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

Thomas Monnier*

CREST, Ecole Polytechnique, IP Paris

October 17, 2024

Click here for the latest version

Abstract

In rapidly urbanizing low- and middle-income countries, many rural migrants work in the informal sector, without benefits and for low wages. Would these migrants be better off if the informal sector did not exist? To answer this question, I develop a novel general-equilibrium model of rural-urban migration based on frictional job search and matching, which I estimate using South African micro data on workers. I find that the urban informal sector serves as a stepping-stone to urban formal jobs. Moreover, I find that it is a valuable outside option for urban formal workers and that its decline can increase the local labour market power of formal firms, which then offer lower wages. This phenomenon makes cities less attractive, even in the absence of direct job destruction, and is exacerbated by the response of rural firms that offer higher wages and retain potential migrants: after a tripling of monitoring costs, 2.2% of the total population decides not to move, equivalent to 2.7 years of urban growth at current rates. The corresponding rural-urban welfare gap falls from 29.2% to 25.5%. 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. However, the aggregate impact is muted because there are now more workers in less productive areas.

*I am grateful to Benoît Schmutz-Bloch for supervising this project ; to Geoffrey Barrows, Roland Rathelot, and Pauline Rossi for following it as part of my PhD committee ; and to all CREST people that I cannot cite here. For helpful comments and suggestions, I thank Kentaro Asai, Pierre-Philippe Combes, Sylvie Démurger, Klaus Desmet, Xiaofang Dong, François Gerard, David Gomtsyan, Nicolas Gravel, Nina Guyon, Tomohiro Hara, Oliver Harman, Jonas Hjort, Clément Imbert, Leonard le Roux, Kwok-Hao Lee, Romaine Loubes, David Margolis, Samuel Marshall, Angelica Martinez Leyva, Pinchuan Ong, Fabien Postel-Vinay, Imran Rasul, Alex Rothenberg, Christian Schluter, Harris Selod, Kohei Takeda, Gabriel Ulyssea, Nicola Viegi, Ao Wang, Yun Xiao, and Huaiping Yuan ; participants at the UCL PhD Seminar, the Paris PhD Seminar on Urban Economics, the 13th European Meeting of the Urban Economics Association, and the 2nd HEC Economics PhD Conference ; the Policy and Strategy team at the City of Cape Town, and faculty members at the University of Cape Town. The views expressed in this paper are those of the author and do not reflect the position of CREST, Ecole Polytechnique, or IP Paris. This research is funded by LabEx ECODEC - Investissements d'Avenir, Institut Louis Bachelier - Just Transition Hub, and EUR DATA EFM.

1 Introduction

According to the World Bank (2023), the global urban population is set to double by 2050, with Sub-Saharan Africa (SSA) and the East Asia and Pacific (EAP) region experiencing the most rapid urban growth. There, long-term rural-to-urban migration plays a significant role in driving urbanization levels, especially in low- and middle-income countries (Wahba Tadros *et al.*, 2021). How do these migrants integrate in cities? Do they manage to improve their livelihood or do they get stuck in unproductive positions? What impact do they have on urban incumbents and the overall economy? Here, I focus on a relatively unexplored aspect of the problem: the prevalence of unregistered informal jobs among the poorest rural migrants in cities. Do such jobs lead to labour misallocation across space in low- and middle-income countries? This paper shows that it is not necessarily so, as I find that reduced informality can lead to higher total output but also lower workers' welfare, with migration choice acting as an important mitigation mechanism.

Informal jobs may be seen as an alternative to formal jobs since they are subject to different information frictions. 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). Urban informal jobs may therefore serve as a stepping-stone for rural migrants in search of higher urban incomes and/or higher urban amenities (Selod & Shilpi, 2021). This is all the more relevant in contexts marked by high information frictions holding back rural-urban migration more specifically (Lagakos, 2020). At the same time, informal jobs are typically of lower quality for workers, as the informal sector tends to shield low-productivity firms from competition (Ulyssea, 2018). With relatively few workers transitioning to or from informal employment who climb to or persist in good jobs (Donovan *et al.*, 2023), they also tend to offer poorer career prospects. Still, formal and informal labour markets appear to be strongly 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 (Ulyssea, 2020). Importantly, matching frictions also generate local labour market power for firms, with informal firms limiting the wage-setting capacity of formal firms by acting as an outside option for formal workers (Donovan & Schoellman, 2023).

Any policy that aims at diminishing the share urban informal employment is therefore likely to generate spillovers across the two sectors, within and across local labour markets (for stayers and movers). As a consequence, the impact on aggregate welfare and output is also ambiguous. In fact, informal employment negatively correlates with many development metrics, notably government revenues and expenditures. This has motivated the adoption of a wide range of policies targeting the informal sector, either through increases in the relative costs of informality or reductions in the relative costs of formality for workers and firms (Ohnsorge & Yu, 2022). Such initiatives have been met with varying success (Gallien & Van den Boogaard, 2021). Interestingly, while urban informal employment negatively correlates with urbanization rates in the cross-section, it is also positively associated with rural-to-urban migration in panel data: this suggests a dynamic adjustment mechanism whereby the informal sector facilitates rural-to-urban moves (Todaro, 1969; Harris & Todaro, 1970; Fields, 1975), triggering economic development that endogenously reduces its importance (Lewis, 1954; Ranis & Fei, 1961; Loayza, 2016). In this paper, I show that urban formalization policies can indeed lead to reduced urbanization rates, although the implications in terms of labour allocation are ambiguous.

To quantify the effect of urban formalization policies and assess how the urban informal sector affects the spatial allocation of labour, I develop a dynamic rural-urban migration model with frictional job search-and-matching. To do so, I 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, subject to frictions and amenity differentials that vary across origin and destination states. 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. Workers in the formal sector benefit from unemployment insurance and severance payment when being fired. 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, and 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 cost can be narrowly interpreted as the expected cost of being inspected and/or fined, or more broadly as the opportunity cost of being excluded from formal land, capital, and financial markets. To the best of my knowledge, this paper is the first to combine migration choice of workers with formality choice of workers and firms, two elements that I show to be complementary.

I estimate my model with a nationally representative South African panel survey covering individuals' migration choices and labour market outcomes every year over the 2008-2017 period. Offer distributions and job arrival and destruction rates that capture underlying search-and-matching frictions are jointly identified by observed wages and transition probabilities across geo-employment states. In counterfactuals, offer distributions are endogenized by fitting urban firms' productivity distribution obtained by model inversion at initial state. I reduce my benchmark sample to low-educated working-age adult males to abstract from the spatial sorting of workers with respect to skills suggested by Young (2013), Alvarez (2020), and Hicks *et al.* (2021). Besides, the low-skilled segment of the population is the most affected by informal employment. This segment of the workforce should be relatively unspecialized, hence substitutable across industries and occupations (Belot *et al.*, 2019). It should also feature relatively low returns to experience (Bobba *et al.*, 2021), which makes it possible to keep a tractable model structure. Focusing on adults also allows me to abstract from schooling decisions (Bobba *et al.*, 2022) and differential returns to schooling across sectors (Joubert, 2015; García, 2015). Moreover, since males typically do not value the flexibility of working conditions provided by informal jobs as much as females do (Berniell *et al.*, 2021; Bernatzky *et al.*, 2024), I abstract from the intensive margin of labour supply too.

My main result is that raising the relative cost of informality (up to a factor of 3) for urban firms increases total output but diminishes workers' welfare. Within this framework, reduced rural-to-urban migration acts as an adaptation strategy for workers in the face of heterogeneous welfare effects across local labour markets. The mechanism at play is as follows. In response to the policy shock, informal firms of varying productivity levels formalize depending on their relative profit opportunities in the formal sector. In my context, they are productive enough not to exit the market. This generates more competition for workers in the formal sector, destroying some of the least productive firms there. 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. In the informal sector, firms reduce their 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 urbanization rate hence decreases, until congestion forces adjust to reflect the new spatial equilibrium.

The rise in urban output generated by the reallocation of informal workers towards the formal sector comes at the cost of lower welfare due to firms' wage-setting power. In rural areas, increased wages and the reallocation of workers towards more productive jobs improve both welfare and output. However, more workers are now staying in rural areas where they are also less productive: 2.2% of the total population decide not to move, which corresponds to 2.7 years of reversed urban growth at current rates. This limits the rise in total output (+2.4%). Moreover, as the rural-urban welfare gap remains high, the increase in rural population does not fully offset the fall in workers' welfare caused by lower urban wages (-0.9%). As for urban informal employment, rural jobs limit the monopsony power of urban firms, which is also a source of local labour misallocation. Indeed, when removing rural-urban migration from the model, the negative welfare effect of the policy is 5.5 times stronger for urban workers than in my main specification. This points to the role of rural jobs as an important alternative outside option for potential migrants when urban informal employment becomes more constrained. The positive output effect is 4.5 times weaker, as the most productive urban firms are also those which cut wages the most, reallocating workers towards the least productive ones.

I contribute to the existing literature in four 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 in isolated labour markets, researchers generally find positive effects on output, but negative (Ulyssea, 2010; Charlot *et al.*, 2015), neutral (Haanwinckel & Soares, 2021; Dix-Carneiro *et al.*, 2024), 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. 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 of workers (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 more closely align with Ulyssea (2010) and Charlot *et al.* (2015), as I show that the 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. As urban informality comes with non-negligible dynamic gains in mine, it is also a more valuable outside option for formal workers. This explains why its reduction increases the monopsony power of formal firms in the labour market. I then discuss the external validity of my findings. 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.

In my context, the urban informal sector appears as a rung on the job ladder for local workers since informal workers are more likely to find a new better job than the unemployed (be it in the formal or informal sector). Furthermore, the lower wages generated by the policy shock cancel the positive effect of formalization in terms of average welfare. The informal sector also provides potential rural-to-urban migrants with relatively good jobs that deteriorate after the policy shock. This leads some of them to stay in rural areas with comparatively lower-quality jobs, even if local conditions improve. I thereby 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, 2024).

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. 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 (2024), who considers local labour markets featuring both self-employment and regular firms with market power. Apart from the fact that I focus on informal jobs generally and not on self-employment, our settings differ in that I incorporate dynamic search-and-matching 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 set rather in high-income country contexts (Kennan & Walker, 2011; Baum-Snow & Pavan, 2012; Schmutz & Sidibé, 2019; Balgova, 2022; Maguain & Koubi, 2022; Martellini, 2022; Porcher, 2022; Bilal, 2023). I adapt them to a middle-income country context with two sectors, a formal and an informal one. For similar endeavours in high-income countries but without a spatial dimension, see Hoffmann & Shi (2016), Shephard (2017), and Bradley *et al.* (2017). Most related to my work, Heise & Porzio (2023) 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 (2023), as welfare and output decrease compared to my baseline results. The allocation of employed urban workers across the formal and informal sectors does not vary much across the two specifications, unlike in Marshall (2024). This may be due to the dominance of frictional informal wage employment over self-employment, deemed to be frictionless in his approach, in my empirical context.

I also add to the reduced-form evidence on the rural-urban income gap by updating estimates from Lagakos *et al.* (2020) with heterogeneity across the urban formal and informal sectors. I find that whereas rural migrants experience a wage gain when moving to the formal sector in cities, they experience a wage cut when doing so in the informal sector (independently of their sector of origin). I rationalize this puzzle through improved future labour market outcomes in cities, regardless of differences in amenities. This can be seen as further motivating evidence for my modelling approach. It is also worth noting that I remain agnostic about the sources of the productivity gap that underlies at least part of the estimated rural-urban income gap (Pulido & Święcki, 2019; Gai *et al.*, 2021; Cenci *et al.*, 2023). This is because I do not explicitly model industry composition (Gollin *et al.*, 2014; Herrendorf & Schoellman, 2018) or agglomeration economies across space.

Third, I 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. More specifically, Imbert & Ulyssea (2024) simulate the impact of an exogenous migration shock in rural areas on urban labour markets with informal employment. In the short-run, they find an increase in urban informal employment, as informal firms absorb most of the labour supply shock under downward wage rigidity in the formal sector. In the long-run, as wages become more flexible, it becomes profitable for informal firms to formalize and urban informal employment actually decreases. This translates into higher urban output but lower welfare, which is consistent with my results. I place myself in a similar long-term perspective, as I consider fully flexible wages in equilibrium, and I add rural production in the model. Although my policy scenario focuses on the impact of an exogenous urban informality shock on urbanization rates, a question that is symmetric to the one asked by Imbert & Ulyssea (2024), my findings suggest a feedback-loop effect that is absent from their model: with endogenous migration choice and frictions, rural-to-urban migration flows should decrease as urban informality and wages fall, mitigating the initial reduction in welfare. The effect on output is ambiguous. Indeed, the rural outside option should improve the productive allocation of labour within the formal sector by limiting firms' monopsony power. However, it should also limit the formalization rate of informal firms that is motivated by lower wages in the formal sector (and not primarily by a rise in monitoring costs).

Finally, I contribute more widely to the recent literature studying the role of labour market frictions - and factor misallocation more generally - in structural transformation (Restuccia & Rogerson, 2017; Poschke, 2019; Hao *et al.*, 2020; Martellini & Menzio, 2021; Buera *et al.*, 2023; Gollin & Kaboski, 2023; Guner & Ruggieri, 2023; Lagakos & Shu, 2023; Feng *et al.*, 2024). For instance, Schwartzman (2024) proposes a (non-spatial) model of structural transformation through endogenous formalization of low-skilled services. My model differs in that I do not account for composition changes across industries or productivity changes within industries, notably because I do not observe overlapping generations of workers (Hobijn *et al.*, 2018; Porzio *et al.*, 2022). In my sample, the relation between rural-to-urban migration and structural change is not clear: as the economy urbanizes, urban employment appears to switch from manufacturing to more labour-intensive consumer services (Lewis, 1954; Imbert *et al.*, 2022; Fan *et al.*, 2023), but so does rural employment. As in Budí-Ors (2023), 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 assume away any link between industry changes and rural-to-urban migration or formalization in my model. Rather, for a fixed rural-urban productivity gap, I show how a given local labour market policy impacts aggregate urbanization, output, and welfare. In other words, I run comparative statics on how spatial labour allocation affects development at a given stage of the structural change 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 estimation results and Section 6 the policy counterfactuals. Section 7 concludes.

2 Data and Motivating Facts

2.1 Context

Compared to countries surveyed by Ulyssea (2020), South Africa features a relatively high rate of unemployment (26% of working-age males in 2023, ILO) and a relatively low (but still substantial) rate of informal employment (41%), which makes it an interesting case study per se. Rodrik (2008) and Banerjee & Chiplunkar (2023) 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-to-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), with an urbanization rate of 69% in 2023 (World Bank). 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 with other low- and middle-income countries in the SSA and EAP regions in terms of urbanization (+0.8% per year over my study period) and informality (-0.2%) trends. However, its relatively high level of urbanization and low level of informality align more closely with emerging economies elsewhere (e.g., Turkey).

Finally, my policy scenario is all the more relevant in the South African context as a National Labour Inspection Task Team was specifically created by the Department of Employment and Labour's Inspection and Enforcement Services in 2022 to target the informal sector. This comes after my study period but could be used in future work for model validation or extensions such as cost-benefit analyses, were the necessary information to become available.

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 over a large number of periods, and a large number of variables

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

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.

I reduce my benchmark sample to males 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) working hours, two distinctive features of the informal sector from which I abstract. This is often associated with high search-and-matching frictions 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, who are declared as household heads in the vast majority of cases, also allows me to abstract from the joint location decision problem in a couple. I further restrict my sample to individuals who stay within the 18-64 year-old range over the study period as I focus on job-related mobility of independent agents.[2] I also restrict it to individuals who never obtain 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 migration choices are not motivated by university or other adult education choices. Finally, I aggregate all sources of individual labour market income to obtain monthly wages 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 3,453 individuals followed over five waves.

One specificity of this data set is that it allows me 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, I know whether the enumeration area (census block group) where individuals live was classified as urban or rural in the National Census of 2011 (based on the continuity of built-up areas).[3] The vast majority of individuals declare to reside permanently (i.e., stay more than four nights a week) in the area where they were interviewed and there is no apparent seasonality in interview dates, ruling out potential temporary migration patterns.[4] Note that attrition is not an absorbing state in my sample: half of the individuals that are lost at some point are recovered at some later point over the study period. For the sake of simplicity, I therefore pool all observations together to study attrition. Out of the 25% of non-responses I obtain when doing so, two-thirds are due to a refusal or non-availability, and one-third are due to a geographic move that was not well followed. Contrary to individuals, households are not identifiable across waves. Hence, I cannot compare the number of untracked moves with an accurate number of geographic moves that are well followed. Still, I can say that it is roughly equal to the number of non-missing observations following a change in districts or geography types, which understates the actual number of moves in my sample. With that in mind, I decide to impute missing values for geography type and employment status based on past or

[2] It suffices to spend 15 nights a year under the same roof and sharing food and resources when staying together to be part of the same household. As a consequence, an individual can be part of many households, and I consider household members independent agents. For a model of migration choice with or without one's family, see Imbert *et al.* (2023).

[3] Three-quarters of my rural population live in communally-owned land (traditional), as opposed to commercial farm land (farms): it is 4.5 times more likely to move from rural to urban areas than to move across traditional and farm areas.

[4] The cases where several migrant workers share the same permanent residence are marginal in my sample.

future states when available to obtain a balanced panel. I further assume 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 there: based on estimates of commuting costs from Pfeiffer *et al.* (2024), 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 70% not travelling at all). As a consequence, I consider that workers also change local labour markets when changing geography types. Furthermore, I abstract from sequential migration as the vast majority of migrants only move once in my sample. Finally, I focus on rural-to-urban migration since it is three times more likely than urban-to-rural migration and I want to study the impact of an urban policy on rural migrants.[5]

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 who do not have 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. Note that most job characteristics are only available for wage workers in the data, and that most self-employed workers are found in the informal sector. Along all the dimensions studied below, there is less heterogeneity between formal and informal jobs in rural than in urban areas. I therefore collapse rural formal and informal jobs into one rural employment category, as my focus is on urban formalization policies. Interestingly, urban informal wage jobs are one-third more likely than formal ones to be obtained through personal networks, which points to heterogeneity in search frictions. Personal connections can also be seen as an alternative to formal contract enforcement. There is no strong heterogeneity in industries (or occupations) across the formal and informal sectors for wage employment, with construction being slightly over-represented in the informal sector compared to manufacturing. Actually, there is more heterogeneity, independently of formality status, across urban and rural areas given the role played by agriculture. Besides, my low-skilled workforce appears to be highly substitutable across industries, since almost half of on-the-job transitions for wage workers imply a change in industries. Note that this is not driven mostly by movers. Finally, given that aggregate informality figures are aligned with the National Census of 2011, I consider the risk of self-reporting bias to be relatively low. Also note that respondents are informed that the survey is anonymous, and that informal job monitoring is notoriously low in South Africa over my study period. Furthermore, it targets mostly large firms (typically in cities). Hence, workers (especially the self-employed) should have few incentives to systematically misreport their status.

When employed, it is as likely to become inactive as it is to become unemployed. When inactive, it is as likely to become active as it is to stay inactive. I therefore merge the non-economically active and the unemployed into a non-employed category. Note that this category may include workers engaging in home production. This allows me to abstract from labour force participation choice, which may drive part of migration choice: in my sample, it is 40% more likely to transition from inactivity to activity for rural-urban movers than for stayers. I further abstract from the intensive margin of labour supply, which may drive part of the (in)formality choice. In fact, informal workers in cities work 3.7 hours more per week than formal workers on average, which is both smaller in magnitude and contrary to the tendency observed in middle-income countries: Bick *et al.* (2022) find that, in this group, workers in the traditional sector work on average 5.8 hours less per week than in the modern sector. The

[5] I observe very few changes in districts within rural or urban areas, but two-thirds of rural-to-urban moves are associated with a change in districts.

difference disappears when keeping wage workers only: I comment on this issue in the next sub-section. Besides, I identify on-the-job transitions within the formal or informal sectors via employment spells lasting less than the time interval between two interview dates. When this information is missing (for non-wage workers), I identify on-the-job transitions through changes in industry, occupation, employment type (wage or self-employment), or district. 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 stay the same as at initial state), and to consider close-to-yearly (13.5 months) time periods. Wages are correspondingly divided by 2. It is worth noting that median wage growth for employed workers who keep the same job is less than 0.5% a year, which I interpret as evidence of low returns to experience for low-skilled workers.

2.3 Summary Statistics

Tables 1 and 2 summarize key descriptive statistics pooled over the study period by mover status and geo-employment state, along with the corresponding worker allocations. As could be expected from the literature, rural migrants are younger than their peers. They are more educated and richer than rural stayers, but less so than urban stayers. In terms of race and employment characteristics, they are similar to rural stayers, with a relatively high propensity to be non-employed. Cities are less ethnically homogeneous and more educated than rural areas. They also feature lower non-employment rates. Age and education are positively correlated with formal employment. Finally, rural and non-employed individuals tend to be part of larger households. These socio-demographics characteristics could bias my parameter estimates for a setting with homogeneous workers if they indeed generate a lot a self-selection across origin-destination pairs of states in my model.

Moreover, whereas the vast majority of formal jobs are wage jobs, less than half of informal jobs are. As a first approach, I assimilate self-employed jobs to wage jobs at one-employee firms, which makes sense when considering that self-employment is not merely a frictionless outside option for workers who still need to search for clients, suppliers, etc. If those frictions are very different from the ones faced by wage workers (Breza *et al.*, 2021), this could be a source of unobserved heterogeneity. More precisely, if heterogeneous job characteristics such as differences in hours worked indeed drive part of the (in)formality choice of workers, it should be reflected in heterogeneous wage profiles and/or transition probabilities, which I use to estimate frictions in my model. I discuss these issues in the next sub-sections.[6]

2.4 Stylized Fact 1: Transition Probabilities

By pooling all the observed transitions in the data and tabulating destination states conditional on origin states, I obtain the transition probability matrix showcased in Table 3. This yields the first set of moments targeted by the model. The key underlying assumption here is that transitions follow a Markov process of order 1, meaning that the probability of a given state at time $t + 1$ only depends on the state at t. In other words, the process is memory-less and repeated observations for a given worker can be treated independently. I support the first assumption by deriving the same transition matrix conditional on each state at $t - 1$. It is not straightforward to interpret the results as some cells feature very few observations and are therefore not significant. At least, the significant values are

[6]For a model of (in)formality choice with self-employment and a life-cycle approach, see Narita (2020).

consistent with my baseline specification. I support the second assumption by dealing with potential unobserved heterogeneity in several ways. First, I recover the corresponding predicted probabilities from a multinomial logit model with added (quadratic) individual controls including race, age, years of education, and household size, taken at mean values.[7] I find results that are close to my main specification. Second, I re-derive my pooled transition matrix by splitting my sample below and above mean values for age and education: results are more heterogeneous but still relatively aligned with my main specification. The same comment holds when splitting the sample for wage and non-wage employment in the informal sector.

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 typically more stable than urban informal ones, with lower job destruction. However, 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. Finally, probabilities to migrate are typically smaller. They are also higher from rural to urban than from urban to rural areas. 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-to-urban migrants are 28% more likely to be informally employed than urban stayers, which conforms to the empirical regularity observed in other contexts.

The relatively high transition probabilities across states further support the use of a dynamic job search-and-matching model with interconnected labour markets. Note that I will not account for migration flows into non-employment in the model, as such moves violate spatial equilibrium conditions: this is a theoretical constraint (see Section 3.1 for a discussion). I will not allow for urban-to-rural moves either, as they prevent me from solving analytically for worker shares across states: this is a numerical limitation. I justify these simplifications by considering such transitions as second-order in the data.

2.5 Stylized Fact 2: Cross-Sectional Wage Distributions

Figure 1 plots pooled cross-sectional log wage distributions for the three employment states of interest. This is the second set of moments targeted by the model. As with transition probabilities, I test for unobserved heterogeneity by residualizing the distributions for individual controls or plotting them over splitted samples: my baseline specification appears to be relatively robust. 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

[7]Adding individual fixed effects would prevent such exercise by identifying transition probabilities only on movers, and would also capture heterogeneity on the firms' side in the absence of matched employer-employee data. As this is part of the model mechanism, I do not want to control for this.

in earnings will not affect workers' welfare directly in the model.[8] Although these distributions reflect the wage distributions in which homogeneous workers should draw depending on their state, they do not reflect the actual wage gains or losses they experience when transitioning from one state to the other. Hence, I now turn to the observational returns to migration.[9]

2.6 Stylized Fact 3: Observational Returns to Migration

Table 4 shows the average monetary returns for rural-to-urban migrants, 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-to-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. Under common preferences, this can only be rationalized through higher urban amenities, better urban job opportunities in the future, or overoptimism regarding those. My model incorporates these different elements and its estimation identifies the dominant effect. 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 actual differences, they are 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. Nonetheless, since model parameters are jointly identified by observed transition probabilities and wage distributions, a bias on the actual wage draws may be compensated by targeting the true transition probabilities (see Section 4.2). In this case, overestimated wage gains for rural migrants into urban formality will be partially offset by underestimated job arrival rates from rural to urban formal jobs. In other words, transition rates will capture unobserved heterogeneity between origin-destination pairs of states, assuming no heterogeneity within pairs.[10] This exercise therefore yields a higher bound on the upward bias of the urban formal option value for rural workers (see Section 5.3).

3 Model

3.1 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, across both the formal and informal sectors. I only distinguish between formal and informal jobs in urban areas. Formal jobs

[8] One way to deal with insurance motives 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 (2023) and Lagakos *et al.* (2023).

[9] A similar exercise can be run on returns to formality within cities.

[10] For a spatial search-and-matching model with heterogeneity within origin-destination pairs, see Heise & Porzio (2023).

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 model. Workers accept job offers so as to maximize their expected lifetime utility stream, and have to pay a fixed (monetary) mobility cost when accepting a job offer in another area to move there.[11] Workers' dynamic utility stream can be decomposed into a flow and an option value. Their flow value consists in their current wage when employed or utility of leisure when non-employed, and relative rural-urban amenities that capture differential factors such as housing prices, public services and infrastructure, local networks, or education opportunities for children. Their option value consists in the expected utility from accepting a job offer or losing their current job.

I do not allow for urban-to-rural moves, but rural-to-rural and urban-to-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-to-urban migration flows dominate urban-to-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: rural outflows equate the observed yearly increase in urban population.[12] 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. Moreover, I do not allow for migration flows into non-employment. This is a direct consequence of 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.[13] 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-to-rural moves. This pins down the value of relative amenities.

When employed, workers can lose their job and become non-employed, but never accept an offer with a lower value than their current one.[14] 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 is a direct consequence of 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.[15] This pins down the value of leisure. Finally, I assume that the shares of employed workers with welfare

[11] 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.

[12] This is similar in spirit to search-and-matching models with population growth, such as Head & Lloyd-Ellis (2012).

[13] Balgova (2022) rationalizes such moves through idiosyncratic location preference shocks that only satisfy the spatial equilibrium condition on average.

[14] For a job-search model allowing for value cuts in on-the-job transitions, see Jolivet *et al.* (2006).

[15] I assume that firms do hire at least some workers locally.

W are at the steady state for all values of W: inflows of workers equate outflows of workers for any such state. 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 (and other assumptions) will be captured in the quality of the model fit, which will allow to quantify the strength of the model assumptions.

Firms are pinned to a location and draw from a (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. They produce with constant returns to scale with 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.[16] 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. 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.

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).[17] Informal firms only incur a cost that is growing and convex in firm size. As for workers, I do not distinguish between formal and informal firms in rural areas. Also note that formal firms cannot hire workers informally in my model. In the absence of complementarities between workers and under constant returns to scale, this should be of second-order for welfare and output. 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.

3.2 Workers' Program

Workers maximize their expected lifetime utility 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

[16]For a model with differentiated formal and informal goods, see Belavadi (2021).

[17]In fact, as of 2018, 40% of formal workers in South Africa are covered by collective bargaining agreements setting minimum wages by sector of activity (Bassier, 2024). As I do not have precise enough information to make firms heterogeneous by sector, such wage floors are lost in my model.

utility of leisure b when non-employed, plus a relative amenity term γ (that can be positive or negative) in rural areas. 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 mobility cost c when applicable. When employed, their 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 w.

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:

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

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

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

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

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

3.3 Stationary Worker Flows

The stationary equilibrium 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:

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

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

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

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

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 when applicable) 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 higher bound. Plugging the results back into the initial system pins down the functions G_i^k. This is where the model solution substantially differs from Meghir *et al.* (2015) or Schmutz & Sidibé (2019).

3.4 Firms' Program

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 static problem:

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

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

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

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.

3.5 Equilibrium Productivity Distributions

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 4.3):

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

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 4.3). 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 initial state 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).

3.6 Equilibrium

Let $\Omega = \{RE, RN, UF, UI, UN\}$, $\mathbb{E} = \{RE, UF, UI\}$, 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).

- 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 Calibrated Parameters

Before describing the estimation procedure, I explain how the model parameters in Table 5 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 observed worker shares in my sample: to do so, I invert equation (9) and solve for ν. Finally, 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 $\frac{M}{N_U}$. The average number of workers per rural firm $\frac{M}{N_R}$ is set so as 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.

4.2 Offer Distributions and Transition Rates

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.

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 2.4. Indeed, there is an analytical relation between their theoretical value and the model parameters: 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. The whole 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 observed in Section 2.5, 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.

4.3 Firm Shares and Informality Cost

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.

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. 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 Estimation Results

5.1 Parameters

Table 6 shows the estimated transition rates for the moves allowed in the model. They capture how frictional each sub-market is independently of origin and destination offer values. The resulting pattern is approximately the same as with transition probabilities featured in Section 2.4. 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-to-urban migrants. It also features a higher job destruction rate.

Table 7 presents the parameters governing the offer value distributions (not to be confused with offered wages) for the three employment states of interest. 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 3.3), similar offers do not directly translate into similar welfare values for workers, as will become clear in Section 5.3.

Table 8 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 initial state, 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 relative 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. 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 their underlying productivity distribution does not change (see Section 6.1).

5.2 Model fit

Table 9 shows the model fit on observed wages from Section 2.5. 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 2.4 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 relative ordering across states is preserved.

Table 10 shows the model fit on workers' and firms' allocation across states. Contrary to Table 9, those are not directly targeted moments. 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 come from the fact that those are the two states which are the furthest away from stationarity in the data, as discussed in Section 3.1.[18] 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 for formal firms to hire workers informally.

5.3 Welfare analysis

Table 11 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.

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.

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: 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 2.6 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 does not help either with the impact of such shock on movers and stayers through wages in equilibrium. I therefore turn to policy simulations in Section 6.2

[18] To improve model fit, a deviation from steady state can 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.

to see how the stepping-stone mechanism plays out in counterfactuals.

5.4 Productivity analysis

Before that, Tables 12 and 13 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 those firms to absorb workers.

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 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, hence are 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.

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, 2024). 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 initial state 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.[19] I also keep the values for informality cost parameters and utility of leisure as

[19] Meghir *et al.* (2015) suggest a way to endogenize job arrival rates based on changes in labour market tightness. In their case, this does not change the direction of the effects but makes them stronger, as this accelerates the worker

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 4.3, in a similar fashion as what I do with observed wage distributions in Section 4.2 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. Remark that the error measure also 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 4.3 within the workers' side estimation of Section 4.2, 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

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 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.

The main results are given in Tables 14 and 15, and can be explained with the help of Tables 16, 17, and 18. 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 which increase wages to retain potential migrants: both local welfare and output rise in rural areas, as workers are reallocated towards the most productive firms. The rural-urban welfare gap goes from 29.2% to 25.5%. Still, this is not sufficient to offset the fall in urban welfare as rural workers are still paid less than urban workers on average: global welfare falls by 0.9%. Because they are also less productive, the rise in global output (+2.4%) is limited by such spatial reallocation: 2.2% of the total population decide not to move, which corresponds to 2.7 years of reversed urban growth at current rates.[20]

reallocation that already takes place through stationary worker flow conditions (Section 3.3).

[20]Considering total output relative to workers' welfare matters for potential redistribution policies. However, since I implicitly consider sticky capital allocation in the model, the impact on output could change with capital reallocation on the very long term.

In fact, the informal sector appears as a stepping-stone on the job ladder to the extent that it 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. In this context, rural jobs play the role of an alternative outside option. In fact, 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, 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.

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 urban informal productivity distribution up (Table 18). 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 (Table 18). 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 16).

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 17): this is because 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. The picture is different for urban formal firms. As observed wages first increase, then decrease along the distribution (Table 17), 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.

This 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 14). Still, the average fall in urban welfare 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 16). At the same time, average urban output per worker increases (Table 15). 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 ones. Output per worker rises in the informal sector as the increase in monitoring costs counts as added government revenues (as do taxes in the formal sector).

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 16) and more productive (Table 18) rural firms. This translates into higher observed wages in Table 17, and a slight decrease in local non-employment (Table 16), hence an increase in average rural welfare. 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 14). This is a direct consequence of the spatial equilibrium condition and corresponds to increased congestion as population grows in rural areas. The positive effect on rural output is even more sizable (Table 15). On aggregate, the effect is less strong for output as there are now more workers in less productive areas (Table 16).

For welfare, in spite of improved conditions, rural workers are still paid less than urban workers. Global welfare therefore decreases, even though the reallocation of workers across space alleviates the even stronger fall in urban welfare: this is confirmed by alternative simulations without rural-urban migration where increased monopsony power of urban firms leads to even more negative outcomes.

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-to-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-to-urban migration may act as an alternative strategy to cope with the negative welfare effects. However, the effect on aggregate welfare and output is muted as more workers then stay in areas where they are less productive and less paid overall.

I therefore draw two main conclusions from this study. First, the urban informal sector can be understood as a stepping-stone on the job ladder to the extent that it 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 with 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, labour market policies with relatively small local effects 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 more 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. In my context more specifically, I think would be especially relevant to consider housing markets in low- and middle-income countries, as they do not conform to standards observed in rich countries and housing choice has been repeatedly shown to be complementary with migration and labour choice. I leave this extension for future work.

References

Abel, M. 2019. Unintended Labor Supply Effects of Cash Transfer Programs: New Evidence from South Africa's Pension. *Journal of African Economies*, **28**(5), 558–581. 7

Abel, M., Carranza, E., Geronimo, K., & Ortega, M. 2022. *Can Temporary Wage Incentives Increase Formal Employment? Experimental Evidence from Mexico*. 4

Allen, J., Nataraj, S., & Schipper, T. 2018. Strict Duality and Overlapping Productivity Distributions Between Formal and Informal Firms. *Journal of Development Economics*, **135**(11), 534–554. 6

Almeida, R., & Carneiro, P. 2009. Enforcement of Labor Regulation and Firm Size. *Journal of Comparative Economics*, **37**(1), 28–46. 4

Almeida, R., & Carneiro, P. 2012. Enforcement of Labor Regulation and Informality. *American Economic Journal: Applied Economics*, **4**(3), 64–89. 4

Alvarez, J. 2020. The Agricultural Wage Gap: Evidence from Brazilian Micro-data. *American Economic Journal: Macroeconomics*, **12**(1), 153–173. 3

Alvarez, Jorge A., & Ruane, Cian. 2024. Informality and aggregate productivity: The case of Mexico. *European Economic Review*, **167**(8), 104791. 6

Amodio, F., & De Roux, N. 2023. Labor Market Power in Developing Countries: Evidence from Colombian Plants. *CEPR Discussion Paper Series*, **16180**. 5

Amodio, F., Medina, P., & Morlacco, M. 2023. *Labor Market Power, Self-Employment, and Development*. 5

Anukriti, S., Herrera-Almanza, C., Pathak, P., & Karra, M. 2020. Curse of the Mummy-ji: The Influence of Mothers-in-Law on Women in India. *American Journal of Agricultural Economics*, **102**(5), 1328–1351. 8

Archibong, B., Annan, F., Benshaul-Tolonen, A., College, B., & Okunogbe, O. 2022. Firm Culture: Examining the Role of Gender in Job Matching in an Online African Labor Market. *PEDL Research Papers*. 8

Armangué-Jubert, T., Guner, N., & Ruggieri, A. 2023. Labor Market Power and Development. *CEPR Discussion Paper Series*, **18536**. 5

Bakker, J., Parsons, C., & Rauch, F. 2019. Migration and Urbanization in Post-Apartheid South Africa. *World Bank Economic Review*, **34**(2), 509–532. 7

Balgova, M. 2022. *Moving to Look or Looking to Move? The Role of Job Search in Migration Decisions*. 5, 13

Banerjee, A.V., & Chiplunkar, G. 2023. *How Important are Matching Frictions in the Labor Market? Experimental and Non-Experimental Evidence from a Large Indian Firm*. 7

Bassier, I. 2023. Firms and Inequality when Unemployment is High. *Journal of Development Economics*, **161**. 5

Bassier, I. 2024. *Collective Bargaining and Spillovers in Local Labour Markets*. 14

Bassier, I., Budlender, J., Zizzamia, R., Leibbrandt, M., & Ranchhod, V. 2021. Locked Down and Locked Out: Repurposing Social Assistance as Emergency Relief to Informal Workers. *World Development*, **139**. 9

Baum-Snow, N., & Pavan, R. 2012. Understanding the City Size Wage Gap. *Review of Economic Studies*, **79**(1), 88–127. 5

Belavadi, T. 2021. *Two Essays in International Trade and Development*. Ph.D. thesis. 14

Belot, M., Kircher, P., & Muller, P. 2019. Providing Advice to Jobseekers at Low Cost: An Experimental Study on Online Advice. *Review of Economic Studies*, **86**(4), 1411–1447. 3

Bernatzky, M., Finamor, L., & Ilieva, B. 2024. *Women, Fertility and Informality*. 3

Berniell, I., Berniell, L., De la Mata, D., Edo, M., & Marchionni, M. 2021. Gender Gaps in Labor Informality: The Motherhood Effect. *Journal of Development Economics*, **150**(5). 3

Bhorat, H., Goga, S., & Tseng, D. 2013. Unemployment Insurance in South Africa: A Descriptive Overview of Claimants and Claims. *Brookings Africa Growth Initiative Working Paper Series*, **8**. 19, 37

Bick, A., Fuchs-Schündeln, N., Lagakos, D., & Tsujiyama, H. 2022. Structural Change in Labor Supply and Cross-Country Differences in Hours Worked. *Journal of Monetary Economics*, **130**(9), 68–85. 9

Bilal, A. 2023. The Geography of Unemployment. *Quarterly Journal of Economics*, **138**(3), 1507–1576. 5

Bobba, M., Flabbi, L., Levy, S., & Tejada, M. 2021. Labor Market Search, Informality, and On-the-Job Human Capital Accumulation. *Journal of Econometrics*, **223**(2), 433–453. 3

Bobba, M., Flabbi, L., & Levy, S. 2022. Labor Market Search, Informality, and Schooling Investments. *International Economic Review*, **63**(1), 211–259. 3

Bradley, J., Postel-Vinay, F., & Turon, H. 2017. Public Sector Wage Policy and Labor Market Equilibrium: A Structural Model. *Journal of the European Economic Association*, **15**(6), 1214–1257. 5

Breza, E., Kaur, S., & Shamdasani, Y. 2021. Labor Rationing. *American Economic Review*, **111**(10), 3184–3224. 10

Brooks, W., Kaboski, J., Li, Y., & Qian, W. 2021. Exploitation of Labor? Classical Monopsony Power and Labor's Share. *Journal of Development Economics*, **150**(5). 5

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

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

Bryan, G., Chowdhury, S., Mobarak, A.M., Morten, M., & Smits, J. 2021. Encouragement and Distortionary Effects of Conditional Cash Transfers. *IZA Discussion Paper Series*, **14326**. 13

Budí-Ors, T. 2023. *Rural-Urban Migration and Structural Change: A Reinterpretation.* 6

Buera, F., Kaboski, J., & Townsend, R. 2023. From Micro to Macro Development. *Journal of Economic Literature*, **61**(2), 471–503. 6

Burdett, K., & Mortensen, D. 1998. Wage Differentials, Employer Size, and Unemployment. *International Economic Review*, **39**(2), 257–273. 3

Cahuc, P., Postel-Vinay, F., & Robin, J.-M. 2006. Wage Bargaining with On-the-Job Search: Theory and Evidence. *Econometrica*, **74**(2), 323–364. 14

Caria, S., & Orkin, K. 2024. Barriers to Search and Hiring in Urban Labour Markets. *VoxDevLit*, **10**(1). 2

Caria, S., Crépon, B., Krafft, C., & Nagy, A. 2021. The Impacts of Subsidized Nurseries on Female Employment in Egypt. *AEA RCT Registry.* 8

Cenci, E., Kleemans, M., & Tjernström, E. 2023. *Selection and Heterogeneity in the Returns to Migration.* 6

Charlot, O., Malherbet, F., & Terra, C. 2015. Informality in Developing Economies: Regulation and Fiscal Policies. *Journal of Economic Dynamics and Control*, **51**(2), 1–27. 4

Chaturvedi, S., Mahajan, K., & Siddique, Z. 2021. Words Matter: Gender, Jobs and Applicant Behavior. *IZA Discussion Paper Series*, **14497**(11). 8

Chowdhury, A.R., Areias, A.C., Imaizumi, S., Nomura, S., & Yamauchi, F. 2018. Reflections of Employers'Gender Preferences in Job Ads in India: An Analysis of Online Job Portal Data. *World Bank Policy Research Working Paper Series*, **8379**(3). 8

De Andrade, G., Bruhn, M., & McKenzie, D. 2016. A Helping Hand or the Long Arm of the Law? Experimental Evidence on What Governments Can Do to Formalize Firms. *World Bank Economic Review*, **30**(1), 24–54. 4

D'Erasmo, P., & Boedo, H. 2012. Financial Structure, Informality and Development. *Journal of Monetary Economics*, **59**(3), 286–302. 6

Dix-Carneiro, R., Goldberg, P., Meghir, C., & Ulyssea, G. 2024. *Trade and Domestic Distortions: The Case of Informality.* 4

Dominguez-Iino, T., & Le Roux, L. 2022. *The Political Economy of Migration Restrictions under Apartheid.* 7

Donovan, K., & Schoellman, T. 2023. The Role of Labor Market Frictions in Structural Transformation. *Oxford Development Studies*, **51**(4), 362–374. 2

Donovan, K., Lu, W.J., & Schoellman, T. 2023. Labor Market Dynamics and Development. *Quarterly Journal of Economics*, **138**(4), 2287–2325. 2

Elgin, C., Kose, M.A., Ohnsorge, F., & Yu, S. 2021. Understanding Informality. *CEPR Discussion Paper Series*, **16497**. 7

Erosa, A., Fuster, L., & Martinez, T. 2023. Public Financing with Financial Frictions and Underground Economy. *Journal of Monetary Economics*, **135**(4), 20–36. 6

Fan, T., Peters, M., & Zilibotti, F. 2023. Growing Like India - The Unequal Effects of Service-Led Growth. *Econometrica*, **91**(4), 1457–1494. 6

Felix, M. 2022. *Trade, Labor Market Concentration, and Wages*. 5

Feng, Y., Lagakos, D., Rauch, J., Venkateswaran, Venky, Waugh, Mike, Wolcott, Erin, Wright, Randy, & Xu, Daniel Yi. 2024. Unemployment and Development. *The Economic Journal*, **134**(658), 614–647. 6

Field, E., Jayachandran, S., & Pande, R. 2010. Do Traditional Institutions Constrain Female Entrepreneurship? A Field Experiment on Business Training in India. *American Economic Review*, **100**(2), 125–29. 8

Fields, G.S. 1975. Rural-Urban Migration, Urban Unemployment and Underemployment, and Job-Search Activity in LDCs. *Journal of Development Economics*, **2**, 165–187. 2

Finamor, L. 2023. *Labor Market Informality, Risk, and Public Insurance*. 12

Fletcher, E., Pande, R., & Troyer Moore, C. 2017. Women and Work in India: Descriptive Evidence and a Review of Potential Policies. *HKS Faculty Research Working Paper Series*, **18-004**. 8

Franklin, S., Imbert, C., Abebe, G., & Mejia-Mantilla, C. 2024. Urban Public Works in Spatial Equilibrium: Experimental Evidence from Ethiopia. *American Economic Review*, **114**(5), 1382–1414. 26

Gai, Q., Guo, N., Li, B., Shi, Q., & Zhu, X. 2021. *Migration Costs, Sorting, and the Agricultural Productivity Gap*. 6

Gallien, M., & Van den Boogaard, V. 2021. Rethinking Formalisation: A Conceptual Critique and Research Agenda. *ICTD Working Paper Series*, **127**. 2

García, I. 2015. Human Capital and Labor Informality in Chile: A Life-Cycle Approach. *RAND Working Paper Series*, **1087**(6). 3

Gentile, E., Kohli, N., Subramanian, N., Tirmazee, Z., & Vyborny, K. 2023. Barriers to Entry: Decomposing the Gender Gap in Job Search in Urban Pakistan. *ADB Working Paper Series*, **707**. 8

Gollin, D., & Kaboski, J. 2023. New Views of Structural Transformation: Insights from Recent Literature. *NBER Working Paper Series*, **31905**. 6

Gollin, D., Lagakos, D., & Waugh, M. 2014. The Agricultural Productivity Gap. *Quarterly Journal of Economics*, **129**(2), 939–993. 6

Guner, N., & Ruggieri, A. 2023. *Misallocation and Inequality*. 6

Haanwinckel, D., & Soares, R. 2021. Workforce Composition, Productivity, and Labour Regulations in a Compensating Differentials Theory of Informality. *Review of Economic Studies*, **88**(6), 2970–3010. 4

Hao, T., Sun, R., Tombe, T., & Zhu, X. 2020. The Effect of Migration Policy on Growth, Structural Change, and Regional Inequality in China. *Journal of Monetary Economics*, **113**(8), 112–134. 6

Harris, J., & Todaro, M. 1970. Migration, Unemployment and Development: A Two-Sector Analysis. *American Economic Review*, **60**(1), 126–142. 2

Head, A., & Lloyd-Ellis, H. 2012. Housing Liquidity, Mobility, and the Labour Market. *Review of Economic Studies*, **79**(4), 1559–1589. 13

Heise, S., & Porzio, T. 2023. *Labor Misallocation Across Firms and Regions.* 5, 12

Herrendorf, B., & Schoellman, T. 2018. Wages, Human Capital, and Barriers to Structural Transformation. *American Economic Journal: Macroeconomics*, **10**(2), 1–23. 6

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

Ho, L., Jalota, S., & Karandikar, A. 2024. Bringing Work Home: Flexible Arrangements as Gateway Jobs for Women in West Bengal. *STEG Working Paper Series*, **80**. 8

Hobijn, B., Schoellman, T., & Vindas, A. 2018. *Structural Transformation by Cohort.* 6

Hoffmann, F., & Shi, S. 2016. Burdett–Mortensen Model of On-the-Job Search with Two Sectors. *Review of Economic Dynamics*, **19**(1), 108–134. 5

Imbert, C., & Papp, J. 2015. Labor Market Effects of Social Programs: Evidence from India's Employment Guarantee. *American Economic Journal: Applied Economics*, **7**(2), 233–263. 26

Imbert, C., & Papp, J. 2020a. Costs and Benefits of Rural-Urban Migration: Evidence from India. *Journal of Development Economics*, **146**(9). 13

Imbert, C., & Papp, J. 2020b. Short-term Migration, Rural Public Works, and Urban Labor Markets: Evidence from India. *Journal of the European Economic Association*, **18**(2), 927–963. 26

Imbert, C., & Ulyssea, G. 2024. *Rural Migrants and Urban Informality: Evidence from Brazil.* 6

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

Imbert, C., Monras, J., Seror, M., & Zylberberg, Y. 2023. *Floating Population: Migration with(out) Family and the Spatial Distribution of Economic Activity.* 8

Jolivet, G., Postel-Vinay, F., & Robin, J.-M. 2006. The Empirical Content of the Job Search Model: Labor Mobility and Wage Distributions in Europe and the US. *European Economic Review*, **50**(4), 877–907. 13

Joubert, C. 2015. Pension Design with a Large Informal Labor Market: Evidence from Chile. *International Economic Review*, **56**(2), 673–694. 3

Juhász, R., Lane, N., & Rodrik, D. 2023. The New Economics of Industrial Policy. *NBER Working Paper Series*, **31538**. 26

Kandpal, E., & Baylis, K. 2019. The Social Lives of Married Women: Peer Effects in Female Autonomy and Investments in Children. *Journal of Development Economics*, **140**(9), 26–43. 8

Kennan, J., & Walker, J. 2011. The Effect of Expected Income on Individual Migration Decisions. *Econometrica*, **79**(1), 211–251. 5

Kuhn, P., & Shen, K. 2013. Gender Discrimination in Job Ads: Evidence from China. *Quarterly Journal of Economics*, **128**(1), 287–336. 8

Lagakos, D. 2020. Urban-Rural Gaps in the Developing World: Does Internal Migration Offer Opportunities? *Journal of Economic Perspectives*, **34**(3), 174–192. 2

Lagakos, D., & Shu, M. 2023. The Role of Micro Data in Understanding Structural Transformation. *Oxford Development Studies*, **51**(4), 436–454. 6

Lagakos, D., Marshall, S., Mobarak, A.M., Vernot, C., & Waugh, M.E. 2020. Migration Costs and Observational Returns to Migration in the Developing World. *Journal of Monetary Economics*, **113**(8), 138–154. 6, 8, 12

Lagakos, D., Mobarak, A., & Waugh, M. 2023. The Welfare Effects of Encouraging Rural-Urban Migration. *Econometrica*, **91**(3), 803–837. 5, 12, 13, 19, 37

Lewis, A. 1954. Economic Development with Unlimited Supplies of Labour. *The Manchester School*, **22**(2), 139–191. 2, 6

Loayza, N. 2016. Informality in the Process of Development and Growth. *World Economy*, **39**(12), 1856–1916. 2

Lochmann, A. 2022. *Diagnosing Drivers of Spatial Exclusion - Places, People, and Policies in South Africa's Former Homelands*. 7

Lopez-Martin, B. 2019. Informal Sector Misallocation. *Macroeconomic Dynamics*, **23**(8), 3065–3098. 6

Maguain, D., & Koubi, M. 2022. *Local Labor Markets? Evidence from a Spatial Job Search Model on Large Scale French Micro-Data*. 5

Mahmud, M., Gutierrez, I., Kumar, K., & Nataraj, S. 2021. What Aspects of Formality Do Workers Value? Evidence from a Choice Experiment in Bangladesh. *World Bank Economic Review*, **35**(2), 303–327. 8

Marshall, S. 2024. *Labor Market Power in Sub-Saharan Africa: The Role of Small Firms, Self-Employment, and Migration*. 5, 23

Martellini, P. 2022. *Local Labor Markets and Aggregate Productivity*. Tech. rept. 5

Martellini, P., & Menzio, G. 2021. Jacks of All Trades and Masters of One: Declining Search Frictions and Unequal Growth. *American Economic Review: Insights*, **3**(3), 339–52. 6

Meghir, C., Narita, R., & Robin, J.-M. 2015. Wages and Informality in Developing Countries. *American Economic Review*, **105**(4), 1509–1546. 3, 4, 16, 19, 20, 22, 23

Meghir, C., Mobarak, A., Mommaerts, C., & Morten, M. 2022. Migration and Informal Insurance: Evidence from a Randomized Controlled Trial and a Structural Model. *Review of Economic Studies*, **89**(1), 452–480. 5

Morten, M. 2019. Temporary Migration and Endogenous Risk Sharing in Village India. *Journal of Political Economy*, **127**(1), 1–46. 5

Munshi, K., & Rosenzweig, M. 2016. Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap. *American Economic Review*, **106**(1), 46–98. 5

Narita, R. 2020. Self-Employment in Developing Countries: A Search-Equilibrium Approach. *Review of Economic Dynamics*, **35**(1), 1–34. 4, 10

Neumark, D., & Simpson, H. 2015. Place-Based Policies. *Handbook of Regional and Urban Economics*, **5**(1), 1197–1287. 26

Ohnsorge, F., & Yu, S. 2022. *The Long Shadow of Informality: Challenges and Policies*. 2

Ordóñez, J. 2014. Tax Collection, the Informal Sector, and Productivity. *Review of Economic Dynamics*, **17**(2), 262–286. 6

Pfeiffer, B., Rabe, c., Selod, H., Viguié, V., Avner, P., & Monnier, T. 2024. *Assessing Urban Policies Using a Simulation Model with Formal and Informal Housing*. 9

Ponczek, V., & Ulyssea, G. 2022. Enforcement of Labour Regulation and the Labour Market Effects of Trade: Evidence from Brazil. *The Economic Journal*, **132**(641), 361–390. 4

Porcher, C. 2022. *Migration with Costly Information*. 5

Porzio, T., Rossi, F., & Santangelo, G. 2022. The Human Side of Structural Transformation. *American Economic Review*, **112**(8), 2774–2814. 6

Poschke, M. 2019. *Wage Employment, Unemployment and Self-Employment across Countries*. 6

Pulido, J., & Święcki, T. 2019. *Barriers to Mobility or Sorting? Sources and Aggregate Implications of Income Gaps across Sectors in Indonesia*. 6

Ranis, G., & Fei, J. 1961. A Theory of Economic Development. *American Economic Review*, **51**(4), 533–565. 2

Restuccia, D., & Rogerson, R. 2017. The Causes and Costs of Misallocation. *Journal of Economic Perspectives*, **31**(3), 151–74. 6

Rodrik, D. 2008. Understanding South Africa's Economic Puzzles. *Economics of Transition*, **16**(4), 769–797. 7

Samaniego, B. 2024. *The Hazards from Informality: Measuring the Consequences of Entering the Labor Market in an Informal Job*. 5

Samaniego, B., & Fernandez, L. 2024. Increasing the Cost of Informal Employment: Evidence from Mexico. *American Economic Journal: Applied Economics*, **16**(1), 377–411. 4

Schmutz, B., & Sidibé, M. 2019. Frictional Labour Mobility. *Review of Economic Studies*, **86**(4), 1779–1826. 3, 5, 13, 16

Schwartzman, M. 2024. *The Roots of Structural Transformation in Low-Skilled Services*. 6

Selod, H., & Shilpi, F. 2021. *Rural-Urban Migration in Developing Countries: Lessons from the Literature*. 2

Shah, K. 2022. *Diagnosing South Africa's High Unemployment and Low Informality Working Papers*. 7

Shephard, A. 2017. Equilibrium Search and Tax Credit Reform. *International Economic Review*, **58**(4), 1047–1088. 5

Todaro, M. 1969. A Model of Labor Migration and Urban Unemployment in Less Developed Countries. *American Economic Review*, **59**(1), 138–148. 2

Tombe, T., & Zhu, X. 2019. Trade, Migration, and Productivity: A Quantitative Analysis of China. *American Economic Review*, **109**(5), 1843–1872. 5

Tsebe, M., Vukeya, V., & Lewis, C. 2018. Firm Dynamics in South Africa. *OECD Economics Department Working Papers*, **1528**. 19, 37

Ulyssea, G. 2010. Regulation of Entry, Labor Market Institutions and the Informal Sector. *Journal of Development Economics*, **91**(1), 87–99. 4

Ulyssea, G. 2018. Firms, Informality, and Development: Theory and Evidence from Brazil. *American Economic Review*, **108**(8), 2015–2047. 2, 4, 6

Ulyssea, G. 2020. Informality: Causes and Consequences for Development. *Annual Review of Economics*, **12**, 525–546. 2, 4, 7

Wahba Tadros, S.N., Wellenstein, A., Das, M., Palmarini, N., D'Aoust, O.S., Singh, G., Restrepo Cadavid, P., Goga, S., Terraza, H. C., Lakovits, C., Baeumler, A., & Gapihan, A.T. 2021. Demographic Trends and Urbanization. *World Bank Report*, **158009**. 2

Yassin, S., & Langot, F. 2018. Informality, Public Employment and Employment Protection in Developing Countries. *Journal of Comparative Economics*, **46**(1), 326–348. 26

Young, A. 2013. Inequality, the Urban-Rural Gap, and Migration. *Quarterly Journal of Economics*, **128**(4), 1727–1785. 3

Tables and Figures

Table 1: Mean summary statistics by mover status over the study period↪

	Black dummy	Age	Educ. yrs	Log(wage)	Non-empl.	Inform. vs. formal
Rur. stayer (42%)	0.92	39.36	6.35	10.00	0.51	0.52
Urb. stayer (45%)	0.69	39.54	7.95	10.35	0.38	0.39
Rur. mover (10%)	0.86	32.81	7.75	10.12	0.47	0.49
N	17,265	17,265	17,265	6,290	17,265	9,693

Notes: National Income Dynamics Study 2008-2017, low-skilled males aged 18-64. Percentages of observations in parentheses. The left panel corresponds to exogenous individual characteristics from which I abstract in the model. The right panel corresponds to endogenous job characteristics accounted for by the model.

Table 2: Mean summary statistics by geo-employment state over the study period↪

	Black dummy	Age	Educ. yrs	Wage empl.
Rur. nonempl. (25%)	0.98	37.89	6.66	n.a.
Urb. nonempl. (19%)	0.71	38.63	7.69	n.a.
Rural empl. (24%)	0.85	39.09	6.42	0.69
Urban formal (19%)	0.72	40.54	8.42	0.98
Urban inform. (13%)	0.69	37.52	7.80	0.40
N	17,265	17,265	17,265	6,491

Notes: National Income Dynamics Study 2008-2017, low-skilled males aged 18-64. Percentages of observations in parentheses. The left panel corresponds to exogenous individual characteristics from which I abstract in the model. The right panel corresponds to endogenous job characteristics from which I also abstract in the model.

Table 3: 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}	$OTJS_{t+1}$	N
RN_t	0.86	0.12	0.01	0.01	0.01	n.a.	7,021
RE_t	0.12	0.79	0.01	0.01	0.01	0.06	6,639
UN_t	0.01	0.00	0.83	0.07	0.09	n.a.	5,515
UF_t	0.00	0.01	0.07	0.86	0.02	0.03	5,170
UI_t	0.00	0.01	0.13	0.07	0.75	0.03	3,279
N	6,910	6,145	5,498	5,202	3,211	658	27,624

Notes: National Income Dynamics Study 2008-2017, low-skilled males aged 18-64. "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 the same job in the same sector). Row probabilities sum up to one.

Table 4: 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.

Table 5: 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. insurance rate	Bhorat *et al.* (2013)	0.08
c	Mobility cost	Lagakos *et al.* (2023)	861
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 per urban firm	Tsebe *et al.* (2018)	117
$\frac{M}{N_R}$	Workers per rural firm	World Bank Enterprise Survey (2020)	117

Table 6: 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.

Table 7: 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.

Table 8: 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.

Table 9: 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.

Table 10: 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.

Table 11: 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-to-rural moves, there is no rural option value in urban areas. Row proportions sum up to one.

Table 12: Comparative worker and firm distributions by productivity level ↪

		Rural	Urban			Wage (log)			Value (log)		
	p (log)	Cumul. worker share	Cumul. worker share	Fract. formal work	Fract. formal 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 13: 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).

Table 14: 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 15: 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.

Table 16: Changes in worker and firm allocation as costs of informality increase ↪

	Baseline $\gamma_f = 1$	Change from baseline $\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
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.

Table 17: Changes in accepted wage distributions as costs of informality increase ↪

	Baseline $\gamma_f = 1$	Change from baseline $\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
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%

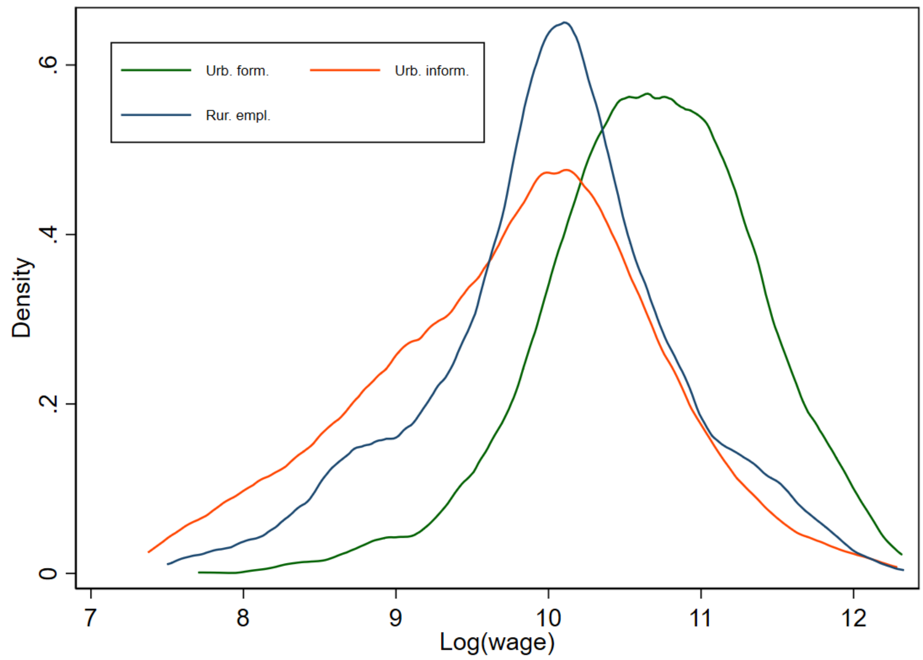
Notes: Baseline columns contain log wages as predicted by the model. Remaining columns are changes from respective baselines.

Table 18: Changes in productivity distributions as costs of informality increase ↪

	Baseline $\gamma_f = 1$	Change from baseline $\gamma_f = 1.1$	$\gamma_f = 1.2$	$\gamma_f = 1.3$
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.

Figure 1: 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.