The Informality Trade-Off: Wages and Rural-Urban Migration in South Africa*

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Abstract

In rapidly urbanizing countries, many urban inhabitants work in the informal sector. Should policy makers try to shrink it? To answer this question, I develop a general-equilibrium model of rural-urban migration based on frictional job search and matching. A key novelty of this approach is to combine migration choice of workers with occupational choice across formal and informal labour markets. I first estimate my model with a South African panel of workers. I find that the urban informal sector serves as a stepping-stone to urban formal jobs. This also makes it a valuable outside option for urban formal workers. Then, I simulate formalization policies by tripling the expected cost of being inspected for urban informal firms. I find a decline in informal employment and wages that is not associated with job destruction, but with wage cuts in the formal sector. This is because urban formal firms now have more labour market power. As a result, cities become less attractive. This is exacerbated by the response of rural firms that offer higher wages and retain potential migrants: the urban population share falls by 4%. Overall, the decline in urban informality improves the allocation of labour, both across sectors in urban areas and towards more productive firms in rural areas, at the cost of lower workers' welfare.

Keywords: rural-urban migration, job search, informal sector, spatial misallocation
JEL Classification: J31, J46, O15, O18, R23

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1 Introduction

According to the World Bank (2023), the global urban population is set to double by 2050, with Sub-Saharan Africa (SSA) and East Asia and Pacific (EAP) experiencing the most rapid urban growth. There, rural-urban migration plays a significant role in driving urbanization rates (compared to demographic trends), especially in low- and middle-income countries (Wahba *et al.*, 2020). In this paper, I focus on an important aspect of this phenomenon whose study dates back to Harris & Todaro (1970) and Fields (1975): the share of job-related moves that depend on informal job opportunities in cities. Are such jobs associated with spatial labour misallocation? This paper shows that it is not necessarily so, as I find that reducing urban informality can lead to higher total output but also lower workers' welfare. In my results, migration choice acts as a substantial adaptation mechanism: a decline in urban population mitigates the fall in welfare and reinforces the rise in output.

Informal jobs designate unregistered positions where firms and workers do not comply with, or are not covered by, laws and regulations. They tend to pay less, and be less productive and stable than their formal counterparts (Donovan *et al.*, 2023), giving further arguments in favour of labour inspection. Because rural jobs are typically characterized as being "traditional" (be it in agriculture or not), existing policies rather focus on urban "modern" jobs whose potential for formalization is higher. To quantify the effect of such labour inspection policies and assess how the urban informal sector affects the productive allocation of labour in space, I develop a general-equilibrium model of rural-urban migration with frictional job search and matching. Indeed, formal and informal labour markets appear to be interconnected: firms with similar productivity levels and operating in the same industries can be found in both sectors. Besides, some informal firms do change status in response to labour supply and demand shocks, and (mostly low-educated) workers do transition between sectors and perform similar tasks across them (Ulyssea, 2020). This generates spillovers that make it difficult to study equilibrium outcomes in reduced form, all the more so when accounting for space.

I therefore build upon the wage-posting model of Burdett & Mortensen (1998). As in Schmutz & Sidibé (2019), homogeneous workers randomly search for jobs locally and remotely, on- and off-the-job. They move from rural to urban areas upon finding a job and incurring a fixed mobility cost. As in Meghir *et al.* (2015), the urban labour market is further divided into a formal and an informal sector: formal workers enjoy welfare benefits when losing their job. Workers search across both sectors, subject to local amenities and frictions that vary across origin and destination states. For workers, these frictions include monetary and psychological search costs, as well as limited networks. For firms, they essentially cover advertising and recruiting costs (Caria & Orkin, 2024). Both types of frictions can be understood as information frictions that have also been shown to be especially relevant for rural-urban migration (Lagakos, 2020). In the model, firms are pinned to a location and are heterogeneous in productivity. They choose whether to enter the market and in which sector to operate based on their expected profits. Then, they post unique wages given existing matching conditions. Whereas formal firms have to pay taxes, informal firms incur a relative cost that is increasing and convex in firm size: this monitoring cost can be interpreted as the expected cost of being inspected and/or fined. A key novelty of this approach is to combine migration choice of workers with formality choice of workers and firms, two elements that I show to be complementary.

The allocation of workers across sectors and locations is obtained by assuming that wage offers are consistent with local reservation and mobility-compatible indifference wages. The latter formalize the dynamic utility trade-off between locations faced by workers. I further assume steady-state conditions on local employment shares. Importantly, I do not assume that relative urban and rural population shares are at the steady state: this is because I deal with countries that are still urbanizing. To solve for workers' allocation, I therefore target a stationary urban growth rate that reflects structural change factors that are not fully micro-founded in the model. This is similar in spirit to search-and-matching models with population growth, such as Head & Lloyd-Ellis (2012), except that I do not assume the same growth rate in each state. My results should therefore be interpreted as a snapshot of labour market outcomes at a given stage of a (slow) structural change process, rather than as a stable equilibrium outcome over the very long term. On the firms' side, I recover wage-posting strategies by inverting the workers' program and assuming that worker flows are also stationary at the firm level. To solve for the allocation of firms across sectors, I assume free entry in cities, and that urban firms are indifferent between the formal and informal sectors over the productivity range where the two overlap.

I estimate my model with a nationally representative South African panel survey covering individuals' migration choices and labour market outcomes more or less every two years over the 2008-2017 period. I start by showing that South Africa is comparable to other low- and middle-income countries in SSA or EAP in terms of urbanization and formalization trends, but that it is closer to emerging economies elsewhere (e.g., Turkey) in levels. Then, I restrict my benchmark sample to working-age adults to study the labor mobility of independent agents, and more specifically workers with low education as they are the most affected by informal employment. I further reduce my analysis to males as a first approach. I present key stylized facts and show that this selection procedure is consistent with my modelling assumptions, notably that my benchmark sample is relatively homogeneous along the dimensions of interest. I also conduct additional checks on the potential bias arising from the spatial sorting of workers with respect to unobserved characteristics suggested by Young (2013), Alvarez (2020), and Hicks *et al.* (2021). Finally, I motivate my modelling approach with an empirical puzzle: how come rural migrants accept urban informal jobs when these imply a wage cut? I show that this can be rationalized by the role of informality as a stepping-stone in urban labour markets, with my model capturing other potential channels. This is also instrumental to understand policy results.

At baseline, offer distributions and transition rates that capture underlying frictions are jointly identified by observed wages and transition probabilities across locations and employment states. The estimated model features a good fit on targeted quantities, and a satisfying one on untargeted quantities (worker and firm shares across states). I find higher average welfare values for urban informal workers than for rural workers, in spite of higher relative rural amenities. Rural migrants selecting into urban informality also do not appear to be overly optimistic compared to those that select into urban formality. The choice of moving into urban informality in spite of wage cuts is therefore rationalized by improved career prospects. More precisely, I find that the option value of future urban formal jobs accounts for 20% of urban informal welfare. The informal sector can therefore be seen as an intermediate rung on the job ladder in my context. Incidentally, I find that urban areas are more productive than rural ones, and that rural firms have more market power than urban ones, as defined by wage markdowns. Within cities, the lower average productivity of informal firms stems from a composition effect: it is never profitable to operate in the informal sector passed some productivity threshold. Still, for a given productivity level, formal and informal firms offer similar values as they partly compete for the same workers: informal firms need to pay higher wages that compensate them for the loss of welfare benefits in order to remain attractive. These factors explain the resulting welfare values in equilibrium.

In counterfactuals, offer distributions and firms' behaviour are endogenized by targeting the underlying productivity distribution in which urban firms draw. It is estimated at baseline and assumed to stay constant across counterfactuals. Correspondingly, the rural-urban productivity gap is fixed, and so is the structural urban growth rate that is supposed to reflect it. The main policy scenario I estimate consists in progressively tripling the monitoring costs that weigh on urban informal firms. This simulates a wide range of labour inspection policies adopted in low- and middle-income countries (Ohnsorge & Yu, 2022), often with varying success (Gallien & Van den Boogaard, 2021). In response to the policy shock, the least productive informal firms switch to the formal sector. In my context, they are productive enough not to exit the market. One way of interpreting this result is to consider that barriers to entry are relatively high in South Africa, even in the informal sector, thereby limiting the scope for firms operating at near-zero productivity levels. As a consequence, the urban share of informal firms decreases by 8% and the urban share of informal workers by 10%. Whether alternative policies may lead to a similar outcome is beyond the scope of this paper.

The shock generates more competition for workers in the formal sector, destroying the least productive firms: 2% exit the market, raising the local unemployment rate by 2%. Still, over most of the productivity distribution, this effect is dominated by relaxed matching conditions for firms which are now competing for a wider pool of workers with fewer outside options. Consequently, formal firms post lower wages on average. This result stems from two factors. First, the competition effect pushing wages up is concentrated in the low end of the productivity range, where firms already have less market power. Second, the matching effect pushing wages down is all the more strong as informality is a valuable outside option in my context, due to relatively low frictions preventing the return to a formal job. Unemployment is more of an absorbing state, hence its high relative share compared to informal employment in South Africa. In the informal sector, firms reduce posted wages to mitigate their increase in size-related costs. Formal and informal firms also compete between each other and match with their respective workers conditionally on their productivity level, but this is second-order since search frictions are larger across than within sectors. As urban wages fall, it becomes profitable for some rural firms to outbid urban firms and retain workers. Such competition pushes the lowest-productivity rural firms out of the market and reallocates workers towards the most productive ones. The urban population share hence decreases by 4%, until congestion forces adjust to reflect the new spatial equilibrium. This corresponds to more than two years of reversed urban growth.

The rise in urban output generated by the reallocation of informal workers towards the formal sector comes at the cost of lower welfare on average due to firms' wage-setting power, even if formal workers are better paid than informal ones. In rural areas, increased wages and the reallocation of workers towards more productive jobs improve both welfare and output. Even though rural workers are less productive than urban ones on average, potential migrants decide to stay only when it is profitable to do so. As a consequence, global output increases more than urban output (+2%), and average aggregate welfare decreases less than average urban welfare (-1%). In fact, rural jobs limit the monopsony power of urban firms, which is also a source of labour misallocation. Indeed, when simulating an isolated city without rural-urban migration, the negative welfare effect of the policy is six times stronger for urban workers than in my main specification. This points to the role of rural jobs as an alternative outside option for potential migrants when urban informal employment becomes more constrained. The positive output effect is five times weaker, as the most productive urban firms are also those which cut wages the most, reallocating workers towards the least productive ones.

Related literature I contribute to the existing literature in three ways. First, I contribute to the labour economic literature dealing with the role of workers' informality in low- and middle-income countries. When simulating negative demand shocks on informal firms, researchers generally find positive effects on output, but negative (Ulyssea, 2010; Charlot *et al.*, 2015), neutral (Dix-Carneiro *et al.*, 2021; Haanwinckel & Soares, 2021), or even positive (Meghir *et al.*, 2015) effects on welfare. For comparison, the corresponding reduced-form literature (Almeida & Carneiro, 2009, 2012; De Andrade *et al.*, 2016; Ponczek & Ulyssea, 2022; Samaniego & Fernandez, 2024) typically finds negative effects on both welfare and output. This is because it mostly deals with law enforcement on formal firms hiring workers informally (Ulyssea, 2018), a possibility that I exclude in the absence of firm data, but that should only have second-order effects in my modelling approach. Compared to the symmetric policy that consists in decreasing the costs of formality for firms through taxes or entry costs (Ulyssea, 2010; Charlot *et al.*, 2015; Narita, 2020; Haanwinckel & Soares, 2021), increasing the costs of informality for firms empirically leads to higher formalization rates (Ulyssea, 2020). This also holds in comparison with the policy that consists in reducing the costs of formality for workers through wage subsidies (Abel *et al.*, 2022). Note that informal workers are rarely targeted directly. I therefore focus on increasing the costs of informality as my main policy scenario in this paper.

Although my approach is closer to the one adopted by Meghir *et al.* (2015) for Brazil, my results are more aligned with Ulyssea (2010) and Charlot *et al.* (2015), as my formalization shock generates a trade-off between lower welfare and higher output. I argue that this is due to different underlying frictions in our empirical settings. I also show that the local effects found in these studies are likely an underestimate of the global effects, as I find that endogenous rural-urban migration choice is associated with stronger positive effects on output and weaker negative effects on welfare. This is because rural employment acts as an alternative outside option limiting urban firms' labour market power in the absence of urban informal employment. Incidentally, I complement the recent reduced-form literature on the role of informality as a stepping-stone for workers (Samaniego, 2024). I also align with existing evidence on firms' local labour market power in low- and middle-income countries (Brooks *et al.*, 2021; Felix, 2022; Amodio & De Roux, 2023; Armangué-Jubert *et al.*, 2023; Bassier, 2023), especially across formal and formal jobs (Amodio *et al.*, 2023), as well as rural and urban jobs (Marshall, 2025).

Second, I bridge the previously cited informality literature with the economic literature dealing with migration models, primarily in low- and middle-income countries with a strong rural-urban divide (Bryan *et al.*, 2014; Munshi & Rosenzweig, 2016; Morten, 2019; Meghir *et al.*, 2022; Lagakos *et al.*, 2023). Compared to most of these papers, I focus on permanent, rather than seasonal migration. My approach is therefore closer to the one adopted by Bryan & Morten (2019) or Tombe & Zhu (2019), who find substantial welfare and productivity gains when removing spatial frictions. Likewise, I motivate my model by documenting the rural-urban income gap (Lagakos *et al.*, 2020) and rural-urban productivity gap (Pulido & Święcki, 2019; Gai *et al.*, 2024; Cenci *et al.*, 2024) when adding heterogeneity across the urban formal and informal sectors. None of these papers endogenize the job search process inherent in many migration decisions, and therefore cannot deal adequately with potential spatial spillovers of local labour market policies. A notable exception is Marshall (2025), who considers local labour markets featuring both self-employment and regular firms with market power, and finds few spatial spillovers. Apart from the fact that I focus on informal jobs generally and not on self-employment specifically, our settings differ in that I incorporate dynamic frictions along with unemployment risk. I see these two elements as key for studying spatial labour misallocation.

My methodology therefore aligns more closely with migration models featuring job search-and-matching, that are often set in high-income countries (Kennan & Walker, 2011; Baum-Snow & Pavan, 2012; Schmutz & Sidibé, 2019; Balgova, 2022; Maguain & Koubi, 2025; Martellini, 2022). I adapt them to a middle-income country context with two sectors, a formal and an informal one, and ongoing urbanization. Most related to my work, Heise & Porzio (2022) find that removing spatial frictions increases both welfare and output, due to an improved worker allocation within rather than across locations. Indeed, removing spatial frictions increases the local competition for workers and diminishes firms' local monopsony power. The simulation I run without rural-urban migration can be seen as an extreme case with infinite spatial frictions.

I find effects that are symmetric with Heise & Porzio (2022), as welfare and output decrease compared to my baseline results. The allocation of urban workers across the formal and informal sectors does not vary much across the two specifications, unlike in Marshall (2025). This may be due to the importance of informal wage employment in my context, compared to self-employment that is deemed to be frictionless in his approach.

I also see my work as complementary to the structural informality literature focusing on firm dynamics (D'Erasmo & Boedo, 2012; Ordóñez, 2014; Allen *et al.*, 2018; Ulyssea, 2018; Lopez-Martin, 2019; Erosa *et al.*, 2023; Alvarez & Ruane, 2024), as opposed to worker dynamics. Most related to my work, Imbert & Ulyssea (2023) simulate the impact of an exogenous migration shock in rural areas on urban labour markets with informal employment. In the long-run, as formal wages become flexible, it becomes profitable for informal firms to formalize and urban informal employment decreases. This translates into higher urban output but lower welfare, which is consistent with my results. I place myself in a similar perspective, as I consider fully flexible wages in equilibrium, and I add rural production. However, my findings suggest a feedback-loop effect that is absent from their model: with search frictions and endogenous migration choice, rural-urban migration flows should decrease as urban informality and wages fall, mitigating the initial effects.

Third, I contribute to the literature studying the role of labour market frictions - and factor misallocation - in structural transformation (Restuccia & Rogerson, 2017; Hao *et al.*, 2020; Martellini & Menzio, 2021; Guner & Ruggieri, 2022; Buera *et al.*, 2023; Donovan & Schoellman, 2023; Gollin & Kaboski, 2023; Feng *et al.*, 2024). For instance, Schwartzman (2025) proposes a (non-spatial) model of structural transformation through endogenous formalization of low-skilled services. In my model, I do not account for technology/skill changes or agglomeration economies across space, notably because I do not observe overlapping generations of workers (Hobijn *et al.*, 2018; Porzio *et al.*, 2022). In fact, the relation between rural-urban migration and industrialization is not clear in my sample: as the economy urbanizes, urban employment appears to switch from manufacturing to more labour-intensive consumer services (Imbert *et al.*, 2022; Fan *et al.*, 2023), but so does rural employment. As in Budí-Ors (2024), the share of agriculture in rural employment decreases, but it also increases in urban employment. There is no clear relation between industry composition and formality status either. I therefore abstract from industrialization: in the model, this translates into a fixed rural-urban productivity gap and urban growth rate across counterfactuals. Rather, I show how a given local labour market policy impacts aggregate urbanization, output, and welfare at a given stage of the industrialization process.

The rest of this paper is structured as follows. Section 2 presents the data and some motivating facts. Section 3 presents the model and Section 4 how it is estimated. Section 5 presents the baseline results and Section 6 the policy counterfactuals. Section 7 concludes.

2 Data and Motivating Facts

2.1 Context

Compared to countries with similar levels of GDP per capita (such as Brazil), South Africa features a relatively high rate of unemployment or inactivity, and a relatively low (but still substantial) rate of informal employment (ILOSTAT, 2023), which makes it an interesting case study per se. This also holds for self-employment (Poschke, 2024), which is mostly informal. Correspondingly, job destruction rates are also comparatively high, and job finding rates comparatively low, in the informal sector (Donovan *et al.*, 2023). Rodrik (2008) and Banerjee *et al.* (2008) point to the legacy of apartheid in explaining low levels of social networks and entrepreneurship needed to support informal activity, whereas Shah (2022) points to substantial spatial frictions within cities (regressive transport costs, zoning, and permits) and competition from the formal sector in a few key industries (hospitality, retail, commercial agriculture). Abel (2019) adds that generous old-age pensions may increase reservation wages of working-age household members sharing expenses with the beneficiaries.

Then, South Africa is likely a good setting for studying rural-urban migration. The fact that cities grew while rural areas stagnated during the apartheid era translates into a strong rural-urban welfare gap that persists to this day (Lochmann, 2022). Moreover, the end of apartheid indeed led to massive out-migration flows for Black people living in rural areas (Dominguez-Iino & Le Roux, 2022). This is an important phenomenon that is still feeding current urban growth (Bakker *et al.*, 2019). The informal employment rate has remained relatively stable over the period, with unemployment rising at the expense of formal employment (Elgin *et al.*, 2021). South Africa is therefore comparable to other low- and middle-income countries in the SSA and EAP regions in terms of urbanization and informality trends. However, its relatively high level of urban population and low level of informality align more closely with emerging economies elsewhere (e.g., Turkey).

Regulations weighing on informal firms are mostly enforced by local governments (Asmal *et al.*, 2024). The authors argue for the easing of such restrictions to facilitate informal activities in the face of high unemployment. However, the creation in 2022 of a National Labour Inspection Task Team by the central government to target the informal sector seems to go in the opposite direction. I will therefore simulate a shock of this type in Section 6. I leave for future work the question of whether the opposite policy can create enough jobs to offset the inefficiencies associated with the informal sector.

2.2 Data

The National Income Dynamics Study[1] (NIDS) is a nationally representative panel survey of South African workers. It samples 28,226 individuals from 7,305 households, starting in 2008, and interviews them again on average every 27 months (2.25 years) until 2017 (i.e., over five waves). It features a relatively low rate of attrition for such a long period (27%), and a large number of variables compared to similar studies set in low- and middle-income countries (Lagakos *et al.*, 2020). Below, I define my benchmark sample as well as my main variables of interest.

Sample selection I reduce my benchmark sample to working-age adults to focus on job-related mobility of independent agents. Note that, even when sampled with other household members, individuals move alone in the vast majority of cases: see Table A1 for more details on co-residence patterns; also see Imbert *et al.* (2023) for a model of joint decision problems. Then, I restrict my sample to individuals without a high-school certification (or equivalent diploma) since the low-skilled are the most affected by informal employment. This is also a way to ensure that mobility patterns are not associated with (adult) education choices (Bobba *et al.*, 2022) and potentially heterogeneous returns to education across the formal and informal sectors (Joubert, 2015; García, 2015).

I further focus on male workers since labour market frictions and preferences vary by gender, especially in low- and middle-income countries. More specifically, female workers tend to favour jobs with fewer (Mahmud *et al.*, 2021) and more flexible (Ho *et al.*, 2024; Berniell *et al.*, 2021; Bernatzky *et al.*, 2024) working hours. These are often found in the informal sector as women face difficulties finding regular, part-time work (Fletcher *et al.*, 2017; Caria *et al.*, 2021). They also may face discrimination from recruiters (Kuhn & Shen, 2013; Chowdhury *et al.*, 2018; Chaturvedi *et al.*, 2021; Gentile *et al.*, 2023), and search differently from men due to the time demands of unpaid domestic work, mobility constraints, limited social networks (Field *et al.*, 2010; Kandpal & Baylis, 2019; Anukriti *et al.*, 2020), or heterogeneous risk-aversion profiles (Archibong *et al.*, 2022). Focusing on men therefore allows me to abstract from these different dimensions as a first approach.

Finally, I aggregate all sources of individual labour market income to obtain monthly wages (including of self-employment) net of taxes. I multiply them to cover full time periods between waves, deflate them to Dec. 2012 levels (using indices included in the data), and de-trend them by residualizing for wave fixed effects, so as to make them comparable across time periods. Then, I drop individuals found in the first and last percentiles of the wage distribution to reduce heterogeneity in the sample. I am left with a panel of 3,453 individuals.

[1] Department of Planning, Monitoring, and Evaluation; Southern Africa Labour and Development Research Unit; DataFirst

Geography One specificity of this data set is that it allows to identify informal employment while following individuals when they change locations. Although I do not have access to a finer geographic scale than the 52 districts of South Africa in the open version of the data, I know whether the enumeration area (census block group) where individuals live was classified as urban or rural in the 2011 National Census (based on the continuity of built-up areas). More precisely, rural areas can be decomposed into communally-owned land and commercial farm land, but I abstract from this heterogeneity margin in the remainder of the paper. Suffices to say here that the more populated traditional areas are characterized by more non-agricultural informal jobs (and non-employment), and farms by more agricultural formal jobs. However, their inhabitants are roughly as likely to move to cities, and almost never move between rural area types (Table A2).

Over the pooled cross-section of observations, I obtain a non-response rate of 22%, not reducible to permanent attrition. Out of these non-responses, only 22% are due to a geographic move that is not well followed (Table A3). Since I do not know whether such moves occur across geography types or not, this is an upper bound on the probability that non-response is due to unobserved rural-urban moves. With that in mind, I decide to impute missing values for geography type (and employment status), based on past or future states, to obtain a balanced panel.

The vast majority of individuals declare to reside permanently (i.e., stay more than four nights a week) in the area where they are interviewed and there is no apparent seasonality in interview dates, ruling out potential temporary migration patterns (Figure A1). Furthermore, I abstract from sequential migration as 80% of migrants only move once in my sample (Table A4). I also consider that respondents work in the same area type as where they live, and more specifically that rural workers do not commute to urban areas. They therefore have to migrate to benefit from local job opportunities: based on estimates of commuting costs from Pfeiffer *et al.* (2025), I find that 90% of the rural subsample for which I have information on transport expenses travel less than 5km to go to work, with 75% not traveling at all (Figure A2).

Informality Since workers do not directly declare themselves as being informal, I follow the definition of informal work used by Bassier *et al.* (2021) with the same data: self-employed workers not registered to VAT or income tax; wage workers without a written contract and who do not contribute to medical aid, unemployment insurance, or pension funds; and workers declaring to work on a "casual" basis. Such objective definition also reduces the self-perception bias respondents may have when considering their formality status. More generally, I consider the self-reporting bias risk to be low in my context, given the anonymous nature of the survey and the fact that penalties are mostly set at the firm level. Besides, they tend to target relatively large firms, and typically not self-employed workers. Finally, aggregate informality figures from the survey are in line with macro estimates from ILOSTAT.

In both urban and rural areas, formal employment is essentially wage employment. Informal employment however can be roughly split as 40% wage employment, 40% casual work, and 20%

self-employment (Table A5). Casual work can be assimilated to wage work on less permanent terms: this potentially points to informal firms (the extensive margin of informality) as opposed to formal firms hiring workers informally (the intensive margin), although the data does not allow me to confirm it. Self-employment does not appear as a frictionless outside option since it features a relatively high job destruction probability. There also appears to be many transitions between informality types, with a higher chance of being promoted to a formal job when working as an informal wage earner. Finally, other statistics are consistent with studies showing that the preference for self-employment increases over the life-cycle (Narita, 2020) and that self-employment can be characterized by a lower labour supply on the intensive margin (Bick *et al.*, 2022): see Table A6 for more details. For the sake of tractability, I abstract from the different types of informality in the rest of this paper, hence these different mechanisms: this can be seen as a limitation of my work. Still, given the dominance of informal wage-like employment in my context, I do not consider this as a first-order issue.

I further collapse rural formal and informal jobs into a unique rural employment category, since my focus is on urban formalization policies. For reference, Table A7 decomposes the observed heterogeneity between formal and informal jobs, in both urban and rural areas: apart from the probabilities of losing one's job, the probabilities to change status when employed in rural areas (be it formality status or geography type) are very similar across formal and informal jobs. It is also worth noting that urban informal wage jobs are one-third more likely than formal ones to be obtained through personal networks. Personal connections can indeed be seen as an alternative to formal contract enforcement. Besides, there is no strong heterogeneity in industries across the wage formal and informal sectors, but there is across urban and rural areas given the role played by agriculture (Table A8). The industry composition of urban and rural areas appears to be relatively stable over time as well (Figure A3). Importantly, the unconditional probability to change industries is relatively high in all states, if not in agricultural jobs. This corresponds to the idea of a low-skilled workforce being highly substitutable across industries (Belot *et al.*, 2019). Also note that the vast majority of transitions out of agriculture occur within rural areas.

Employment When employed, it is roughly as likely to become inactive as it is to become unemployed. When inactive, it is roughly as likely to become active as it is to stay inactive (Table A9). I therefore merge the non-economically active and the unemployed into a non-employed category in the remainder of the paper. Note that this category may include workers engaging in non-remunerated home production. Hence, I abstract from labour force participation choice, which may be complementary to migration choice: in my sample, it is almost twice as likely to transition from inactivity to activity for rural-urban movers than for rural stayers.

I identify on-the-job transitions within the formal and informal sectors via employment spells lasting less than the time interval between two interview dates (imputed from modal months when dates are missing). The duration of employment spells is available for wage workers only. For non-wage workers, I identify on-the-job transitions through changes in employment type (wage, casual, or self-employment), district, or geography type (traditional, farms, or urban).

Finally, I make use of a retrospective variable yielding employment states in between periods. This allows me to correct for non-employment spells in between employment periods and employment spells in between non-employment periods (assuming other job characteristics do not change), and to consider close-to-yearly (13.5 months) time periods. Wages are correspondingly divided by two. It is worth noting that median wage growth for employed workers who keep the same job is close to zero, which I interpret as evidence of low returns to experience for low-skilled workers (Bobba *et al.*, 2021). On the contrary, changing jobs tends to be associated with a wage increase, especially when changing formality status or geography type (Table A10).

Table 1: Aggregate summary statistics by mover status and geo-employment state

	Mover status				Geo-employment state				
	R-R	U-U	R-U	U-R	RE	RN	UF	UI	UN
Nb of obs.	7,295	7,815	1,710	445	4,172	4,247	3,348	2,173	3,325
Tot. share (%)	42.25	45.26	9.90	2.58	24.16	24.60	19.39	12.59	19.26
Black (y/n)									
Mean	0.92	0.69	0.86	0.87	0.85	0.98	0.72	0.69	0.71
SD	0.27	0.46	0.35	0.34	0.36	0.15	0.45	0.46	0.45
Age (yrs)									
Mean	39.36	39.54	32.72	39.53	39.09	37.89	40.54	37.52	38.63
SD	11.65	11.51	9.92	12.77	10.69	12.78	10.61	10.81	12.49
Educ. yrs									
Mean	6.35	7.95	8.15	7.54	6.42	6.66	8.42	7.80	7.69
SD	3.75	2.97	3.27	3.28	3.76	3.71	2.77	3.11	3.06
HH size									
Mean	5.14	4.31	4.34	3.45	4.22	6.03	3.77	3.88	4.78
SD	3.70	2.80	3.36	2.70	3.49	3.62	2.58	2.82	2.92

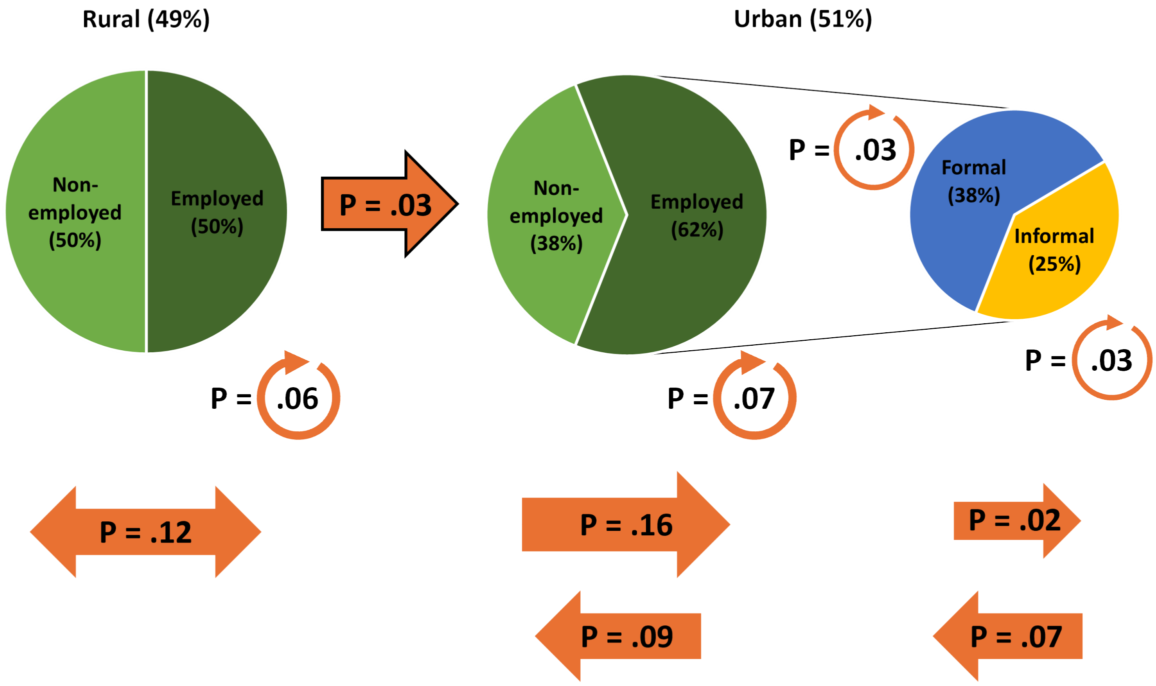
Notes: National Income Dynamics Study 2008-2017, males without a high-school certification, aged 18-64. Mover status on the left panel identifies individuals according to their geographic moves over time: 'R-R' stands for rural stayers, 'U-U' for urban stayers, 'R-U' for rural-urban movers, and 'U-R' for urban-rural movers. Geo-employment state on the right panel identifies individuals at a given point in time according to their geography and employment types: 'RE' stands for rural employed, 'RN' for rural non-employed, 'UF' for urban formal, 'UI' for urban informal, and 'UN' for urban non-employed. All statistics are pooled over the study period.

Summary statistics Table 1 summarizes key individual statistics over the pooled cross-section of observations, across mover statuses and geo-employment states. I attribute a mover status to individuals in the sample depending on whether they change geography types at least once over the study period. Those who never do are classified as either rural (R-R) or urban (U-U) stayers, and those who do as either rural (R-U) or urban (U-R) movers depending on the area type where they enter the sample. As specified above, I do not deal with more complex migration patterns. Note however that so-called stayers may include movers within a given geography type: this contributes to explain the attractivity of large urban agglomerations, but also some rural districts (Figure A4). Likewise, I only consider five geo-employment states: rural non-employed (RN), rural employed (RE), urban non-employed (UN), urban formal (UF), and urban informal (UI). Contrary to mover status, an individual can change geo-employment types over the study period

Rural and urban stayers have similar age profiles, but urban stayers are likely to be more educated, live in smaller households, and belong to a non-Black population group (typically Coloureds in the Western Cape province). Rural-urban movers tend to be Black, but are more like urban stayers in other respects, except that they are younger. Urban-rural movers share similar characteristics but are typically older. This would suggest a life-cycle pattern in which rural natives move back to rural areas after some time in the city. In fact, 20% of urban-rural moves can be characterized as a return to the district of birth, whereas only 6% of rural-urban moves can. This also means that urban-rural moves are less likely to be motivated by job search (Table A11). For this reason, and because they are also four times less frequent, I abstract from such moves in the remainder of this paper. Within rural and urban areas, the non-employed also tend to fit a more "traditional" profile, being younger, less educated, and living in larger households. However, the heterogeneity is less strong than across mover statuses. This is even more so across urban formal and informal workers. I will therefore focus on rural-urban migration when studying the potential bias arising from self-selection across states in my model.

2.3 Stylized Facts

Figure 1: Pooled worker stocks and flows across geo-employment states



Notes: National Income Dynamics Study 2008-2017, males without a high-school certification, aged 18-64. The pie charts in light and dark green display the allocation of workers across employment and non-employment within urban and rural areas. The pie chart in blue and yellow displays the allocation of workers across formal and informal jobs within urban employment. The circular arrows display the periodic probability of accepting a new job conditional on initial employment state. The straight arrows display the periodic probability of moving to a new geo-employment state, conditional on the initial one.

Worker stocks and flows Figure 1 displays the worker allocation within geography types and across employment states of interest in my model (recovered from Table 1), along with the yearly periodic probabilities of transitioning to a new geo-employment state conditional on the initial one. Because I abstract from them, urban-rural migration flows are not shown in the diagram. In the interest of space, I also do not decompose rural-urban flows according to employment state at destination, and urban employment-nonemployment bilateral flows according to formality status (see Table A12 for the detailed values). Also note that worker stocks and flows are pooled over the entire study period. This is because I do not have enough observations to study transition histories in a satisfying way. In the model, this will be mapped into a memory-less Poisson point process.

Indeed, transition probabilities will serve as the first set of targeted moments in Section 4. Worker shares across geo-employment states will serve as a set of untargeted moments to validate the approach. An important assumption allowing me to pool geo-employment flows together is that of worker homogeneity. This will be discussed further in the next sub-section. Suffices to say here that the mean-adjusted predicted probabilities recovered from a multinomial logit model that controls for worker observable characteristics (Table A13) do not substantially differ from the ones found in Table A12.

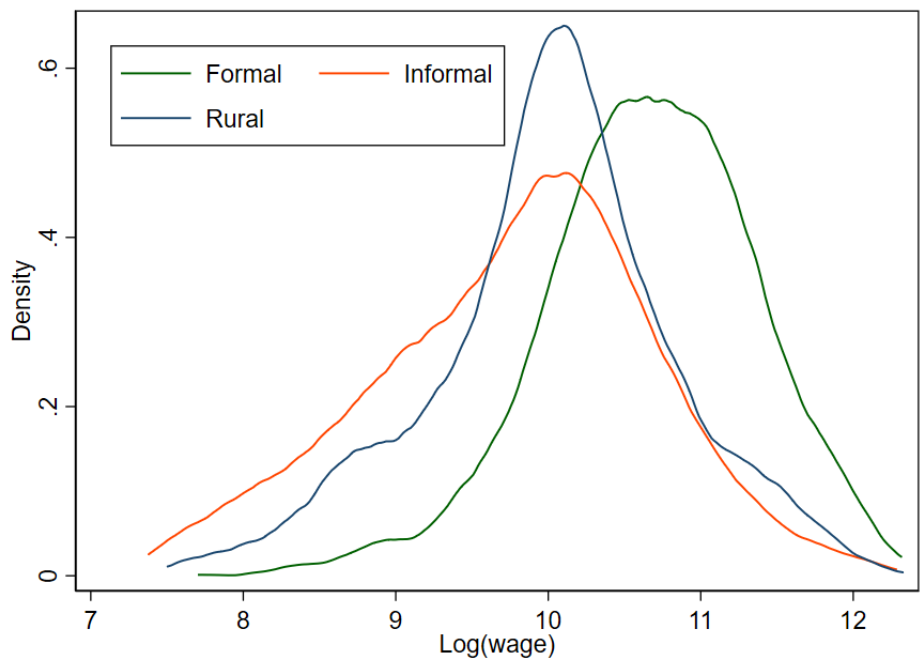
Regarding worker stocks, the rural-urban population shares, non-employment, and informality rates are somewhat larger than those found in macro data from the World Bank and ILOSTAT due to sample selection. As expected, cities seem to offer more job opportunities with a lower (if still high) non-employment rate (one-third) compared to rural areas (one-half), but also a substantial informality margin (one-third of urban employment).

Regarding worker flows, let us first remark that, at every period, the most likely outcome is to stay in the same state with no on-the-job transitions. Then, there is some probability for employed workers to succeed in on-the-job search (either within the same sector or across formality status) or to lose their job, and for non-employed workers to find a job locally. Those probabilities are of the same order of magnitude. If anything, job-finding probabilities are higher and job-losing probabilities are lower in cities than in rural areas. It is worth noting that urban formal jobs are more stable than urban informal ones, with lower job destruction. Still, the urban non-employed appear to find informal jobs more easily than formal ones, and transition probabilities from informal to formal employment are actually higher than on-the-job transition probabilities within the informal sector: this points to potential negative side-effects of formalization policies on the non-employed, even if informal jobs are replaced one-to-one by formal jobs.

Probabilities to migrate are typically smaller. One has to keep in mind that this is still one order of magnitude above what is found in high-income countries: whereas the aggregate urban population share in South Africa has grown by 8% over my study period, it has only done so by 2% in the United States (World Bank). Also note that, although probabilities to migrate into urban informality are not substantially different from probabilities to migrate into urban formality, rural-urban migrants are one-quarter more likely to be informally employed than urban stayers, which conforms to the empirical regularity observed in other contexts. Still, if informal jobs are replaced one-to-one by formalization policies, heterogeneous search frictions among migrants should not be the primary driver behind changes in urbanization rates.

Finally, note that I will also abstract from migrations into non-employment in the remainder of the paper, although they are non-negligible in the data. This is because, under spatial equilibrium conditions, such moves can only be rationalized through idiosyncratic preferences that are only affected indirectly by labour market conditions: see Balgova (2022) for a discussion. I therefore do not consider this simplification as being first-order given my current focus.

Figure 2: Pooled cross-sectional log wage distributions by model employment state



Notes: South African National Income Dynamics Study 2008-2017, low-skilled males aged 18-64. Wages are deflated for interview date, de-trended for wave fixed effects, and multiplied to cover one full period in the model (approximately one year), so as to be comparable across individuals and time periods. They include all sources of labour income.

Wage distributions Figure 2 plots pooled cross-sectional log wage distributions for the three employment states of interest. This is the second set of moments targeted in the model. Along with transition probabilities, they will jointly identify friction parameters and offer distributions.

As with the transition matrix in Table A13, I compute mean-adjusted wages that account for the variation in worker characteristics and plot them across sub-groups in Figure A5: selection on observables does not seem to explain most of the heterogeneity across employment states. However, selection on unobservables could still play a role. Indeed, if the plotted wage distributions do not properly reflect the wages of workers upon transitioning from one state to the other, using the aggregate transition probabilities from Table A12 could lead to biased estimates in Section 4. I therefore study self-selection into migration more specifically in the next sub-section, since it is the main potential source of bias.

The three distributions share roughly the same support, but urban formal wages dominate the others, and rural wages slightly dominate urban informal wages. The variance is also higher for urban informal than urban formal wages, and lower for rural wages. However, as I will assume risk-neutral agents, volatility in earnings will not affect workers' welfare directly in the model. One way to deal with insurance motives in future work would be to calibrate the insurance value of formal vs. informal jobs — and urban vs. rural jobs — as lump-sum transfers, using results from Finamor (2024) and Lagakos *et al.* (2023) for instance.

Interestingly, if these distributions indeed reflect the accepted offers from workers, conditional on their employment state, then workers moving from rural to urban informal employment do incur a wage cut on average. The model will allow to rationalize such moves, by distinguishing between the effect of amenities, career prospects, and potential overoptimism.

2.4 Observational Returns to Migration

Table 2: Linear regression of log wages over an urban dummy

	Formal jobs			Informal jobs		
	(1)	(2)	(3)	(4)	(5)	(6)
Urban	0.639***	0.193***	0.291***	-0.249***	-0.220***	-0.173
	(0.040)	(0.060)	(0.104)	(0.044)	(0.082)	(0.165)
Obs.	4,978	629	392	3,990	471	297
Adj. R^2	0.150	0.566	0.433	0.019	0.455	0.439
Controls	No	Yes	Yes	No	Yes	Yes
Ind. FE	No	Yes	Yes	No	Yes	Yes
Sample	All	Movers	Rural movers	All	Movers	Rural movers

Clustered standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: South African National Income Dynamics Study 2008-2017, low-skilled males aged 18-64. The left panel accounts for urban formal jobs, the right panel for urban informal jobs. Controls are quadratic and include age, education, and household size.

To test to which extent the cross-sectional wage gains differ from the actual gains experienced by movers, Table 2 focuses on rural-urban migrants, and shows the average monetary returns separately for urban formal and informal jobs. This is not a set of moments targeted by the model, but it can be used to quantify the importance of residual self-selection.

Each panel shows the estimated coefficients for three distinct linear regressions of log wages over an urban dummy. Columns (1) and (4) show the raw regression coefficients and reflect the cross-sectional wage gaps. Columns (2) and (5) include individual fixed effects and time-varying controls for the subset of movers. Columns (3) and (6) show the coefficients estimated on the sub-sample of rural-urban movers. This is essentially the same set of regressions estimated in Lagakos *et al.* (2020) but with a selected sample, individual income instead of household income per person, and an heterogeneity analysis based on urban formality status.

Several remarks are in order. First, rural movers incur a wage cut when accepting an informal job in cities, no matter the specification. Second, the coefficient for urban informal jobs does not change much across specifications. I interpret this as evidence of little self-selection of rural migrants into urban informality: no matter their differences, they are as likely to draw from the same wage distributions as stayers in origin and destination states. This is not the case for urban formal jobs, given the reduction observed between columns (1) and (2). Fixed effects are driving most of the difference. At least, the formal urban wage gap remains significantly positive, and its value is robust to restricting the sample to rural-urban migrants.

Since self-selection across origin-destination pairs will be captured by observed transition probabilities, only the unobserved heterogeneity that remains within pairs will bias my estimates (see Section 4.2.1). The gap between cross-sectional and observational returns to migration (for urban formal jobs) is therefore an upper bound on the actual bias on wage draws experienced by such movers in my model (for a spatial search-and-matching model with heterogeneity within origin-destination pairs, see Heise & Porzio (2022)). I will show in Section 5.3 how this affects the option value of urban formal jobs for rural workers, and why this should not drive most of my results. I now turn to the formulation of the model to define more explicitly the meaning of these terms.

3 Model

3.1 Workers' Program

Environment Let us consider two local labour markets: a rural and an urban one. Workers are infinitely lived, homogeneous, and risk-neutral. They inelastically supply one unit of labour. They randomly search for jobs in a memory-less fashion, on- and off-the-job, locally and remotely. They do so across both the formal and informal sectors. I only distinguish between formal and informal jobs in urban areas. Formal jobs provide workers with unemployment benefits and severance payment paid as a lump-sum transfer when they get destroyed. This assumption allows me to keep the model independent of time and is without loss of generality under risk neutrality. The contribution of pensions and medical aid to welfare is lost as there is no corresponding standardized plan to incorporate in the homogeneous model.

Problem Workers accept job offers so as to maximize their expected lifetime utility stream W_i^k in area $i \in \{Rural, Urban\}$ and sector $k \in \{Nonemployed, Employed\}$ for rural areas or $k \in \{Nonemployed, Formal, Informal\}$ in urban areas, discounted at calibrated rate r. They take as given their current wage w when employed or utility of leisure b when non-employed, plus a relative amenity term γ (that can be positive or negative) in rural areas: this captures distinct factors such as housing prices, public services and infrastructure, local networks, or education opportunities for children. These terms sum up to workers' flow utility value.

They receive job offers with values W_j^l distributed according to exogenous cumulative distributions F_j^l (and complementary functions $\overline{F_j^l}$) with supports $[\underline{W_j^l}, \overline{W_j^l}]$, that arrive at exogenous rates λ_{ij}^{kl} (from state ik to state jl) according to a Poisson process. They accept job offers whose value is higher than their current one, plus a compensating differential for calibrated monetary mobility cost c when mobing from rural to urban areas. The largest share of migration costs is likely to be non-monetary (Imbert & Papp, 2020a; Bryan *et al.*, 2021; Lagakos *et al.*, 2023), but Schmutz & Sidibé (2019) show that migration costs are not separately identified from spatial frictions without additional structure: the non-monetary component is therefore captured by job arrival rates in my model. When employed, workers' job gets destroyed at exogenous Poisson rate δ_i^k. When losing a formal job, workers benefit from unemployment insurance at calibrated rate UIF and severance payment at calibrated rate s, that are paid upfront as a fixed fraction of their current wage. These terms sum up to workers' option utility value.

Workers only move from one area to the other with a job in hands: this pins down relative amenities in equilibrium as the constraint $W_R^N \geq W_U^N - c$ is saturated (spatial equilibrium condition). Besides, non-employed workers accept all the offers they are made within their current local labour market: this pins down utility of leisure in equilibrium as the reservation value is set to $W_R^N = \underline{W_R^E}$ in rural areas and $W_U^N = \underline{W_U^I}$ in urban areas, assuming $\underline{W_U^I} \leq \underline{W_U^F}$ (reservation value condition). After integrating by parts, the Bellman equations associated with the workers' problem are:

$$rW_R^N = \gamma + b + \lambda_{RR}^{NE}\left(\int_{\underline{W_R^E}}^{\overline{W_R^E}} x dF_R^E(x) - W_R^N\right) + \lambda_{RU}^{NF}\int_{W_R^N+c}^{\overline{W_U^F}} \overline{F_U^F}(x)dx + \lambda_{RU}^{NI}\int_{W_R^N+c}^{\overline{W_U^I}} \overline{F_U^I}(x)dx \tag{1}$$

$$\begin{aligned} rW_R^E(w) =& \gamma + w + \delta_R^E\left[W_R^N - W_R^E(w)\right] \\ &+ \lambda_{RR}^{EE}\int_{W_R^E(w)}^{\overline{W_R^E}} \overline{F_R^E}(x)dx + \lambda_{RU}^{EF}\int_{W_R^E(w)+c}^{\overline{W_U^F}} \overline{F_U^F}(x)dx + \lambda_{RU}^{EI}\int_{W_R^E(w)+c}^{\overline{W_U^I}} \overline{F_U^I}(x)dx \end{aligned} \tag{2}$$

$$rW_U^N = b + \lambda_{UU}^{NF}\left(\int_{\underline{W_U^F}}^{\overline{W_U^F}} x dF_U^F(x) - W_U^N\right) + \lambda_{UU}^{NI}\left(\int_{\underline{W_U^I}}^{\overline{W_U^I}} x dF_U^I(x) - W_U^N\right) \tag{3}$$

$$\begin{aligned} rW_U^F(w) =& w \\ &+ \delta_U^F\left[W_U^N + (UIF+s)w - W_U^F(w)\right] + \lambda_{UU}^{FF}\int_{W_U^F(w)}^{\overline{W_U^F}} \overline{F_U^F}(x)dx + \lambda_{UU}^{FI}\int_{W_U^F(w)}^{\overline{W_U^I}} \overline{F_U^I}(x)dx \end{aligned} \tag{4}$$

$$rW_U^I(w) = w + \delta_U^I\left[W_U^N - W_U^I(w)\right] + \lambda_{UU}^{IF}\int_{W_U^I(w)}^{\overline{W_U^F}} \overline{F_U^F}(x)dx + \lambda_{UU}^{II}\int_{W_U^I(w)}^{\overline{W_U^I}} \overline{F_U^I}(x)dx \tag{5}$$

Equilibrium conditions Let us comment on the underlying assumptions. When employed, workers can lose their job and become non-employed, but never accept an offer with a lower value than their current one (for a job-search model allowing for value cuts in on-the-job transitions, see Jolivet *et al.* (2006)). I do not see this as a critical assumption given that median wage growth for employed workers who change jobs is 2.8%, which is not only positive but also substantially higher than wage growth for workers who keep the same job. There is no wage renegotiation or firms' response to outside offers, and the only way for workers to increase their wage is through on-the-job transitions.

When non-employed, workers accept any local offer they are made. This corresponds to the reservation value condition stating that, in equilibrium, the value of local non-employment is equal to the lower bound of local employment values: for values above the threshold, firms have a profitable incentive to downgrade their offers; for values below the threshold, firms naturally upgrade their offers as they are unable to recruit local workers at such low values (I assume that firms do hire at least some workers locally).

Finally, I do not allow for migration into non-employment. This corresponds to the spatial equilibrium condition stating that, in equilibrium, no non-employed worker can be worse off than what they would be if they moved into non-employment in the other location. Indeed, if it were the case, all non-employed workers in one area would move to the other, which is counterfactual: Balgova (2022) rationalizes such moves through idiosyncratic location preference shocks that only satisfy the spatial equilibrium condition on average. In my context, this means that rural non-employed workers' welfare is greater or equal to urban non-employed workers' welfare minus migration costs. In practice, this constraint is saturated to be consistent with the assumption of no urban-rural moves.

3.2 Stationary Worker Flows

Geography I do not allow for urban-rural moves, as adding them prevents me from solving analytically for worker shares in the equations below: this is a numerical limitation. However, both rural-rural and urban-urban moves are implicitly captured by on-the-job transitions within a given geography type.

Importantly, my sample is not at a geographic steady state to the extent that rural-urban migration flows dominate urban-rural ones: at the end of my study period, the urban population share has grown linearly by 13%. I therefore have to target this observed urban growth to close the model. This accounts for structural urban growth factors, assumed to be constant over the study period, that are implicitly captured in model parameters but not fully micro-founded since they do not only depend on search-and-matching in the labour market.

Even with urban-rural moves, assuming a geographic steady state to close the model would therefore be a crude approximation of labour market conditions in urbanizing countries. However, given that I consider infinitely-lived agents and a fixed urban growth rate, solving the model out of steady state would lead to empty rural areas over the very long run. In reality, the urban growth rate decreases slowly in macro data (World Bank). My stationary results should therefore be interpreted as transitory outcomes at a given stage of a slow structural change process, rather than as stable equilibrium outcomes over the very long term. As a side note, one could impose a geographic steady state in the model by having overlapping generations of workers with a higher rate of natural population growth in rural than in urban areas, but this is counterfactual (Jedwab *et al.*, 2017).

Employment To solve the model, I additionally assume that the shares of employed workers with welfare W are at the steady state for all values of W. The shares of non-employed workers therefore adjust in the stationary equilibrium to reflect both the steady-state and the urban growth conditions. The empirical deviations from steady state will be captured in the quality of the model fit, which will allow to quantify the strength of the model assumptions more generally.

Problem The stationary equilibrium hence features a fixed worker allocation across employment $\{m_R^E, m_U^F, m_U^I\}$ and non-employment $\{u_R, u_U\}$ states in urban and rural areas, such that $m_R^E + u_R + m_U^F + m_U^I + u_U = 1$. To recover these quantities analytically, and to express (unobserved) offered value distributions F_i^k as a function of (observed) accepted value distributions G_i^k, I assume that worker inflows equate outflows in any employment state for any point of the welfare distribution, and that rural worker outflows equate targeted urban population growth. This translates into three steady-state equations for employment states in the model and one structural urban growth equation for urban and rural shares. After integrating by parts, this yields:

$$m_R^E G_R^E(W) d_R^E(W) + m_R^E \left(\lambda_{RU}^{EF} \int_{\underline{W_R^E}+c}^{W+c} G_R^E(x-c) dF_U^F(x) + \lambda_{RU}^{EI} \int_{\underline{W_R^E}+c}^{W+c} G_R^E(x-c) dF_U^I(x) \right)$$
$$= u_R \lambda_{RR}^{NE} F_R^E(W) \tag{6}$$

$$m_U^F G_U^F(W) d_U^F(W) + m_U^F \lambda_{UU}^{FI} \int_{\underline{W_U^F}}^{W} G_U^F(x) dF_U^I(x) = u_U \lambda_{UU}^{NF} F_U^F(W) + u_R \lambda_{RU}^{NF} \left[F_U^F(W) - F_U^F(\underline{W_R^E}+c) \right]^+$$
$$+ m_U^I \lambda_{UU}^{IF} \int_{\underline{W_U^I}}^{W} G_U^I(x) dF_U^F(x) + \mathbb{1}_{[W>\underline{W_R^E}+c]} m_R^E \lambda_{RU}^{EF} \int_{\underline{W_R^E}+c}^{W} G_R^E(x-c) dF_U^F(x) \tag{7}$$

$$m_U^I G_U^I(W) d_U^I(W) + m_U^I \lambda_{UU}^{IF} \int_{\underline{W_U^I}}^{W} G_U^I(x) dF_U^F(x) = u_U \lambda_{UU}^{NI} F_U^I(W) + u_R \lambda_{RU}^{NI} \left[F_U^I(W) - F_U^I(\underline{W_R^E}+c) \right]^+$$
$$+ m_U^F \lambda_{UU}^{FI} \int_{\underline{W_U^F}}^{W} G_U^F(x) dF_U^I(x) + \mathbb{1}_{[W>\underline{W_R^E}+c]} m_R^E \lambda_{RU}^{EI} \int_{\underline{W_R^E}+c}^{W} G_R^E(x-c) dF_U^I(x) \tag{8}$$

$$
\begin{aligned}
&u_R\left(\lambda_{RU}^{NF}\overline{F_U^F}(\underline{W_R^E}+c)+\lambda_{RU}^{NI}\overline{F_U^I}(\underline{W_R^E}+c)\right)\\
&\quad+m_R^E\left(\lambda_{RU}^{EF}\int_{\underline{W_R^E}+c}^{\overline{W_U^F}}G_R^E(x-c)dF_U^F(x)+\lambda_{RU}^{EI}\int_{\underline{W_R^E}+c}^{\overline{W_U^I}}G_R^E(x-c)dF_U^I(x)\right)=\nu\left(u_U+m_U^F+m_U^I\right)
\end{aligned}
\tag{9}
$$

where $[...]^+ = max\{..., 0\}$, $d_i^k(W)$ is the total job destruction rate for jobs in area i and sector k with values W, and ν is the calibrated urban growth rate.

Equations (6)-(8) state that the share of workers in state ik whose value is below some threshold W and who either lose their job, receive an offer higher than W in any state, or an offer lower than W but higher than their current value (including compensating differentials c) in state $jl \neq ik$ (left-hand side) is equal to the share of all non-employed workers plus the share of employed workers in state $jl \neq ik$ who accept an offer below W in state ik (right-hand side). Equation (9) states that the share of rural workers who receive an urban offer higher than their current value plus mobility costs (left-hand side) is equal to the share of urban newcomers at any period (right-hand side).

Pulling equations (6)-(8) together and solving for G_i^k yields analytical relations between G_i^k and F_i^k. Together with equation (9), they form a new system that can be solved for worker shares independently of G_i^k, by setting W to its upper bound. Plugging the results back into the initial system pins down the functions G_i^k. This is where the model substantially differs from Meghir *et al.* (2015) or Schmutz & Sidibé (2019).

3.3 Firms' Program

Environment Firms are pinned to a location and draw from an (ex-ante) local productivity distribution that I only explicitly model in urban areas. Conditional on their (ex-post) productivity draws, they choose whether to enter the market and to operate either in the formal or the informal sector so as to maximize (static) profits. Note that firms' optimality conditions yield a one-to-one mapping between worker values and ex-post productivity distributions, which allows me to recover them even in the absence of data on firms.

Production They produce with constant returns to scale and labour as the only factor of production, and post unique offer values. Even though I focus on the labour market, my model is consistent with perfect competition in an homogeneous market for goods, with productivity capturing technology differences across firms times a constant price level, both of which are assumed to be constant over time (for a model with differentiated formal and informal goods, see Belavadi (2021)).

I consider constant returns to scale to remain agnostic about the impact of population growth on structural change: increasing returns would reflect agglomeration economies and decreasing returns would reflect a decline in labour productivity under sticky capital allocation within firms.

It is not clear which effect dominates the other in existing studies. Besides, I do not observe a clear relation between activity sectors and urbanization or formalization over my study period.

Posted wages directly depend on posted offer values through inversion of workers' value functions. Following Cahuc *et al.* (2006), I consider that low-skilled workers have zero bargaining power, which justifies the wage-posting assumption. All the heterogeneity in wages therefore depends on firms facing heterogeneous matching conditions along the productivity distribution.

Informality Formal firms have to pay corporate and payroll taxes, as well as severance payment when firing workers. There is no minimum wage in my model as the National Minimum Wage Law was only voted in 2018 (after my study period). In reality, as of 2018, 40% of formal workers in South Africa are covered by collective bargaining agreements setting minimum wages by sector of activity (Bassier, 2022). As I do not have precise enough information to make firms heterogeneous by sector, such wage floors are lost in my model.

Informal firms only incur a cost that is growing and convex in firm size: this stands for monitoring costs or opportunity costs of operating in the informal sector. I do not distinguish between formal and informal firms in rural areas. Also note that formal firms cannot hire workers informally in my model, contrary to Ulyssea (2018). In the absence of complementarities between workers and under constant returns to scale, this should be of second-order for welfare and output.

Equilibrium conditions I make of couple more innocuous assumptions on firms' behaviour in equilibrium. First, formal and informal firms operating at the same productivity level should have equal profits to rationalize the coexistence of such firms: this is a sector indifference condition. Then, profits at the lower bound of active firms' productivity distribution should be equal to zero, as potential entrants enter the market until it is not profitable to do so: this is a free entry condition. Both conditions pin down firm shares and informality cost function parameters. Finally, I assume that firm sizes are in steady state at any point of the productivity distribution: inflows of workers equate outflows for any such firm.

Problem Active firms are heterogeneous in productivity p and choose in which sector to operate based on their expected profits π_i^k when in urban areas. They produce using labour l_i^k with constant returns to scale. In the formal sector, they are subject to calibrated corporate taxes t and payroll taxes τ, and must pay a calibrated fraction s of wage w_i^F when firing a worker at the exogenous job destruction rate δ_i^F. In the informal sector, firms incur a relative cost function C (with exogenous parameters) that is increasing and convex in firm size l_i^I. They post unique values W, which in turn determine wages w_i^k and firm sizes l_i^k, so as to maximize profits π_i^k. This yields the following problem:

$$\pi_R^E(p) = \underset{W}{max} \left\{ \left(p - w_R^E(W)\right) l_R^E(W) \right\} \tag{10}$$

$$\pi_U^F(p) = \underset{W}{max} \left\{ (1-t) \left[p - (1+\tau+\delta_U^F s) w_U^F(W) \right] l_U^F(W) \right\} \tag{11}$$

$$\pi_U^I(p) = \underset{W}{max} \left\{ \left[p - w_U^I(W) \right] l_U^I(W) - C\left(l_U^I(W) \right) \right\} \tag{12}$$

Wage functions can be recovered by inverting equations (2), (4), and (5) for w. At the steady state, the flow of workers leaving any given firm should be equal to the flow of workers entering that firm, which yields the following expression for firm size:

$$l_i^k(W) = \frac{M}{N_i n_i^k} \frac{h_i^k(W)}{d_i^k(W)} \tag{13}$$

with M the total number of workers, N_i the total number of either urban or rural firms (including inactive firms), n_i^k the share of potential entrants in location i operating in sector k, and h_i^k the share of contacts between firms and workers willing to accept a job of value W. The ratios $\frac{M}{N_i}$ are calibrated and firm shares n_i^k are determined in equilibrium (see next sub-section).

This relation between firm size and offer values underlines the non-linearity of firms' behaviour in equilibrium. Indeed, firm size grows non-linearly in offer values. This is because the number of firms and the number of workers they are actually competing for under search frictions do not grow monotonously with productivity. As productivity increases, firms therefore offer higher values and grow in size, but their profit rate evolves non-monotonously, as do wage markdowns. This reflects local labour market power under heterogeneous matching conditions.

3.4 Equilibrium Productivity Distributions

Problem The first-order optimality conditions associated with equations (10)-(12) yield the productivity support of active firms in each area and sector:

$$(K_R^E)^{-1}(W) = w_R^E(W) + (w_R^E)'(W) \frac{l_R^E(W)}{(l_R^E)'(W)} \tag{14}$$

$$(K_U^F)^{-1}(W) = (1+\tau+\delta_U^F s) \left[w_U^F(W) + (w_U^F)'(W) \frac{l_U^F(W)}{(l_U^F)'(W)} \right] \tag{15}$$

$$(K_U^I)^{-1}(W) = w_U^I(W) + (w_U^I)'(W) \frac{l_U^I(W)}{(l_U^I)'(W)} + C'(l_U^I(W)) \tag{16}$$

where $K_i^k(p) = W^*$ or $(K_i^k)^{-1}(W^*) = p$, and "$*$" superscript denotes optimal quantities.

The firms' sector indifference condition ($\forall p \in \left[max\{\underline{p_U^F}, \underline{p_U^I}\}, min\{\overline{p_U^F}, \overline{p_U^I}\} \right]$, $\pi_U^F(p) = \pi_U^I(p)$) and firms' free entry condition ($\pi \left(min\{\underline{p_U^F}, \underline{p_U^I}\} \right) = 0$) in urban areas pin down firm shares and the partial productivity distributions in each sector (see Section 4.2.2):

$$\Xi_U^k(p) = n_U^k F_U^k(W^*) \tag{17}$$

with support $p \in [\underline{p_U^k}, \overline{p_U^k}]$.

Then, the aggregate productivity distribution (for all potential entrants) in urban areas can be expressed as:

$$\forall p \in [\underline{p_U}, \overline{p_U}],\ \Xi_U(p) = n_U^N + \Xi_U^F(p) + \Xi_U^I(p) \tag{18}$$

with n_U^N the local share of inactive firms.

Considering that $n_U^N = \Xi_U(\underline{p})$, the truncation of unobserved function Ξ_U over the active firms' productivity range can be expressed as the observed productivity distribution of urban firms. Under some parametric assumptions, this pins down the form of Ξ_U and the value of n_U^N (see Section 4.2.2). The function Ξ_U corresponds to the ex-ante local distribution in which firms draw their productivities before deciding on their behaviour. It is an equilibrium outcome at baseline that will be used to endogenize firm distributions in counterfactuals. As I do not explicitly model firm entry in rural areas, I take $n_R^N = 0$ and $n_R^E = 1$ at baseline. In counterfactuals, changes in the composition of rural firms will be captured by the evolution of rural firm productivities, in accordance with urban recruiting of rural migrants (see Section 6.1).

3.5 Equilibrium

Let us define $\Omega = \{RE, RN, UF, UI, UN\}$, $\mathbb{E} = \{RE, UF, UI\}$, and $\mathbb{G} = \{R, U\}$. A stationary equilibrium in the labour market consists of a set of welfare distributions $\{G_i^k(W)\}_{ik\in\mathbb{E}}$, value of leisure b, relative rural amenities γ, employed worker shares $\{m_i^k\}_{ik\in\mathbb{E}}$, non-employed worker shares $\{u_i\}_{i\in\mathbb{G}}$, value-posting policies $\{K_i^k(p)\}_{ik\in\mathbb{E}}$, firm sizes $\{l_i^k(W)\}_{ik\in\mathbb{E}}$, and firm shares $\{n_i^k(p)\}_{ik\in\Omega}$ such that:

- Workers accept offers to maximize their expected present discounted values (equations (1)-(5)) taking as given offered value distributions $\{F_i^k(W)\}_{ik\in\mathbb{E}}$, job arrival rates $\{\lambda_{ij}^{kl}\}_{ik\in\Omega, jl\in\mathbb{E}}$, job destruction rates $\{\delta_i^k\}_{ik\in\mathbb{E}}$, utility of leisure b, and relative rural amenities γ.
- Utility of leisure satisfies the reservation value condition and relative rural amenities satisfy the spatial equilibrium condition.
- Active firms set values $\{K_i^k(p)\}_{ik\in\mathbb{E}}$ to maximize overall profits (equations (14)-(16)), taking as given the functions mapping offer values to wages $\{w_i^k(W)\}_{ik\in\mathbb{E}}$, firm sizes $\{l_i^k(W)\}_{ik\in\mathbb{E}}$, and informality costs $C(l_U^I(W))$.
- Offer distributions are consistent with firms' optimal decisions (equations (10)-(12)).
- Worker distributions $\{m_i^k\}_{ik\in\mathbb{E}}$ and $\{u_i\}_{i\in\mathbb{G}}$ and welfare distributions $\{G_i^k(W)\}_{ik\in\mathbb{E}}$ satisfy

the stationary equations (6)-(9), and firm sizes satisfy the stationary equation (13). Model stationarity yields a transitory equilibrium assuming infinitely-lived agents and a fixed urban growth rate.

- Offer distributions, informality costs, and firm shares $\{n_i^k(p)\}_{ik\in\Omega}$ are consistent with firms' partial and aggregate productivity distributions (equations (17)-(18)), hence firms' sector indifference and free entry conditions.

The model does not admit analytical solutions for offer distributions, transition rates, firm shares, informality costs, and urban firms' aggregate productivity distribution, which need to be estimated.

4 Estimation

4.1 Externally Calibrated Parameters

Table 3: Calibrated parameters

Parameter	Meaning	Source	Value
r	Discount rate	Federal Reserve Economic Data (FRED)	0.10
s	Severance pay rate	Basic Conditions of Employment Act (BCEA)	0.02
UIF	Unemp. insur. rate	Bhorat *et al.* (2013)	0.08
c	Mobility cost	Lagakos *et al.* (2023)	861.43
t	Corporate tax rate	South African Revenue Service (SARS)	0.28
τ	Payroll tax rate	Horizons	0.03
ν	Urban growth rate	Internal fit with observed worker shares	0.02
$\frac{M}{N_U}$	Workers p. urban firm	Tsebe *et al.* (2018)	117.24
$\frac{M}{N_R}$	Workers p. rural firm	World Bank Enterprise Survey (2020)	117.09

Before describing the estimation procedure, I explain how the model parameters in Table 3 are calibrated.

The discount rate r is the average of annual discount rates for South Africa over the study period taken from the Federal Reserve Economic Data (FRED) and adjusted to period lengths in the model.

Section 41 of the Basic Conditions of Employment Act (BCEA) sets the minimum legal severance pay rate to one week's remuneration for each completed year of continuous service. Considering that employment spells are uninterrupted between model periods, I set the value of parameter s accordingly.

Bhorat *et al.* (2013) show that the average income replacement rate (IRR) for first-instance (89% of cases) unemployment insurance male claimants is 48%. Given that the number of credit days is set to one for every six days of employment and cannot be larger than 238, I set the value of parameter UIF accordingly.

Lagakos *et al.* (2023) set the permanent migration monetary cost to twice the seasonal migration monetary cost, which is equal to 10% of rural expenditures over six months. Again, I set the value of mobility cost c accordingly.

The corporate income tax rate t is directly set by the South African Revenue Service (SARS) from where I take its value.

There are no unified payroll taxes in South Africa but the private platform *Horizons* estimates that average social contribution rates from firms are 1% for unemployment insurance, 1% for the Skills Development Levy (SDL), and 0.65% for the Compensation for Occupational Injuries and Diseases Act (COIDA): I sum up those values to obtain parameter τ.

The structural urban growth rate ν is set to fit the observed worker shares in my sample: to do so, I invert equation (9) and solve for ν.

The average number of workers per urban firm $\frac{M}{N_U}$ is obtained by targeting the average formal firm size taken from Tsebe *et al.* (2018): to do so, I take the expected value of equation (13) and solve for $\frac{M}{N_U}$.

Finally, the average number of workers per rural firm $\frac{M}{N_R}$ is set to make rural firms half the size of urban formal firms on average, as the World Bank Enterprise Survey for South Africa (2020) suggests that firms in majoritarily rural provinces are roughly half the size of firms in majoritarily urban provinces. The fact that I consider all rural firms as being active pushes the calibrated value of $\frac{M}{N_R}$ up. In any case, the impact of this parameter should be negligible under constant returns to scale.

4.2 Estimated Parameters

4.2.1 Offer Distributions and Transition Rates

Method To simplify the estimation procedure, let us assume that values W_i^k follow a beta distribution with parameters $\alpha_i^k \geq 1$ and $\beta_i^k > 1$, and support $[\underline{W_i^k}, \overline{W_i^k}]$. These distributions offer the advantage of bounded support, guarantee the smoothness of density functions, and are flexible enough while only depending on a limited number of parameters. The estimation procedure can be further simplified by expressing $\underline{W_R^E}$, $\overline{W_R^E}$, $\underline{W_U^I}$ and $\overline{W_U^F}$ as functions of other model parameters. Therefore, let us define $\theta = \{\alpha_i^k, \beta_i^k, \underline{W_U^F}, \overline{W_U^I}\}_{ik\in\mathbb{E}}$ and $\vartheta = \{\lambda_{ij}^{kl}, \delta_j^l\}_{ik\in\Omega, jl\in\mathbb{E}}$. I follow Meghir *et al.* (2015) and estimate these two sets of parameters jointly with an iterative two-step method of moments that I describe below.

Step 1: Transition rates Let us start with an initial guess on θ and ϑ. The estimate of ϑ is updated by matching the transition probabilities presented in Section 2.3. Indeed, there is an analytical relation between their theoretical value and the model parameters (see Section B): the probability to accept a given job directly depends on the job arrival rate from origin to destination state and the offer distribution at destination. I therefore define the quadratic distance:

$$Q_1(\vartheta|\theta) = \sum_{ik,jl\in\Omega} \left(\widehat{D_{ij}^{kl}} - D_{ij}^{kl}\right)^2 \tag{19}$$

where $\widehat{D_{ij}^{kl}}$ are the transition probabilities observed in the data and D_{ij}^{kl} their theoretical counterparts.

After computing Q_1, the value of ϑ is updated by solving for ϑ with $\widehat{D_{ij}^{kl}}$ substituted for D_{ij}^{kl} its theoretical expression. The value of G_i^k is updated accordingly using equations (6)-(8), and so is the value of Q_1. The process is iterated until the value of Q_1 falls below a precision threshold that I set at 0.001 for each of the sum components.

Step 2: Offer distributions The above procedure is repeated for several discrete values of θ. Considering that wages w_i^k follow the same distribution as values W_i^k due to the one-to-one mapping from equations (2), (4) and (5), I define for each iteration the quadratic distance:

$$Q_2(\theta|\vartheta) = \sum_{ik\in\mathbb{E}} \sum_{q=1}^{M} \left(\widehat{G_i^k}(w_q) - G_i^k(W_q)\right)^2 \tag{20}$$

where $\widehat{G_i^k}$ are the wage distributions from Figure 2, and q denotes M main quantiles taken over observed wages such that $w_{i,q}^k = w(W_{i,q}^k)$. The iteration ends by selecting the set of parameters $\{\theta, \vartheta\}$ that minimize the function Q_2.

4.2.2 Firm Shares and Informality Cost

Method For the sake of simplicity, I assume that informality cost C has a standard span-of-control form: $C\left(l_U^I(W)\right) = c_f l_U^I(W)^{\gamma_f}$, where $c_f > 0$ and $\gamma_f \geq 1$. I still follow Meghir *et al.* (2015) by first estimating $\widetilde{n}_U^I = \frac{n_U^I}{n_U^F + n_U^I}$, $\widetilde{c}_f = c_f\left(\frac{M}{(n_U^F + n_U^I)N_U}\right)^{\gamma_f - 1}$ and γ_f, then separately estimate n_U^N and finally recover values for n_U^F, n_U^I, and c_f.

Step 1: Active firms only Substituting $\widetilde{n}_U^F = 1 - \widetilde{n}_U^I$, $\widetilde{n}_U^I$, and $\widetilde{c}_f$ for n_U^F, n_U^I and c_f in equations (13) and (15)-(16), and plugging the results back into equations (11)-(12), I define the quadratic distance:

$$Q_3\left(\widetilde{n}_U^I, \widetilde{c}_f, \gamma_f|\theta, \vartheta\right) = \widetilde{\pi}\left(min\{\underline{p_U^F}, \underline{p_U^I}\}\right)^2 + \sum_{q=1}^{M} \omega_q \left[\widetilde{\pi}_U^F(p_q) - \widetilde{\pi}_U^I(p_q)\right]^2 \tag{21}$$

where q denotes M equally spaced points taken over the overlapping productivity range of formal and informal firms, and ω_q are weights accounting for the mass of firms around productivity quantile p_q.

The first term of the sum captures the free entry condition in urban areas, the second term of the sum captures the sector indifference condition for firms of equal productivity. By minimizing quadratic distance Q_3, I therefore select the set of parameters that best fit these two equilibrium conditions. I do so by scanning discrete values of the parameter set.

Step 2: All potential entrants Then, I define partial productivity distributions $\widetilde{\Xi}_U^k$ by substituting $\widetilde{n}_U^k$ for n_U^k in equation (17). A transformation of equation (18) yields:

$$\forall p \in [\underline{p_U}, \overline{p_U}],\ \Xi_U(p) = n_U^N + (1 - n_U^N)\left[\widetilde{\Xi}_U^F(p) + \widetilde{\Xi}_U^I(p)\right] \tag{22}$$

Fitting a log-normal distribution with parameters μ and σ on function Ξ_U over $[0, \overline{p_U}]$ by fitting a truncated log-normal distribution with same parameters on $\widetilde{\Xi}_U^F + \widetilde{\Xi}_U^I$ over $[\underline{p_U}, \overline{p_U}]$ (using the fact that $\Xi(\underline{p_U}) = n_U^N$ and $\Xi(\overline{p_U}) = 1$), I recover the equilibrium value of n_U^N. Since $n_U^F + n_U^I = 1 - n_U^N$, the expressions for n_U^F, n_U^I, and c_f directly follow.

5 Baseline Results

5.1 Parameters

Table 4: Estimated transition rates ϑ_{ij}^{kl} between states ik and states jl over one period

ik \jl	RN	RE	UN	UF	UI
RN	.	0.128	.	0.008	0.008
RE	0.140	0.192	.	0.038	0.031
UN	.	.	.	0.074	0.101
UF	.	.	0.079	0.118	0.123
UI	.	.	0.147	0.209	0.128

Notes: "RN" stands for rural non-employed, "RE" for rural employed, "UN" for urban non-employed, "UF" for urban formal, "UI" for urban informal, and "OTJS" for on-the-job search (distinct from keeping same job in same sector). Parameters of Poisson distributions corresponding to yearly arrival rates.

Transition rates Table 4 shows the estimated transition rates (not to be confused with transition probabilities) for the moves allowed in the model. They capture how frictional each sub-market is independently of origin and destination offer values. Interestingly, local on-the-job arrival rates are typically higher than job destruction rates, be it within or across sectors: this is because workers receive more offers than they accept.

The stepping-stone potential of the urban informal sector is confirmed as the urban non-employed indeed receive more informal job offers than formal ones, and the urban informal receive more formal job offers than the non-employed do. However, the urban informal sector does not appear to be less frictional than the urban formal sector for rural-urban migrants. It also features a higher job destruction rate. If informal jobs are replaced one-to-one by formal jobs in counterfactuals, the change in rural-urban worker allocation will be mostly driven by changes in offer values for fixed transition rates.

Also note that, because the transition rates from rural employment towards urban formal and informal employment are similar, it is very unlikely that rural migrants are overly optimistic regarding informal jobs.

Table 5: Estimated offer distribution parameters θ_i^k for employment states ik

ik	α_i^k	β_i^k	$\underline{W_i^k}$	$\overline{W_i^k}$
RE	1.00	5.55	$1.578{\cdot}10^5$	$4.776{\cdot}10^5$
UF	1.00	17.61	$1.579{\cdot}10^5$	$1.353{\cdot}10^6$
UI	1.00	5.52	$1.579{\cdot}10^5$	$4.776{\cdot}10^5$

Notes: "RE" stands for rural employed, "UF" for urban formal, and "UI" for urban informal. Parameters of non-standard beta distributions fir yearly welfare values.

Offer distributions Table 5 presents the parameters governing the offer value distributions (not to be confused with offered wages) for the three employment states of interest. Note that I do not enforce shape parameters to be equal to one, which is an outcome of the estimation procedure.

Offers from rural firms and from urban informal firms appear to be very similar, whereas offers from urban formal firms are more skewed towards higher values. However, since accepted offers depend on both offered values and transition rates (see Section 3.2), similar offers do not directly translate into similar welfare values for workers, as will become clear in Section 5.3.

Table 6: Other worker and firm parameters

γ	b	c_f	γ_f	μ	σ
2,483	5,612	2,256	1.00	10.27	0.63

Notes: Left panel stands for relative rural amenities and utility of leisure, middle panel for informality cost function parameters, and right panel for aggregate productivity distribution parameters.

Other parameters Table 6 presents remaining model parameters. As such, relative rural amenities and utility of leisure are endogenous outcomes of the model and are not estimated. They are both positive and substantial as a share of welfare (see Section 5.3). Importantly, I do not take any stance on the sign of those parameters beforehand. Positive relative rural amenities therefore suggest that, at baseline, rural characteristics such as lower housing prices or stronger social networks are more valuable for workers than urban characteristics such as better-quality infrastructure or local public goods. A high positive value of leisure points to high reservation wages, which is consistent with the relatively high rates of non-employment and low rates of informal employment found in South Africa.

The parameters governing the distribution of informality costs are such that they form a substantial share of mean revenues (see Section 6.2) and grow linearly with firm size: again, I do not impose lineaerity beforehand.

Finally, the parameter values of the aggregate productivity distribution for all potential entrants in urban areas are of no intrinsic interest. They will be kept fixed in counterfactuals to pin down the endogenous response of firms, assuming the underlying productivity distribution does not change (see Section 6.1).

5.2 Model fit

Targeted quantities Table 7 shows the model fit on observed wages from Figure 2. It features for each distribution the five quantiles that are targeted in the estimation. I do not include the model fit on transition probabilities from Section 2.3 as it is perfect by construction: the analytical relation between theoretical probabilities and model parameters ensures the efficiency of the estimation procedure. The fit on wages is good overall, especially in the middle of the distributions. Apart from that, the predicted distributions appear to be slightly skewed to the left, but the relative ordering across states is preserved.

Table 7: Model fit on log wage percentiles

	Rural employed		Urban formal		Urban informal	
	Actual	Model	Actual	Model	Actual	Model
$P10$	8.90	8.69	9.80	9.64	8.49	7.96
$P25$	9.60	9.54	10.23	10.22	9.18	9.27
$P50$	10.06	10.12	10.68	10.70	9.88	9.98
$P75$	10.49	10.49	11.14	11.13	10.40	10.40
$P90$	11.02	10.72	11.52	11.46	10.87	10.65

Notes: South African National Income Dynamics Study 2008-2017, low-skilled males aged 18-64.

Untargeted quantities Table 8 shows the model fit on workers' and firms' allocation across geo-employment states. Contrary to Table 7, those are not directly targeted moments (even though the total urban population share is targeted indirectly through the urban growth parameter). Taking this into account, the fit on worker shares appears to be satisfying, compared to Meghir *et al.* (2015) for instance.

The major discrepancies from observed data are an underestimated urban non-employment share and an overestimated urban formal employment share. This may stem from the fact that those are the two states which are the furthest away from stationarity in the data, as discussed in Section 3.2. To improve the model fit, a deviation from steady state could be calibrated and added to the equations, in a similar fashion as for urban growth. However, the evolution of employment shares is not linear in the data, and it is harder to interpret it as the manifestation of fixed structural factors. It may therefore lead to overfitting in counterfactuals.

As explained in Section 4.1, the average urban firm size is directly targeted in the model. However, I have no data to validate average urban informal firm size. Still, taking these at face value, I impute what the actual urban firm shares (unobserved) would be given the actual worker shares (observed). The fit on urban firm shares appears to be more precise than for urban worker shares. If anything, the relative overestimation of informal firm share may be due to the impossibility to hire workers informally for formal firms.

Table 8: Model fit on workers' and firms' allocation

	Actual	Model
Worker shares		
u_R	0.246	0.260
m_R^E	0.242	0.200
u_U	0.193	0.105
m_U^F	0.194	0.303
m_U^I	0.126	0.133
Firm shares		
n_U^N	0.093	0.082
n_U^F	0.487	0.422
n_U^I	0.420	0.496

Notes: Actual firm shares imputed from actual worker shares and model firm sizes. Worker shares and local firm shares sum up to one.

5.3 Welfare analysis

Table 9 shows the average discounted welfare values for each state in the model and presents the respective shares of their individual components. First, let us remark that the urban non-employed feature similar option values across the formal and the informal sectors: this is because lower wages in the informal sector are compensated for by lower frictions. They also feature a substantial value of leisure, as the rural non-employed do, equal to more than one-third of their overall welfare. Relative rural amenities are also important, as they account for between 10% and 20% of rural welfare values.

Profitable transitions Importantly, average values for employment states are ranked as expected: $E(W_R^E) < E(W_U^I) < E(W_U^F)$. It means that urban formal jobs are indeed more valuable than urban informal jobs on average, essentially due to higher wages and lower job destruction rates. It also means that it is profitable for rural migrants to move to urban informality on average, even when they experience a wage cut. This is in spite of relative rural amenities being positive. Moreover, as transition rates from rural to urban informal are not higher than to urban formal (Section 5.1), such moves should not be driven by lower frictions (or overoptimism) either. Under common preferences, I therefore justify them by higher dynamic gains in urban compared to rural labour markets.

Stepping-stone mechanism Indeed, it appears that the option value from future formal jobs when informally employed in cities accounts for 20% of the average discounted welfare value:

Table 9: Average discounted welfare decomposition

	Value	Amenities	Exp. wage / leisure	Rur. empl. opt.	Urb. form. opt.	Urb. inform. opt.
rW_R^N	15,220	0.16	0.37	0.41	0.03	0.03
$rE(W_R^E)$	22,120	0.11	0.70	0.13	0.04	0.02
rW_U^N	15,300	.	0.37	.	0.31	0.32
$rE(W_U^F)$	26,620	.	0.89	.	0.07	0.04
$rE(W_U^I)$	23,030	.	0.73	.	0.20	0.07

Notes: Amenities are relative to urban baseline and are therefore only accounted for in rural areas. Expected wage/leisure includes both the flow value of current wage and option value of unemployment risk when employed, or utility of leisure when non-employed. Other columns cover option values of future job opportunities: as I do not allow for urban-rural moves, there is no rural option value in urban areas. Row proportions sum up to one.

this quantifies how much workers value the stepping-stone potential of informal jobs. Likewise, the option values of urban jobs for rural workers show that they similarly value formal and informal job opportunities in cities, since they account for between 2% and 4% of their welfare values. The upward bias on urban formal option values discussed in Section 2.4 therefore seems to be limited, as it is unlikely that formal jobs are actually valued less than informal jobs on average.

Finally, the value of informal jobs says nothing of the share of such jobs that would be destroyed or formalized following an exogenous shock. It is not informative either on the impact of such shock on movers and stayers through wages in equilibrium. I therefore turn to policy simulations in Section 6.2 to see how the stepping-stone mechanism plays out in counterfactuals.

5.4 Productivity analysis

Before that, Tables 10 and 11 show respectively firm-specific distributions and characteristics by joint productivity level. They help explain the differences between the estimated welfare distributions. First of all, wages, offer values, and firm sizes grow monotonously with productivity, which is the most important factor driving these values. Then, let us remark that urban workers are more represented on the right end of the firms' productivity distribution compared to rural workers, especially in the formal sector. This is due to either a higher share of firms in those quantiles, or a higher capacity of these firms to absorb workers: in any case, urban areas are more productive than rural ones.

Wages and productivity For a given productivity level, firm size grows with the size of the worker pool available locally (through ratio $\frac{M}{N_i}$), but also with the ease of recruiting conditions (through matching rate $\frac{h_i^k(W)}{d_i^k(W)}$). Interestingly, informal firms tend to offer higher wages than formal firms as productivity grows. This is because, as informality costs fall as a share of revenues, informal firms face relatively fewer costs than formal firms subject to taxes. They

Table 10: Comparative worker and firm distributions by productivity level

		Rural	Urban			Wage (log)			Value (log)		
	p (log)	Cumul worker share	Cumul. worker share	Fract. form. work	Fract. form. firms	*RE*	*UF*	*UI*	*RE*	*UF*	*UI*
P10	9.88	0.00	0.06	0.62	0.42	.	8.99	8.12	11.96	12.06	12.05
P25	10.35	0.00	0.20	0.60	0.43	.	9.76	9.75	11.96	12.22	12.21
P50	10.66	0.15	0.34	0.62	0.43	9.10	10.13	10.20	12.09	12.35	12.34
P75	10.89	0.47	0.45	0.64	0.45	10.06	10.34	10.45	12.29	12.46	12.43
P90	11.23	0.75	0.57	0.70	0.50	10.49	10.56	10.73	12.47	12.60	12.57
P99	13.06	0.99	0.81	1.00	0.99	11.03	11.07	11.32	12.81	13.00	12.98
$\overline{p}$	14.70	1.00	0.89	1.00	1.00	11.21	11.32	.	12.93	13.20	.

Notes: Cumulative worker share = fraction of all workers employed at firms with productivity less than p; Fraction of formal firms = probability of drawing a formal job conditional on drawing a job of productivity p; Fraction of formal workers = share of formal workers among employees at jobs of productivity p; Wage is wage offer of firms of productivity p; Value is corresponding welfare value; $\overline{p}$ corresponds to the 0.999 quantile of the total aggregate productivity distribution (effectively the max).

Table 11: Comparative firm characteristics by productivity level

		Profit rate			Firm size		
	p (log)	*RE*	*UF*	*UI*	*RE*	*UF*	*UI*
P10	9.88	.	0.42	0.71	.	14.61	12.91
P25	10.35	.	0.31	0.38	.	30.36	30.43
P50	10.66	0.79	0.28	0.31	14.25	51.40	48.90
P75	10.89	0.56	0.29	0.31	26.67	71.79	65.58
P90	11.23	0.52	0.34	0.36	41.87	101.48	88.46
P99	13.06	0.87	0.62	0.82	58.86	182.50	116.56
$\overline{p}$	14.70	0.97	0.69	.	59.70	223.00	.

Notes: Profit rate = profit flow divided by output; $\overline{p}$ corresponds to the 0.999 quantile of the total aggregate productivity distribution (effectively the max).

are therefore able to offer workers compensating differentials for the absence of unemployment insurance or lower dynamic gains. Actually, the corresponding offer values are almost the same. Note that such compensating differentials are compatible with higher wages on average for urban formal firms since they are also more productive: this is a composition effect. Indeed, passed some threshold, it is never profitable for urban firms to operate informally and they all choose the formal sector.

Labour market power Relatively lower wages (and welfare values) for rural firms have to do with higher local labour market power, as rural workers have fewer outside options than urban workers and rural firms are able to capitalize on this. This is reflected in higher profit rates overall, and is aligned with existing evidence of higher local labour market power in rural areas (Marshall, 2025). They also tend to be larger in the informal compared to the formal sector. Interestingly, profit rates are not monotonous with respect to productivity level: this is because they depend on the mass of competitors and the mass of workers, which are not uniformly distributed across the productivity support. This will create non-monotonicities in firm behaviour in counterfactuals. Besides, they are quite large. This will also matter in counterfactuals as informal firms will be able to absorb a substantial share of the shock before the formal sector becomes a profitable alternative. This will depend on the net effect between added competition from incoming firms and more relaxed matching conditions from incoming workers in the formal sector, and will also generate non-monotonous responses of firms. Because the direction of this net effect is not clear a priori, I now turn to policy simulations to assess it quantitatively.

6 Policy Simulations

6.1 Estimation procedure

To compute counterfactuals, I replicate the estimation procedure described at baseline with a few key modifications. First, I do not re-estimate transition rates which stay constant across simulations. This boils down to considering that they are mostly driven by information frictions, assumed to be fixed in counterfactuals. Meghir *et al.* (2015) suggest a way to endogenize job arrival rates based on changes in labour market tightness: I leave this extension for future work. In their case, this does not change the direction of the effects but makes them stronger, as this accelerates the worker reallocation that already takes place through stationary worker flow conditions (Section 3.2).

I also keep the values for informality cost parameters and utility of leisure as exogenous, but allow relative amenities to adapt to reflect congestion forces on the workers' side. Then, I re-estimate offer distributions by targeting the urban aggregate productivity distribution obtained at the end of Section 4.2.2, in a similar fashion as what I do with observed wage distributions in Section 4.2.1, but with added weights to account for the mass of firms associated with equally spaced productivity points. This consists in minimizing the following quadratic distance:

$$Q_4\left(\theta|\vartheta, c_f, \gamma_f, \{n_U^k\}_{k\in\{N,F,I\}}\right) = \sum_{q=1}^{M} \omega_q \left(\Xi_U^*(p_q) - \Xi_U(p_q)\right)^2 \tag{23}$$

where Ξ_U^* is the target productivity distribution and Ξ_U the predicted one.

The rationale is that firms' underlying productivity distribution should remain unchanged in counterfactuals as I abstract from any structural change effect. Likewise, the structural urban growth rate is fixed: all the reallocation effects will be captured by new worker shares across geo-employment states, and not through changes in migration (or other transition) rates. Given that urban firms hire rural migrants, targeting the productivity distribution of urban potential entrants suffices to identify model parameters in both urban and rural areas.

Also remark that the error measure depends on predicted firm shares $\{n_U^k\}_{k\in\{N,F,I\}}$. This is because the algorithm now embeds the firms' side estimation from Section 4.2.2 within the workers' side estimation of Section 4.2.1, instead of dealing with it sequentially. Indeed, the local firm shares have an impact on the simulated aggregate productivity distribution which is now used to select the appropriate solution. Note that I need to go through this non-standard procedure because the policy shock I am considering will affect firms' entry and sector decisions, as well as their wage-posting strategy. It is therefore not possible anymore to identify offer distributions through accepted offers, since they will change as an equilibrium outcome in counterfactuals.

6.2 Increasing the cost of informality

Scenario My main scenario consists in increasing the informality cost elasticity parameter γ_f incrementally by steps of 0.1 from its initial value of 1.0 towards 1.3. This can be understood as increasing monitoring costs on urban informal firms. Before any behavioural changes from firms, this consists in a non-linear rise of mean cost per revenues from 13% to 36%. I stop there not to extrapolate results too far out of sample. Note that this could be mapped to the creation by the Department of Employment and Labour's Inspection and Enforcement Services of a National Labour Inspection Task Team in 2022 (after my study period) to target the informal sector.

The informality trade-off The main results are given in Tables 12 and 13, and can be explained with the help of Tables 14, 15, and 16. The bottom line is that the policy generates a rise in urban output due to a reallocation of workers from the informal to the formal sector. However, this benefits firms more than workers, as workers' welfare actually decreases in the face of wage cuts. This trade-off between welfare and output is mitigated by rural firms that increase wages to retain potential migrants: both local welfare and output rise in rural areas, as workers are reallocated towards the most productive firms. Global output therefore increases to a larger extent than urban output (+2.4%). Still, this is not sufficient to offset the fall in urban welfare: global welfare falls by 0.9%. Overall, the urban population share falls by 4.1%. This

Table 12: Welfare effects of increasing the costs of informality

	Baseline	Change from baseline		
	$\gamma_f = 1$	$\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
rW_R^N	15,220	-0.80%	-1.35%	-2.36%
$r\mathbb{E}(W_R^E)$	22,123	+1.94%	+4.18%	+4.14%
Rural	18,219	+0.76%	+1.81%	+1.35%
W_U^N	15,303	-0.80%	-1.34%	-2.34%
$r\mathbb{E}(W_U^F)$	26,624	-0.63%	-0.69%	-0.60%
$r\mathbb{E}(W_U^I)$	23,027	-0.98%	-2.36%	-4.91%
Urban	23,541	-0.73%	-1.07%	-1.53%
Total	21,096	-0.37%	-0.37%	-0.88%
WF gap	*0.29*	*-6.51%*	*-12.51%*	*-12.57%*

Notes: Average discounted welfare per worker is aggregated within rural and urban areas and for the total population, based on estimated worker shares in each state.

Table 13: Output effects of increasing the costs of informality

	Baseline	Change from baseline		
	$\gamma_f = 1$	$\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
$\mathbb{E}(p_R^E l_R^E) \cdot \frac{N_R^E}{M_R^E}$	76,068	+6.85%	+13.47%	+15.08%
Rural	33,044	+7.54%	+14.89%	+16.71%
$\mathbb{E}(p_U^F l_U^F) \cdot \frac{N_U^F}{M_U^F}$	174,868	+0.35%	-0.20%	-1.64%
$\mathbb{E}(p_U^I l_U^I) \cdot \frac{N_U^I}{M_U^I}$	57,587	+1.59%	+4.10%	+8.31%
Urban	112,024	+0.62%	+1.13%	+1.57%
Total	75,747	+1.01%	+1.96	+2.39%
Output gap	*2.39*	*-9.12%*	*-16.99%*	*-18.40%*

Notes: Average output per worker is aggregated within rural and urban areas and for the total population, based on estimated worker shares in each state.

corresponds to 2.2% of the total population, or 2.7 years of reversed urban growth at current rates.

Considering total output relative to workers' welfare matters for potential redistribution policies or investments in local public goods. However, since I implicitly consider sticky capital allocation in the model, the impact on output could change with capital reallocation over the very long term. I leave these extensions for future work.

Table 14: Changes in worker and firm allocation as costs of informality increase

	Baseline	Change from baseline		
	$\gamma_f = 1$	$\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
Worker shares				
Rural	0.46	+2.13%	+4.21%	+4.84%
Non-empl. rate	*0.57*	*-0.49%*	*-0.96%*	*-1.09%*
Urban	0.54	-1.81%	-3.58%	-4.11%
Non-empl. rate	*0.19*	*+0.16%*	*+0.62%*	*+1.62%*
Informal rate	*0.25*	*-0.64%*	*-3.84%*	*-10.07%*
Informal vs. empl.	*0.31*	*-0.61%*	*-3.69%*	*-9.72%*
Urban firm shares				
Active	0.92	-0.01%	-0.91%	-2.24%
Informal rate	*0.54*	*-2.02%*	*-5.02%*	*-8.08%*
Mean firm sizes				
Rural employed	23.35	+2.79%	+5.51%	+6.34%
Urban formal	46.66	-3.55%	-5.92%	-4.95%
Urban informal	35.19	-0.22%	+0.19%	+0.63%

Notes: Figures in italics are defined within the geography type stated above.

Wages and rural-urban migration In fact, the informal sector maintains urban employment levels by acting as an outside option for workers (which I have shown to be valuable), thereby limiting the local labour market of formal firms, hence their propensity to cut wages in counterfactuals. This is the first main contribution of this paper. Note however that I consider atomistic firms and therefore do not consider strategic competition for workers as an added source of labour market power.

In this context, rural jobs play the role of an alternative outside option: simulating an isolated city without rural-urban migration yields stronger negative welfare effects (by a factor of 5.5) and weaker positive output effects (by a factor of 4.5) following the policy shock (see Tables A14-A16), as the most productive urban firms are also the ones which cut wages the most. This is the second main contribution of this paper. I will now give more details on the model mechanisms.

Firms' formalization Following the policy shock, urban informal firms of relatively low productivity do formalize as it is too costly for them to absorb the shock, which pushes the

Table 15: Changes in accepted wage distributions as costs of informality increase

	Baseline	Change from baseline		
	$\gamma_f = 1$	$\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
Rural wages				
P10	8.69	+7.18%	+15.03%	+17.33%
P25	9.54	+8.09%	+16.81%	+19.09%
P50	10.12	+7.63%	+15.73%	+17.69%
P75	10.49	+6.97%	+14.24%	+15.98%
P90	10.72	+6.32%	+12.86%	+14.46%
P99	11.01	+5.12%	+10.27%	+11.61%
Urban formal wages				
P10	9.65	-0.53%	+0.87%	+3.45%
P25	10.22	-0.64%	-0.55%	-0.49%
P50	10.70	-0.98%	-1.97%	-3.69%
P75	11.13	-1.43%	-3.59%	-7.32%
P90	11.46	-1.49%	-4.15%	-8.88%
P99	11.85	-1.26%	-3.59%	-7.92%
Urban informal wages				
P10	7.96	-4.04%	-17.54%	-44.49%
P25	9.27	-2.42%	-8.89%	-21.00%
P50	9.98	-1.94%	-6.90%	-16.22%
P75	10.40	-1.61%	-5.80%	-13.97%
P90	10.65	-1.44%	-5.16%	-12.58%
P99	10.90	-1.21%	-4.69%	-11.63%

Notes: Baseline columns contain log wages as predicted by the model. Remaining columns are changes from respective baselines.

Table 16: Changes in productivity distributions as costs of informality increase

	Baseline	Change from baseline		
	$\gamma_f = 1$	$\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
Rural productivities				
P10	10.60	+8.47%	+17.66%	+19.72%
P25	10.64	+7.40%	+15.19%	+16.69%
P50	10.74	+6.18%	+12.55%	+13.67%
P75	10.96	+5.69%	+11.69%	+13.00%
P90	11.28	+5.70%	+11.85%	+13.56%
P99	12.37	+6.96%	+13.12%	+14.98%
Urban formal productivities				
P10	9.66	-0.16%	+2.24%	+5.88%
P25	9.97	-0.34%	+1.28%	+4.02%
P50	10.37	-0.52%	+0.45%	+2.51%
P75	10.81	-0.70%	+0.05%	+2.28%
P90	11.31	-1.01%	-0.23%	+2.81%
P99	12.97	-1.23%	-3.00%	-5.62%
Urban informal productivities				
P10	9.77	+4.77%	+9.91%	+15.04%
P25	9.93	+4.16%	+8.85%	+13.90%
P50	10.27	+3.02%	+6.53%	+10.51%
P75	10.67	+1.97%	+4.19%	+6.99%
P90	11.03	+1.05%	+2.10%	+3.51%
P99	11.74	-0.41%	-2.80%	-6.45%

Notes: Baseline columns contain log productivities as predicted by the model. Remaining columns are changes from respective baselines.

urban informal productivity distribution up (Table 16). None of these firms are destroyed given that the lower bound of informal productivity that I estimate is still higher than the lower bound for urban formal firms: they are therefore productive enough to survive taxes and competition in the formal sector. This stands in contrast with other contexts where jobs are directly destroyed in the wake of such policies. If anything, this should strengthen my findings as an increase in non-employment should reduce workers' welfare and increase firms' labour market power.

As the shock becomes stronger and more productive firms formalize, urban formal productivities actually increase with the newcomers after an initial drop. This added competition pushes the lowest-productivity formal firms out of business. These moves are reflected in the evolution of relative active firm shares (Table 14): 2.2% of urban firms are destroyed.

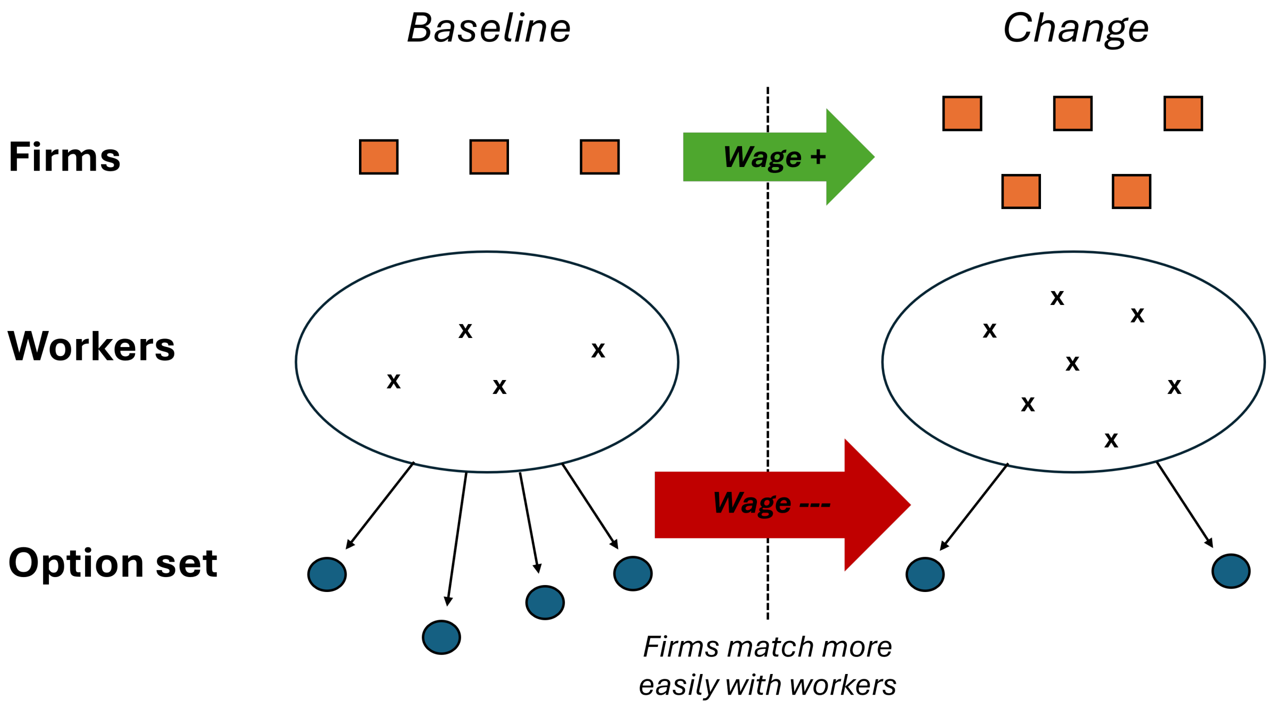
All else equal, this should push observed wages up. On the contrary, they fall in the urban informal sector, especially in the lower quantiles (Table 15): this is because the remaining firms still need to absorb the increase in cost, especially in the most affected quantiles, and they do so by lowering their offers independently of matching conditions. The net effect between reduced competition among firms and a depleted pool of available workers on wage-posting in the informal sector is unclear. Also note that it is difficult to directly show the evolution of wage markdowns following the policy shock, as the productivity grid on which the model is estimated varies across counterfactuals.

The picture is different for urban formal firms. As observed wages first increase, then decrease along the distribution, it would seem that added competition in the quantiles most affected by firms' formalization pushes wages up (although the increase in productivity levels could also play a role), but that easier matching conditions push wages down in the higher parts of the distribution. Figure 3 summarizes these wage-posting effects: more firms are competing for workers — which pushes wages up — but the pool of workers they are competing for is both larger and with fewer outside options — which pushes wages down. The second effect is dominant in equilibrium.

Workers' formalization The effect on wages translates into lower welfare values for urban formal and informal workers, although the effect is mostly marked for informal workers. The value of urban non-employment also falls to reflect this new situation (Table 12). Still, the reduction in urban welfare (-1.5%) is mitigated by the reallocation of urban workers from the informal to the formal sector, which pays better overall. Mean firm sizes adapt accordingly (Table 14): the share of informal workers in cities fall by 10.1%, whereas the share of non-employed workers rise by 1.6% only.

At the same time, average urban output per worker increases by 1.6% (Table 13). Again, the reallocation of workers from the informal towards the more productive formal sector plays the main role. However, it is worth noting that average formal output per worker decreases slightly, which limits the potential gains. This is in spite of the rise in productivity levels, as larger firms with more market power cut wages the most, reallocating workers towards the least productive

Figure 3: Diagram of wage-posting effects for the urban informal sector in counterfactuals



ones. Output per worker rises in the informal sector as the increase in monitoring costs counts as added government revenues (as for taxes).

Spatial reallocation At the new welfare levels, it becomes profitable for some potential rural migrants to stay in rural areas. Actually, it also becomes profitable for some rural firms to outbid urban firms offering lower wages, thereby retaining even more workers. As firms raise wages, they also increase the local competition for workers, which crowds out the least productive ones: this is reflected in fewer active, but larger (Table 14) and more productive (Table 16) rural firms.

This translates into higher observed wages in Table 15, and a slight decrease in local non-employment (Table 14), hence an increase in average rural welfare. The positive effect on rural output is even more sizable (Table 13).

Note however that the rise in welfare is mitigated by a fall in relative rural amenities that is reflected in the lower value of rural non-employment (Table 12). This is a direct consequence of the spatial equilibrium condition and corresponds to increased congestion as population grows in rural areas.

On aggregate, the positive effect is stronger for global output, and the negative effect weaker for global welfare, compared with the urban baseline. This is because potential rural migrants only stay in rural areas (Table 14) when it is profitable to do so. They are therefore better paid put to more productive use than average rural workers (which are still below urban workers in counterfactuals).

The role of rural-urban migration as an important adaptation mechanism is confirmed in simulations of an isolated urban labour market without rural-urban migration (Tables A14-A16). As for urban informality, having rural jobs as an outside option limits the local labour market power of urban formal firms: removing them allows the most productive firms to cut wages the most, further reallocating workers towards less productive and less well-paid jobs within the formal sector (which remains more valuable than the informal sector otherwise).

7 Conclusion

In this paper, I undertook to study the role played by informal employment for spatial labour misallocation in low- and middle-income country contexts. By focusing on rural-urban migration and by taking South Africa as my case study, I found the role of urban informality more specifically to be ambiguous. Indeed, imposing more stringent regulations on urban informal firms locally improves output through worker reallocation towards more productive jobs, but it also reduces welfare as firms then offer lower wages. This is because the informal sector limits the local labour market power of formal firms by offering a valuable outside option to workers. Importantly, when this option becomes unavailable, reduced rural-urban migration may act as an alternative strategy to cope with the negative welfare effects.

I therefore draw two main conclusions from this study. First, the urban informal sector indirectly provides jobs to potential rural migrants by maintaining local wage levels in the formal sector. This effect holds independently of potential job destruction in the wake of a formalization shock, in contexts where informal jobs indeed provide workers with substantial dynamic gains. This argues for formalization policies that better take matching frictions in consideration. For instance, it has been shown that public employment can act as a substitute for informal employment (Yassin & Langot, 2018). By offering guaranteed wages, local public work programs can therefore provide workers with a valuable alternative. These have been shown to generate positive spillovers on wages in the private sector, be it in urban (Franklin *et al.*, 2024) or rural (Imbert & Papp, 2015, 2020b) areas. I consider such policies as a more promising avenue than national minimum wages in this regard, since most of the wage cuts I simulate happen above floor levels.

Second, local labour market policies can generate sizable spatial spillovers that can drastically change policy recommendations. Indeed, when simulating a closed urban economy, the trade-off between aggregate welfare and output appears to be substantially larger than it actually is with rural-urban migration. This suggests substantial gains from reducing spatial frictions, and argues for detailed spatial analyses of place-based policies more generally (Neumark & Simpson, 2015; Juhász *et al.*, 2023).

As with any policy study, I would need more information on implementation costs to draw a proper cost-benefit analysis from this paper. I also think it would be especially relevant to consider the specificity of housing markets in low- and middle-income countries (notably informal housing), as job-related mobility partly depends on housing choice. Finally, biased beliefs (Baseler, 2023) and job-specific preferences (Blattman & Dercon, 2018; Feld *et al.*, 2022) may also play a role. I leave these extensions for future work.

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Appendix

A Additional Tables and Figures

Table A1: Relation to household head decomposition by co-residence status in the sample

	Other HH members		
	No	Yes	Total
Rel. w/ HH head			
Brother			
Frequency	598	332	930
Percent	4.54	9.97	5.64
Grandson			
Frequency	488	206	694
Percent	3.71	6.19	4.21
HH head			
Frequency	7,663	745	8,408
Percent	58.23	22.38	50.99
Husband			
Frequency	1,079	136	1,215
Percent	8.20	4.09	7.37
Other			
Frequency	997	486	1,483
Percent	7.58	14.60	8.99
Son			
Frequency	2,334	1,424	3,758
Percent	17.74	42.78	22.79
Total			
Frequency	13,159	3,329	16,488
Percent	100.00	100.00	100.00

Table A2: Heterogeneity analysis by rural area type

	Rural type		
	Tradi.	Farms	Total
Nb of obs.	4,804	1,719	6,523
Tot. share (%)	73.65	26.35	100.00
Black (y/n)			
Mean	1.00	0.67	0.91
SD	0.05	0.47	0.28
N	4,804	1,719	6,523
Age			
Mean	38.11	38.59	38.24
SD	12.27	10.57	11.84
N	4,804	1,719	6,523
Educ. yrs			
Mean	6.96	5.71	6.63
SD	3.61	3.83	3.71
N	4,804	1,719	6,523
HH size			
Mean	5.55	3.78	5.08
SD	3.74	3.01	3.65
N	4,804	1,719	6,523
R-U move (y/n)			
Mean	0.04	0.06	0.04
SD	0.19	0.24	0.21
N	4,804	1,719	6,523
R-R move (y/n)			
Mean	0.01	0.02	0.01
SD	0.07	0.15	0.10
N	4,804	1,719	6,523
Non-empl. (y/n)			
Mean	0.60	0.17	0.49
SD	0.49	0.38	0.50
N	4,804	1,719	6,523
Informal (y/n)			
Mean	0.64	0.33	0.51
SD	0.48	0.47	0.50
N	1,927	1,422	3,349
Log wage			
Mean	9.94	10.13	10.02
SD	0.93	0.59	0.81
N	1,546	1,125	2,671
Agri. job (y/n)			
Mean	0.18	0.71	0.47
SD	0.39	0.45	0.50
N	879	1,075	1,954
Wage empl. (y/n)			
Mean	0.52	0.94	0.69
SD	0.50	0.24	0.46
N	1,684	1,143	2,827

Table A3: Sample decomposition by interview outcome

	Frequency	Percent
Interview outcome		
Succesful interview	13,503	78.21
Proxy answered	1,568	9.08
Refused/unavailable	1,381	8.00
Not tracked/located	813	4.71
Total	17,265	100.00

Figure A1: Seasonality analysis by interview phase

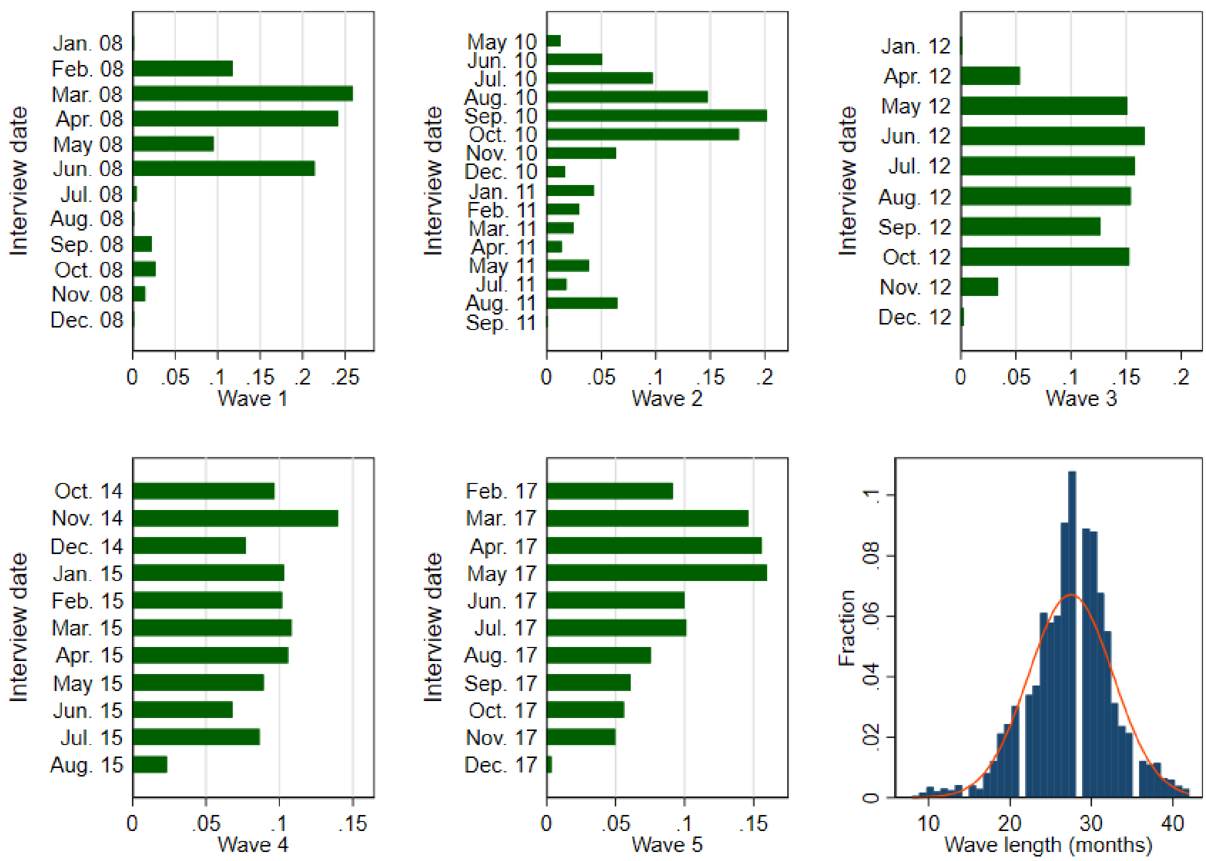

Table A4: Sample decomposition by migration pattern

	Frequency	Percent
Migration pattern		
R	7,295	42.25
R-U	1,385	8.02
R-U-R	310	1.80
R-U-R-U	15	0.09
U	7,815	45.26
U-R	340	1.97
U-R-U	105	0.61
Total	17,265	100.00

Figure A2: Estimated commuting distance by geography type

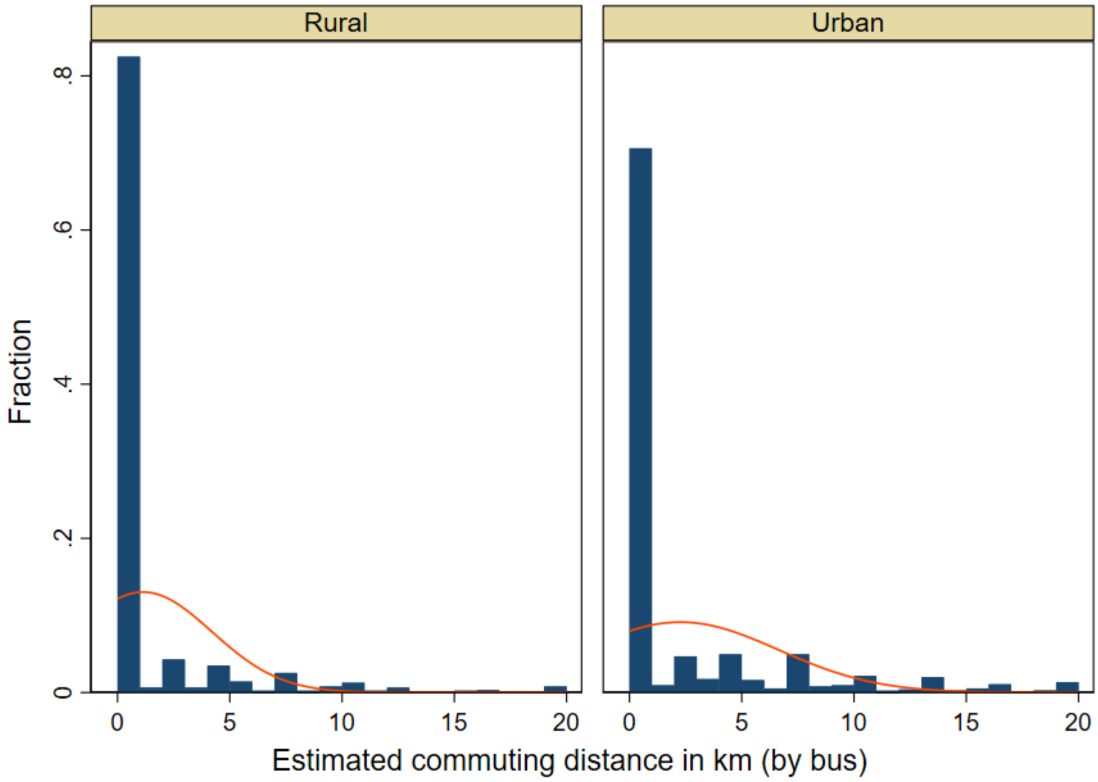

Table A5: Employment type decomposition by geo-employment state

	Geo-employment state				
	RF	RI	UF	UI	Total
Empl. type					
Casual work					
Frequency		522		521	1,043
Percent		35.83		38.76	16.11
Self-empl.					
Frequency	16	328	48	285	677
Percent	1.16	22.51	2.09	21.21	10.45
Wage empl.					
Frequency	1,359	607	2,252	538	4,756
Percent	98.84	41.66	97.91	40.03	73.44
Total					
Frequency	1,375	1,457	2,300	1,344	6,476
Percent	100.00	100.00	100.00	100.00	100.00

Table A6: Heterogeneity analysis by informality type

	Informality type					
	Rur. CW	Rur. SE	Rur. WE	Urb. CW	Urb. SE	Urb. WE
Nb of obs.	522	328	607	521	285	538
Tot. share (%)	18.64	11.71	21.67	18.60	10.17	19.21
Black (y/n)						
Mean	0.98	0.99	0.88	0.68	0.82	0.68
SD	0.14	0.10	0.33	0.47	0.38	0.47
N	522	328	607	521	285	538
Age						
Mean	38.15	41.17	37.47	36.85	39.55	36.70
SD	11.81	10.58	10.90	11.03	10.56	10.79
N	522	328	607	521	285	538
Educ. yrs						
Mean	6.58	7.17	5.64	7.97	8.22	7.81
SD	3.66	3.68	3.93	3.07	2.82	3.06
N	522	328	607	521	285	538
HH size						
Mean	5.24	4.54	3.94	3.95	3.60	3.71
SD	3.85	3.06	3.08	2.91	2.36	2.83
N	522	328	607	521	285	538
I-F move (y/n)						
Mean	0.06	0.04	0.19	0.14	0.08	0.20
SD	0.24	0.19	0.39	0.35	0.28	0.40
N	522	328	607	521	285	538
I-I move (y/n)						
Mean	0.12	0.07	0.09	0.14	0.11	0.12
SD	0.32	0.26	0.28	0.35	0.31	0.32
N	522	328	607	521	285	538
I-N move (y/n)						
Mean	0.41	0.30	0.16	0.20	0.20	0.14
SD	0.49	0.46	0.37	0.40	0.40	0.34
N	522	328	607	521	285	538
Log wage						
Mean	9.33	9.75	9.82	9.40	9.87	10.07
SD	0.79	0.95	0.63	0.87	1.06	0.75
N	383	315	607	497	277	538
Hrs p. week						
Mean	45.69	39.95	43.11	56.03	36.50	43.11
SD	52.80	35.89	20.90	56.77	33.49	23.27
N	451	282	586	439	238	510

Table A7: Heterogeneity analysis by geo-employment state

	Geo-employment state			
	RF	RI	UF	UI
Nb of obs.	2,033	2,139	3,348	2,173
Tot. share (%)	20.97	22.07	34.54	22.42
Black (y/n)				
Mean	0.77	0.93	0.72	0.69
SD	0.42	0.26	0.45	0.46
N	2,033	2,139	3,348	2,173
Age				
Mean	39.84	38.37	40.54	37.52
SD	10.22	11.07	10.61	10.81
N	2,033	2,139	3,348	2,173
Educ. yrs				
Mean	6.63	6.22	8.42	7.80
SD	3.69	3.83	2.77	3.11
N	2,033	2,139	3,348	2,173
HH size				
Mean	4.00	4.42	3.77	3.88
SD	3.46	3.51	2.58	2.82
N	2,033	2,139	3,348	2,173
Geo. change (y/n)				
Mean	0.05	0.05	0.02	0.02
SD	0.22	0.21	0.14	0.13
N	2,033	2,139	3,348	2,173
Formal. change (y/n)				
Mean	0.08	0.09	0.06	0.11
SD	0.27	0.28	0.23	0.32
N	2,033	2,139	3,348	2,173
Job destr. (y/n)				
Mean	0.08	0.21	0.07	0.13
SD	0.27	0.41	0.26	0.33
N	2,033	2,139	3,348	2,173
Network search (y/n)				
Mean	0.61	0.72	0.60	0.79
SD	0.49	0.45	0.49	0.41
N	1,331	588	2,200	527
Agri. job (y/n)				
Mean	0.45	0.51	0.11	0.15
SD	0.50	0.50	0.31	0.36
N	1,353	607	2,237	537
Log wage				
Mean	10.36	9.66	10.66	9.77
SD	0.66	0.80	0.69	0.92
N	1,373	1,305	2,300	1,312
Hrs p. week				
Mean	44.83	43.32	42.90	46.56
SD	14.46	37.75	15.07	41.29
N	1,345	1,319	2,269	1,187

Table A8: Industry decomposition by geo-employment state

	Geo-employment state				
	RF	RI	UF	UI	Total
Industry					
Priv. HH					
Frequency	32	58	38	64	192
Percent	2.37	9.56	1.70	11.92	4.06
P(change)	0.31	0.17	0.29	0.13	0.20
Agri.					
Frequency	615	309	246	81	1,251
Percent	45.45	50.91	11.00	15.08	26.43
P(change)	0.07	0.07	0.18	0.05	0.09
Mining					
Frequency	126	7	180	11	324
Percent	9.31	1.15	8.05	2.05	6.84
P(change)	0.10	0.00	0.11	0.18	0.10
Manuf.					
Frequency	138	38	420	47	643
Percent	10.20	6.26	18.78	8.75	13.58
P(change)	0.33	0.24	0.20	0.26	0.23
Utilities					
Frequency	23	4	47	4	78
Percent	1.70	0.66	2.10	0.74	1.65
P(change)	0.17	0.25	0.23	0.50	0.23
Construct.					
Frequency	93	67	232	113	505
Percent	6.87	11.04	10.37	21.04	10.67
P(change)	0.14	0.09	0.19	0.10	0.15
Retail					
Frequency	99	50	384	91	624
Percent	7.32	8.24	17.17	16.95	13.18
P(change)	0.28	0.24	0.17	0.16	0.19
Transport					
Frequency	42	29	137	55	263
Percent	3.10	4.78	6.12	10.24	5.56
P(change)	0.26	0.03	0.20	0.11	0.17
Finance					
Frequency	67	10	166	18	261
Percent	4.95	1.65	7.42	3.35	5.51
P(change)	0.15	0.20	0.28	0.06	0.23
Social serv.					
Frequency	118	35	387	53	593
Percent	8.72	5.77	17.30	9.87	12.53
P(change)	0.14	0.09	0.11	0.19	0.12
Total					
Frequency	1,353	607	2,237	537	4,734
Percent	100.00	100.00	100.00	100.00	100.00
P(change)	0.14	0.11	0.18	0.13	0.15

Figure A3: Evolution of industry shares across geography types

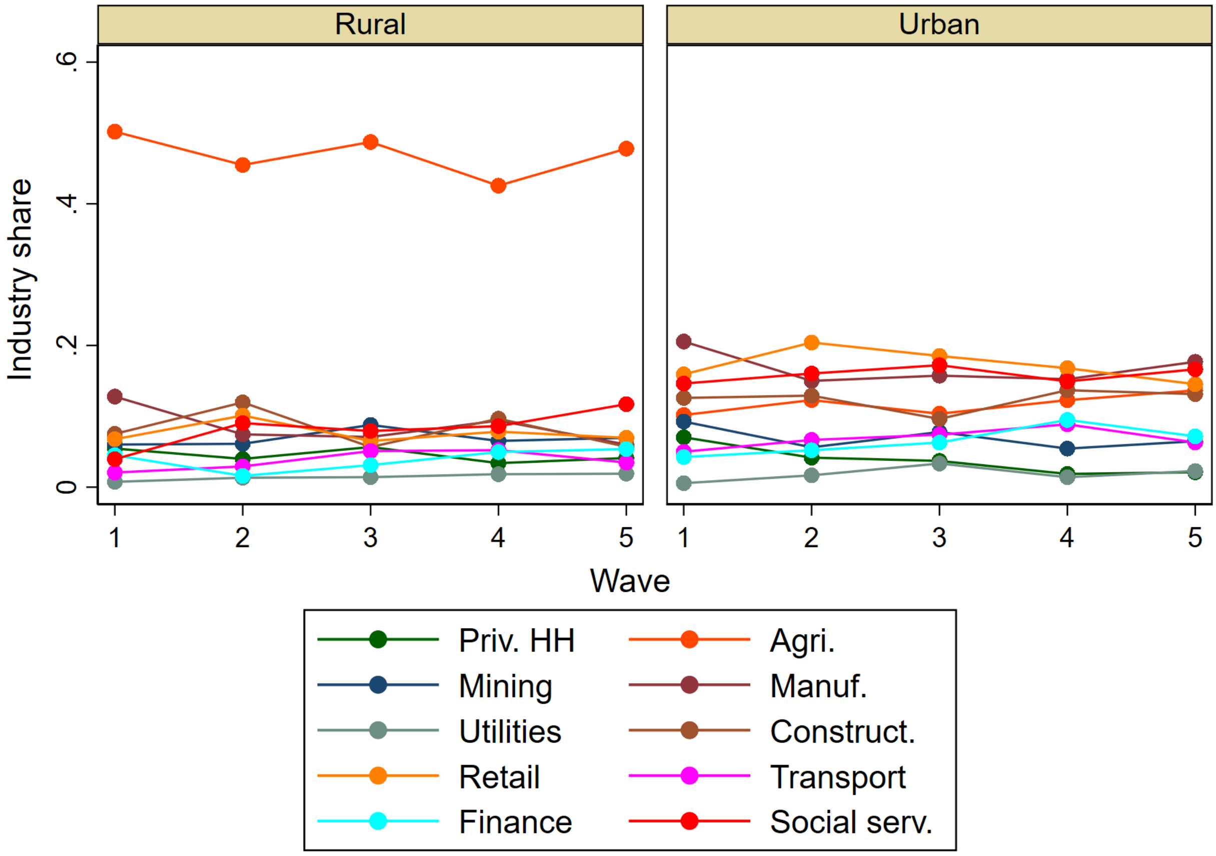

Table A9: Transition probability matrix with an extensive margin of labour supply

	State at t+1						
	REmpl.	RInact.	RUnempl.	UForm.	UInact.	UInform.	UUnempl.
State at t							
REmpl.							
Frequency	2,599	367	205	93	22	63	19
Percent	77.17	10.90	6.09	2.76	0.65	1.87	0.56
RInact.							
Frequency	263	604	192	14	11	22	6
Percent	23.65	54.32	17.27	1.26	0.99	1.98	0.54
RUnempl.							
Frequency	234	208	199	15	5	18	4
Percent	34.26	30.45	29.14	2.20	0.73	2.64	0.59
UForm.							
Frequency	42	15	8	2,135	102	177	110
Percent	1.62	0.58	0.31	82.46	3.94	6.84	4.25
UInact.							
Frequency	8	10	5	81	342	119	122
Percent	1.16	1.46	0.73	11.79	49.78	17.32	17.76
UInform.							
Frequency	26	6	4	244	144	1,172	118
Percent	1.52	0.35	0.23	14.24	8.40	68.38	6.88
UUnempl.							
Frequency	6	2	3	117	169	134	124
Percent	1.08	0.36	0.54	21.08	30.45	24.14	22.34

Table A10: Inter-quartile wage growth profiles across types of job change

	Q1	Q2	Q3	N
Wage growth				
No job change	-0.25	0.00	0.40	1,695
OTJS change	-0.33	0.03	0.54	762
G-empl. change	-0.29	0.11	0.77	483
Total	-0.28	0.02	0.49	2,940

Figure A4: Cross-district migrant shares over urban population shares

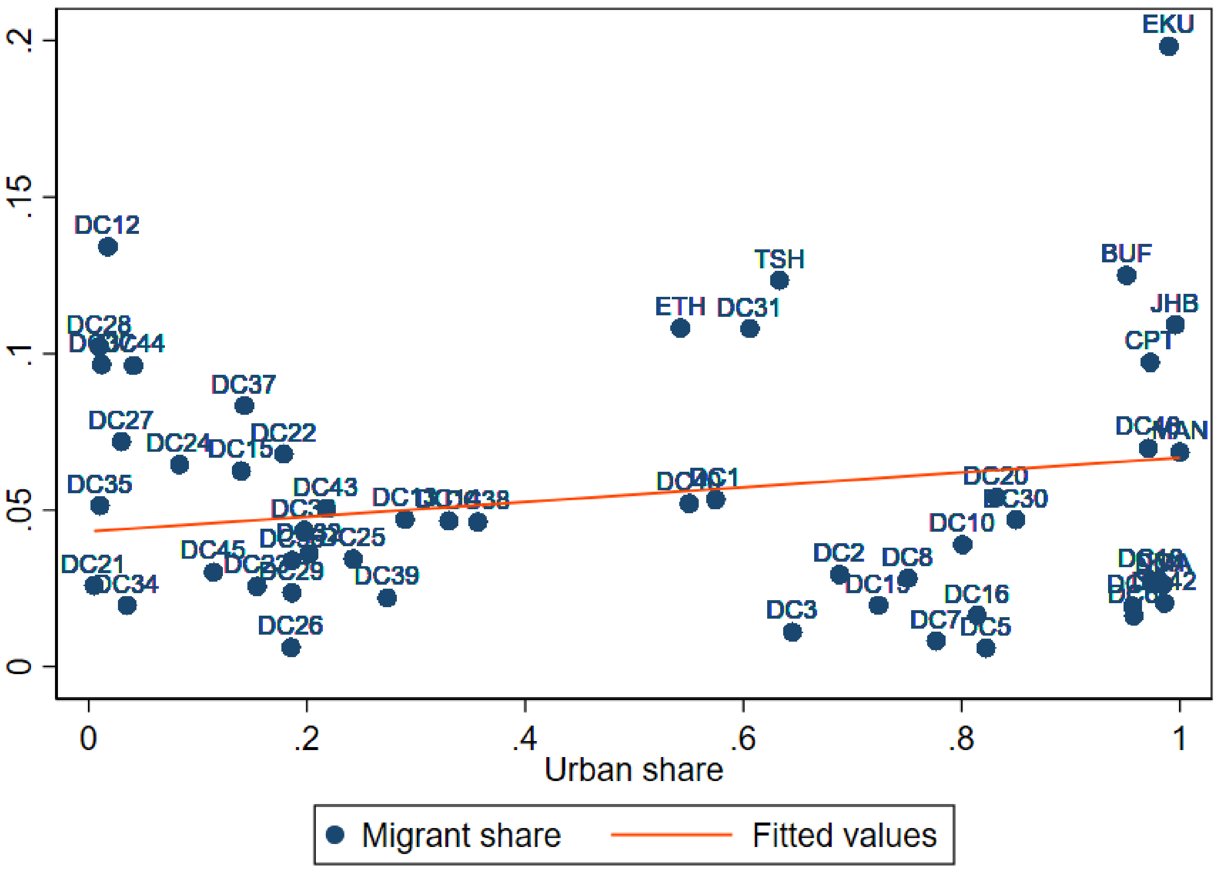

Table A11: Return migration decomposition across mover status

	Mover status		
	R-U	U-R	Total
Return migr.			
No			
Frequency	1,605	355	1,960
Percent	93.86	79.78	90.95
Yes			
Frequency	105	90	195
Percent	6.14	20.22	9.05
Total			
Frequency	1,710	445	2,155
Percent	100.00	100.00	100.00

Table A12: Transition probabilities towards model states at $t+1$ conditional on state at t

	RN_{t+1}	RE_{t+1}	UN_{t+1}	UF_{t+1}	UI_{t+1}	*Obs.*
RN_t	0.856	0.120	0.010	0.007	0.007	7,021
RE_t $+OTJS$	0.125	0.786 +0.059	0.006	0.014	0.009	6,639
UN_t	0.006	0.003	0.830	0.068	0.093	5,515
UF_t $+OTJS$	0.004	0.008	0.072	0.862 +0.029	0.023	5,170
UI_t $+OTJS$	0.003	0.008	0.133	0.070	0.751 +0.034	3,279
Obs.	6,910	6,538	5,498	5,354	3,324	27,624

Table A13: Estimated transition probabilities from multinomial logit model with controls

	RN_{t+1}	RE_{t+1}	UN_{t+1}	UF_{t+1}	UI_{t+1}	*Obs.*
RN_t	0.819 (0.006)	0.153 (0.005)	0.011 (0.001)	0.008 (0.001)	0.009 (0.001)	7,021
RE_t $+OTJS$	0.117 (0.004)	0.794 (0.005) +0.058	0.007 (0.001)	0.015 (0.002)	0.010 (0.001)	6,639
UN_t	0.006 (0.001)	0.003 (0.001)	0.829 (0.005)	0.067 (0.003)	0.094 (0.004)	5,515
UF_t $+OTJS$	0.005 (0.001)	0.008 (0.001)	0.079 (0.004)	0.854 (0.005) +0.030	0.025 (0.002)	5,170
UI_t $+OTJS$	0.003 (0.001)	0.008 (0.002)	0.139 (0.006)	0.069 (0.005)	0.748 (0.008) +0.033	3,279
Obs.	6,910	6,538	5,498	5,354	3,324	27,624

Table A14: Welfare effects of increasing the costs of informality (no migration)

	Baseline	Change from baseline		
	$\gamma_f = 1$	$\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
W_U^N	11,874	-3.37%	-22.68%	-12.65%
$r\mathbb{E}(W_U^F)$	22,605	-0.43%	-4.78%	-5.41%
$r\mathbb{E}(W_U^I)$	19,498	-4.79%	-18.21%	-17.98%
Total	18,139	-1.67%	-10.64%	-8.35%

Figure A5: Mean-adjusted log wage distributions by model employment state

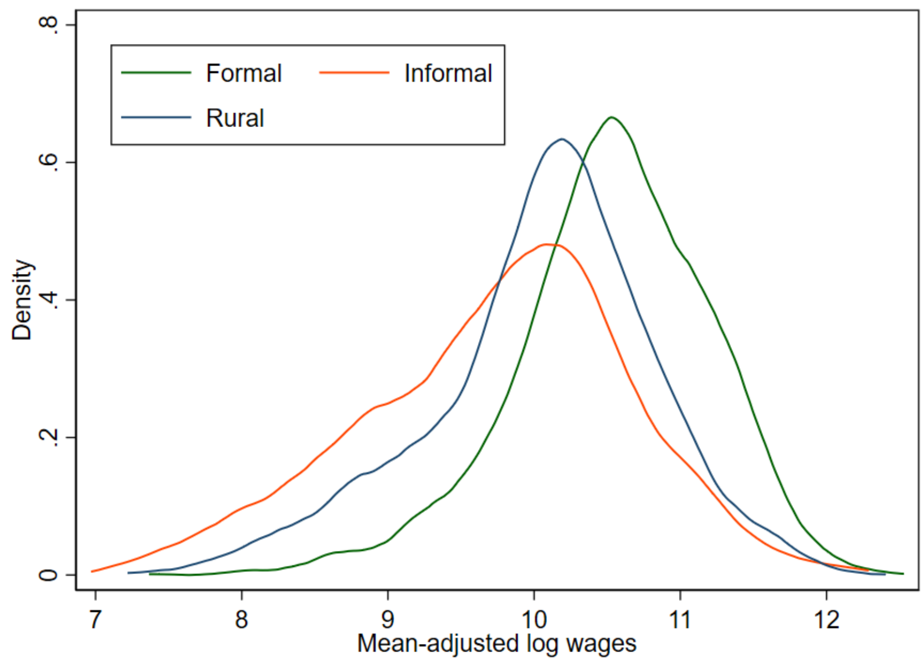

Table A15: Output effects of increasing the costs of informality (no migration)

	Baseline	Change from baseline		
	$\gamma_f = 1$	$\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
$\mathbb{E}(p_U^F l_U^F) \cdot \frac{N_U^F}{M_U^F}$	192,727	-1.80%	-3.16%	-4.58%
$\mathbb{E}(p_U^I l_U^I) \cdot \frac{N_U^I}{M_U^I}$	78,092	-2.64%	-5.28%	-3.70%
Total	101,110	-0.29%	+0.47%	+0.35%

Table A16: Changes in worker/firm allocation as costs of informality increase (no migration)

	Baseline	Change from baseline		
	$\gamma_f = 1$	$\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
Worker shares				
Non-empl. rate	0.36	-0.48%	-1.13%	-1.45%
Formal rate	0.45	+3.02%	+7.34%	+9.20%
Informal rate	0.19	-6.05%	-14.79%	-18.47%
Firm shares				
Active	0.92	+1.07%	+5.41%	+3.92%
Informal rate	0.58	-1.08%	-3.37%	-8.63%
Mean firm sizes				
Formal	85.41	+1.40%	+1.38%	-1.90%
Informal	64.30	-3.47%	-11.02%	-6.90%

B Additional Mathematical Derivations

$$\forall k \in \{F, I\},\ D_{UU}^{Nk} = \frac{\lambda_{UU}^{Nk}\left(1 - e^{-\left(\lambda_{UU}^{NF} + \lambda_{UU}^{NI}\right)}\right)}{\lambda_{UU}^{NF} + \lambda_{UU}^{NI}}$$

$$D_{RR}^{NE} = \frac{\lambda_{RR}^{NE}\left(1 - e^{-\left(\lambda_{RR}^{NE} + \lambda_{RU}^{NF}\overline{F_U^F}(W_R^N + c) + \lambda_{RU}^{NI}\overline{F_U^I}(W_R^N + c)\right)}\right)}{\lambda_{RR}^{NE} + \lambda_{RU}^{NF}\overline{F_U^F}(W_R^N + c) + \lambda_{RU}^{NI}\overline{F_U^I}(W_R^N + c)}$$

$$\forall k \in \{F, I\},\ D_{RR}^{Nk} = \frac{\lambda_{RU}^{Nk}\overline{F_U^k}(W_R^N + c)\left(1 - e^{-\left(\lambda_{RR}^{NE} + \lambda_{RU}^{NF}\overline{F_U^F}(W_R^N + c) + \lambda_{RU}^{NI}\overline{F_U^I}(W_R^N + c)\right)}\right)}{\lambda_{RR}^{NE} + \lambda_{RU}^{NF}\overline{F_U^F}(W_R^N + c) + \lambda_{RU}^{NI}\overline{F_U^I}(W_R^N + c)}$$

$$\forall ik \in \{RE, UF, UI\},\ D_{ii}^{kN} = \int_{\underline{W_i^k}}^{\overline{W_i^k}} \frac{\delta_i^k}{d_i^k(x)}\left(1 - e^{-d_i^k(x)}\right) dG_i^k(x)$$

$$\forall ik, il \in \{RE, UF, UI\},\ D_{ii}^{kl} = \int_{\underline{W_i^k}}^{\overline{W_i^k}} \frac{\lambda_{ii}^{kl}\overline{F_i^l(x)}}{d_i^k(x)}\left(1 - e^{-d_i^k(x)}\right) dG_i^k(x)$$

$$\forall k \in \{F, I\},\ D_{RU}^{Ek} = \int_{\underline{W_R^E}}^{\overline{W_R^E}} \frac{\lambda_{RU}^{Ek}\overline{F_U^k(x + c)}}{d_R^E(x)}\left(1 - e^{-d_R^E(x)}\right) dG_R^E(x)$$