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Climate Policy and Inequality in Urban Areas: Beyond Incomes

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Abstract: Opposition to climate policies is partly due to their impacts on inequality. But with most economic studies focused on income inequalities, the quantitative spatial effect of economic climate policy instruments is poorly understood. Here, using a model derived from the standard urban model of urban economics, we simulate a fuel tax in Cape Town, South Africa, decomposing its impacts by income class, housing type, and location, and over different timeframes, assuming that agents gradually adapt. We find that in the short term, there are both income and spatial inequalities, with low-income households or suburban dwellers more negatively impacted. These inequalities persist in the medium and long terms, as the poorest households, living in informal or subsidized housing, have few or no ways to adapt to fuel price increases by changing housing type, size or location, or transportation mode. Low-income households living in formal housing are also impacted by the tax over the long term due to complex effects driven by competition with richer households in the housing market. Complementary policies promoting a flexible labor market, affordable public transportation, or subsidies that help low-income households live closer to employment centers will be key to the social acceptability of climate policies.

JEL Codes: R13, R14, R48, Q54, H23, C63

Keywords: Urban Economics; Land Use – Transport Integrated Models; Fuel Taxation; Emission Mitigation; Redistributive Impacts; Housing Markets

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1. Introduction

The transportation sector was responsible for 23% of global energy-related carbon dioxide (CO₂) emissions in 2010 (Sims et al., 2014) and decarbonizing transportation is a major challenge for climate change mitigation (Creutzig et al., 2015). However, implementing transportation mitigation policies that are both efficient and encounter strong public support is a challenge. To mitigate transportation greenhouse gas (GHG) emissions, standard economics recommends internalizing the externalities related to polluting transportation by taxing polluting transportation modes and/or subsidizing clean ones (Baranzini et al., 2017). In its most simple form, taxing polluting transportation modes could take the form of carbon pricing, and 61 national or subnational jurisdictions have implemented or scheduled such a pricing initiative (World Bank, 2020). Many environmental economists advocate for this policy, arguing that, theoretically, it will incentivize people to shift transportation mode or move closer to their jobs and other frequent destinations, simultaneously mitigating emissions and maintaining household welfare (Borck and Brueckner, 2018; Creutzig, 2014).

But in practice, a lack of public support prevents or slows down its implementation (Carattini et al., 2019). For example, in 2016 and 2018, more than half of voters in Washington state opposed a carbon tax, while France froze its carbon pricing policy following the *Gilets Jaunes* or Yellow Vests protests in 2018. Opposition to climate policies seems to arise, at least partly, from their effects on spatial inequalities. The Yellow Vest movement in France, for example, was mainly led by suburban and rural households, who are more impacted by the fuel price increase as they commute longer distances and have less access to public transportation. Studies show that the Yellow Vests were not protesting against fuel taxation in general, but rather against the specific French carbon tax, which they deemed inequitable and non-transparent (Mehleb et al., 2021). This underscores the importance of considering specific policy designs and spatial contexts at the local level (Bulkeley et al., 2014).

Geographers have extensively studied the critical role the spatial dimension plays in understanding the equity impacts of climate policies in urban areas. Dodson and Sipe's (2007) seminal work shows that low socioeconomic status cumulates with higher car dependency in Australian cities. Similarly, Roberto (2008) finds that higher commuting costs cumulate with higher housing costs for low-income households in US cities. Connecting car dependency to climate policies, Morton et al. (2018) assess the spatial vulnerability of different census tracts to low-emission zones (LEZs) based on household vehicle ownership, income levels, and public transport accessibility in Edinburgh, Scotland. Overall, this body of literature demonstrates that the equity impacts of climate policies hinge on specific urban characteristics and population distribution. For instance, a comparison of the impact of the Brussels and London LEZs reveals that, although the poorest households in both cities tend to own non-compliant cars, in Brussels, where they live in the city center and have good access to public transport, the overall equity impact of the LEZ is positive. In London, on the other hand, the impact is detrimental, as the poorest households live further out and have poor access to public transport (Verbeek and Hincks, 2022).

The economic literature, so far, has insufficiently engaged with the spatial dimensions of the impacts of climate policies in cities. Instead, studies primarily examine climate policies through the lens of income inequalities, showing that climate policy impacts vary across income groups and can be progressive in low-income countries and for transportation sector policies (see, for instance, Bureau, 2011; Dorband et al., 2019; Fullerton et al., 1980; Ohlendorf et al., 2021; Wang et al., 2016). But these studies often overlook the spatial dimension, and lack a quantitative assessment of the equity impact of economic policy

instruments that precisely account for spatial heterogeneity. This is also intertwined with the temporal dimension, as households might adapt to climate policies—for example, by adjusting their transportation mode or dwelling choices—at different timings, depending on their spatial location.

This paper aims to understand how transportation climate policies impact inequalities, particularly spatial inequalities. As a simple example of climate policy, we simulate a fuel tax, affecting either private vehicles only or private vehicles and polluting public transportation modes. We use the model derived from urban economics from Pfeiffer et al. (2019) to decompose its welfare impacts between (i) direct impacts on transportation costs, (ii) impacts on employment subcenter and modal choice, (iii) rents, (iv) dwelling sizes, and (v) household locations, to provide a spatial analysis of the direct and indirect impacts of the policy on households and inequalities. We also analyze the mechanisms that might impact household ability to adapt to climate policies, to determine the role of land and housing markets. We aim to understand how climate policies design could reduce negative impacts or "unfair" consequences and become more acceptable to everyone.

In the context of our study, *income inequality* refers to the degree to which the impacts of the fuel tax are equitably distributed among income classes, thereby influencing the overall uniformity of the income distribution. *Spatial inequality* refers to the equitable distribution of tax impacts across different geographical locations. This encompasses *income inequalities*, as different impacts of the tax between locations may arise due to variations in income level or housing type. *Spatial inequalities* also consider that households in different parts of the city may be affected differently by the tax, even if they have similar income levels, at least in the short or medium term.

Our contribution is twofold. Methodologically, we argue that city modeling based on urban economics insufficiently accounts for spatial and temporal dimensions—which are crucial for evaluating and implementing climate policies—and propose a framework that addresses these limitations by revealing spatial and temporal heterogeneity in an urban model. From a practical perspective, we analyze the mechanisms involved in implementing a fuel tax in the complex setting of Cape Town, assessing the most affected groups and providing detailed results based on income level, housing submarket, spatial location, and timeframe.

2. Context: the city of Cape Town

We chose Cape Town as our case study, for two reasons. First, its high levels of income and spatial inequality allow us to illustrate the distributional impacts of climate policies, and second, because it faces significant environmental challenges.

Cape Town, a rapidly sprawling middle-income city of 4.2 million residents, has an extremely high level of income inequality, inherited from the Apartheid era. Indeed, the apartheid policies, in the mid-20th century, formalized racial segregation, relegating non-White populations to townships on the outskirts while reserving the city center for White residents. It led to institutionalized racial inequalities with Black and Coloured populations subjected to inferior living conditions, and limited access to quality education, healthcare, and economic opportunities. The end of the apartheid era, in the early 1990s, brought hopes of a more equitable development, which have not been fulfilled: while some progress was achieved in terms of improved access to basic services, education, and healthcare, disparities persisted, due on one hand to the stagnant economy following international sanctions and the turmoil of the transition, and on

the other hand to the national policy of reconciliation, rather than redistribution, that followed the end of the apartheid (Turok et al., 2021).

Today, inequalities remain high in Cape Town, with its Gini index of 0.63¹ being one of the highest in the world. The city's population is 46% Black African, 40% mixed descent, 13% White, and 1% Indian/Asian, with inequalities strongly correlated with race. To illustrate these income inequalities, Table 1 shows the four income classes we use in this study: in 2011, 38.6% of the total population had an annual income of less than R38,200 (approximately US\$6,000), while 15.8% earned more than R300,000 (US\$45,000).

Table 1. Income classes used in the simulation

Income class	Annual income range in 2011 (rand)	Average 2011 income (rand)	Percentage of total population in 2011 (%)
1	1–38,200	19,580	38.6
2	38,200–76,400	57,300	16.7
3	76,400–307,600	170,140	28.9
4	> 307,600	780,723	15.8

Note: Average income and percentage of total population are both estimated using the 2011 Census.

Inequalities also manifest spatially. During the apartheid era, non-White populations were relegated to townships on the outskirts of the city. Today, this spatial segregation persists: many low-income households keep living in informal settlements historically located on the urban periphery. The government has responded to this issue through large-scale housing programs that provide subsidized homes for low-income households. These houses are typically large (about 40 square meters with a 70-square meter garden), and most are built in the city's periphery. However, the programs are insufficient to meet the large demand, and many low-income households reside in informal settlements. Some households also live in informal settlements in the backyards of these subsidized houses, gaining security against a rent paid to the subsidized houses' inhabitants. As a result, Cape Town's housing market remains extremely segregated and characterized by the coexistence of formal, subsidized, and informal housing. This results in strong locational constraints for those who cannot afford formal housing.

These housing issues combine with transportation challenges. Informal settlements and subsidized housing are typically located on the urban periphery (IRR, 2020), necessitating long daily commutes for low-income households to access employment opportunities in the city center (Vanderschuren et al., 2021). Rising housing prices in the city center, driven by the increasing attractiveness of the central business district (CBD), further contribute to keeping low-income households confined to the periphery. And while middle- and high-income households commute by formal public transport and private car, low-income households cannot afford private cars, so tend to walk or rely on formal and informal public transportation, such as minibuses/taxis, which are often slow. This means that, living far from the city center and with limited access to affordable transportation, they have to allocate a substantial portion of their income (up to two-thirds) to transportation expenses (Teffo et al., 2019).

Cape Town also faces strong environmental challenges, including rapid urban sprawl leading to biodiversity loss, low carbon sequestration, low water quality, and increased transportation emissions (City of Cape Town and TDA, 2018). Transportation is South Africa's second-most emitting subsector. But

¹ UN-Habitat Global Indicators Database 2020. <https://data.unhabitat.org/pages/social-inclusion-indicators>, accessed 25/04/2022.

the lack of affordable transportation options available for low-income households mean that attempts to mitigate transportation emissions in Cape Town could have large welfare and distributional impacts.

3. Methods

We aim to investigate the impact of transportation climate policies on inequalities, particularly spatial inequalities. Our approach builds on the work of Avner et al. (2017), who examined the consequences of transit subsidy removal in Buenos Aires using an urban economics modeling approach. Their study analyzed how this removal affected transportation costs, rents, housing, and household transportation budgets. Notably, their paper explored the spatial variation in these impacts, recognizing that the effects on households vary in different parts of the city.

The model of Avner et al. (2017) did not incorporate income inequalities, precluding an examination of the interplay between income and spatial disparities. In our study, we extend this research by using a more sophisticated model to assess the influence of a transport policy on spatial inequalities. We adopt Pfeiffer et al.'s (2019) model, based on a two-dimensional discrete version of the standard urban economics land-use model, specifically tailored to and calibrated for Cape Town. Notably, this model accounts for four income classes, four housing types, and polycentricity, enabling us to investigate the heterogeneous impacts of the policy and accurately represent the polycentric nature of the city.

3.1. Urban economics modeling

This section introduces our urban modeling framework, developed and fully described in Pfeiffer et al. (2019).

Urban modeling is based on the closed-city version of the Alonso-Muth-Mills (AMM) standard model of urban economics, which allows spatial forecasting of housing construction, population density, rents, and transportation choices based on distance to the city center and CBD in a monocentric city. This model relies on two main mechanisms: (i) households are willing to pay higher rents to live closer to the city center and decrease their transportation costs; and (ii) private developers decide on the housing they build and its capital intensity based on their expected profit, which depends on construction costs and rents that households are willing to pay. As a result, with standard utility and construction functions, we expect areas close to the city center to be denser, with more expensive dwellings. Households derive utility from the consumption of housing—a composite good—and local amenities and disamenities, such as proximity to district parks, the ocean, or protected natural areas. We use the closed city version of this model, assuming exogenous city population growth scenarios.

We use a modified version of the AMM standard model, enriched in four ways. First, we use a polycentric version of the model. Second, we account for five transportation modes—private car, walking, minibus/taxi, bus, and train—which differ in terms of monetary cost and opportunity cost of time. Third, we define four income classes to account for income inequalities, as detailed in the context section. We assume that only income class 1 (the poorest households) is eligible for subsidized housing and that only income classes 1 and 2 live in informal settlements or informal backyard housing. Fourth, we account for inertia in formal private housing construction, assuming that it takes three years to build a new dwelling and that buildings depreciate over 100 years.

The main feature of the Pfeiffer et al. (2019) model is that it accounts for four housing types, and we make the following assumptions. (i) Formal housing is modeled as in the standard model of urban economics,

with households trading off between housing size and transportation costs and private developers maximizing their profit, leading to higher densities, higher rents, and lower dwelling sizes near employment centers. Hence, rent, dwelling size, and population density are all endogenous. There are few land use constraints on formal housing, as all locations are available except areas with natural constraints and those used for subsidized and informal housing. (ii) We assume that subsidized housing is exogenously provided for free by the state in predetermined areas and is available for the poorest (income class 1) households only. We assume that all subsidized houses have an exogenously given size of 40 square meters and a garden of 70 square meters. (iii) Households can build informal settlements in the backyards of subsidized houses. We assume that these dwellings have an exogenously given size of 14 square meters. Inhabitants of these informal backyard dwellings pay an (endogenous) rent to the owners of the subsidized houses, and subsidized homeowners decide on the share of their backyards they open to informal housing based on these rents, so that the density of informal dwellers in backyards is endogenous in the model. (iv) Finally, informal settlements also have an exogenously fixed size of 14 square meters and are only possible in some specific locations. Informal rents paid to the informal landowner and settler density are both endogenous.

We assume a disamenity parameter associated with informal settlements and informal backyard housing, capturing the fact that informal dwellings are of a lower quality than formal dwellings and associated with a certain probability of eviction. We have spatially calibrated this parameter to fit the 2011 population distribution. At each location, each income class chooses the housing type that maximizes its utility, so that at each location, one income class can only live in one housing type.

3.2. Policy scenarios

We simulate a simple climate policy and look at its impacts, particularly in terms of income and spatial inequalities. We assume that a fuel tax increases fuel prices by 20%, starting in 2020, broadly corresponding to a level of carbon pricing of US\$50–100 per tonne of carbon dioxide, the level required to cost-effectively reduce emissions in line with the Paris Agreement temperature goals (World Bank, 2020).

We consider two variants. In Scenario 1, the fuel tax increases the variable component of the monetary cost of private cars by 20% but does not impact walking or public transport costs. In Scenario 2, the fuel tax increases the variable component of the monetary cost of private cars, buses, and minibuses/taxis by 20%. Trains (already electrified) and walking costs are unchanged. These are two extreme scenarios, and the implementation of a fuel tax is likely to stand between the two: in the first scenario, we assume that public transport modes are fully subsidized and therefore not impacted by the tax, or that they become electrified; in the second, we assume that public transport fares are fully indexed on fuel price.

In practice, as transportation costs are composed of: a fixed monetary cost (such as depreciation of private car or subscription to public transportation); a variable monetary cost (such as fuel price or public transportation ticket); and an opportunity cost of time. Of these, only the variable monetary cost is impacted by the policy, so a 20% fuel tax translates into an increase in transportation costs of less than 20%. So, in Scenario 1, the fuel tax translates into a 2.9% average increase in transportation costs for income class 1 car users (maximum of 4.8%), and a 0.4% average increase for income class 4 car users (maximum of 0.6%). This increase is more important for low-income households, as their opportunity costs of time are low, so their transportation costs are mainly driven by their monetary transportation costs.

We compute the equilibrium in the city with and without a fuel tax, and decompose the changes between them into five steps, assuming they happen sequentially:

1. *Transportation costs increase* for workers commuting by private car (Scenario 1) or by private car, bus, or minibus/taxi (Scenario 2).
2. *Households change their employment subcenter and modal choice* to maximize their income net of transportation costs, accounting for the transportation costs increase. More precisely, workers choose the transportation mode that minimizes their transportation costs, and the probability of choosing each employment subcenter depends on income net of commuting cost.
3. *Rents are adjusted*, as changes in transportation costs modify the relative attractiveness of locations in the urban area. All else equal, locations that are furthest from jobs and where households largely commute by transportation modes subject to the tax become less attractive because they are tied to higher transportation costs. As a result, housing rents in these locations will decrease proportionally more than rents in more central or job-dense locations.
4. *Households adjust their dwelling sizes* in reaction to rent changes, if they live in the formal private sector (as we assume a fixed size for informal, backyard, and formal subsidized housing).
5. *Households change locations*, as they move within the urban area to maximize their utility.

4. Data, calibration, and validation

4.1. Data and calibration

Using the same data as Pfeiffer et al. (2019), we take the spatial distribution of the population from national censuses for 2001 and 2011, and incomes from the 2011 census, reclassified into four groups. For transportation, we use the transport model used by the City of Cape Town to retrieve transportation times between pairs of transport zones for each mode and job locations. We also use aggregated statistics on modal shares and residence-workplace distances derived from Cape Town's 2013 Transport Survey. We use housing prices from the City of Cape Town's housing sales registry. Concerning land use, we identify subsidized housing areas from the cadastre of the City of Cape Town, estimating available backyard housing area as the yard size of these units. We take informal settlement areas from the 2011 census. Finally, we take amenities from various sources (see Pfeiffer et al., 2019). To estimate the model's parameters, we also use property price data from the City of Cape Town's geocoded data set on property transactions for 2011, and dwelling size data made available to us by the City of Cape Town.

As described in Pfeiffer et al. (2019), we need to estimate three sets of parameters. The first consists of minimum lot size, informal dwelling backyard size, and agricultural rents; these are directly derived from the available data without solving the model. The second consists of housing production function parameters, utility function parameters, wages, and amenities, as calibrated in Pfeiffer et al. (2019) using partial relations from the model. For the third set, we spatially calibrate the disamenity parameters for informal housing and informal settlements by running the entire model to replicate the population distribution by housing type from the 2011 census.

4.2. Validation and baseline

We perform some validation checks to assess the validity of our modeling approach. All results can be found in Appendix A. First, at the aggregate level, we check that the number of households per income class and housing type simulated by the model in 2011 matches the census data (Appendix A1). Then, we

compare simulated population spatial distribution for each housing type in 2011 with the census data (Appendix A2). Finally, we compare simulated rents and housing prices data (Appendix A3).

Regarding housing types, our simulations fit the data: we slightly overestimate the number of households living in formal private housing and informal backyard housing, and underestimate the number of households living in informal settlements (Figure 8 in Appendix A1). This slight discrepancy can be explained by the difficulty in attributing a value to the disamenity parameter for living in informal settlements or informal backyard housing in certain locations, a modelling requirement. For informal backyard housing, for instance, the land-use data (which provides information on where informal backyard housing can potentially take place) might not match the population distribution data, as land-use data are from the cadastre whereas population distribution data are from the census. In addition, we assumed that informal backyard housing is only possible in the backyard of subsidized houses whereas, in some cases, it can also be possible in the backyard of formal private housing. Another difficulty might come from the fact that we assume the size of informal dwellings as fixed and exogenous whereas it might vary spatially. By construction, our calibration matches the number of households living in subsidized housing. Regarding densities, the overall fit is good. Looking at the detail by housing type, we can see that the fit between data and simulations is very good for informal settlements and informal backyard housing, due to our calibration of the disamenity parameter, and the fit is also good for formal private housing, even if we tend to overestimate densities in some parts of the city (Figure 9 in Appendix A2). Finally, our model allows reproducing housing prices, except for one peak in the city center (Figure 10 in Appendix A3).

The rest of this section shows some elements of context for housing type, population density, employment, and transportation in Cape Town before policy implementation. Table 2 shows the number of households per income class and their distribution among housing types in 2020, from the model's simulations. In terms of number of households, income class 1 (poorest) is the biggest group, with 516,594 households, followed by income class 3, 2, and 4. Income class 1 households live in subsidized housing, informal settlements, or informal backyard housing; they cannot afford formal private housing. Income class 2 households could technically live in informal housing, but most decide to live in formal housing; they are the poorest households in the formal private housing market. Finally, income classes 3 and 4 all live in formal private housing.

Table 2. Households, by income class and housing type (2020)

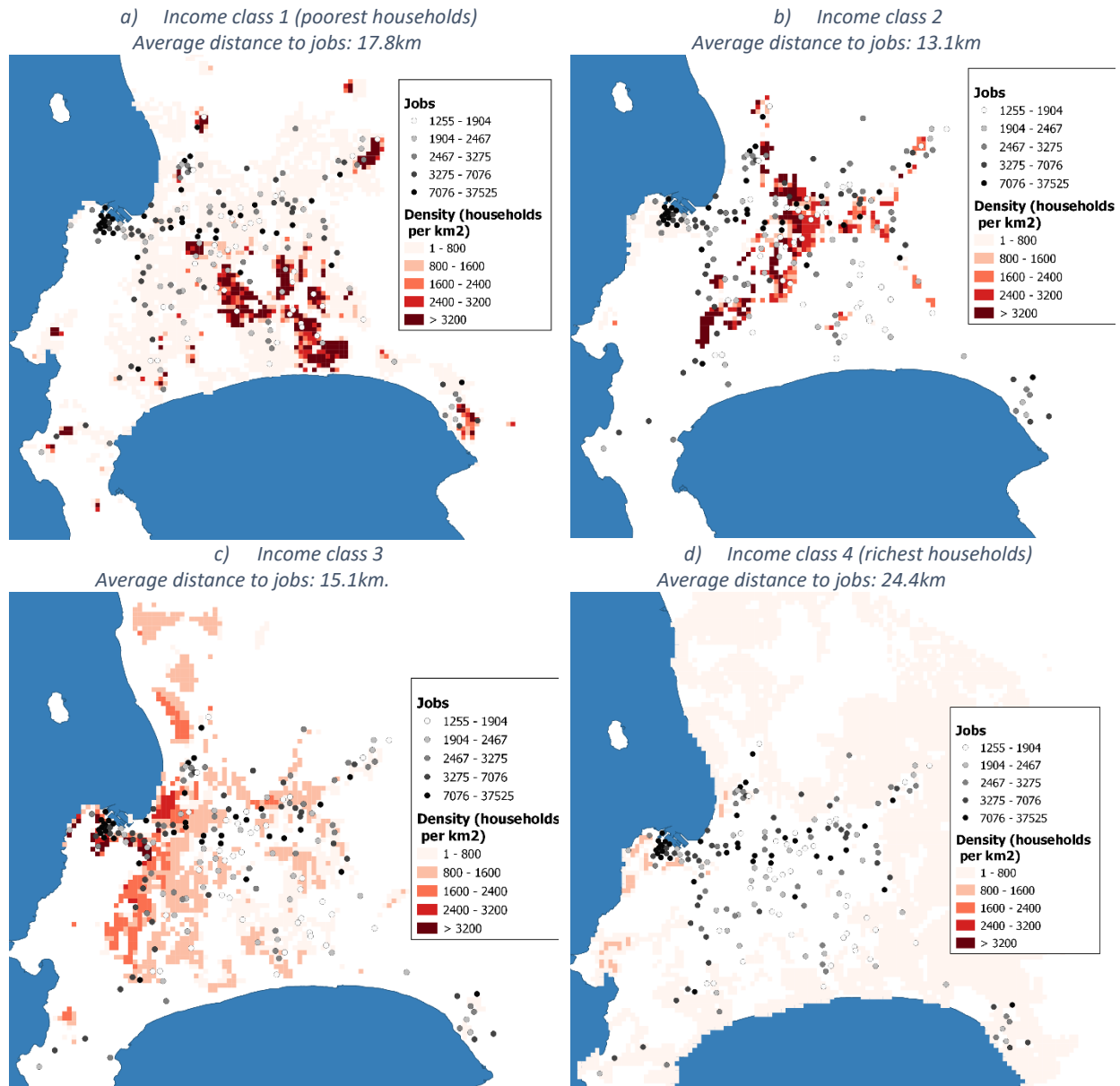
Households	Income class 1 (poorest)	Income class 2	Income class 3	Income class 4 (richest)
Total number of households	516,594	223,515	388,234	209,640
Percentage in formal private housing	0%	99.6%	100%	100%
Percentage in backyard housing	19.6%	0.18%	0%	0%
Percentage in informal settlements	29.4%	0.18%	0%	0%
Percentage in subsidized housing	51.0%	0%	0%	0%

Source: Authors' computations

Next, we focus on the spatial distribution of the population before policy implementation. Figure 1 shows the spatial distribution of the population of each income class and employment centers in 2020, from the model's simulations, and the average distance to jobs by income class. The poorest households (income class 1) live far from employment centers, mostly in informal settlements, subsidized housing or backyard dwellings in the city periphery. Households from income classes 2 and 3 live closer to employment centers,

while the richest (income class 4) can afford to live in larger dwellings very far from employment centers, commuting by private car (IRR, 2020).

Figure 1 - Spatial distribution of the population by income class in 2020. Source: model's outputs



Our modeling of the spatial distribution of the population and transportation choices allows us to retrieve the modal shares by income class (Table 3). To the best of our knowledge, no data on modal shares for the City of Cape Town are available for comparison. However, compared with the data from the *National Household Travel Survey 2013*² for the Western Cape region,³ we correctly estimate the modal shares of

² <https://www.statssa.gov.za/publications/P0320/P03202013.pdf>, accessed June 5th, 2023.

³ About two-thirds of people in the Western Cape region live in Cape Town.

private cars (27.7% of total trips, compared to 37.1% in the data), walking (20.2% compared to 17.1%), and trains (7.6%, compared to 10.6%). We are less good at differentiating between buses and minibuses/taxis, largely overestimating the modal share of buses (41.2% instead of 7.3%) and underestimating the share of minibuses/taxis (3.3% instead of 25.7%). But this has little impact on our results, as these modes are taxed the same way in our simulations. The overall picture remains valid: low-income households (class 1 and 2) commute mainly by public transportation and walking, and hardly use private cars; middle-income households (class 3) hardly walk and commute mainly by private car and public transport; and high-income households (class 4) commute mainly by private car.

Table 3. Modal shares, by income class (2020)

Transportation mode	Income class 1	Income class 2	Income class 3	Income class 4	Total
Walking	20.9%	13.0%	2.6%	0.0%	20.2%
Train	18.7%	18.7%	0.3%	0.0%	7.6%
Private car	1.6%	0.9%	18.5%	97.2%	27.7%
Minibus/taxi	10.8%	1.1%	1.1%	0.0%	3.3%
Bus	47.9%	60.3%	77.6%	2.7%	41.2%

Source: Authors' computations

5. Spatial impacts of the fuel tax

In this section, we analyze what happens when a fuel tax is implemented, quantifying the channels through which households are impacted and focusing on the spatial dimension of this impact. For the sake of simplicity, we display the results and figures for Scenario 2 only (fuel tax impacts the cost of private cars, buses, and minibuses/taxis).

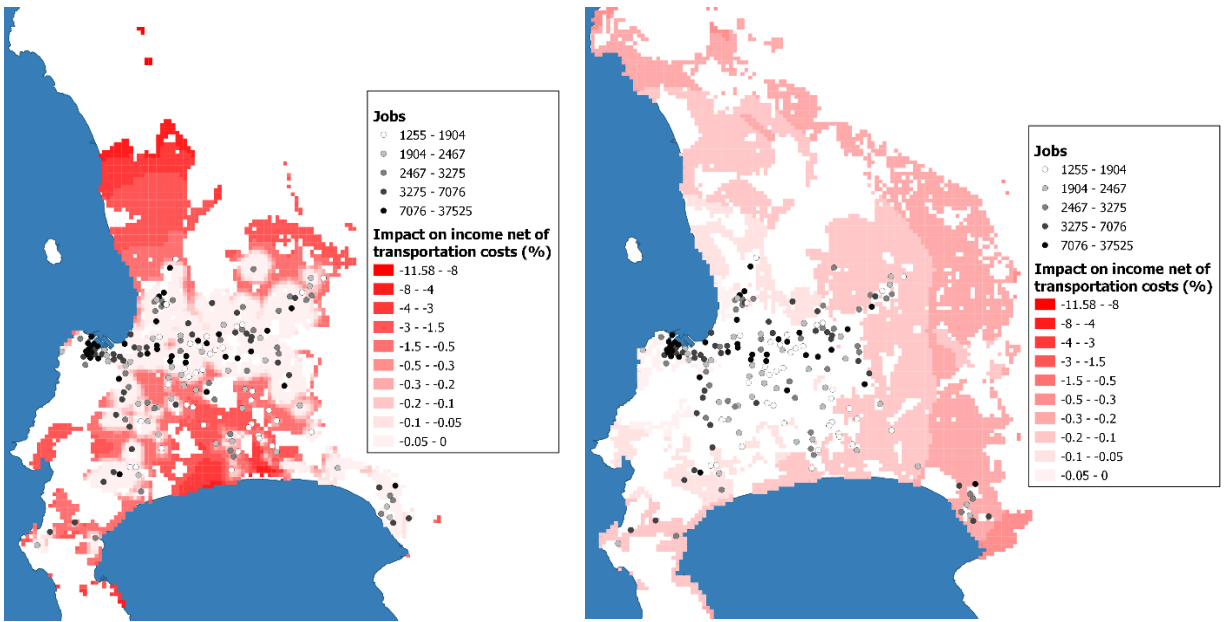
5.1. Direct impact on income net of transportation costs

We start by analyzing the direct impact of the fuel price increase, assuming that, in the short run, workers do not adapt by changing employment center, transportation mode, or location. Figure 2 shows the direct impact of the fuel tax on incomes net of generalized transportation costs, in Scenario 2, for income classes 1 and 4. These results are valid for the short run and show the immediate impacts of the policy. They also inform on potential opposition to the policy from the populations and the areas and people that are more likely to need support to adjust to the change in fuel prices.

Figure 2. Direct impact of fuel tax on poorest and richest household incomes, net of generalized transportation costs (Scenario 2: taxing all polluting modes)

a) Income class 1 (poorest households)

b) Income class 4 (richest households)



Regarding income inequalities, direct impacts of the fuel tax on the poorest households are larger than for the richest households, with net income losses up to -11.6% for income class 1 against -0.34% for income class 4 in Scenario 2 (taxing all polluting modes). Indeed, for high-income workers, the costs are mainly in the opportunity cost of transportation time, as the monetary cost is low compared with their income. For low-income workers, however, the monetary cost weighs heavily in their budgets; as such, they are more impacted by an increase in monetary cost. In Scenario 1, the fuel tax impacts only private cars, so few low-income workers are affected; but the low-income workers that are impacted also suffer strong income net of transportation cost losses compared with higher-income workers.

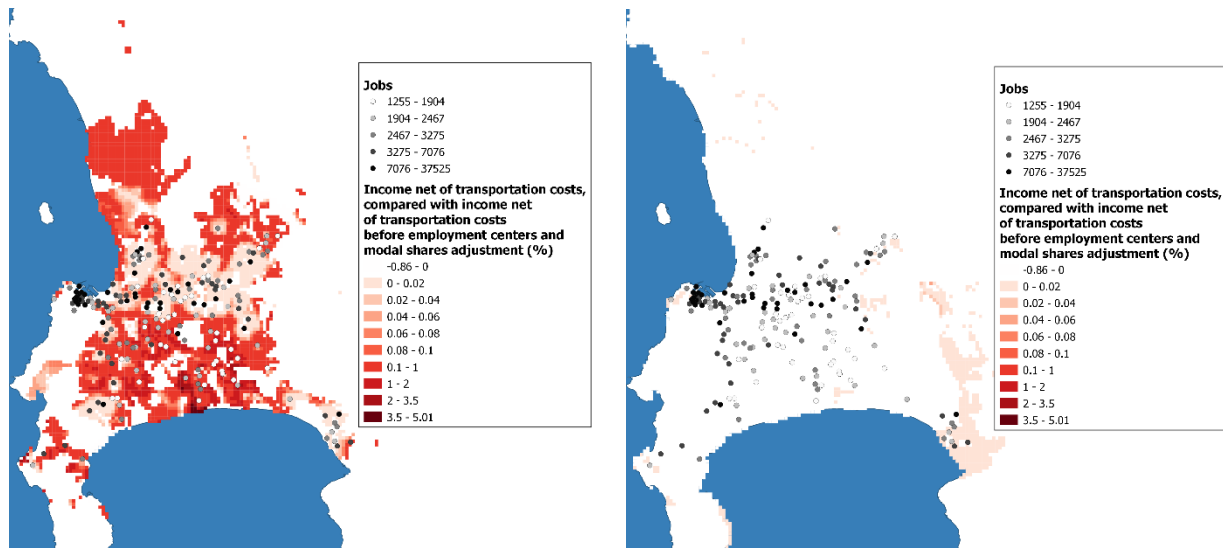
Figure 2 shows evidence of spatial inequalities in Scenario 2, for low- and high-income workers. In both cases, workers living far from employment centers are more affected by the fuel price increase than those living nearby, with the effect depending on the employment center and mode of transportation. Therefore, in the short term, there can be huge differences in the way the fuel tax affects two households in the same income class. Analyzing distributional impacts by looking at aggregated statistics per income class only would have hidden these effects; a spatial lens is necessary to identify the most affected households that would have the most to lose from the measure.

The next step is to understand how households can adapt to the fuel tax by changing their transportation modes and employment centers. Figure 3 shows household incomes, net of transportation costs, after changing their employment centers and mode choices, compared with their income before adjustment. Since our framework jointly optimizes transportation modes and employment center choices by household (see Pfeiffer et al., 2019), we do not distinguish them. But in reality, while it is relatively easy to switch transportation modes, labor market rigidities may make it more difficult to switch employment centers.

Figure 3. Impact of changing transportation modes and employment centers on poorest and richest household incomes, net of transportation costs (Scenario 2: taxing all polluting modes)

a) Income class 1 (poorest households)

b) Income class 4 (richest households)



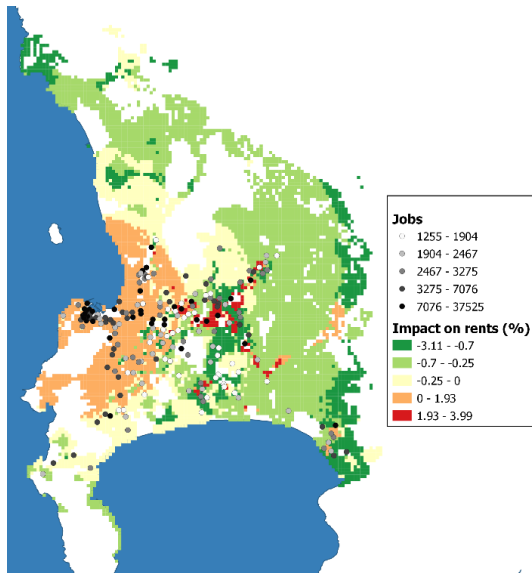
We can see that the households most affected by the fuel tax are also those that adapt the most, with the poorest households adapting more than the richest, and, within each income class, households living far from employment centers adapting more than those living nearby. This ability to adapt is, however, mitigated by the availability of transportation modes, allowing households to switch to a non-taxed transportation mode or to change employment centers. For instance, Lucas (2011) finds that low-income workers who cannot afford private cars or formal public transportation (trains, buses) or do not have access to formal public transport options⁴ are captive of informal transportation modes (minibuses/taxis) or over-rely on walking.

5.2. Rent

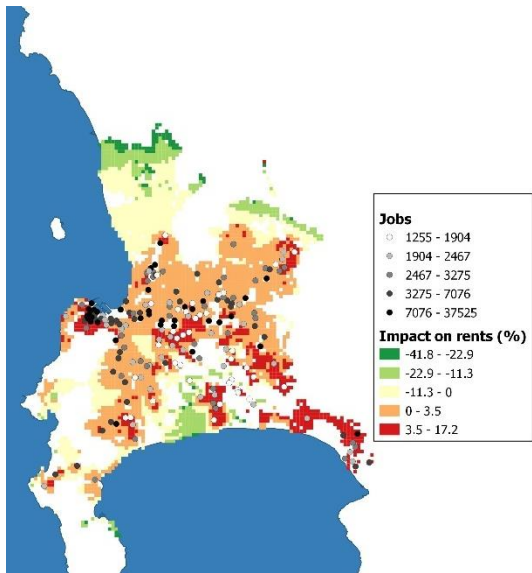
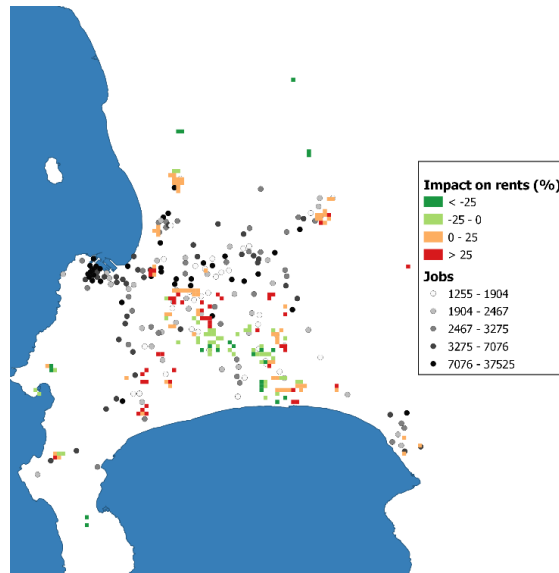
Figure 4 shows the impact of the fuel tax on rents per square meter for each housing type, except for subsidized formal housing, which the government supplies for free. It also shows locations of employment centers and number of jobs per employment, as changes in transportation costs to these employment centers will lead to changes in rent.

Figure 4. Impact of the fuel tax on rents (per square meter), by housing type (Scenario 2: taxing all polluting modes)
 a) Formal private households
 b) Households in informal settlements

⁴ For example, the poor quality of roads in informal settlements limits the opportunity for regular urban transportation implementation (Onyango, 2018).



c) Informal backyard households



For all housing types, we can see an overall trend of increasing rents near employment centers and decreasing rents in the periphery. Indeed, the fuel tax makes central locations more desirable, while the increase in transportation costs makes households less willing to pay for housing far from employment centers. Due to the polycentric nature of the Cape Town, rents can increase in places that are far from the main CBD, but close to other employment subcenters.

Our simulations indicate that the fuel tax can bring large changes in the rents paid for informal settlements and informal backyard housing relatively to their levels in the no-tax scenario. Indeed, in this case, rents correspond to informal rents extracted by informal landowners or subsidized houseowners⁵, and are

⁵ Mechanisms are described in Brueckner et al. (2019) for informal dwellings in backyards and by Brueckner and Selod (2009), for instance, for informal settlements.

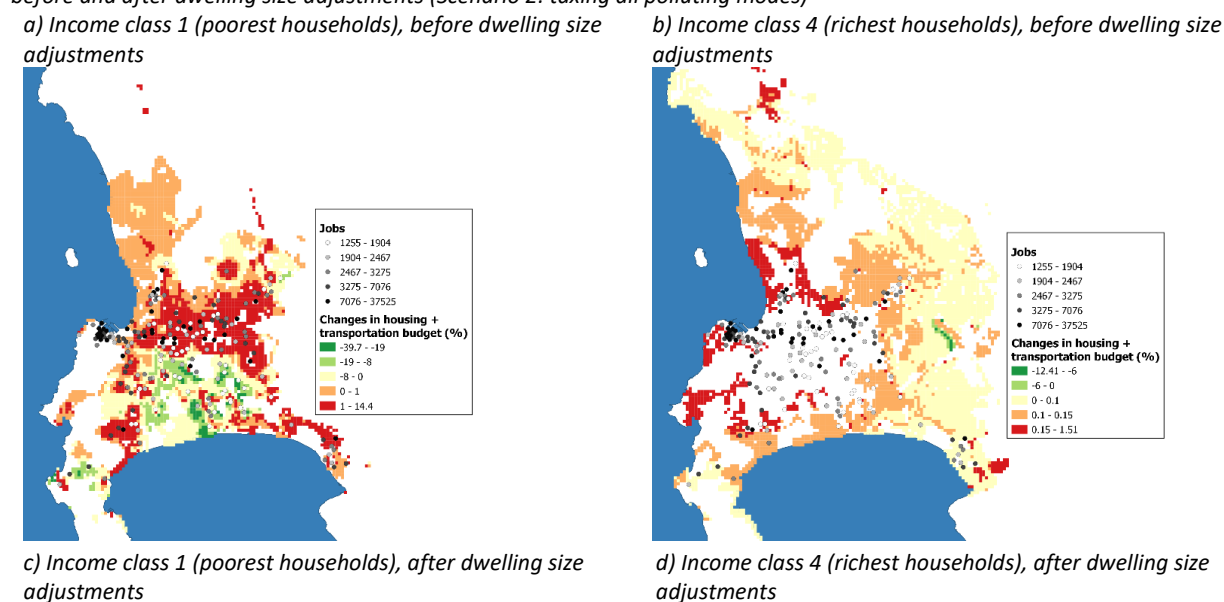
generally very low in the no-tax scenario⁶, so that even moderate changes in rents in absolute terms, triggered by the fuel tax, can translate into large percentage point variations, in particular large increases in informal rents near employment centers. However, the lack of data on informal rents makes it difficult to validate this part of the model. Informal settlements and backyard housing also depend on strong locational amenities and disamenities—such as the probability of eviction, the flood risk, or the availability of electricity or municipal water networks—and this might explain the variability in the impact of the fuel price between two close locations.

Formal housing rents, on the other hand, are more stable, with variations of -3.2% to +4.0% per square meter. One critical parameter, however, is the share of homeowners, compared with tenants, as an increase in rent, which negatively impacts tenants, is beneficial for homeowners. In South Africa, around 35% of people own their home (Statistics South Africa, 2018), and although there are no statistics on the subject, this share is likely to vary with income class.

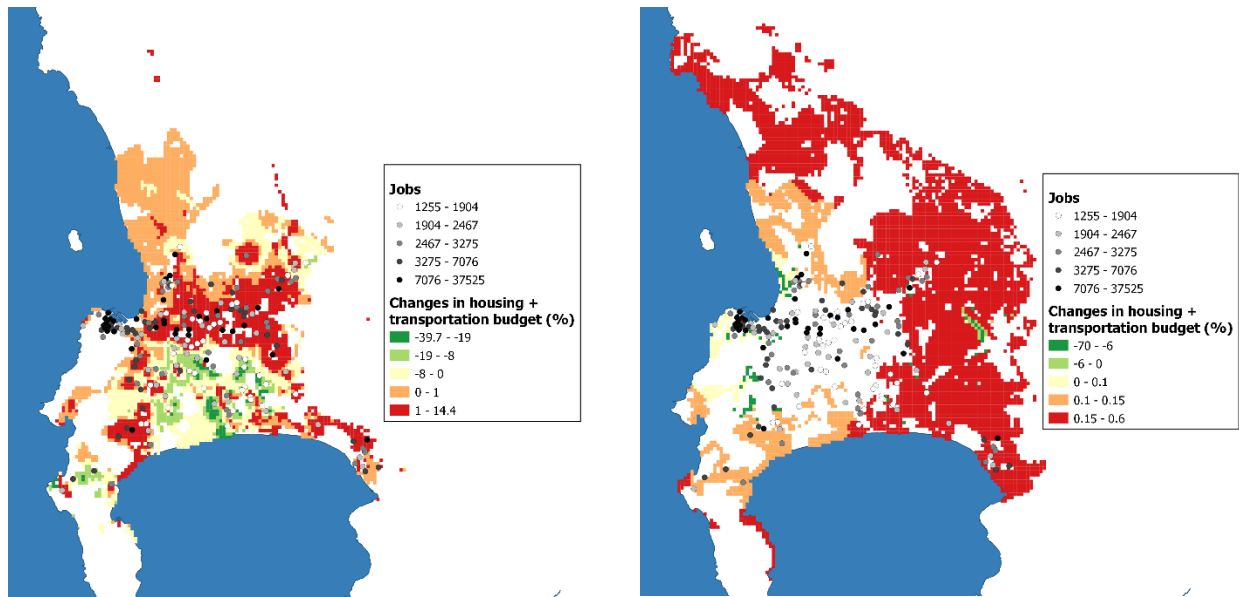
5.3. Housing and transportation budget

Figure 5 shows the impact of the fuel tax on constrained expenses (housing and transportation), after adjusting transportation mode, employment center, and rent. A decrease in these expenses (green and yellow) therefore means a better situation after taxation, while an increase in these expenses (red and orange) means a worse situation after taxation. The panels a and b show the impact before dwelling size adjustments; panels c and d show the impact after making these adjustments.

Figure 5. Impact of the fuel tax on constrained expenses (housing and transportation) for the poorest and richest households, before and after dwelling size adjustments (Scenario 2: taxing all polluting modes)



⁶ 95% of the rents paid for informal settlements and 76% of the rents paid for informal dwellings in backyards are lower than R200 per month (Social Housing Foundation, 2008).



Three effects are at play. First, the fuel tax increases households' transportation budget. Second, rents per square meter increase near employment centers and slightly decrease in the city periphery, with an ambiguous effect on constrained expenses, except for subsidized housing, which remains free. Third, dwelling sizes tend to compensate rent variations, and therefore decrease in the city center and slightly increase in the periphery. However, this only applies for formal housing, as informal settlements, backyard informal dwellings, and subsidized housing are of fixed size. In practice, households are likely to move to smaller dwellings as they won't be able to afford their rents, which they can combine with a relocation to a more central area to mitigate their transport cost. However, there is a strong inertia in households' relocations (Akbari et al., 2020), so that we should consider dwelling size adjustment to be medium to long-term adjustments. Reducing dwelling size allows households to reduce their constrained expenses, thus compensating for the fuel tax; but living in a smaller dwelling also impacts their welfare. However, these effects are complex, as rents are driven by competition between households of the different income classes that have access to each housing type.

Comparing the poorest and richest households, before dwelling size adjustments, we can see evidence of income and spatial inequalities. The poorest (income class 1) households can be more impacted by the fuel tax than the richest (income class 4) households, with constrained expenses for income class 1 increasing up to 14.5%, against 1.5% for income class 4. Spatially, both the poorest and richest households living close to employment centers seem to be most impacted by the fuel tax, as their transportation costs increase moderately and their rents also rise. However, after dwelling size adjustments, the richest households most impacted by the fuel tax are those living in the city periphery: indeed, those living in the city center adapt by reducing their dwelling size, and those in the periphery by increasing their dwelling size. Adjusting dwelling size also allows income class 4 households to mitigate their constrained expense increases (it does not exceed +0.6% after dwelling sizes adjustment).

On the contrary, the poorest households cannot adapt by reducing their dwelling size in the city center or increasing their dwelling size in the periphery, as they mostly live in informal settlements, informal backyard housing, and subsidized housing, which we assume to be of fixed size. For this reason, figure 5 panels a and c are almost identical. In practice, informal settlements are typically small (between 6 and

20 square meters), and the largest ones host multiple families (Sustainable Energy Africa, 2014), so downscaling is extremely unlikely. Regarding subsidized houses, they are provided by the government at fixed prices (assumed as free in our framework), in fixed sizes and fixed locations. Even if these programs increase the welfare of low-income households by giving them access to housing, they do not allow households to trade off between location and dwelling size—for example, by moving closer to the city center and reducing their dwellings size to adapt to the fuel price increase.

6. Aggregated impacts on welfare

6.1. Final welfare impact: comparing Scenarios 1 and 2

Table 4 shows the final welfare impact of the fuel tax after adjusting modal choices, employment centers, rents, dwelling sizes, and household locations. In the long run, the overall impact on final welfare is low, and never exceeds -1%.⁷ In Scenario 1, the impact on the welfare of the poorest households is low, as low-income workers barely commute by private car and live in informal housing, so are almost unaffected by real estate market adjustments. The impact on the richest households is also low, as the fuel tax is low compared with their income. The most impacted households are in income classes 2 and 3. As such, qualifying this policy as progressive or regressive is insufficient in this analysis, as its impacts are U-shaped, impacting middle-class households most, as the poorest and richest are unaffected, because they cannot afford private cars or the tax is low compared to their incomes.

Table 4. Final welfare impacts, by income class and scenario

Scenario	Income class 1	Income class 2	Income class 3	Income class 4	Average
1. Taxing private cars only	-0.03%	-0.19%	-0.21%	-0.06%	-0.06%
2. Taxing all polluting modes	-0.57%	-0.98%	-0.35%	-0.06%	-0.49%

Note: In the model, *welfare* is derived from the consumption of housing and a composite good, and impacted by local amenities and a disamenity parameter for households living in informal settlements or informal backyard housing.

In Scenario 2—where the fuel tax affects private cars, buses, and minibuses/taxis—the final welfare impact remains low for the richest households. But, because the fuel tax affects more transportation modes, it does have an impact on the welfare of low-income households. The most impacted households are in income classes 1 and 2. Qualifying the policy as progressive or regressive is also insufficient in this case, as its effects depend on the interplay between income and spatial considerations: income classes 1 and 2 tend to use less polluting transportation modes, as these are less expensive, but the tax weighs more heavily in their budgets because they are poorer; while most income class 1 and 2 households live in informal or subsidized housing, and are therefore constrained to live far from employment centers.

6.2. Welfare impacts, by income class

We decompose the welfare impacts of the fuel tax in Scenario 2 by comparing the equilibria with and without the tax. Assuming that the different steps—transportation costs increase, mode choice and employment, rent adjustments, and dwelling size and location adjustments—happen sequentially, we

⁷ For the sake of comparison, a 5% reduction in income leads to a 4.2% loss of welfare for class 1 income households, 7.1% for class 2, 4.3% for class 3, and 4.1% for class 4.

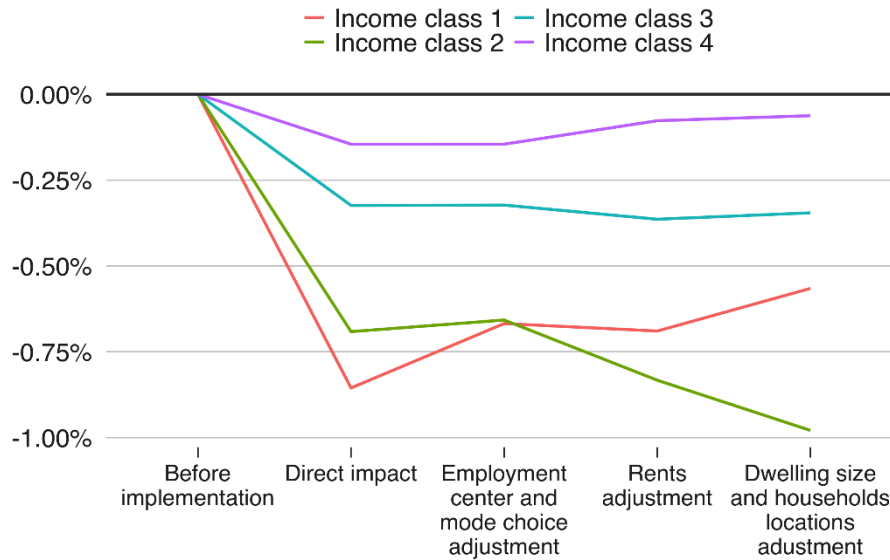
estimate the impact of each step on welfare by computing the corresponding counterfactuals. Results are displayed in Table 5 and Figure 6.

Table 5. Welfare impacts, by income class (Scenario 2: taxing all polluting modes)

Impact and adjustment	Income class 1	Income class 2	Income class 3	Income class 4
Direct impact	-0.86%	-0.69%	-0.32%	-0.15%
With employment center and transportation mode adjustment	+0.19 pp	+0.03 pp	+0.00 pp	+0.00 pp
With rent adjustment	-0.02 pp	-0.18 pp	-0.04 pp	+0.07 pp
With dwelling size and household location adjustment	+0.12 pp	-0.15 pp	+0.02 pp	+0.01 pp
Final welfare impact	-0.57%	-0.98%	-0.35%	-0.06%

Note: Employment centers and mode choice adjustments cannot be distinguished, as they are optimized together in the model; pp = percentage points.

Figure 6. Welfare impacts, by income class (Scenario 2: taxing all polluting modes)



First, the direct impact of the fuel tax on welfare before any adjustment is more important for income classes 1 (-0.86%) and 2 (-0.69%) than for income classes 3 (-0.32%) and 4 (-0.15%). Second, employment center and transportation mode adjustments unambiguously mitigate the impact of the fuel price increase on welfare; this effect is particularly important for income class 1, which has been more impacted by the tax in the first place. Still, at this stage, income classes 1 and 2 remain the most impacted. After that, adjusting rent, dwelling size, and location also allows households to mitigate the effect of the tax, but this strongly depends on income group. In some (typically central) locations, this could be a rent increase; in other (typically periphery) areas, it could be a decrease. This explains why the richest households (income class 4), who generally live in the farthest suburbs, benefit, with a decrease in rent (table 5 shows that rent adjustments reduce the impact on the welfare of the fuel tax of 0.07 percentage points for income class 4). Adjusting dwelling size and household location increases welfare for income classes 1, 3, and 4, but decreases welfare for income class 2. This surprising result comes from competition between the different income classes on the housing market. With income class 2 households being the poorest on the formal housing market, they are negatively impacted by adjustments on this market.

Graphically representing this welfare decomposition (Figure 6) provides clear evidence of income inequalities in the short run, with income class 1 and, to a lesser extent, income class 2 most affected by the direct impacts of the fuel tax. These short-term impacts are important for both these income classes. In the long run, income inequalities are mitigated (remaining below 1%), but persistent, especially for income classes 1 and 2. For income class 1, what matters here seems to be the timing of the adjustment: if changing mode choices seems feasible in the short run, employment center or housing location adjustments can only take place in the medium or long run. Policies facilitating adjustments in the housing or employment markets could therefore prove efficient to reduce short-term inequalities related to the fuel tax. As the poorest households on the formal housing market, income inequalities are crucial for income class 2. Financial assistance to help households compensate for the tax should therefore target priority low-income households.

6.3. Welfare impacts, by housing type

Understanding how welfare impacts depend on housing type helps us understand the persistence of inequalities between income classes, even in the long run. Table 6 decomposes the impact of the fuel tax by housing type. We do not show impacts on household location, because, after adjusting location, households living in each housing type are not necessarily the same, as people can switch housing type to maximize utilities when they are impacted by a change in transportation costs.

Table 6. Welfare impacts, by housing type (Scenario 2: taxing all polluting modes)

Impact and adjustment	Formal private	Informal backyard	Informal settlement	Formal subsidized
Direct impact	-0.22%	-0.47%	-0.95%	-0.91%
Employment center and transportation mode adjustment	+0.00 pp	+0.08 pp	+0.20 pp	+0.21 pp
Rent adjustment	+0.03 pp	-0.26 pp	+0.07 pp	+0.00 pp
Dwelling size adjustment	+0.94 pp	+0.00 pp	+0.00 pp	+0.00 pp

Note: Employment centers and mode choice adjustments cannot be distinguished, as they are optimized together in the model; pp = percentage points.

The direct impact of the fuel tax is more important for households in informal backyard housing, informal settlements, and subsidized housing than those in formal private housing. This is mainly because the former belongs to the two poorest income classes, so the increase in monetary transportation costs due to the fuel tax weighs heavily in their budgets. These housing types are also under strong land-use constraints, as they are only possible in some exogenous locations, often far from employment centers, giving households less flexibility to adjust and mitigate the increase in transport costs.

Adjustments in employment centers and transportation mode partially mitigate this direct impact for all housing types. Rent adjustments do the same, except for people living in subsidized housing, as subsidized houses are provided free by the state. Households in formal private housing can also mitigate the direct impact by adjusting their dwelling size. As subsidized and informal housing are of fixed size, households cannot adjust them to mitigate impacts.

After these adjustments, households can change housing type and location. However, people living in informal settlements, informal backyard housing, and subsidized housing often lack the financial resources to afford formal private housing, and are therefore forced to remain in the same housing type. Informal settlements, informal backyard housing, and subsidized housing are also spatially constrained, with informal settlements only possible in certain locations with publicly owned vacant land, and subsidized (and by extension, most backyard) housing locations exogenously decided by the state.

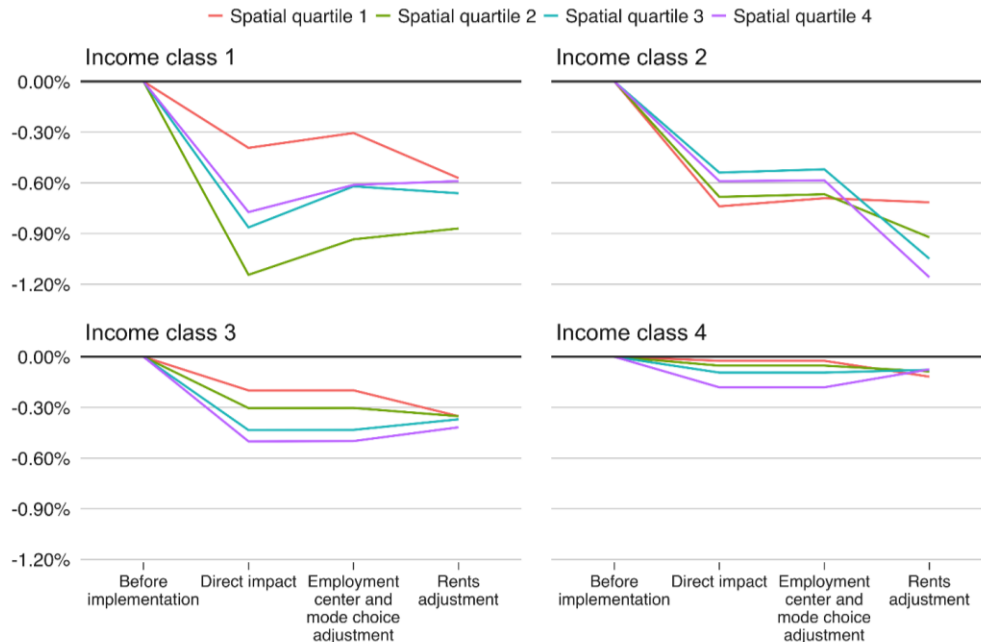
We can draw two conclusions from this analysis. First, low-income households living in informal settlements, backyard informal housing, or subsidized housing are more affected by the direct impacts of the fuel tax, as their incomes are generally low. Second, they have fewer opportunities to adapt to the fuel tax as they are under stronger land use constraints, and can rarely switch to formal private housing or adjust their rent or dwelling size. This shows the limitations of the subsidized housing program as a

fixed provision of housing units at exogenously determined locations and explains why Cape Town considers giving up on this policy.⁸

6.4. Welfare impacts, by spatial quartile

For each income class, we define spatial quartiles in relation to the weighted average distance to jobs: spatial quartile 1 corresponds to the 25% of households closest to jobs and spatial quartile 4 corresponds to the 25% of households farthest from jobs. In figure 7, we decompose the welfare impacts of the fuel price increase by income class and spatial quartile.

Figure 7. Welfare impacts, by income class and spatial quartile (Scenario 2: taxing all polluting modes)



For income classes 3 and 4, as expected, we can see that the direct impact of the fuel tax strongly depends on location, with spatial quartile 4 more affected than quartile 1. Employment center and transportation mode adjustments slightly attenuate the welfare impact of the fuel price increase. Finally, rents increase for households living near the city center and decrease for those living further out, and as a result, the fuel tax has a similar impact on all households within an income class. By construction, in the long run, after adjustment, utilities of all households within each income class will be equal.

Figure 7 does not show the last step—adjusting dwelling size and housing location—because, after adjusting location, households are no longer in the same spatial quartile. So even if, by construction, all households within an income class have the same utility in the end, we focus here on the convergence process: there are inequalities between spatial quartiles in the short run, and these can be important if the convergence process takes time.

For income classes 1 and 2, the effects at play in the convergence process are less clear. First, for income class 2, there are few differences between spatial quartiles. Second, the direct impact of the fuel tax varies with spatial quartiles, but in a non-linear way. One explanation might be that, contrary to the richest

⁸ <https://www.businessinsider.co.za/government-is-calling-for-the-downscaling-of-housing-projects-heres-how-it-will-work-2020-12>

households, almost all of whom commute by polluting vehicle, the poorest households sometimes commute by non-polluting transportation modes. Finally, by construction, after adjusting dwelling size and housing location, utilities within each income class are equal and spatial inequalities disappear. However, in the medium run, we find evidence of persisting spatial inequalities, especially within income class 2.

7. Aggregated impact on emissions

Table 7 shows the impact of the fuel price increase on passenger kilometers for each transportation mode, as well as the further decomposition between the variations due to modal shift and changes in workplace-residence distances. The last column estimates the impact on emissions, using emissions per kilometer data from WWF (2016).

Table 7. Impact of fuel tax on transportation demand and estimated impact on transportation emissions

Scenario and variation	Passenger-km variations					Emissions variations
	Walking	Train	Private car	Minibus/taxi	Bus	
Scenario 1	+0.45%	+1.24%	-9.34%	+4.52%	+9.13%	-5.04%
Modal share variations	+0.15%	+1.06%	-11.74%	+3.49%	+7.63%	
Average distance variations	+0.30%	+0.18%	+2.72%	+1.00%	+1.40%	
Scenario 2	+22.26%	+46.79%	+1.64%	-28.97%	-23.49%	-0.59%
Modal share variations	+19.63%	+49.94%	+5.41%	-10.91%	-18.99%	
Average distance variations	+2.20%	-2.10%	-3.58%	-20.27%	-5.56%	

Scenario 1—where only private cars are impacted by the fuel price increase—is more efficient in terms of emissions mitigation than Scenario 2, where buses, minibuses, and taxis are also impacted. This result, which implies that taxing all polluting transportation modes does not necessarily lead to higher emissions reduction, can seem counterintuitive. There are two reasons for this.

First, there are more modal shifts in Scenario 1 than in Scenario 2. Indeed, in Scenario 1, taxing private cars leads to a strong reduction in their modal share, to the profit of buses and minibuses/taxis, which are less fuel-consuming travel modes. In Scenario 2, as private cars, buses, minibuses, and taxis are taxed, the modal share of private cars increases. Because buses, minibuses, and taxis are slow, a tax makes them unattractive, leading to a modal shift toward private cars, which are more expensive due to the tax, but also faster than other modes. This effect depends on the relative increase in private car transportation costs compared to the relative increase in bus and minibus costs. It depends on the share of variable monetary cost across total transportation costs, which varies by income group and location.

Second, the decomposition of passenger kilometer variations between modal share and average distance variations shows that passenger kilometer variations are mostly driven by modal shift and not by average distance variations. Indeed, informal settlements, backyard housing, and subsidized housing are strongly constrained in our model, while inertia in housing supply slows down potential formal housing relocations. As a result, urban reconfigurations have low potential for emissions reduction in our model.

We also conducted two sensibility checks (see Appendix B). First, we implemented a fuel tax of the same monetary amount (10 cents per kilometer) for all transportation modes (Table 8). Second, we looked at the result after 20 years, to give formal housing supply time to adjust despite inertia (Table). In both

cases, Scenario 1 remains more efficient in terms of emissions mitigation, and urban reconfigurations play a small role compared with modal shares.

This shows that taxing polluting public transportation modes might be less efficient in terms of emissions mitigation than taxing private cars only, and policy makers should in priority account for potential modal shifts induced by the tax. This result is in line with Avner et al. (2014), which finds that, in Paris, reducing transportation emissions requires a lower level of gasoline tax if a dense network of public transportation is available; indeed, having public transportation options allows policy makers to rely on modal shift, as well as urban reconfiguration, to reduce emissions.

The outputs of the model also allow us to provide a rough estimate of the monetary value of improved health through reduced air pollution due to the tax (Appendix C). Overall, Scenario 1 allows a US\$3.1 million gain, and Scenario 2 a US\$2.1 million gain, partially offsetting the tax's welfare impacts. This rough estimate does not allow us to disaggregate health benefits based on income class. Yet, as individuals from low-income backgrounds tend to experience higher levels of air pollution exposure (Banzhaf et al., 2019; see also Mumm et al., 2017 for a Cape Town case study), they are more likely to derive greater advantages from the health enhancements attributable to the tax.

8. Discussion

Beyond income inequalities, this work allows us to decompose the spatial dynamics of implementing a climate transportation policy. In the short run, the climate policy results in increased transportation costs, strongly impacting households living in the city periphery and commuting by polluting transportation modes. Then, equilibrium effects tend to mitigate the impacts of the fuel price increase: workers adjust employment centers and transportation mode choices, rents increase in the city center and decrease in the periphery, and households adjust their location and housing type to live closer to the city center and job-dense locations.

We find that spatial inequalities reinforce income inequalities. In the short term, we have strong evidence of income inequalities, with low-income households disproportionately affected by the fuel price increase. There is also evidence of spatial inequalities, as the direct impact of the fuel tax increase varies with distance from the city center. These spatial and income inequalities persist in the medium and long terms: low-income households living in informal settlements or subsidized housing have limited or no means to adapt by changing their housing type or adjusting their dwelling size or location, as in certain areas, only informal and subsidized housing options are available. Low-income households living in formal housing are also impacted by the tax in the long run, due to the complex effects of competing with wealthier households in the housing market.

In terms of aggregate impacts, city-scale aggregated welfare losses due to the fuel tax are limited; but this is partially offset by the health co-benefits related to reduced air pollution. In Cape Town, implementing a fuel tax on private cars only impacts mostly the richest households as low-income households cannot afford private cars, whereas a fuel tax on private cars, buses, minibuses, and taxis has a higher impact on low-income households. The city-scale aggregated welfare loss is higher when all polluting transportation modes are impacted than when cars only are impacted. A fuel tax affecting private cars only is also more efficient in terms of emissions reduction, as it generates a modal shift from private cars to other transportation modes. Therefore, we do not find an efficiency-equity trade-off: our results suggest that in Cape Town, it makes sense to tax private cars only—or equivalently to tax fuel and subsidize public

transportation. As taxing all polluting transportation modes is both less efficient in terms of emissions reduction and more regressive, it could trigger political economy effects that push households to oppose climate policies.

But although the long-term, aggregated welfare losses are limited—averaging around -0.06% or -0.49%, depending on the scenario—short-term welfare losses can be substantial. This is especially so for low-income households or households located far from employment centers, where after deducting transportation costs, income can be reduced by up to 12%. From a methodological point of view, this demonstrates the importance of decomposing the impact of climate policies spatially and over different timeframes.

This work might be relevant for public policy. First, in terms of political economy, implementing a fuel tax can be perceived as strongly unfair. In the short run, some households are more directly impacted by the tax, while in the long run, not all households have the same opportunity to adapt to the tax. Policy makers should therefore consider designing integrated policies on transportation, land use, and real estate that allow households impacted by the tax to adapt by changing employment subcenter, transportation mode, housing type, and location. In practical terms, policy makers might help households adapt to the fuel tax by providing targeted cash assistance, for instance to switch to less polluting transport modes (e.g. buying a bike or a public transport yearly pass) or to relocate. Building affordable or subsidized housing near employment centers would also help low-income households adapt to the fuel tax. The subsidized housing programs that used to be implemented in Cape Town significantly improved the welfare of low-income households, but did not provide flexibility and made them less resilient to transportation cost shocks. Policymakers could also design affordable public transportation that is not affected by the tax. Policies aiming at influencing the spatial distribution of jobs, while not straightforward, are also worth considering. Developing employment subcenters out of the CBD while helping smooth the transitions in the labor market, for instance by providing financial assistance for people switching jobs or targeted career advice, might also help households to adapt. Finally, one of the paper's main results suggests that a fuel tax that would only apply to individual cars, instead of cars and various public transport modes, would be both more efficient in curbing CO₂ emissions from transport, have lower aggregate welfare impacts, and be less regressive, making it a much more appealing policy proposal.

Despite a very city-specific real estate market—notably due to the coexistence of two informal housing types and subsidized housing—we believe these results can have implications for other cities. In political economy terms, people will only perceive a climate transportation policy as fair and acceptable if all households have an equal chance to easily adapt to it, through access to alternative transportation modes in the short run, and by having the chance to adjust their residence location in the long run. Segregated or gentrified cities therefore present major challenges for climate change mitigation.

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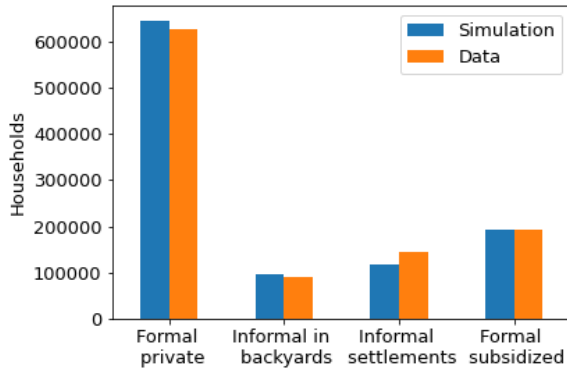
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Appendix A. Validation

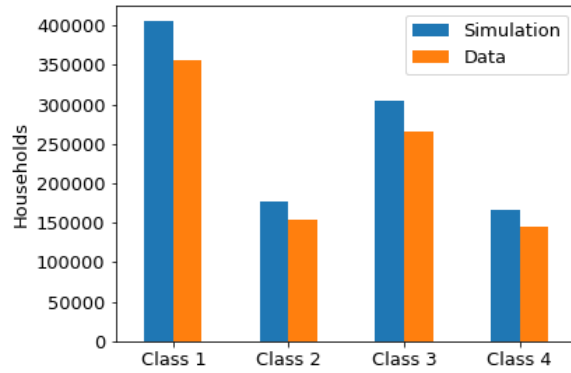
A1. Housing types and income classes

Figure 8. Housing types and income classes: data (source: Census 2011) and simulation.

a) Housing types



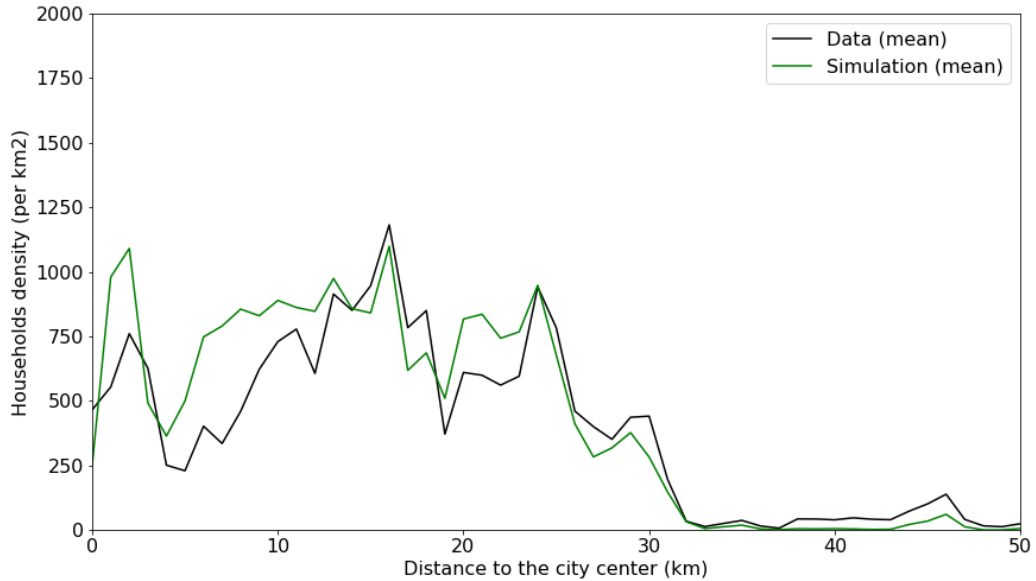
b) Income classes



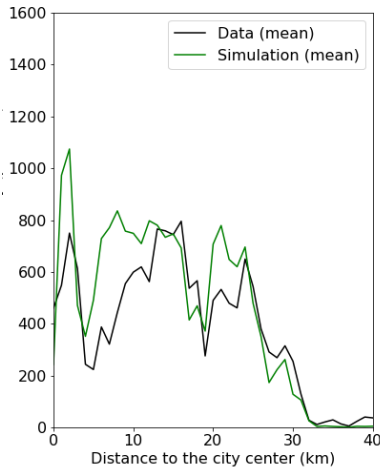
A2. Spatial distribution of the population

Figure 9. Population density: data (source: Census 2011) and simulations.

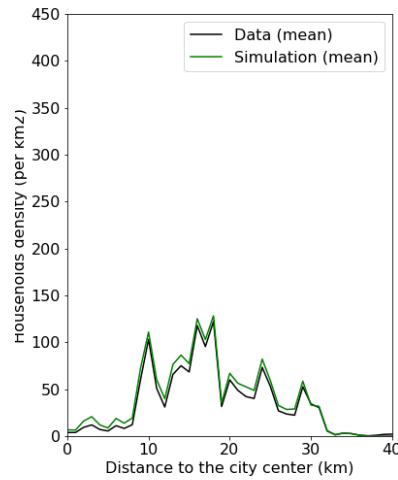
a) All housing types



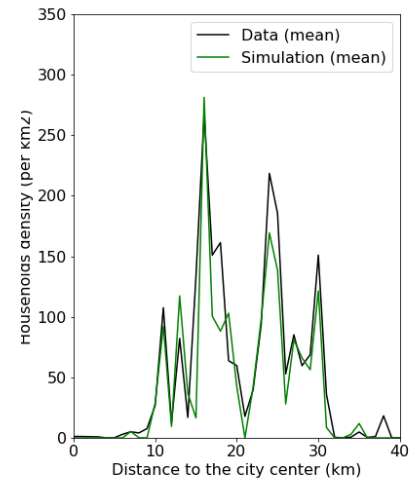
b) Formal housing



c) Backyard housing

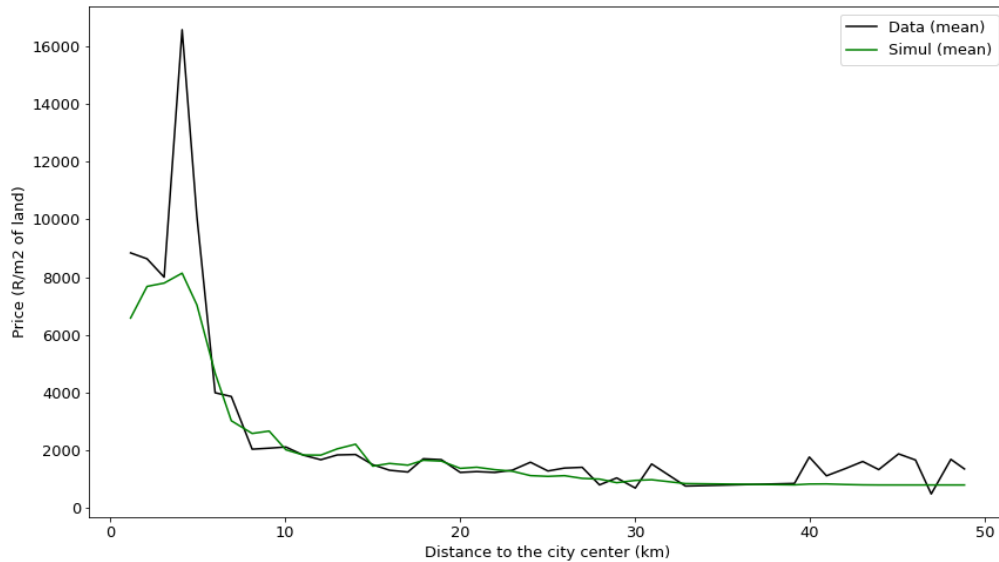


d) Informal settlements



A3. Housing prices

Figure 10. Housing prices: data v simulation



Appendix B. Sensitivity check

Table 8. Impact of fuel tax on transportation demand and estimated impact on transportation emissions, with a monetary tax of 10 cents per kilometer

Scenario and variation	Passenger-kilometer variations					Emissions variations
	Walking	Train	Private car	Minibus/taxi	Bus	
Scenario 1: Tax on private cars	+0.47%	+0.90%	-8.57%	+1.93%	+8.32%	-4.67%
Modal share variations	+0.33%	+0.82%	-10.65%	+1.15%	+7.08%	
Average distance variations	+0.14%	+0.07%	+2.33%	+0.77%	+1.16%	

Scenario 2: Tax on all polluting vehicles	+21.29%	+37.83%	+0.58%	-28.69%	-20.11%	-1.27%
Modal share variations	+18.58%	+41.58%	+3.36%	-11.21%	-16.46%	
Average distance variations	+2.29%	-2.65%	-2.68%	-19.69%	-4.37%	

Table 9. Impact of fuel tax on transportation demand and estimations of its impact on transportation emissions after 20 years, to capture potential changes in urban forms that would occur in the long term

Scenario and variation	Passenger-kilometer variations					Emissions variations
	Walking	Train	Private car	Minibus/taxi	Bus	
Scenario 1: Tax on private cars	+1.04%	+12.35%	-12.48%	+0.63%	+24.08%	-7.74%
Modal share variations	+0.65%	+12.16%	-11.21%	+0.72%	+18.66%	
Average distance variations	+0.39%	+0.17%	-1.43%	-0.09%	+4.57%	
Scenario 2: Tax on all polluting vehicles	+16.72%	+28.23%	+1.86%	-19.85%	-39.55%	-0.27%
Modal share variations	+13.30%	+30.77%	+4.21%	-17.09%	-32.67%	
Average distance variations	+3.03%	-1.96%	-2.25%	-3.33%	-11.53%	

Appendix C. Air pollution

We computed our estimates of the monetary gains from improved health, resulting from reduced air pollution, in the following way:

- Total passenger-kilometers per year for private cars, buses, and minibuses/taxis are outputs of our model. We do not account for walking, as it does not generate air pollution, or for trains, assuming they are electrified.
- Using the WWF (2016) data, we compute the corresponding CO₂ emissions.
- From CO₂ emissions, we derive the liters of fuel that have been used, assuming that 1 liter of fuel emits 2.4 kilograms of CO₂. From this estimate of liters of fuel used per year, we derive the monetary cost of air pollution through reduced health using the values provided by the World Bank's Carbon Pricing Assessment Tool model (US\$0.022 per liter of gasoline and US\$0.268 per liter of diesel). We assume that 35% of the vehicles are diesel vehicles, following the International Energy Agency, <https://www.iea.org/articles/fuel-economy-in-south-africa> [accessed April 27, 2022].

We find that the monetary cost of air pollution per year is US\$57.1 million in 2020 when no fuel tax is implemented, US\$54 million in Scenario 1, and US\$55 million in Scenario 2.