f	0.641*	0.825	0.715	12.490***	12.869***	12.887***
	(0.324)	(0.519)	(0.529)	(0.100)	(0.147)	(0.151)
$s_f\, s_d$	-0.457	-0.439*	-0.409	0.030**	0.011	0.008
	(0.276)	(0.258)	(0.273)	(0.012)	(0.011)	(0.011)
$s_f \times \widehat{ENC}$		-0.495	1.037		-1.289***	-1.226*
		(1.722)	(2.329)		(0.470)	(0.654)
$\widehat{ENC}$		-0.711***	-1.009***		0.003*	0.007*
		(0.090)	(0.116)		(0.002)	(0.004)
$s_f\, s_d \times \widehat{ENC}$		-7.538	-26.486*		-3.028*	-7.077*
		(7.406)	(15.918)		(1.803)	(3.891)
Firms	3880	3880	3880	3880	3880	3880

Notes: The table presents the first stage estimation results for the between-firm elasticity η. s_f is the firm's share of firm-employment in the local market, s_d is the share of employment in the local market that is engaged in wage-work, $\widehat{GAP}$ is the predicted exposure to the minimum wage, and $\widehat{ENC}$ is the predicted share of employees paid below the minimum wage, log employment is the log of total employment in the district, inclusive of self-employment. Robust standard errors clustered by district in parenthesis. $^{*}p < .1,^{**} p < .05,^{***} p < .01$

Table A.1 Continued: First Stage Estimation Results for the Between-Firm Elasticity

	Dependent Variable: log wage $\times s_f s_d$		
	(1)	(2)	(3)
$\widehat{GAP}$	-0.007***		0.003*
	(0.001)		(0.002)
$s_f \times \widehat{GAP}$	-2.489***		0.077
	(0.583)		(0.507)
$s_f\, s_d \times \widehat{GAP}$	31.622***		0.627
	(4.489)		(6.752)
s_f	0.976***	1.063***	1.067***
	(0.116)	(0.132)	(0.136)
$s_f\, s_d$	-0.005	-0.005	-0.004
	(0.011)	(0.007)	(0.007)
$s_f \times \widehat{ENC}$		-2.341***	-2.385***
		(0.539)	(0.803)
$\widehat{ENC}$		-0.010***	-0.015***
		(0.002)	(0.003)
$s_f\, s_d \times \widehat{ENC}$		25.680***	25.309***
		(5.051)	(8.948)
Firms	3880	3880	3880

Notes: See Table A.1 footnote for details.

Table A.2: Berger et al. (2022) Between-Firm Elasticity Estimation Method

	(1) log wage	(2) log empl	(3) log wage	(4) log empl
$\widehat{ENC}$	-0.711***	-1.944***		
	(0.090)	(0.281)		
$s_f \times \widehat{ENC}$	-0.495	-2.286		
	(1.722)	(12.896)		
$s_f\, s_d \times \widehat{ENC}$	-7.538	336.738***		
	(7.406)	(93.952)		
s_f	0.825	0.882	0.782**	5.440***
	(0.519)	(3.418)	(0.362)	(2.003)
$s_f\, s_d$	-0.439*	2.717***	-0.456	2.525***
	(0.258)	(0.866)	(0.280)	(0.943)
$\widehat{GAP}$			-0.207***	-1.008***
			(0.049)	(0.069)
$s_f \times \widehat{GAP}$			-1.227	-25.282**
			(1.723)	(9.889)
$s_f\, s_d \times \widehat{GAP}$			1.450	572.645***
			(18.115)	(77.508)
Firms	3880	3880	3880	3880
Region FE			Y	Y
$\hat{\eta}$		2.736		4.859
std. err.		(0.379)		(1.011)
Instruments				

Notes: Robust standard errors clustered by district in parenthesis. $^{*}p < .1,^{**}p < .05,^{***}p < .01$

Table A.3: Sensitivity of the Migration Elasticity θ to Alternative Estimating Strategies

	Dependent Variables: n_{od}					
	Census Migration			Survey Migration		
	(1)	(2)	(3)	(4)	(5)	(6)
W_d/W_o	1.398***	1.399***	0.857***	2.200***	2.014***	1.287***
	(0.116)	(0.116)	(0.207)	(0.214)	(0.205)	(0.332)
$\log \tau_{od}$	0.422***	0.421***		0.492***	0.413***	
	(0.015)	(0.016)		(0.024)	(0.026)	
log distance			-0.835***			-0.620***
			(0.088)			(0.145)
log migrant stock			0.195***			0.443***
			(0.029)			(0.071)
log employment ratio			1.049***			0.711***
			(0.112)			(0.179)
F-statistic	1345.804	1346.053	604.535	1345.804	1378.737	604.535
Region Pairs	552	546	552	552	335	552
Origin FE	Y	Y	Y	Y	Y	Y
η	2.5	2.5	2.5	2.5	2.5	2.5
γ	1.5	1.5	1.5	1.5	1.5	1.5
Restriction	None	Migrating Pairs	None	None	Migrating Pairs	None

Notes: The table presents IV-Poisson estimation results for the migration elasticity θ. See Table 8 for variable definitions. All wages are spatially deflated. Robust standard errors in parenthesis. Reporting the Kleibergen and Paap (2006) weak identification F-statistic. $^{*}p < .1,^{**} p < .05,^{***} p < .01$

Table A.4: District Level estimation of the Migration Elasticity θ

	Dependent Variable: n_{od}					
	(1)	(2)	(3)	(4)	(5)	(6)
$W_d(\underline{w})/W_o(\underline{w})$	0.233***			0.088***		
	(0.014)			(0.017)		
W_d/W_o		0.418***	0.755***		0.111***	0.243***
		(0.033)	(0.052)		(0.035)	(0.048)
$\log \tau_{od}$	0.486***	0.496***	0.488***			
	(0.005)	(0.005)	(0.005)			
log distance				-0.756***	-0.744***	-0.753***
				(0.024)	(0.023)	(0.024)
log migrant stock				0.189***	0.195***	0.191***
				(0.006)	(0.006)	(0.006)
log employment ratio				0.707***	0.753***	0.723***
				(0.027)	(0.026)	(0.027)
F-statistic			1.3e+04			1.2e+04
District Pairs	14042	14042	14042	14042	14042	14042
Origin FE	Y	Y	Y	Y	Y	Y
η	2.5	2.5	2.5	2.5	2.5	2.5
γ	1.5	1.5	1.5	1.5	1.5	1.5
Estimation	Poisson	Poisson	IV-Poisson	Poisson	Poisson	IV-Poisson

Notes: The table presents Poisson and IV-Poisson estimation results for the migration elasticity θ at the district level. See Table 8 for variable definitions. All wages are spatially deflated. Robust standard errors in parenthesis. Reporting the Kleibergen and Paap (2006) weak identification F-statistic. $^{*}p < .1, ^{**}p < .05, ^{***}p < .01$

Table A.5: Competitive Equilibrium Counterfactual with Endogenous Amenities and Productivity

	Baseline (1)	Congestion Only (2)	Agglomeration Only (3)	Congestion & Agglomeration (4)	High Congestion (5)
Total Output	1.048	1.048	1.049	1.049	1.046
Output per Worker					
Rural	0.892	0.892	0.891	0.891	0.892
Urban	1.601	1.603	1.604	1.606	1.615
Welfare	1.051	1.051	1.051	1.051	1.051
Average Firm Wage	1.834	1.834	1.836	1.837	1.839
Average Income	1.088	1.088	1.089	1.089	1.087
Urban-Rural Income Gap	1.532	1.533	1.537	1.538	1.545
Urban-Rural Wage Gap	1.026	1.027	1.029	1.030	1.034
Self-Emp Income Gap	1.992	1.992	1.994	1.995	2.000
Markdown					
Rural	1.000	1.000	1.000	1.000	1.000
Urban	1.000	1.000	1.000	1.000	1.000
Employment Share					
Firm	0.183	0.183	0.184	0.183	0.182
Urban	0.152	0.152	0.153	0.153	0.149
λ	0.000	-0.040	0.000	-0.040	-0.500
ϕ	0.000	0.000	0.050	0.050	0.000

Notes: The table reports the simulated competitive equilibrium counterfactual under various assumptions on the engoeneity of amenities and productivity. Output and welfare can be interpreted relative to a baseline value of one in the labor market power equilibrium. Column 1 restates the competitive equilibrium counterfactual reported in Table 11. Column 2 endogenizes amenities only; column 3 endogenizes productivity only; column 4 endogenizes both productivity and amenities. Column 5 has very high congestion forces and no agglomeration forces.

Table A.6: Changing the Firm Size Distribution Holding Total Productivity Fixed

	Labor Market Power (1)	Monopsony Limit (2)	2X Rural Firms (3)	2X All Firms (4)
Total Output	1.000	1.001	0.919	0.860
Output per Worker				
Rural	0.894	0.894	0.869	0.926
Urban	1.643	1.641	1.781	1.463
Firm	3.105	3.098	2.548	2.078
Welfare	1.000	1.001	0.988	0.980
Average Firm Wage	1.429	1.438	1.179	0.961
Average Income	0.978	0.980	0.936	0.906
Markdown				
Rural	0.705	0.714	0.710	0.710
Urban	0.714	0.714	0.714	0.714
Employment Share				
Firm	0.139	0.140	0.129	0.121
Urban	0.142	0.142	0.144	0.137

Notes: Column 1 reports the baseline equilibrium under labor market power. Column 2 reports the equilibrium under the monopsony limit counterfactual in which all firms markdown their wages proportionally. Column 3 divides each rural firm in two. Column 4 divides all firms in two.

Table A.7: Asymmetric Reductions in Migration Costs

	Baseline (1)	Symmetric (2)	To Urban Only (3)	From Urban Only (4)	Rural to Rural (5)
Total Output	1.000	0.958	1.038	0.986	0.950
Output per Worker					
Rural	0.894	0.894	0.902	0.897	0.897
Urban	1.643	1.916	1.284	1.772	2.040
Welfare	1.000	2.002	1.144	1.076	1.894
Average Firm Wage	1.429	1.461	1.305	1.455	1.471
Average Income	0.978	0.945	0.991	0.970	0.940
Urban-Rural Income Gap	1.414	1.646	1.096	1.520	1.743
Urban-Rural Wage Gap	1.030	1.182	0.799	1.105	1.248
Self-Emp Income Gap	1.579	1.677	1.412	1.621	1.697
Markdown					
Rural	0.705	0.704	0.705	0.704	0.704
Urban	0.714	0.714	0.714	0.714	0.714
Employment Share					
Firm	0.139	0.125	0.174	0.131	0.122
Urban	0.142	0.104	0.257	0.118	0.090

Notes: Columns (1) and (2) restates the results in columns (1) and (5) in Table 12. Column (3) reduces migration costs by 10% only when the destination is an urban district, *i.e.* $\tau_{od} = 0.9 * \tau_{od}^{data} + 0.1 * 1$ if d urban. Column (4) reduces migration costs by 10% only when the origin is an urban district, *i.e.* $\tau_{od} = 0.9 * \tau_{od}^{data} + 0.1 * 1$ if o urban. Column (5) reduces migration costs by 10% only when both the origin and destination are rural districts, *i.e.* $\tau_{od} = 0.9 * \tau_{od}^{data} + 0.1 * 1$ if o and d are rural.

B Mathematical Appendix

Labor Supply Under the distributional assumptions on the amenities, the probability that a worker from o chooses firm f or self-employment s in market d, can be expressed as

$$
\begin{aligned}
\Pr(w_{f(d)}|\omega,o) =& \frac{(b_f w_f)^\eta}{\sum_{f\in d}(b_f w_f)^\eta} \times \frac{\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}}}{\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}} + w_{ad}^\gamma} \\
&\times \frac{(B_d\tau_{od})^\theta \left(\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}} + w_{ad}^\gamma\right)^{\frac{\theta}{\gamma}}}{\sum_d \left((B_d\tau_{od})^\theta \left(\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}} + w_{ad}^\gamma\right)^{\frac{\theta}{\gamma}}\right)}
\end{aligned}
$$

$$
\Pr(w_{ad}|\omega,o) = \frac{w_{ad}^\gamma}{\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}} + w_{ad}^\gamma} \times \frac{(B_d\tau_{od})^\theta \left(\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}} + w_{ad}^\gamma\right)^{\frac{\theta}{\gamma}}}{\sum_d \left((B_d\tau_{od})^\theta \left(\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}} + w_{ad}^\gamma\right)^{\frac{\theta}{\gamma}}\right)}
$$

Total labor supply is then found by aggregating

$$
\begin{aligned}
n_{fdo} &= \int_{\omega\in o} \Pr(w_{f(d)}|\omega,o)\,\partial F(L) \\
n_{fdo} &= \frac{(b_f w_f)^\eta}{\sum_{f\in d}(b_f w_f)^\eta} \times \frac{\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}}}{\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}} + w_{ad}^\gamma} \times \frac{(B_d\tau_{od})^\theta \left(\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}} + w_{ad}^\gamma\right)^{\frac{\theta}{\gamma}}}{\sum_d \left((B_d\tau_{od})^\theta \left(\left(\delta_d^\eta \sum_{f\in d}(b_f w_f)^\eta\right)^{\frac{\gamma}{\eta}} + w_{ad}^\gamma\right)^{\frac{\theta}{\gamma}}\right)} L_o \\
n_{fdo} &= \left(\frac{b_f w_f}{W_{fd}}\right)^\eta \left(\frac{\delta_d W_{fd}}{W_d}\right)^\gamma \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^\theta L_o
\end{aligned}
$$

Where the aggregates W_{df}, W_d and $\mathbf{W_o}$ are those defined in the main text. Following the same logic, it can be shown that the labor supply to self-employment in d from o is given by:

$$
n_{ado} = \left(\frac{w_a}{W_d}\right)^\gamma \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^\theta L_o
$$

Firm's problem Firms choose wages taking the labor supply curve as given to maximize profits

$$
\Pi = \max_{w_f} \quad A_f n_f^\alpha - w_f n_f \quad ; \quad n_f = \sum_o n_{fdo} \quad ; \quad n_{fdo}(w) = \left(\frac{b_f w_f}{W_{fd}}\right)^\eta \left(\frac{\delta_d W_{fd}}{W_d}\right)^\gamma \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^\theta L_o
$$

The FOC is

$$\sum_o \left(\alpha A_f n_f^{\alpha-1} \frac{\partial n_{fdo}}{\partial w_f} - n_{fdo} - w_f \frac{\partial n_{fdo}}{\partial w_f} \right) = 0$$

For ease of notation, define the market share quantities

$$s_f = \left(\frac{b_f w_f}{W_d}\right)^{\eta} \quad ; \quad s_d = \left(\frac{\delta_d W_{fd}}{W_d}\right)^{\gamma}$$
$$s_{od} = \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^{\theta} \quad ; \quad s_m = \sum_o \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^{\theta} L_o = \sum_o s_{od} L_o$$

It is also useful to define the following partials

$$\begin{aligned}
\frac{\partial W_{fd}}{\partial w_f} &= \frac{b_f^{\eta} w_f^{\eta-1}}{W_{fd}^{\eta-1}} = \frac{W_{fd}}{w_f} s_f \\
\frac{\partial W_d}{\partial W_{fd}} &= \frac{\delta_d^{\gamma} W_{fd}^{\gamma-1}}{W_d^{\gamma-1}} = \frac{W_d}{W_{fd}} s_d \\
\frac{\partial \mathbf{W_o}}{\partial W_d} &= \frac{(\tau_{od} B_d)^{\theta} W_d^{\theta-1}}{\mathbf{W_o}^{\theta-1}} = \frac{\mathbf{W_o}}{W_d} s_{od}
\end{aligned}$$

The partial is

$$\begin{aligned}
\frac{\partial n_{fdo}}{\partial w_f} =& \underbrace{\eta \left(\frac{b_f w_f}{W_{fd}}\right)^{\eta-1} \left(\frac{W_{fd} b_f - b_f w_f \frac{\partial W_{fd}}{\partial w_f}}{W_{fd}^2} \right) s_d s_{od} L_o}_{\text{firm partial}} \\
& \underbrace{+ s_f \gamma \left(\frac{\delta_d W_{fd}}{W_d}\right)^{\gamma-1} \left(\frac{W_d \delta_d \frac{\partial W_{fd}}{\partial w_f} - \delta_d W_{fd} \frac{\partial W_d}{\partial W_{fd}} \frac{\partial W_{fd}}{\partial w_f}}{W_d^2} \right) s_{od} L_o}_{\text{market partial}} \\
& \underbrace{+ s_f s_d \theta \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^{\theta-1} \left(\frac{\mathbf{W_o} \tau_{od} B_d \frac{\partial W_d}{\partial W_{fd}} \frac{\partial W_{fd}}{\partial w_f} - \tau_{od} B_d W_d \frac{\partial \mathbf{W_o}}{\partial W_d} \frac{\partial W_d}{\partial W_{fd}} \frac{\partial W_{fd}}{\partial w_f}}{\mathbf{W_o}^2} \right) L_o}_{\text{aggregate partial}}
\end{aligned}$$

Appealing to the wage index partials defined above, the firm partial can be reduced as

$$\begin{aligned}
&\eta\left(\frac{b_f w_f}{W_{fd}}\right)^{\eta-1}\left(\frac{b_f}{W_{fd}}-\frac{b_f w_f}{W_{fd}^2}\frac{W_{fd}}{w_f}s_f\right)s_d s_{od}L_o\\
=&\eta\frac{1}{w_f}\left(\frac{b_f w_f}{W_{fd}}\right)^{\eta}(1-s_f)\,s_d s_{od}L_o=\eta\frac{s_f}{w_f}(1-s_f)\,s_d s_{od}L_o\\
=&\eta\frac{n_{fdo}}{w_f}(1-s_f)
\end{aligned}$$

Where the final expression follows from the fact that $n_{fdo} = s_f\, s_d\, s_{do} L_o$. Similarly, the market partial reduces to

$$\begin{aligned}
&s_f\gamma\left(\frac{\delta_d W_{fd}}{W_d}\right)^{\gamma-1}\left(\frac{\delta_d}{W_d}\frac{W_{fd}}{w_f}s_f-\frac{\delta_d W_{fd}}{W_d^2}\frac{W_d}{W_{fd}}s_d\frac{W_{fd}}{w_f}s_f\right)s_{od}L_o\\
=&s_f\gamma\left(\frac{\delta_d W_{fd}}{W_d}\right)^{\gamma}\left(\frac{s_f}{w_f}-s_d\frac{s_f}{w_f}\right)s_{od}L_o\\
=&\gamma s_f s_d s_{od}L_o\frac{s_f}{w_f}(1-s_d)\\
=&\gamma\frac{n_{fdo}}{w_f}s_f(1-s_d)
\end{aligned}$$

Finally, the aggregate partial reduces to

$$\begin{aligned}
&s_f s_d\theta\left(\frac{\tau_{od}B_d W_d}{\mathbf{W_o}}\right)^{\theta-1}\left(\frac{\tau_{od}B_d}{\mathbf{W_o}}\frac{W_d}{W_{fd}}s_d\frac{W_{fd}}{w_f}s_f-\frac{\tau_{od}B_d W_d}{\mathbf{W_o}^2}\frac{\mathbf{W_o}}{W_d}s_{od}\frac{W_d}{W_{fd}}s_d\frac{W_{fd}}{w_f}s_f\right)L_o\\
=&s_f s_d\theta\left(\frac{\tau_{od}B_d W_d}{\mathbf{W_o}}\right)^{\theta}\left(\frac{s_f s_d}{w_f}-s_{od}\frac{s_f s_d}{w_f}\right)L_o\\
=&\theta s_f s_d s_{od}L_o\frac{s_f s_d}{w_f}(1-s_{od})\\
=&\theta\frac{n_{fdo}}{w_f}s_f s_d(1-s_{od})
\end{aligned}$$

Returning to the first order condition, we have

$$\frac{\partial n_{fdo}}{\partial w_f}=\frac{n_{fdo}}{w_f}\left(\eta(1-s_f)+\gamma s_f(1-s_d)+\theta s_f s_d(1-s_{od})\right)$$

And the labor supply elasticity to firm f from o can be expressed as

$$\varepsilon_{of}=\frac{\partial n_{fdo}}{\partial w_f}\frac{w_f}{n_{fdo}}=\left(\eta(1-s_f)+\gamma s_f(1-s_d)+\theta s_f s_d(1-s_{od})\right)$$

The first order condition for the firm can then be rewritten to express wages as a share of marginal product

$$
\begin{aligned}
&\sum_o \left(\alpha A_f n_f^{\alpha-1} \varepsilon_{of} \frac{n_{fdo}}{w_f} - n_{fdo} - \varepsilon_{of}\, n_{fdo} \right) = 0 \\
&\frac{\alpha A_f n_f^{\alpha-1}}{w_f} \left(\sum_o \varepsilon_{of} n_{fdo} \right) = n_f + \left(\sum_o \varepsilon_{of}\, n_{fdo} \right) \\
&w_f = \alpha A_f n_f^{\alpha-1} \left(\frac{\sum_o \varepsilon_{of} n_{fdo}}{n_f + \left(\sum_o \varepsilon_{of}\, n_{fdo}\right)} \right) \\
&w_f = \alpha A_f n_f^{\alpha-1} \left(\frac{\sum_o \varepsilon_{of} n_{fdo}/n_f}{1 + \left(\sum_o \varepsilon_{of}\, n_{fdo}/n_f\right)} \right)
\end{aligned}
$$

Then we can express the aggregate labor supply elasticity to the firm as

$$
\begin{aligned}
\varepsilon_f =& \sum_o \frac{n_{fdo}}{n_f} \left(\eta \left(1 - s_f\right) + \gamma s_f \left(1 - s_d\right) + \theta s_f s_d \left(1 - s_{od}\right) \right) \\
\varepsilon_f =& \eta \left(1 - s_f\right) + \gamma s_f \left(1 - s_d\right) + \theta s_f s_d \left(1 - \frac{\sum_o s_{od}^2 L_o}{s_d} \right)
\end{aligned}
$$

Which yields the main expression in the text $w_f = mrpl_f \frac{\varepsilon_f}{1+\varepsilon_f}$

B.1 Alternative Assumptions on Labor Competition

In Appendix B.1, I derive the expressions for wages under alternative assumption on the competition between firms.

Perfect Competition Under perfect competition, firms are price takers. This is a less natural analogue since firms are choosing wages in each of the other cases. In this form of competition, firms choose employment and the firms' wage can be expressed as

$$
w_f = \alpha A_f n_f^{\alpha-1}
$$

Firms will pay workers their marginal product, but there will still be variation in wages across firms on account of each firm facing its own labor supply curve.

Monopsonistic Competition Under monopsonistic competition, firms internalize the effect of their wages on labor supply to their own firm, but do not internalize the effect on the local market, *i.e.*

$\partial W_{fd}/\partial w_f = 0$. This implies that

$$\begin{aligned}\frac{\partial n_{fdo}}{\partial w_f} =& \eta \left(\frac{b_f^\eta w_f^{\eta-1}}{W_{fd}^\eta} \right) s_d s_{od} L_o \\ \frac{\partial n_{fdo}}{\partial w_f} =& \frac{\eta}{w_f} \left(\frac{b_f w_f}{W_{fd}} \right)^\eta s_d s_{od} L_o \\ \frac{\partial n_{fdo}}{\partial w_f} =& \eta \frac{n_{fdo}}{w_f} \\ \rightarrow \varepsilon_f = \eta\end{aligned}$$

That is, the markdown is constant.

Intermediate Local Oligopoly Under this form of competition, firms internalize the effect of their wage on the wages in other firms, but not how that affects total labor supply to firms. That is, $\partial W_{fd}/\partial w_f \neq 0$ but $\partial W_d/\partial W_{fd} = 0$. Following the same logic as above, the labor supply elasticity here is

$$\varepsilon_f = \eta \left(1 - s_f\right) + \gamma s_f$$

Local Oligopoly A more sensible version of local oligopoly is that in which firms internalize the effect of changes in their wage on each of the aggregates except for the aggregate market indices, That is, $\partial \mathbf{W_o}/\partial W_d = 0$. This is consistent with each market being small relative to the entire market. Here the labor supply elasticity is

$$\varepsilon_f = \eta \left(1 - s_f\right) + \gamma s_f \left(1 - s_d\right) + \theta s_f s_d$$

B.2 Additional Results

Employment Elasticity Total firm-employment in each market can be expressed as the sum of employment in each firm

$$n_d = \left(\frac{\delta_d W_{fd}}{W_d} \right)^\gamma \left[\sum_o \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}} \right)^\theta L_o \right]$$

The employment elasticity can be found by differentiating n_d with respect to W_{fd}

$$\begin{aligned}\frac{\partial n_d}{\partial W_{fd}} =& \gamma \left(\frac{\delta_d W_{fd}}{W_d}\right)^{\gamma-1} \left(\frac{W_d \delta_d - \delta_d W_{fd} \frac{\partial W_d}{\partial W_{fd}}}{W_d^2}\right) s_m(d) \\ &+ \sum_o s_d \theta \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^{\theta-1} \left(\frac{\mathbf{W_o} \tau_{od} B_d \frac{\partial W_d}{\partial W_{fd}} - \tau_{od} B_d W_d \frac{\partial \mathbf{W_o}}{\partial W_d} \frac{\partial W_d}{\partial W_{fd}}}{\mathbf{W_o}^2}\right) L_o \\ =& \frac{\gamma}{W_{fd}} \left(\frac{\delta_d W_{fd}}{W_d}\right)^{\gamma} (1 - s_d)\, s_m(d) + \sum_o s_d \theta \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^{\theta} \left(\frac{s_d}{W_{fd}} - \frac{s_d}{W_{fd}} s_{od}\right) L_o \\ =& \gamma \frac{n_d}{W_{fd}} (1 - s_d) + \theta \sum_o \frac{s_d s_{od} L_o}{W_{fd}} s_d (1 - s_{od})\end{aligned}$$

For s_{od} small, this can be approximated as

$$\begin{aligned}\frac{\partial n_d}{\partial W_{fd}} =& \gamma \frac{n_d}{W_{fd}} (1 - s_d) + \theta \frac{n_d}{W_{fd}} s_d \\ \rightarrow \varepsilon_d =& \gamma (1 - s_d) + \theta s_d\end{aligned}$$

Migration Appealing to the expression for s_{od}, total migration from $o - d$ is given by

$$n_{od} = s_{od} L_o = \left(\frac{\tau_{od} B_d W_d}{\mathbf{W_o}}\right)^{\theta} L_o$$

Then the ratio of migration from $o - d$ to non-migration is

$$\frac{n_{od}}{n_{oo}} = \left(\frac{B_d \tau_{od} W_d}{B_o W_o}\right)^{\theta} \tag{15}$$

Rearranging (15) yields the estimation equation in the main text

$$n_{od} = n_{oo} \exp \left[\theta \log \left(\frac{W_d}{W_o}\right) + \theta \log \tau_{od} + \theta \log \left(\frac{B_d}{B_o}\right)\right]$$

Where the migration cost terms are estimated via the existing migration network and the distance between pairs and the ratio of the amenities are the error terms. Returning to (15), the exact τs are finally calculated as

$$\frac{n_{od}}{n_{oo}} \frac{n_{do}}{n_{dd}} = \left(\frac{B_d \tau_{od} W_d}{B_o W_o} \frac{B_o \tau_{do} W_o}{B_d W_d}\right)^{1+\theta} = \left(\tau_{od} \tau_{do}\right)^{\theta}$$

By the assumption that $\tau_{od} = \tau_{do}$, the migration cost is

$$\tau_{od} = \left(\frac{n_{od}}{n_{oo}} \frac{n_{do}}{n_{dd}}\right)^{\frac{1}{2\theta}}$$

Ten-year Migration Flows Let π_{od} denote the share of migrants from o to d. The number of individuals remaining in o after one year is then given by $n_o * \pi_{oo}$. Appealing to this logic, the total number of migrants in a ten year period can be extrapolated from the number of migrants in a single year as

$$
\begin{aligned}
n_{od}^{10} =& n_o * \pi_{od} + n_o * \pi_{oo} * \pi_{od} + n_o * \pi_{oo}^2 * \pi_{od} + \ldots + n_o * \pi_{oo}^9 * \pi_{od} \\
n_{od}^{10} =& n_o * \pi_{od} \left(1 + \pi_{oo} + \pi_{oo}^2 + \ldots \pi_{oo}^9\right) \\
n_{od}^{10} =& n_o * \pi_{od} \left(\frac{1 - \pi_{oo}^{10}}{1 - \pi_{oo}}\right)
\end{aligned}
$$

Where the final line follows from the difference of the two infinite geometric sums. Then our decadal migration shares can be expressed as

$$
\pi_{od}^{10} = \pi_{od} \left(\frac{1 - \pi_{oo}^{10}}{1 - \pi_{oo}}\right) \quad ; \quad \pi_{oo}^{10} = \pi_{oo}^{10}
$$

C Minimum Wage Law

Tanzania's Employment and Labour Relations Act, 2004 set forth a broad set of regulations "to promote economic development through economic efficiency, productivity and social justice" (p. 6). Links to the source document held by the International Labor Organization online can be found here. The act applied to all laborers in the country, both public and private, except for those in the People's Defense force, the police force, prison services and the national service (Employment and Labour Relations Act, 2004, p. 5). The legislation made it illegal for children under the age of 14 to work (and under the age of 18 in hazardous sectors). The maximum number of usual hours that an employee could work were set at 9 hours per day, 6 days per week and 45 hours per week (p. 19). The penalty for violating these laws was up to one year in jail and a 5 million shilling fine (p. 79). The legislation did not set an official binding minimum wage, but made a provision to set one within three years, laying the groundwork for creating a national minimum wage (p. 84).

Progress continued with the 2007 Labour Institutions Act, which allowed for the creation of sectoral wage boards that would determine the minimum wage within their sector. In 2010, minimum wages were passed into law in eight sectors. I report the monthly minimum wages for these sectors in Column 3 of Table A.8. Each minimum wage stipulated an hourly, daily, weekly, fortnightly, and monthly rate. Adding further complexity, several sectors provided different levels for subsectors, creating 20 total minimum wages. The differences within sectors could be large; for domestic and hospital services the monthly minimum wage ranged from 65,000 TSH for domestic workers to 150,000 TSH for tourist hotels. Employers in any sector not mentioned were required to pay all employees at least 80,000 TSH per month for full time work. The "all other sectors" minimum wage equaled that for health services and commerce, industry, and trade, and exceeded the minimum wage for agriculture (70,000 TSH per month) and domestic workers (65,000 TSH per month). These sectoral minimum wages remained in place until July 2013 when the 2010 Wage Order was repealed and replaced.

Table A.8: 2010 Sectoral Minimum Wage Details

Sector	ISIC Code	Monthly Wage
Agricultural Services	1-2	70000
Marine and Fishing	3	165000
Mining Primary Licenses	5-9	150000
Mining License/ Prospecting licenses	NA	350000
Mining Dealers licenses	NA	250000
Mining Brokers licenses	NA	150000
Trade, Industry and Commerce	10-33	80000
Transport Services: Inland Transport	49, 491-493	150000
Transport Services: Aviation	51	350000
Transport Services: Clearing and Forwarding	52	230000
Hotels: Medium Hotels	55	100000
Hotels: Potential and Tourists hotel	NA	150000
Hotels: Restaurants, Guest Houses and Bars	56	80000
Telecommunication	61-63	300000
Private security: other	80	80000
Private security: International or potential security Companies	NA	105000
Health Services	86-88	80000
Domestic Services: Other	97 98	65000
Domestic Services: Diplomats	NA	90000
Domestic Services: Entitled Officers	NA	80000
Domestic Services: Other	97 98	65000
Other	35, 36-39, 50, 52, 53	80000

Notes: The table reports for each sector that was specified in the 2010 Wage Order, the corresponding ISIC codes used in the analysis and the monthly minimum wage.

Table A.9: EES Firm Employment Summary Statistics

	min wage	wage	employees	casual	hires	female
	(1000 TSH)		% of total			(%)
	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture						
2005-2007		123.3	4.2	23.8		30.0
2010-2013	70	317.4	3.9	31.9	2.6	30.2
2014 - 2017	100	413.2	4.1	25.1	3.9	22.0
Fishing						
2005-2007		105.9	0.2	0.5		18.3
2010-2013	165	262.2	0.3	0.4	0.0	13.5
2014 - 2017	200	173.7	0.2	0.4	0.0	9.7
Mining						
2005-2007		203.9	0.5	2.2		12.8
2010-2013	150	407.7	0.9	1.1	0.2	12.2
2014 - 2017	200	664.5	1.4	1.1	0.9	8.1
Manufacturing, Commerce, Trade						
2005-2007		195.8	13.0	42.2		22.5
2010-2013	80	236.2	21.7	41.2	16.6	24.2
2014 - 2017	115	356.0	25.1	37.2	13.7	19.3
Energy Services						
2005-2007		441.5	0.7	0.8		17.2
2010-2013	80	766.1	0.8	0.4	0.5	19.0
2014 - 2017	150	933.6	1.2	0.2	0.2	23.1
Construction						
2005-2007		248.9	1.5	5.7		15.4
2010-2013	80	331.0	2.1	5.0	1.2	15.9
2014 - 2017	250	493.9	2.2	7.0	1.6	8.4
Inland Transport						
2005-2007		199.8	1.2	0.3		9.3
2010-2013	150	350.1	1.5	0.9	1.1	13.0
2014 - 2017	200	419.2	1.5	1.4	1.8	7.8
Aviation Services						
2005-2007		323.9	0.2	0.1		24.6
2010-2013	350	534.6	0.1	0.1	0.0	38.9
2014 - 2017	300	1084.5	0.2	0.0	0.1	21.9
Clearing and Forwarding						
2005-2007		151.9	1.2	1.7		17.8
2010-2013	230	432.5	1.5	1.7	1.5	22.7
2014 - 2017	300	624.6	1.1	0.4	0.7	17.8
Hotels						
2010-2013	100	164.3	4.0	1.8	4.9	49.7
2014 - 2017	150	195.7	4.2	2.3	6.0	29.8

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EES Firm Employment Summary Statistics – *continued from previous page*

	min wage	wage	employees	casual	hires	female
	(1000 TSH)		(%) of total			(%)
	(1)	(2)	(3)	(4)	(5)	(6)
Restaurants						
2005-2007		88.6	3.9	3.1		50.9
2010-2013	80	163.1	3.7	2.5	4.0	56.8
2014 - 2017	130	188.8	2.7	1.4	4.4	27.1
Information Services						
2005-2007		267.2	1.4	1.0		37.4
2010-2013	80	447.0	0.8	0.2	0.3	38.7
2014 - 2017	150	585.8	1.0	0.6	0.6	25.1
Telecommunication Services						
2005-2007		263.3	1.2	1.0		38.7
2010-2013	300	795.1	0.6	0.0	0.4	32.0
2014 - 2017	400	824.3	1.1	10.6	0.9	24.7
Financial Services						
2005-2007		1542.1	3.2	0.2		40.8
2010-2013	80	842.7	2.1	0.1	2.6	42.9
2014 - 2017	400	1227.3	2.1	0.2	2.4	29.7
Private Security						
2010-2013	80	183.7	1.5	0.4	2.8	18.8
2014 - 2017	100	200.3	2.7	0.4	6.2	12.0
Education						
2005-2007		208.5	11.7	4.3		32.3
2010-2013	80	433.9	17.3	2.3	27.8	43.5
2014 - 2017	140	656.7	19.7	2.9	26.3	28.6
Health Services						
2005-2007		186.8	6.3	0.9		56.3
2010-2013	80	384.9	7.3	1.6	9.0	60.4
2014 - 2017	132	507.5	7.3	1.9	11.6	44.2
All Others						
2005-2007		288.8	49.6	12.1		31.5
2010-2013	80	436.2	29.7	8.3	24.4	34.9
2014 - 2017	100	640.6	22.2	7.1	18.6	24.4

Notes: Reporting the average values during each of the three periods. Columns(1) and (2) report the minimum wage and average monthly wage in thousands of Tanzanian Shillings. Columns (3)-(5) report the employment, casual employment, and hires as a percentage of the total. Column (6) reports the share of workers in that sector-period that are female.

Table A.10: EES Firm Size Summary Statistics

	min wage	Firms	employees (% of total)		Private	Districts
	(1000 TSH)	Total	5-49	50+	(%)	
	(1)	(2)	(3)	(4)	(5)	(6)
Agriculture						
2005-2007		1722	59.6	6.0	96.7	105
2010-2013	70	1090	70.1	15.2	85.5	111
2014 - 2017	100	1584	69.3	19.0	95.0	100
Fishing						
2005-2007		205	47.7	2.3	73.6	38
2010-2013	165	240	93.4	2.5	93.1	29
2014 - 2017	200	382	98.5	1.2	98.8	12
Mining						
2005-2007		142	69.8	15.6	89.9	30
2010-2013	150	161	81.7	17.0	97.2	29
2014 - 2017	200	508	77.4	15.0	97.4	60
Manufacturing, Commerce, Trade						
2005-2007		7321	67.5	4.3	94.9	96
2010-2013	80	15735	62.9	3.8	98.7	114
2014 - 2017	115	23876	61.9	4.3	98.9	124
Energy Services						
2005-2007		317	71.9	9.0	5.9	74
2010-2013	80	138	55.9	37.1	23.1	69
2014 - 2017	150	130	33.1	64.2	41.6	39
Construction						
2005-2007		860	76.8	4.0	87.5	69
2010-2013	80	1422	80.1	5.7	95.9	88
2014 - 2017	250	2182	85.2	6.0	98.2	67
Inland Transport						
2005-2007		493	51.6	7.8	70.6	40
2010-2013	150	837	73.4	6.3	95.7	42
2014 - 2017	200	1231	78.2	8.8	93.6	55
Aviation Services						
2005-2007		114	69.2	3.6	57.5	12
2010-2013	350	62	74.1	5.9	58.5	14
2014 - 2017	300	154	44.6	6.1	70.2	20
Clearing and Forwarding						
2005-2007		632	67.0	4.4	82.5	21
2010-2013	230	585	77.2	8.8	80.5	41
2014 - 2017	300	683	79.5	7.8	86.2	31
Hotels						
2010-2013	100	4084	70.8	2.2	100.0	100
2014 - 2017	150	6707	68.5	2.7	100.0	113

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EES Firm Size Summary Statistics – *continued from previous page*

	min wage (1000 TSH)	Firms Total	employees (% of total) 5-49	50+	Private (%)	Districts
	(1)	(2)	(3)	(4)	(5)	(6)
Restaurants						
2005-2007		4899	68.7	0.9	99.3	83
2010-2013	80	5829	71.4	0.5	99.6	102
2014 - 2017	130	6994	74.5	0.4	100.0	105
Information Services						
2005-2007		738	66.8	5.7	56.3	49
2010-2013	80	502	52.5	6.2	51.9	95
2014 - 2017	150	768	81.5	9.2	76.2	51
Telecommunication Services						
2005-2007		2314	16.8	1.4	48.9	108
2010-2013	300	249	57.6	9.2	75.2	59
2014 - 2017	400	675	66.5	8.2	87.2	57
Financial Services						
2005-2007		2686	88.0	1.4	16.4	103
2010-2013	80	1269	66.3	4.5	59.4	89
2014 - 2017	400	2166	68.6	4.3	58.3	82
Private Security						
2010-2013	80	357	70.3	25.6	98.7	34
2014 - 2017	100	779	73.1	24.1	100.0	41
Education						
2005-2007		7092	82.5	3.0	15.3	116
2010-2013	80	3063	76.7	11.2	81.4	124
2014 - 2017	140	5080	76.9	13.9	81.3	123
Health Services						
2005-2007		2479	69.7	10.0	52.1	113
2010-2013	80	2480	64.6	13.7	86.6	123
2014 - 2017	132	3786	69.8	15.6	84.5	123
All Others						
2005-2007		25986	52.5	4.0	11.3	119
2010-2013	80	11230	57.6	8.6	50.0	123
2014 - 2017	100	14083	62.1	8.2	60.4	123
All						
2005-2007		58009	61.5	3.9	39.2	119
2010-2013		49332	65.5	6.1	83.6	124
2014 - 2017		71783	67.4	6.8	87.5	124

Notes: Reporting the average values during each year in each of the three periods. Column (2) reports the total number of firms in that sector-period. Columns (3)-(6) report the share of those firms with 5-49 employees, at least 50 employees and that are private, respectively. Column (6) reports the number of districts in which there are at least one firm in that sector operating in the sample.