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Spatial Inequality in South Africa: Causes and Policy Options

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Spatial Inequality in South Africa: Causes and Policy Options
Prepared by Sergii Meleshchuk and Johanna Schauer

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ABSTRACT: South Africa exhibits one of the highest levels of income inequality globally, reflecting persistent spatial exclusion. This paper examines the extent and causes of spatial inequality using household microdata, microsimulations, and a structural spatial general-equilibrium model. The microdata analysis indicates that inequality within (rather than across) urban and rural areas accounts for the majority of overall inequality, with long commuting times strongly associated with higher unemployment and lower incomes. The simulation analysis suggests that reducing commuting costs can meaningfully lower unemployment and inequality. The structural modeling results point to transportation and housing policies as effective tools to promote spatial integration and reduce income inequality.

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SELECTED ISSUES PAPERS

Spatial Inequility in South Africa: Causes and Policy Options

South Africa

Prepared by Sergii Meleshchuk and Johanna Schauer [1]

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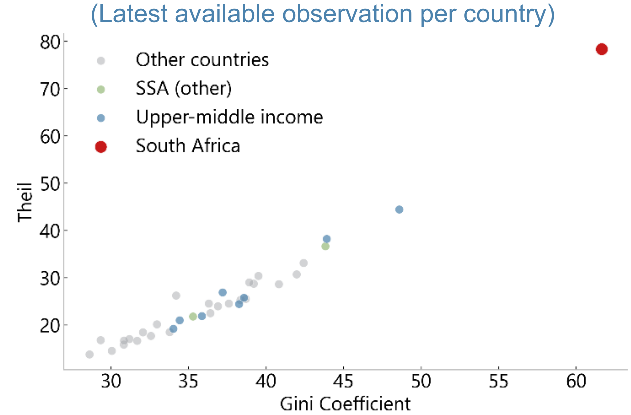
A. Introduction

1. **South Africa's inequality is one of the highest in the world.** Despite significant fiscal redistribution, South Africa's Gini coefficient, estimated at about 0.65, points to one of the most unequal market incomes in the world (Figure 1, World Bank, 2018; Stats SA, 2023). The Theil index (described in Box 1) paints a similar picture. The literature highlights a number of drivers of inequality, including weak growth, product and labor-market rigidities (IMF 2024, OECD 2022, Nattrass & Seekings, 2019), premature deindustrialization, skills-biased technological change, and high unemployment (Rodrick 2008). However, what sets South Africa apart from other countries is the deep racial and geographical disparities that are legacies of the apartheid era. As the Black majority was geographically confined to economically marginal territories and systematically deprived of access to quality education, skilled employment, and productive assets (Harvard Growth Lab, 2023), this resulted in a large underprivileged population with low initial incomes and limited opportunities, laying the foundation for persistently high spatially-driven inequality – i.e. systematic disparities in economic and social outcomes across geographic areas within the country (Manysheva and others, 2025).

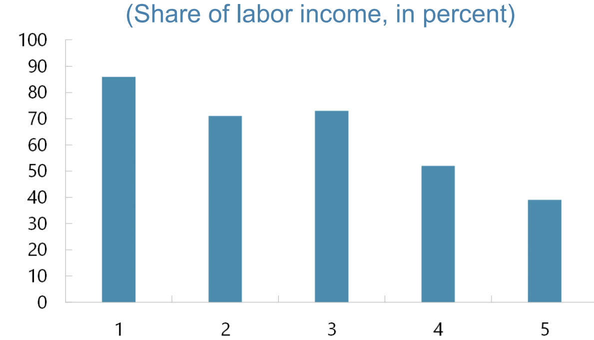
Figure 1. Inequality Measures Across Countries
(Latest available observation per country)



Source: WIID Database.

2. **This paper focuses on spatial inequality as a critical determinant of overall income inequality in South Africa.** As noted above, Apartheid policies systematically excluded Black South Africans from access to infrastructure, education, and labor market opportunities. In rural regions, the creation of under-resourced "homelands" confined populations to areas far from economically productive centers, perpetuating chronic poverty (World Bank, 2018; Harvard Growth Lab, 2023). The establishment of peripheral townships entrenched the physical and economic isolation of urban Black communities, resulting in high commuting costs, fragmented labor markets, and constrained access to quality education (Manysheva and others, 2025; Harvard Growth Lab, 2023). Despite policy efforts to address these issues in the post-apartheid period, low-income populations remain situated far from employment centers (Shah and Sturzenegger, 2022). Commuting is particularly burdensome: transport alone consumes about 17 percent of wages, rising to over 30–40 percent when accounting for time lost (Kerr, 2015). For public transit users, total commuting costs can reach 80 percent of net income, discouraging employment (Figure 2, Shah and Sturzenegger, 2022) and leading to a paradox of high unemployment and a small informal sector (Rodrik, 2008; Shah and Sturzenegger, 2022, Harvard Growth Lab, 2023).
[2] In rural areas, poor connectivity further limits opportunities.

Figure 2. Transport Cost by Income Quintile
(Share of labor income, in percent)



Source: Shah and Sturzenegger (2022). The bars depict average total transport cost (monetary and non-monetary) as a share of labor income by quintile to household per capita income.

[2] Low levels of informality in South Africa may also stem from regulatory barriers and low productivity in the informal sector (Shah, 2022, Shah and Sturzenegger, 2022, Harvard Growth Lab, 2023)

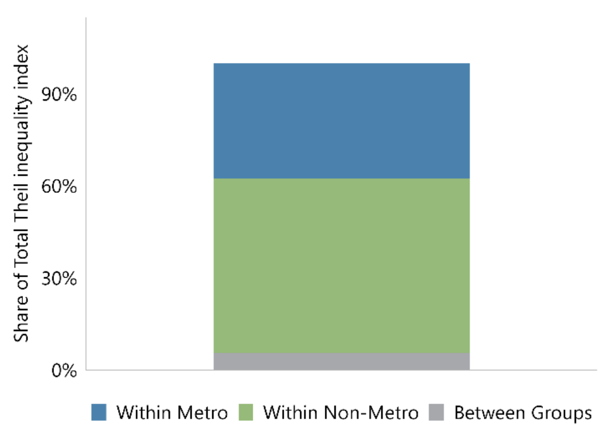
3. **The paper combines microdata, microsimulations, and structural modeling to estimate the extent of spatial inequality in South Africa and analyze policy options that could help address it.** Leveraging nationally representative data from the 2024 General Household Survey, the analysis quantifies how disparities in geographic access to economic opportunities contribute to persistent income and employment gaps across urban and rural areas (section II). A microsimulation framework (similar to Bourguignon and Spadaro, 2006) imposes exogenous employment shocks on household-level data to trace the distributional effects of improved labor-market access (section III). Finally, a structural spatial general-equilibrium model developed by Manysheva and others (2025), calibrated to reflect South Africa's urban dynamics, is utilized to evaluate the impact of alternative policy interventions—such as improved transport infrastructure, densification of urban housing, and targeted subsidies—on inequality in urban labor markets (section IV). Section V concludes with some policy recommendations.

B. Microdata Analysis of Spatial Inequality

4. **This analysis draws on the 2024 South Africa General Household Survey (GHS), to assess spatial inequality in South Africa.** This nationally representative dataset captures household- and individual-level data on demographic and socioeconomic characteristics, including province, metropolitan status, educational attainment, labor income, and access to basic services. Importantly, it also includes spatial indicators such as distance to the nearest transport facility, enabling an examination of geographic and structural drivers of inequality. These features make the GHS a critical source for analyzing both distributional outcomes and the spatial dimensions of economic opportunity across South Africa. While the Gini coefficient is the more widely used index to study inequality, the Theil index is another measure of inequality that can be decomposed into contributions from different populations, for example, urban and rural dwellers. Hence, given the focus of this paper on spatial inequality, the Theil index will be used extensively in this analysis (see Box 1 for details on the decomposition of the Theil inequality index).

5. **Spatial income[3] inequality in South Africa is driven primarily by disparities within urban and rural areas rather than differences between them.** According to the GHS data (Figure 3), inequality within rural areas accounts for about 57 percent of overall income inequality, while inequality within metropolitan areas contributes an additional 38 percent. In contrast, differences in average income levels between urban and rural areas explain only about 5 percent of total inequality, as measured by the Theil index. This decomposition highlights that reducing inequality will require addressing structural disparities inside both urban and rural economies, rather than focusing solely on narrowing the urban–rural income gap.

Figure 3. Theil Decomposition by Metro Status
(Share of total inequality, 2024)

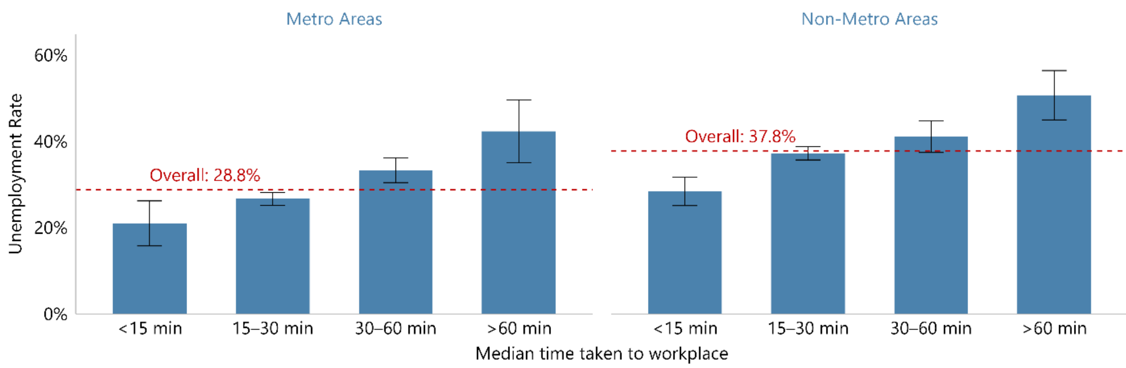


Source: GHS (2024), and IMF staff calculations.

[3] We calculate individual income using total household income (which includes wages and non-wage income) divided by household size.

6. **Spatial exclusion is a significant driver of unemployment in South Africa** (Figure 4). Long commuting times continue to limit access to labor markets and economic opportunities. Using GHS data on travel time to work, we estimate median commuting times for each geographic area and compare them with local unemployment rates. The results show a strong and statistically significant relationship: in both urban and rural areas, unemployment rates are more than20 percentage points higher in locations where the median commute exceeds one hour compared to areas where it is under 15 minutes.[4]

Figure 4. Unemployment Rate by Median Time to Workplace



Source: GHS (2024), and IMF staff calculations.

7. **To assess the impact of commuting times on unemployment, we estimate an increase in probability of being unemployed as a function of distance to work.** First, we estimate a logistic regression model where the dependent variable, Y_i, is unemployment status. The equation is specified as

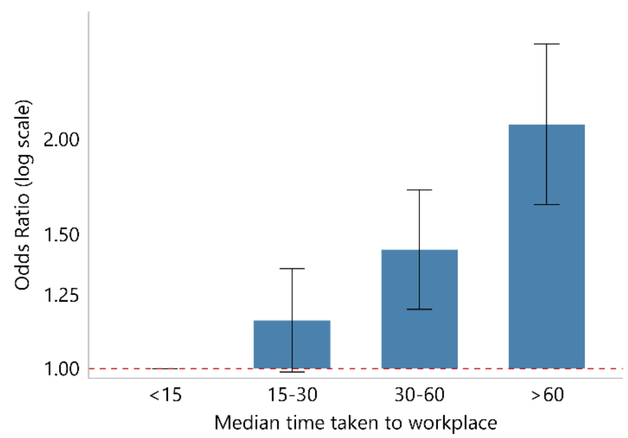
$$\log\left(\frac{P(Y_i = 1)}{1 - P(Y_i = 1)}\right) = \sum \beta_k X_{ik} + sum_{k=1}^{4} \delta_k TravelTime_{ik} + \varepsilon_i,$$

where X_k is one of the control variables (age, gender, education, race, province, dummy for metro area) and $TravelTime_k$ is a categorical variable that captures median travel time at the primary sampling unit level, with "travel time less than 15 minutes" being the omitted reference category). Then, we calculate odds ratios as $OR_k = exp(\delta_k)$ for all other commuting categories. The odds ratio indicates how much more likely an individual residing in an area with median travel time category k is to be unemployed compared with an individual in the reference category, conditional on all other factors.

[4] Results are qualitatively and quantitatively similar when restricting the sample to individuals under age 35. In areas where the median commute exceeds one hour, unemployment rates are higher by 21 percentage points in urban locations and 25 percentage points in rural locations, relative to areas with median commutes below 15 minutes.

8. **The probability of unemployment increases substantially with commuting time.** After controlling for observable individual characteristics, the likelihood of being unemployed is about 20 percent higher for individuals residing in areas with a median commute of 15–30 minutes compared with those in the reference group. For individuals living far from their workplace, this probability roughly doubles when commuting time increases from less than 15 minutes to more than one hour (Figure 5).[5]

Figure 5. Unemployment Odds Ratios by Travel Time to Work
(Relative to <15 min commute)



Source: GHS (2024), and IMF staff calculations.

[5] While estimates condition on observable characteristics such as years of schooling, they cannot account for unobserved factors—most notably differences in education quality—which may influence outcomes.

Box 1. Theil Inequality Index: A Primer

The Theil inequality coefficient (Theil 1967) is a statistical measure used to quantify economic inequality. It is derived from information theory and measures the entropy, or disorder, in the distribution of income or wealth among individuals or groups. The Theil index ($\boldsymbol{T}$) is calculated using the formula:

$$\boldsymbol{T} = \left(\frac{\boldsymbol{1}}{\boldsymbol{N}}\right) * \boldsymbol{\Sigma_i} \left(\frac{\boldsymbol{y_i}}{\boldsymbol{\mu}}\right) * \boldsymbol{ln}\left(\frac{\boldsymbol{y_i}}{\boldsymbol{\mu}}\right):$$

Where – $\boldsymbol{N}$ is the number of individuals, $\boldsymbol{y_i}$ is the income of individual $\boldsymbol{i}$, $\boldsymbol{\mu}$ is the mean income, and $\boldsymbol{ln}$ denotes the natural logarithm.

A Theil index of 0 indicates perfect equality, where everyone has the same income. Higher values indicate increasing levels of inequality. This index is particularly useful because it can be decomposed into within-group and between-group components, allowing analysts to understand how much of the total inequality is due to disparities within subgroups versus disparities between subgroups.

Let the population be divided into G groups. The total Theil index T can be decomposed as follows:

$$\boldsymbol{T} = \boldsymbol{T_W} + \boldsymbol{T_B}$$

Where $\boldsymbol{T_W}$ and $\boldsymbol{T_B}$ stand for within- and between-group components

$\boldsymbol{T_W}$ = Within-group inequality component

The within-group component is calculated as:

$$\boldsymbol{T_W} = \sum \left(\frac{\boldsymbol{n_g}}{\boldsymbol{n}}\right) * \boldsymbol{T_g}$$

Where $\boldsymbol{n\_g}$ is the population of group $\boldsymbol{g}$, n is the total population, and $\boldsymbol{T\_g}$ is the Theil index within group $\boldsymbol{g}$.

The between-group component is calculated as:

$$\boldsymbol{T_B} = \sum \left(\frac{\boldsymbol{n_g}}{\boldsymbol{n}}\right) * \boldsymbol{ln}\left(\frac{\boldsymbol{\bar{y}_g}}{\boldsymbol{\mu}}\right)$$

Where $\boldsymbol{\bar{y}_g}$ is the mean income of group $\boldsymbol{g}$.

A high within-group component indicates that most inequality is due to disparities within subgroups (e.g., within regions or demographic groups), while a high between-group component suggests that inequality is primarily due to differences in average income across groups.

C. Microsimulation Analysis

9. **In this section, we use partial equilibrium counterfactual analysis to understand better the extent to which spatial exclusion affects inequality in South Africa.** To do so, we employ a microsimulation framework following the tradition of tax–benefit and labor supply models (Bourguignon and Spadaro, 2006), imposing exogenous employment shocks on household-level microdata to trace their impact on income and inequality. Employment probabilities using survey-weighted empirical rates within demographic cells defined by age, location, sex, and education, with hierarchical back-off when cell counts are insufficient. (DiNardo, Fortin, and Lemieux, 1996), while wages are assigned via hot-deck matching techniques (Little and Rubin, 2019; Rosenbaum and Rubin, 1983).

10. **The analysis relies on Monte Carlo simulations that exploit the richness of the GHS microdata.** The simulations proceed in three steps: (i) a subset of unemployed individuals is reclassified as employed under specified assumptions; (ii) wages for these new jobs are imputed from currently employed individuals;

and (iii) incremental labor income is added to household resources before recalculating per capita incomes, unemployment rates, and the Theil index across repeated random draws.

11. We simulate the impact of lower commuting time on inequality and compare it to the impact of an increase in aggregate income. In our main simulation scenario (”reducing distance to work”), only unemployed individuals in areas with long median commuting times (30–60 minutes or more than 60 minutes) are treated as if local travel conditions improved to the “15–30 minute” category, with their employment probabilities set equal to those of comparable individuals in that category. In this scenario, wages for new jobs are assigned through demographic matching, selecting from workers with similar observable characteristics (age, education, sex, location). For comparison purposes, we also simulate an alternative scenario (“higher aggregate growth”), where a positive productivity shock converts 40 percent of unemployed individuals (weighted by survey design) to employment—broadly consistent with conditions under which South Africa’s economy would have expanded by 3 percent annually during 2000–24, rather than 1.5 percent on average, without an effect on the level of wages (i.e. keeping labor productivity fixed). This scenario assigns wages through simple random sampling from all employed workers, without matching on characteristics. Further details on the simulations are provided in Box 2

12. The results suggest significant scope to reduce income inequality through improved spatial access. Reducing commuting times as described above lowers the unemployment rate by about 4½ percentage points, raises average household income by more than one-third, and reduces inequality—measured by the Theil index) —by 0.08, or roughly 9 percent of its initial level (Figure 6A). While a substantial share of inequality persists, this reduction is economically meaningful and comparable to the estimated effect of eliminating racial wage differentials (IMF, 2024). In comparison, under a “higher aggregate growth” scenario, the decline in unemployment is nearly three times larger, but reductions in inequality are only slightly larger than in the scenario reducing commuting times. This underscores that residents of remote urban and rural areas face not only a lower probability of employment, but also systematically lower wages when they are employed. This highlights the importance of spatial integration for inclusive growth. Notably, the effects of reducing commuting distances are more pronounced in metropolitan areas, whereas rural areas benefit relatively more from aggregate growth.[6]

[6] Rural areas have higher unemployment rates so relatively more people become employed in the “aggregate growth” scenario. Urban areas have, on average, higher wages in areas with shorter commute times, leading to higher gains for people who become employed in the “reducing distance to work” scenario.

Figure 6a. Scenario Comparison: Inequality, Unemployment, and Income (All Areas)

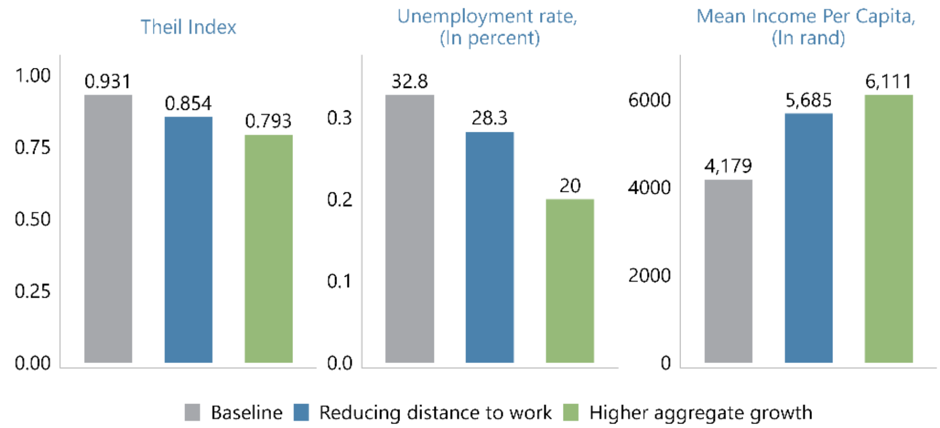


Figure 6b. Scenario Comparison: Inequality, Unemployment, and Income (Metro)

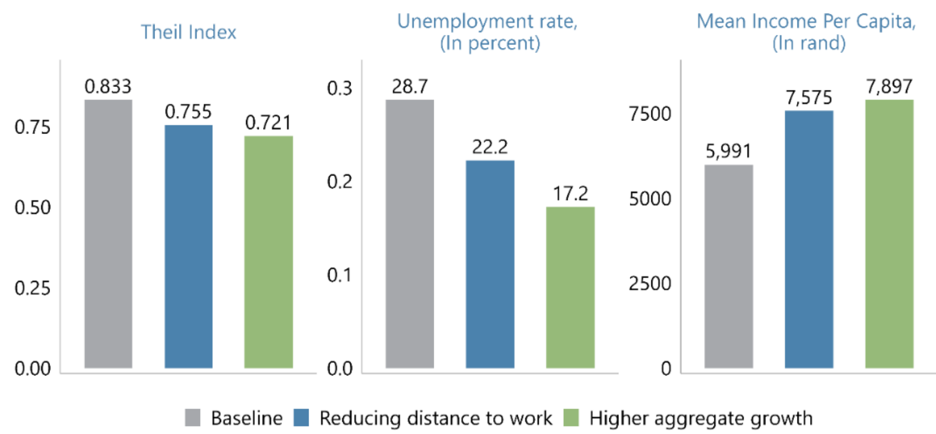
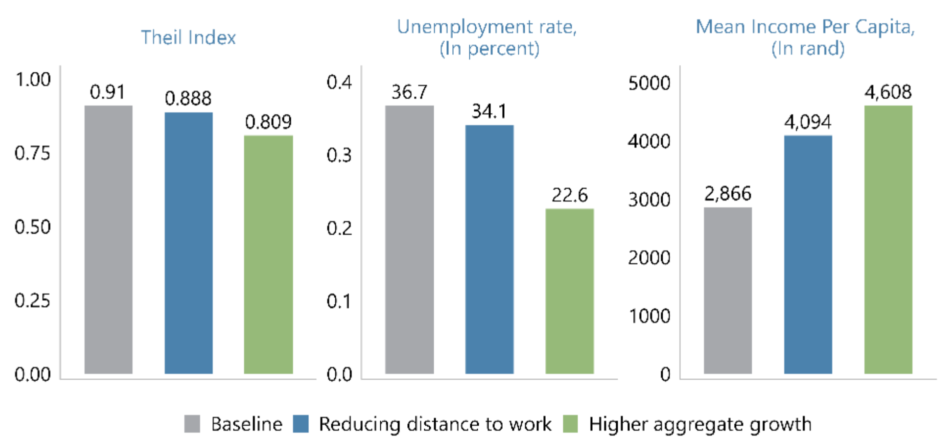


Figure 6c. Scenario Comparison: Inequality, Unemployment, and Income (Non-Metro)



Sources: GHS (2024), and IMF staff calculation.

Box 2. Microsimulations Methodology

Reducing Distance to Work

First, for unemployed individuals living in primary sampling units with median travel time ≥30 minutes (categories 3 or 4), we construct a counterfactual by reassigning them to the 15–30 minutes category (category 2). The counterfactual employment probability uses an empirical matching approach:

$$p_i^{emp,cf} = \bar{E}_{cat2}(X_i),$$

where $\bar{E}_{cat2}(X_i)$ is the survey-weighted employment rate among individuals in travel time category 2 (15–30 minutes) who match individual i on characteristics X_i (age band, population, sex, education, metro, province). If no exact match exists, we use hierarchical back-off: (i) drop province and calculate rate within remaining characteristics, (ii) drop metro area dummy, and (ii) use overall category 2 employment rate as final fallback. The gain in employment probability from the intervention is:

$\Delta p_i = p_i^{emp,cf}$ Second, we conduct 100 Monte-Carlo simulations. In every simulation, for each affected unemployed individual i with $\Delta p_i > 0$, we draw employment transition:

$$T_i^{(s)} \sim Bernoulli(\Delta p_i)$$

For individuals transitioning from unemployment to employment in the simulation, wages are assigned via cell-based hot deck imputation. Each newly employed individual is matched to an employed donor from the category-2 travel time pool based on exact matching on demographics (age band, race, sex, education band, metro area dummy, province). When exact matches are unavailable, we employ hierarchical back-off, sequentially dropping province, then metro status, until a suitable donor pool is found. Within each matched cell, one donor is randomly selected (with replacement), and their wage is assigned to the newly employed individual. Donors with positive wages are preferred when available."

Finally, in each simulation we recompute income inequality and report the averages.

Higher Aggregate Growth

In a second set of simulations, we simulate a 20 percent employment boost, which is roughly equivalent to a scenario where South Africa GDP grew by 3 percent on average between 2000-24, keeping total factor productivity constant and capital growing at the same rate as labor. The difference from the previous approach is that the counterfactual probability of employment is now the same for all unemployed. These simulations incorporate a stylize macroeconomic employment uplift among the unemployed, similar to techniques reviewed in Bourguignon, Bussolo, and Pereira da Silva, 2008.

D. Dynamic Structural Spatial General-Equilibrium Analysis

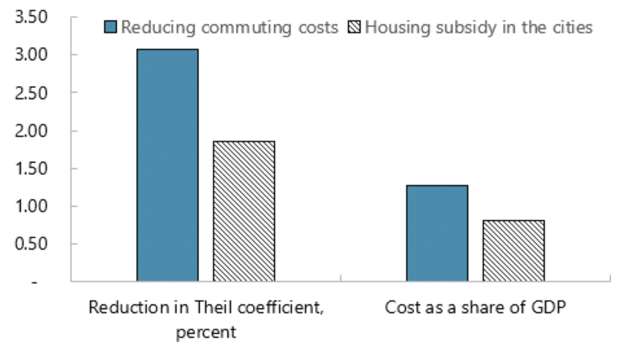
13. **To evaluate the impact of alternative urban policy interventions, this section employs the dynamic spatial general equilibrium model of urban areas developed by Manysheva and others (2025).**[7] The model incorporates overlapping generations, heterogeneous agents, and incomplete markets to capture the persistence of inequality in post-Apartheid South Africa. Households differ by race, wealth, education, talent, and location, with dynastic preferences linking generations. As noted earlier, under Apartheid, non-White households were confined to townships; while these restrictions were lifted after 1994, inherited disadvantages and market imperfections continue to shape outcomes. The framework features endogenous choices over education, occupation, savings, and location, segmented housing and labor markets, exogenous school quality differences, and commuting costs, reflecting spatial frictions. Calibrated to census and survey data, the model replicates key moments, including the Apartheid steady state and a counterfactual
race-blind equilibrium. Counterfactual experiments consider two interventions: halving commuting costs

[7] This paper extends the analysis in Manysheva and others (2025) by explicitly evaluating two targeted policy scenarios – reducing commuting costs and providing housing subsidies.

through a transport subsidy and introducing a housing subsidy covering 10 percent of costs to purchase a house for low-income individuals in central city areas. This approach complements the results from microsimulations as it captures general equilibrium effects, including endogenous price adjustments at the cost of sacrificing granular heterogeneity across households and individuals that is present in the survey microdata.

14. **Results suggest that reducing commuting costs and providing housing subsidies can lower inequality.** Halving transportation costs between townships and metropolitan areas reduces inequality by roughly 3.1 percent, compared with a reduction of slightly under 1.9 percent with a housing subsidy (Figure 7). However, the fiscal cost of the commuting subsidy in the model is estimated to be about 1.3 percent of GDP, compared to 0.8 percent of GDP for the cost of housing subsidy.[8] The results of the model imply that the commuting subsidy is a slightly more cost-efficient way to reduce inequality—a percentage point increase in commuting subsidies reduces the Theil inequality coefficient in urban areas by 2.4 percent, when a comparable increase in housing subsidy reduces it by 2.3 percent. While the model expresses these interventions in monetary terms, they can be interpreted more broadly: a commuting subsidy could reflect reductions in travel time achieved through transport infrastructure improvements, while a housing subsidy could correspond to lower housing costs resulting from increased supply in well-located areas.

Figure 7. Policy Experiments
(Structural model)



Source: IMF staff calculations.

E. Conclusions and Policy Recommendations

15. **The results from the various analyses employed in this paper suggest that spatial exclusion is a major driver of inequality and unemployment in South Africa**. Microdata analysis reveals that long commuting times are strongly associated with higher unemployment rates, with individuals in areas where the median commute exceeds one hour facing unemployment rates more than 20 percentage points higher than those in areas with? commutes under 15 minutes. Microsimulation results show that reducing commuting times for disadvantaged groups could lower the unemployment rate by about 4½ percentage points, raise average household income by over one-third, and reduce the Theil index of inequality by roughly 9 percent. In contrast, a stylized aggregate employment shock yields a larger reduction in unemployment but only marginally greater gains in inequality, highlighting the importance of spatial integration. Similarly, structural model simulations indicate that halving commuting costs through transport subsidies could reduce inequality by over 3 percent, while housing subsidies could reduce inequality by 2 percent, underscoring that targeted improvements in spatial access and urban policy interventions are key to foster inclusive growth.

16. **South Africa's Operation Vulindlela includes new reforms to address spatial disparities.** These include demand-side rental and mortgage subsidies to support densification, accelerated release of public land and buildings for affordable housing, a new capital subsidy to incentivize private rental developers, and clearing the backlog of title deeds to enable property ownership and access to credit. Progress to date

[8] For comparative context, the Department of Human Settlements' FY2025/26 budget amounts to R34 billion (0.7 percent of GDP). More than 90 percent of this allocation is transferred to provincial and municipal governments through settlement and development grants.

includes the Titling Symposium, which produced an action plan to clear title deed backlogs, a comprehensive analysis of title deed data across metros and provinces, and ongoing work to redesign the First Home Finance program and develop a demand-side subsidy for affordable rental housing.

17. These reforms efforts will need to be deepened and complemented by additional policy interventions:

- **In urban areas, prioritizing high-capacity public transport to lower commuting costs remains key to reducing spatial inequality**. Expanding Bus Rapid Transit (BRT) systems with dedicated lanes and integrated ticketing is critical for efficiency and affordability (World Bank, 2023 and OECD, 2025). Modernizing commuter rail for reliability and safety in dense corridors can provide a backbone for mass transit, supported by conditional financing linked to performance (World Bank, 2025). The minibus taxi sector could be formalized and integrated as feeder services to BRT and rail, supported by fleet renewal and electrification incentives (World Bank, 2023). Institutional coordination across municipalities and transport agencies, combined with predictable financing and smart technology (real-time data, integrated payment systems), will be key to delivering an efficient, inclusive, and sustainable urban transport system (World Bank, 2025).

- **Improving rural connectivity in South Africa requires a focus on basic access and affordability**. Priority actions include upgrading gravel and earth roads to all-weather surfaces to ensure year-round access to markets, schools, and health facilities (World Bank, 2012). The light delivery vehicle sector could be formalized and regulated for safety and reliability, while subsidized bus services can serve longer rural–urban routes where demand justifies scheduled operations (Wosiyana, 2014, Munwana, 2018, SSATP 2-21). Institutional reforms are also essential and should include: embedding rural transport in Integrated Development Plans (IDPs), securing predictable maintenance funding, and strengthening coordination across government levels (Charizawa and Ma, 2019). Digital solutions (e.g., mobile ticketing, route information) and climate-resilient infrastructure should be promoted to enhance sustainability and reduce vulnerability to extreme weather (World Bank 2024, World Bank 2025).

- **In urban areas, housing policies will need to focus on facilitating movement of people to areas with job opportunities.** On the housing subsidies side, it is important to shift from supply-side policies which provide housing far from city centers, toward demand-driven subsidies as envisaged under Operation Vulindlela. To complement this shift, increasing housing supply in well-located urban areas will also be needed, by relaxing restrictive zoning regulations, promoting higher-density development, and accelerating the release of state-owned and municipal land for affordable housing (World Bank, 2024; DAG, 2024). These measures would need to be supported by streamlined permitting processes, infrastructure investment, and partnerships with private developers to reduce costs and expand supply (OECD, 2023).

18. Broader structural reforms are also important to support potential growth, accelerate job creation, and reduce inequality (IMF, 2025). Infrastructure reforms in electricity and logistics remain critical to remove impediments to growth and enable productive activity and employment gains. At the same time, horizontal product-market reforms streamlining regulatory burdens and compliance costs can help support SMEs and job creation. Governance reforms strengthening institutional integrity and rebuilding public trust are equally crucial to support growth, while complementary labor market measures can bolster market flexibility and job creation. Such a package of reforms, appropriately sequenced, can not only boost real output but also help generate much needed jobs. Coupled with the targeted interventions noted above, these reforms have the potential to lower inequality and support better standards of living for all.

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