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Energy policies and pollution in two developing country cities: A quantitative model*

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ABSTRACT

We study the effect of energy and transport policies on pollution in two developing country cities. We use a quantitative equilibrium model with choice of housing, energy use, residential location, transport mode, and energy technology. Pollution comes from commuting and residential energy use. The model parameters are calibrated to replicate key variables for two developing country cities, Maputo, Mozambique, and Yogyakarta, Indonesia. In the counterfactual simulations, we study how various transport and energy policies affect equilibrium pollution. Policies may be induce rebound effects from increasing residential energy use or switching to high emission modes or locations. In general, these rebound effects tend to be largest for subsidies to public transport or modern residential energy technology.

Keywords: pollution, energy policy, discrete choice, developing country cities
JEL Codes: Q53, Q54, R48

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1 Introduction

The world has become more and more urbanized, and the bulk of the ongoing and future urbanization will happen in developing countries. However, cities in low and middle income countries are often ill equipped to deal with the consequences of this urbanization. Air pollution is one of the major drawbacks of rapid urbanization. According to the WHO, 98% of cities in low- and middle income countries with more than 100,000 inhabitants do not meet WHO air quality guidelines, whereas in high-income countries, that percentage decreases to 56%. Low income countries suffer the highest mortality burden from pollution. According to the WHO, while the age-standardized death rate attributed to household and ambient air pollution in 2016 was 36.3 per 100,000 in Europe and 29.7 in the Americas, it was 180.9 in Africa and 165.8 in South-East Asia.[1] Indeed, according to the WHO, more than 90% of air pollution-related deaths occur in low- and middle-income countries, mainly in Asia and Africa.[2]

The reasons for high pollution levels are many and run deep, but undoubtedly, air pollution from transport and residential energy use is driven both by poor technology, such as cars with inefficient mileage and inefficient residential energy technologies as well as by policies such as subsidies to fossil fuel use, poor infrastructure and inadequate public transport. In this paper, we use a quantitative spatial model to address the consequences of household choices and energy policies for urban air pollution in developing cities. In the model, households choose their residential location as well as their transportation mode and energy use. We include features that are specific to developing country cities, such as use of traditional cooking technologies (charcoal or wood), and use of motorcycles and informal public transport (minibuses).[3]

This type of model is useful for several reasons. First and most obviously, it can be used to quantify ex ante the effect of policies aimed at reducing pollution. Second, because of the equilibrium analysis and the consideration of several choice margins, it can account for potential rebound effects of well meant policies. For example, income effects of (clean) energy subsidies may increase energy demand, and policies aimed to reduce transport emissions may affect residential energy use and vice versa. Also, the interaction of energy policies and location choices may prove important since some types of policies may lead to

[1] https://apps.who.int/gho/data/view.sdg.3-9-data-reg?lang=en

[2] https://www.who.int/news-room/detail/02-05-2018-9-out-of-10-people-worldwide-breathe-polluted-air-but-more-countries-are-taking-action

[3] While traditional fuels are a major contributor to indoor air pollution, they also significantly affect outdoor air pollution, see e.g. Chafe *et al.* (2014) and Goldemberg *et al.* (2018).

suburbanization which increases commuting and residential energy use.

We calibrate the model to data from Maputo, Mozambique and Yogyakarta, Indonesia. For both cities we have consistent, detailed and spatially explicit data, while these two cities feature transport and energy (policy) characteristics that are typical for many cities in developing countries at different stages of development, and that matter a great deal for urban air pollution – including the dominant use of minibuses and motorcycles, the emergence of private car use, a mix of biomass and modern fuel use for cooking, fuel subsidies and substantial income differences. We use our model to conduct counterfactual policy analysis that reduces the cost of public transport or the costs of using modern and more efficient energy technologies.

We are not the first to study the link between energy policies and pollution (see the literature review below). However, as far as we know, we are the first to study the interaction of transport and energy policies and urban pollution in developing country cities in a quantitative spatial model. This is an important extension for several reasons. On a practical level, studying pollution in cities and potential effects of policies seems especially important in developing countries, as argued above. On a methodological level, developing and developed country cities obviously differ in many ways that may limit the transferability of policies. For one, transport mode choice is different in developing countries. Whereas commuting in developed countries is mainly by car and public transport (in some cities also walking and biking), in developing countries individuals often commute via motorcycles and informal forms of (semi-) public transport such as minibuses. Second, electricity and modern fuels such as heating oil or LPG are not as widely available in developing countries. Households often use 'traditional' fuels such as wood, charcoal or dung, which cause severe problems of indoor and outdoor pollution. Our paper aims to capture some of these differences in a quantitative model.

Literature. Our paper relates to a large literature on transport and energy policies.

Several strands of research have analyzed the effect of public transport on pollution. Among others, Parry and Small (2009) use a theoretical transport model to quantitatively evaluate welfare effects of transit subsidies. Their model is very detailed in the modelling of externalities and margins of response, but it is not spatial. Several computable general equilibrium studies have analyzed similar questions, e.g. Proost and Van Dender (2001), also in a non-spatial model. Tscharaktschiew and Hirte (2012) use a spatial CGE model to study the effect of various policies related to public transport. While they also consider transport related pollution, the focus of their paper is on congestion and pollution does not seem to figure directly in utility; furthermore, in their model, emissions accrue from commuting only, while this paper also looks at the response of residential emissions.

There is also a literature studying the effect of public transport on pollution using quasiexperiments. For instance, Bauernschuster *et al.* (2017) find that transit strikes increase pollution, while Gendron-Carrier *et al.* (2022) find that opening a subway network reduces a city's air pollution by 4%.[4] This literature, however, is typically limited to making statements about the particular experiment studied, and the welfare consequences are not based on structural modelling.

Our study also relates to research on the effect of energy policies on urban air pollution in low and middle income countries. The adoption of "clean" cooking technologies in low income countries and its relation to indoor and outdoor pollution has been studied, *inter alia*, by Jeuland *et al.* (2018), Martínez *et al.* (2017), Imelda (2020), Das *et al.* (2022), and Berkouwer and Dean (2022). In a review of the evolution of (urban) air pollution of China, Zheng and Kahn (2017) show that in many of China's urban areas levels of particulates have been decreasing during the last 10 to 15 years while rising incomes tend to raise the demand for environmental amenities and thus increase political pressure for environmental protection. Many papers now analyze the effects of policies on air pollution in developing countries. For example, Bel and Holst (2018) use a difference-in-difference (DiD) design to study the effect introducing a Bus Rapid Transit (BRT) system in Mexico city on air pollution. Goel and Gupta (2015) study the impact of the Delhi Metro expansion and find a strong short-run reduction in carbon monoxide (CO) pollution. Zheng *et al.* (2019) use the DiD method to estimate the impact of the opening of the first subway line in Changsha, China and find a reduction in CO in areas close to subway stations. Li *et al.* (2019) study the effect of the Beijing subway on air pollution using IV and DID estimation. They find that increasing subway density reduced air pollution. We add to this strand of literature a general equilibrium perspective, to study the direct and indirect effects of energy and transport policies in a spatial setting.

This paper is also closely related to a new literature on quantitative evaluation of transport infrastructure using spatial models (Allen and Arkolakis, 2022; Severen, 2023; Tsivanidis, 2023). A small but growing number of papers uses quantitative models to study pollution, e.g. Larson *et al.* (2012), Borck and Pflüger (2019), Borck and Brueckner (2018),

[4]Other papers in this vein include Davis (2008) on driving restrictions in Mexico City and Gallego *et al.* (2013) on the same policy and a public transport reform in Santiago, Chile. Both of these papers do not find that these reforms reduced pollution.

Aldeco *et al.* (2019) and Colas and Morehouse (2022).

The paper is most closely related to Borck (2019). We amend that model in several ways: most notably, whereas the model in Borck (2019) is calibrated to American cities, we calibrate the present model to developing country cities. This is important because, as argued above, developing and developed country cities differ in many ways that may impact pollution. In particular, we try to include choice margins that are relevant to developing country cities. First, in addition to cars and public transport, we include a third mode: motorcycles in Yogyakarta and minibuses in Maputo. This extension is motivated by our data, which shows that 78% of households commute by motorcycle in Yogyakarta, and 51% commute by minibus in Maputo. Since these modes differ in their pollution intensity from either cars or public transport, this choice is relevant for the effect of energy policies. Second, we include the choice of energy residential mode in the model: a modern one (such as electricity or gas) or a traditional fuel (such as charcoal, wood, animal dung or other forms of biomass). Since modern energy tends to be cleaner than traditional one in terms of indoor and outdoor pollution, this margin seems relevant for studying the impact of energy policies on pollution. In fact, while traditional energy is not very important in Yogyakarta, in Maputo almost half of all households use traditional energy. Finally, the choice of residential energy use is modeled directly here, whereas in Borck (2019) it is assumed proportional to housing space. This allows for a better modelling of residential energy as long as energy use is not strictly proportional to dwelling size.

While the literature using spatial models of transport policies has been growing, the effects of residential energy policies such as taxes have not been widely studied in this kind of model. One study along those lines is Borck and Brueckner (2018), who study analyze taxation in a monocentric city model. Since residential energy use is proportional to building surface, they show that socially efficient energy taxes can be mimicked by a combination of a tax on commuting, a tax on residential floorspace, and a tax on land (the latter in order for developers to build taller and more energy efficient buildings). Another example is an early paper by Small (1980) who discussed the likely effect of rising energy prices on household and firm location choices. He argued that any relocation incentives between suburbs and city centers would be mitigated by other adjustment margins such as vehicle choices or trip lengths, heating choices, retrofitting of buildings etc.

Finally, there is a growing literature in urban economics on cities in developing countries. In particular, a few recent papers have deployed quantitative spatial economic models to analyze policy issues in developing country cities, such as land tenure systems (Bird and

Venables, 2020) or flood protection and infrastructure improvement (Bird and Venables, 2019). To our knowledge, however, there are no quantitative spatial models that study the effect of policies on pollution in developing country cities.

The paper proceeds as follows. The next section presents the model basics. Section 3 presents some background on the two cities and a description of the data we use. Section 4 contains the model calibration and Section 5 the results of the counterfactual simulations. Section 6 concludes the paper.

2 The model

Model setup. The model has three discrete choice margins: choice of residential location, transport mode choice and choice of cooking fuel.[5] In addition, households choose their consumption of housing floor space and residential energy. We consider a city made up of the city center (indexed $k = 1$) and suburb ($k = 2$). The available transport modes are private transport (mainly cars, $j = A$) and public transport or bus ($j = B$). In addition, there is a third mode ($j = C$), which is motorcycles in Yogyakarta and minibus in Maputo.[6] This choice is driven by the observed distribution of mode choice in the two cities. Cooking fuel can be either modern, $\ell = M$ (mainly LPG), or traditional (wood, charcoal), $\ell = T$. There are N_i households of type $i = P, R$ (poor, rich) who have wage incomes w_i which are location independent.[7]

Individuals have heterogeneous preferences over locations, modes and energy source. A type ω individual with income type $i \in \{P, R\}$ who lives in part $k \in \{1, 2\}$ of the city and commutes via mode $j \in \{A, B, C\}$ and uses fuel $\ell \in \{M, T\}$ has Stone-Geary utility

$$u^{\omega}_{ijk\ell} = \eta^{\omega}_{ijk\ell} c^{1-\alpha-\gamma}_{ijk\ell} (q_{ijk\ell} - q_0)^{\alpha} (h_{ijk\ell} - h_0)^{\gamma} E_k^{-\beta},$$

where q is housing consumption in sq. meters, c consumption of a composite good, h is residential energy use, q_0 and h_0 are minimum housing and energy consumption, and E_k is pollution at the residential location.[8] The parameter $\eta^{\omega}_{ijk\ell}$ measures household ω's

[5]Heating is not an issue in the cities we study, since the climate is warm year round.

[6]In Maputo, motorcycles are lumped together with cars as private transport.

[7]Borck (2019) considers an extension where jobs can be either in the center or the suburb with location dependent wages.

[8]A more realistic assumption might be that utility depends on pollution concentration, i.e. emissions divided by surface area (if we neglect vertical diffusion of emissions). However, since area is constant and pollution enters utility multiplicatively, this would not affect our results for a given relocation response of households.

idiosyncratic taste for living in part k of the city, using mode j and technology ℓ (see below). We assume that all households consume electricity whereas their energy use may consist of modern or traditional energy sources (see more below).

The Stone-Geary form is a simple non-homothetic utility function which has some properties that are attractive for our analysis. In particular, the expenditure shares for housing and energy consumption are decreasing in income. As we will see in Section 4, this is the case in our survey data.

Individuals living in part $k = 1, 2$ of the city commute distance d_k to work and pay rent p_k per square meter. Housing rent is assumed to accrue to absentee land owners. Commuting via mode $j = A, B, C$ incurs a fixed cost F_{ij} for a type-i household, as well as a variable cost τ_{ijk} per km of distance travelled. The variable cost is made up of a monetary cost, m_{jk}, as well as a time cost, $\vartheta_{jk} w_i$, which is proportional to the wage w_i. The parameter ϑ_{jk} measures the fraction of working time lost due to commuting.[9]

Using fuel $\ell = M, T$ incurs a variable cost $z_\ell h_\ell$ and a fixed investment cost Z_ℓ (such as a furnace).

The individual budget constraint is

$$w_i = p_k q_{ijk\ell} + F_{ij} + \tau_{ijk} d_k + Z_\ell + z_\ell h_{ijk\ell}. \tag{1}$$

Maximizing utility subject to (1) gives optimal housing consumption and residential energy use as well as indirect utility, v:

$$\begin{aligned} q_{ijk\ell} &= q_0 + \frac{\alpha(w_i - F_{ij} - \tau_{jk} d_k - Z_\ell - p_k q_0 - z_\ell h_0)}{p_k} && (2) \\ h_{ijk\ell} &= h_0 + \frac{\gamma(w_i - F_{ij} - \tau_{jk} d_k - Z_\ell - p_k q_0 - z_\ell h_0)}{z_\ell} && (3) \\ v_{ijk\ell} &= (w_i - F_{ij} - \tau_{jk} d_k - Z_\ell - p_k q_0 - z_\ell h_0) p_k^{-\alpha} z_\ell^{-\gamma} E_k^{-\beta}. && (4) \end{aligned}$$

The Stone-Geary utility gives rise to a linear expenditure system, where the expenditure shares of housing and energy are decreasing in income. In Section 4, we will fit the parameters of the utility function to the observed household choices in the data.

In the spirit of the discrete choice literature, individuals are assumed to have heterogeneous tastes for which part of the city to live in, as well as which mode and which fuel

[9] Technically, it is the inverse of travel speed (hours per km) times 2 (for two-way commuting) times the daily wage.

to use.[10] We assume that households draw their idiosyncratic taste parameter $\eta^{\omega}_{ijk\ell}$ from a Fréchet distribution

$$G(\eta^{\omega}_{ijk\ell}) = e^{-\mathcal{B}_{ijk\ell}(\eta^{\omega}_{ijk\ell})^{-\epsilon}}, \tag{5}$$

where the scale parameter $\mathcal{B}_{ijk\ell}$ gives the average utility for type i households of using mode j and fuel ℓ in part k of the city, and the shape parameter $\epsilon > 1$ controls the dispersion of idiosyncratic utility. The variance of idiosyncratic tastes decreases with ϵ. Since taste idiosyncracies become less important with lower variance, this implies that individuals become more responsive to policy changes when ϵ increases.

The choice probabilities of i-type households for mode j, city part k, and fuel ℓ are given by

$$\pi_{ijk\ell} = \frac{\mathcal{B}_{ijk\ell} v^{\epsilon}_{ijk\ell}}{\sum_{o=A}^{C}\sum_{r=1}^{2}\sum_{s=M}^{T}\mathcal{B}_{iors} v^{\epsilon}_{iors}}, \quad i = P, R,\ j, o = A, B, C,\ k, r = 1, 2,\ \ell, s = M, T. \tag{6}$$

We assume that housing supply in part k of the city has constant price elasticity θ, $H_k = \Theta p_k^{\theta_k}$. We allow the supply elasticity to vary between center and suburb. In line with reality, we allow land for formal or informal housing to be more abundant in the suburbs, so $\theta_1 < \theta_2$. The housing market clearing conditions are

$$H_k = \sum_{i=P}^{R}\sum_{j=A}^{C}\sum_{\ell=M}^{T} n_{ijk\ell} q_{ijk\ell}, \quad i = P, R, j = A, B, C, \ell = M, T, \tag{7}$$

where $n_{ijk\ell}$ is the number of residents in part k of the city who commute via mode j and use fuel type ℓ.

Total city population is exogenous and given by $N = N_P + N_R$. To close the model, the location equilibrium is defined by the following equations:

$$n_{ijk\ell} = \pi_{ijk\ell} N_i, \quad i = P, R, j = A, B, C, k = 1, 2, \ell = M, T. \tag{8}$$

Given (4), (6), and (7), the equilibrium is defined by the 24 equations in (8). This pins down the number of i-type individuals using mode j and fuel type ℓ in part k of the city.

In order to compute the welfare effects of transit policies, later on in the counterfactual

[10] For a classic application in travel demand, see McFadden (1974). For an early paper using this approach in urban economics, see Anas (1990). See Redding and Rossi-Hansberg (2017) for a recent overview of "quantitative spatial economics".

simulations, we will compute the expected welfare of a type-i resident

$$\mathbb{E}(v_i) = \Gamma\left(\frac{\epsilon-1}{\epsilon}\right)\left[\sum_{j=A}^{C}\sum_{k=1}^{2}\sum_{\ell=M}^{T}\mathcal{B}_{ijk\ell}v_{ijk\ell}^{\epsilon}\right]^{1/\epsilon}, \tag{9}$$

where $\Gamma(\cdot)$ is the gamma function.

Pollution. We model local air pollution in location k as coming from two sources: commuting and residential energy use. We assume all households use electricity for lighting and basic appliances. In terms of pollution, however, we concentrate on energy use from burning fuel for space heating, cooling, and cooking. Pollution from commuting is proportional to the total distance travelled by the city's residents. Let e_ℓ be the emissions factor on residential energy use, i.e. the emissions produced by households per unit of residential energy use (other than electricity), conditional on fuel type ℓ. Likewise, let $e_j, j = A, B, C$, be the emissions factors for commuting, that is, the emissions produced by commuting one person km on mode j.[11] Then total emissions at residential location k are

$$E_k = \sum_{i=P}^{R}\sum_{j=A}^{C}\sum_{\ell=M}^{T} n_{ijk\ell}(e_\ell h_{ijk\ell} + e_j d_k). \tag{10}$$

We use PM_{10} as the local pollutant for which we assign the emission intensities (see Section 4).

We are interested in how policies which affect the attractiveness of different transport modes or energy technologies impact pollution. In practice, this could happen through subsidizing fares or infrastructure provision, such as constructing new lines, increasing travel speed via traffic control policies, and so on. Alternatively, we could tax private transport, increase fuel prices through taxes, etc. In terms of the model, we will think of policies that change either the fixed or variable cost of the corresponding transport mode.[12] Likewise, we can subsidize or tax the costs of different energy modes, for instance, tax traditional "dirty" cooking fuels or subsidize modern and clean ones.

Inspection of (10) together with (6) and (8) shows the following margins of adjustment to policy changes. When transit is subsidized, first, since the user cost falls relative to

[11] Note that we abstract from pollution from electricity use.

[12] Note that we do not assume a balanced budget, that is, we do not consider the financing of energy related taxes or subsidies. From the view of the model, this is mostly inconsequential: if for instance, a subsidy for public transport were financed by taxes, this will generally have no or very small effects on the outcome as long as the tax is independent of individuals' choices of location, transport and energy mode.

cars and semi-public transit, some individuals will switch from driving to transit. As long as the emissions factor for public transport is lower than that for cars, this effect reduces pollution. Second, depending on whether the cost decrease is larger in the city center or the suburb, some individuals will relocate. Commuting distances may therefore rise or fall depending on the direction of this effect. And third, subsidies will increase net incomes and therefore affect the demand for residential energy use. It turns out, though, that in our data, energy use is very inelastic, so this last effect is small. The total effect depends on the balance of these three effects.

Consider now a subsidy of modern energy use, either through a subsidy of the fixed costs (e.g. of buying a modern furnace) or through subsidizing variable costs, e.g. the costs of purchasing gas. The direct effect is that since modern technology becomes more attractive, some households now switch from traditional to modern energy sources. This will decrease emissions as long as the modern technology is cleaner than the traditional one. The indirect effects mirror those described in the previous paragraph: there may be some relocation effects induced, households will consume more energy, and there will be an effect on mode choice; in particular, since net incomes rise, some households may switch from public/semi-public transport to cars, which would tend to increase emissions.

In both cases, the sign of the total effect depends on the strength of the different reaction margins as well as various emissions factors and cannot be determined analytically. Therefore, in the next section, we simulate the model numerically. This will also allow a quantitative evaluation of the pollution effect of public transport policies.

3 Background and data

We calibrate the model parameters for households in the metropolitan areas of Yogyakarta, Indonesia, and Maputo, Mozambique. Mozambique is a low-income country located in the south-eastern part of sub-Saharan Africa; it ranks 180th at the Human Development Index (HDI), with per capita GDP of $1,136, a population of about 20 million people and an urbanization ratio of 36%. Indonesia is a lower-middle income country in East-Asia; it ranks 116th at the HDI with per capita GDP of $11,189, a population of about 267 million people and an urbanization ratio of 55%. Both countries face strong economic and population growth and (thus) rapid urbanization. Since 2010 per capita GDP grew at a rate of about 25% in Mozambique, and 42% in Indonesia. Over the same period average population growth in Mozambique has been almost 3% – making the country ranking 13th on the list of countries with the highest population growth (UN 2019) – against 1.2% in Indonesia. The urbanization level in Mozambique increased by 5 percentage points since 2010, implying that about 3.5 million people have been added to Mozambique's urban population since 2010. In Indonesia, the urbanization level increased by 6 percentage points since 2010, which equals an increase in Indonesia's urban population of about 31 million people over the last decade.

Maputo is the capital and most populous city of Mozambique, whereas Yogyakarta is a provincial capital and medium-sized city in Indonesia. The metropolitan area of Maputo comprises about 2.9 million and that of Yogyakarta 3.6 million inhabitants (2017 censuses). Although Maputo was home to one of the first electric tramway systems in Africa (1904-1936), the city's transportation needs are since long mainly served by minibus taxis called "chapas", which transport the majority of the city's commuters. Increasingly they are complemented with ordinary buses in an effort to resolve the public transport crisis in the city. Three-wheeled bikes ("tchopelas"), commonly known as tuk-tuks or rickshaws in some Asian countries, were introduced over the last years, but like motorbikes they play only a marginal role in the urban transport system. In contrast, Yogyakarta has for many years had an extensive system of public city buses, as well as taxis and three-wheelers locally known as "becaks", whereas minibuses only play a marginal role. Like in much of Asia, motorbikes are by far the most commonly used mode of urban transport in Yogyakarta. The city features over 900 registered motorcycles per 1,000 people, which is the second-highest rate in Java (after the Indonesian capital city of Jakarta) and 10 times more than the number of registered passenger cars. About 95% of the households in Yogyakarta own a motorcycle and almost 30% of the households own more than 2 motorcycles. In both cities, lack of adequate public transport facilities encourages private car ownership, which leads to rapidly increasing number of residents who own an automobile and thus to more traffic jams.

The data on socio-economic characteristics, transport behavior and energy use of households that we use in this paper originate from newly collected household survey data. In addition, we collected emission (conversion) factors from several global data sources. Microdata for households have been collected through detailed field-surveys by a team of Eduardo Mondlane University October 2015 (Maputo) and a team of Satya Wacana Christian University in February 2016 (Yogyakarta), under coordination of one us (P.M.). The design of these surveys was based on the questionnaire survey and accounting methodology by Lin *et al.* (2013), which was used for household interviews in Xiamen City in south-east China. We adapted the questionnaire to the specifics of the Maputo and Yogyakarta context. The survey includes questions about i) household information: residential status, marital status, household size, age, education, household income; and ii) residential energy consumption for dwelling and transportation needs; and iii) information on housing (like house size) and transportation destination, mode of transport, trip frequency, travel time. After correction for missing data, our data for Maputo comprise information for 1048 households across 19 (sub)urban districts, including Maputo City and the adjacent districts Matola and Marracuene; data for Yogyakarta comprise information for 748 households across 42 (sub)urban districts including Yogyakarta City and the adjacent districts Sleman Regency and Bantul Regency. We identified the area around Avenida 25 de Septembro (Maputo) and the Malioboro region (Yogyakarta) as the Central Business District (CBD) of the two respective metropolitan areas.

Policies. In Section 5, we study the effect of energy and transport policies on pollution, distribution, and welfare. The counterfactual policies are modeled on the blueprint of similar policies that have been used or discussed in our two sample cities. Here, we describe those policies. Section 5 then describes the model implementation in more detail.

In Indonesia, LPG consumption for residential use has long been subsidized (Andadari *et al.*, 2014; Suharsono and Lontoh, 2022). The main objective of the subsidy is to encourage low-income households to adopt cleaner cooking fuels than kerosene or even biomass; therefore, only the small canisters (3 kg) are subsidized (by about 70%), while the larger cylinders (5 or 12 kg) are not. Similarly, Indonesia subsidizes a form of gasoline (pertalite) by about 20% to support low-income households. In addition, the Indonesian government has recently provided subsidies for the purchase of electric scooters, bicycles and cars. As a result, the adoption of electric scooters and bicycles is emerging, while the adoption of electric cars is still at a very low level (especially in the capital city of Jakarta).

Maputo's extensive network of minibuses has been complemented over the years by a gradually expanding network of formal public buses. In addition, a Bus Rapid Transit (BRT) system is likely to be implemented in the foreseeable future. Although plans for a BRT have been around for a long time, the latest news is that construction could begin in 2026. Compared to regular buses, the BRT is expected to have a 50% higher average speed, thus reducing travel time.

Below, we therefore model the following stylized counterfactuals, modeled on the blueprint of the policies we just described: (i) decrease variable costs of modern residential energy

Table 1: Variables and calibrated parameters

Parameter	Description	Yogyakarta	Maputo	Source
w_P	Income poor	5,866	4,685	survey
w_R	Income rich	21,330	23,529	survey
F_{PA}	Fixed cost car poor	75.26	95.8	survey
F_{RA}	Fixed cost car rich	273.64	440.9	survey
F_{PB}	Fixed cost pub. transp. poor	0	0	survey
F_{RB}	Fixed cost pub. transp. rich	0	0	survey
F_{PC}	Fixed cost motorcycle/minibus poor	42.5	0	survey
F_{RC}	Fixed cost motorcycle/minibus rich	154.6	0	survey
m_A	Variable monetary cost car (per km)	0.67	0.40	survey
m_B	Variable monetary cost pub. transp. (per km)	0.12	0.08	survey
m_C	Variable monetary cost motorcycle/minibus (per km)	0.58	0.11	survey
ϑ_{1A}	1/(Travel speed car center) (min/km)	0.081	0.119	survey
ϑ_{1B}	1/(Travel speed pub. transp. center) (min/km)	0.161	0.129	survey
ϑ_{1C}	1/(Travel speed motorcycle/minibus center) (min/km)	0.116	0.078	survey
ϑ_{2A}	1/(Travel speed car suburb) (min/km)	0.061	0.087	survey
ϑ_{2B}	1/(Travel speed pub. transp. suburb) (min/km)	0.082	0.084	survey
ϑ_{2C}	1/(Travel speed motorcycle/minibus suburb) (min/km)	0.079	0.093	survey
d_1	Commuting distance center (km)	3.44	4.48	survey
d_2	Commuting distance suburb (km)	5.32	10.81	survey
Z_M	Fixed cost modern tech.	3.42	12.16	survey
Z_T	Fixed cost traditional tech.	0	0	survey
z_M	Variable cost modern tech. (per kwh)	0.14	0.17	survey
z_T	Variable cost traditional tech. (per kwh)	0.10	0.08	survey
α	Housing exponent	0.0157	0.0055	calibrated
q_0	Min. housing consumption	76.67	84.8	calibrated
γ	Energy exponent	0.0016	0.0043	calibrated
h_0	Min. energy consumption	4076.87	9088.9	calibrated
ϵ	Fréchet parameter	5.5	5.5	Lit.
θ_1	Housing elasticity downtown	0.875	0.875	Lit.
θ_2	Housing elasticity suburb	1.75	1.75	Lit.
β	disutility of pollution	0.03	0.014	calibrated

Note: all monetary variables are in international dollars per year.

technology by 70%, (ii) increase variable monetary private transport costs by 33%, (iii) decrease time costs of public transport by 50%, (iv) decrease the variable and fixed monetary costs of electric motorcycles by 33% (and 67%).

4 Calibration

We now describe the numerical simulation. We first present our choice of common parameters and the parameters for our two cities, Maputo and Yogyakarta. All variables and calibrated parameters are listed together with the source in Tab. 1.

4.1 Choice of parameters

Common parameters. For want of better information, we set the baseline elasticity of housing supply to the average value for the US, 1.75, from Saiz (2010). However, we will assume that the supply elasticity is lower in the center, so we set $\theta_1 = 0.875, \theta_2 = 1.75$. We set the Fréchet parameter ϵ to 5.5 like in Borck (2019). This is in line with the values estimated (in models without mode and energy choice) by Ahlfeldt *et al.* (2015) for Berlin, Heblich *et al.* (2020) for London, Balboni *et al.* (2020) for Dar es Salaam, and Monte *et al.* (2018) for US commuting zones.[13] We will also later present variations of those parameters, which may take on different values in developing than in developed countries.

Yogyakarta. We use the following values for the calibration (see Tab. 1). We define households with income below the median household income in the survey as poor and those with higher income as rich. Income is set at the annual average *household* income by type in the survey, \$5,866 for the poor and \$21,330 for the rich. We compute commuting distances of 3.44 km for households in the center and 5.32 in the suburb. Travel speed in the center is 12.28 km/h for car users, 6.22 km/h for bus users, and 8.63 km/h for motorcycle users. Travel speed in the suburb is 16.52 km/h for cars, 12.21 km/h for bus users, and 12.73 motorcycle users.[14]

The monetary variable costs are 0.67 \$/km for cars, 0.12 \$/km for bus users and 0.58 \$/km for motorcycles. We set the fixed cost for public transit to zero. For cars, we set the fixed cost to \$273.64 per year for the rich and \$75.26 for the poor; for motorcycles the corresponding numbers are \$154.6 and \$42.5.

Finally, the variable costs are set to \$0.10 per kwh for traditional fuels and \$0.14 per kwh for modern fuels. We set the fixed cost for traditional technology to zero and the fixed cost of modern technology to \$3.42.

We calibrate the parameters of the utility function, α, q_0, γ and h_0 as follows. We first impute the housing consumption and residential energy use for the household types where we have one or zero observations in the survey.[15] We then compute the housing

[13] Bryan and Morten (2019) estimate a lower value of around 3 for migration in Indonesia.

[14] There are no minibus users in the survey. To compute time costs, we assume that individuals work 10 hours per day for 200 days per year; we then compute the time costs as the inverse of speed times the fraction of the yearly wage lost commuting, times one half (following Small (2012)).

[15] If we have no observation, obviously we have to impute economic quantities. If we have one observation, we also impute consumption since the observed variables may be too noisy. We do this by regressing housing consumption and energy use on dummy variables for residential location (center/suburb), mode choice (automobile/bus/minibus), energy use (modern/traditional) and income (poor/rich) and then using

consumption and energy use of all household types based on the model, using the share of types by city part, mode etc. from the data. Finally, we choose α, q_0, γ and h_0 to minimize the mean absolute deviation between model and data. This results in $\alpha = 0.023, q_0 = 73.99, \gamma = 0.001$, and $h_0 = 4138.11$. Following the same procedure we get $A_1 = 5.15 \times 10^6$ and $A_2 = 5.83 \times 10^6$.

We calibrate the pollution disutility parameter β to target the share of health costs of $PM_{2.5}$ in income. The data in World Bank (2020) give a cost share of 3% for Indonesia. We adjust this figure to account for (i) the lower health costs of PM_{10} relative to $PM_{2.5}$, and (ii) the higher health costs in urban areas relative to the national averages. We then solve for the value of β to target this cost in our baseline equilibrium, which gives $\beta = 0.03$ (see Appendix A for details). In any case, variations of β have only very minor effects on the results.

We collect emissions factors for the different transport modes and energy sources from various sources described in the Appendix. The values we use are shown in Tab. A.1.

Maputo. Income is set at the annual average value in the survey, \$4,685 for the poor (below median income) and \$23,529 for the rich (above median income). We compute commuting distance of 4.48 km for households in the center and 10.81 in the suburb. Travel speed in the center is 8.11 km/h for private mode (car + motorcycle) users, 7.77 km/h for bus users and 12.84 for minibus users. Travel speed in the suburb is 11.51 km/h for private mode users, 11.95 km/h for bus users and 10.79 for minibus users.

The monetary variable costs are 0.40 \$/km for private mode users, 0.08 km/h for bus users and 0.11\$/km for minibus users. We set the fixed cost for public transit and minibuses to zero, and the fixed cost for cars to \$440.9 per year for the rich and \$95.8 for the poor.

The variable costs for energy use are set to \$0.08 per kwh for traditional fuels and \$0.17 per kwh for modern fuels. We set the fixed cost for traditional technology to zero and the fixed cost of modern technology to \$12.16.

Proceeding as above to calibrate the remaining parameters, we get $\alpha = 0.01, q_0 = 49.99, \gamma = 0.0051, h_0 = 8896.4, A_1 = 8.06 \times 10^6$ and $A_2 = 3.94 \times 10^6$.

The World Bank (2020) value for the share of pollution costs in income for Mozambique is 1.4%. Following the same adjustments as for Yogyakarta and solving for β gives $\beta = 0.014$ (see Appendix A).

The emission factors for Maputo are shown in Table A.1.

the estimated coefficients to predict missing values.

4.2 Calibration

We assume that the survey response gives us the equilibrium population distribution. That is, we have the number of people living in center and suburb, using car, bus, and minibus and modern or traditional fuels, for both cities. We can then solve the twelve equations in (8), together with (4), (6), and (7), for the twelve unknown parameters $\mathcal{B}_{ijk\ell}$ which give the average attractiveness of living in part k of the city, using mode j and fuel ℓ.

Yogyakarta. For Yogyakarta, the baseline distribution of the population among the 24 choice categories is shown in Table A.2.

We substitute these equilibrium population values into our equilibrium system (8). We set $\mathcal{B}_{1AM} = 1$, and then solve the system for the values of the remaining amenity values $\mathcal{B}_{ijk\ell}$. These values reflect the preference for cars and for modern technology. One way to interpret these is that given our assumed cost parameters, there is a difference in quality which leads households to prefer cars and modern technology.

We then use equations (10) to compute total emissions by transport mode and fuel technology, separately by pollutant. In addition to the residential shares, emissions are determined by the emissions factors for each pollutant. The share of transport in total emissions is 8.8%.

Fig. 1 shows the model output v. data. For energy use, on average across all cells, the deviation between model and data (in absolute value) is 19.6%. The expenditure share for the poor is 9.4% on average and for the rich 2.7%. For housing, the average deviation between model and data is 28.7%. The expenditure share for the poor is 6.6% on average and for the rich 3.38%.

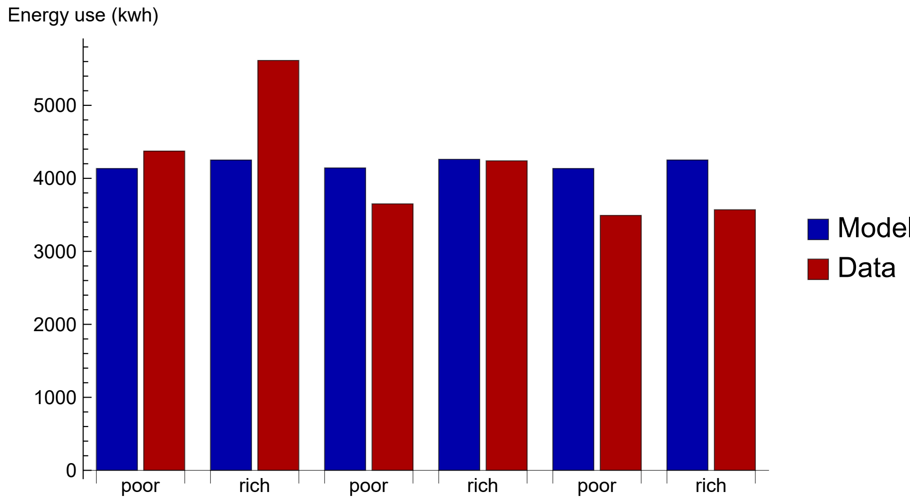
One observation to note is that energy demand is very inelastic, with respect to both income and prices. This implies that the counterfactual policies we study below do not have large equilibrium effects on demand. Rather, the bulk of any equilibrium effects will come from the composition of demand by location and modes.

Maputo. For Maputo, the baseline distribution of the population among the 24 choice categories is shown in Table A.2. The same procedure as before gives us the equilibrium values for the amenity factors.

Total emissions are computed from the equilibrium as before. The share of transport in total emissions is 0.3%.

Fig. 2 shows the model output v. data for energy use. On average across all cells, the

Figure 1: Energy use Yogyakarta: Model v. data



Note: Modes from left to right: car, bus, motorcycle

deviation between model and data (in absolute value) is 21.4%. The expenditure share for the poor is 24% on average and for the rich 5.2%.

5 Counterfactual simulation

Once we have the $\mathcal{B}_{ijk\ell}$ from our calibration, we can perform counterfactual simulations. We can then gauge how transport and energy policies affect urban pollution.

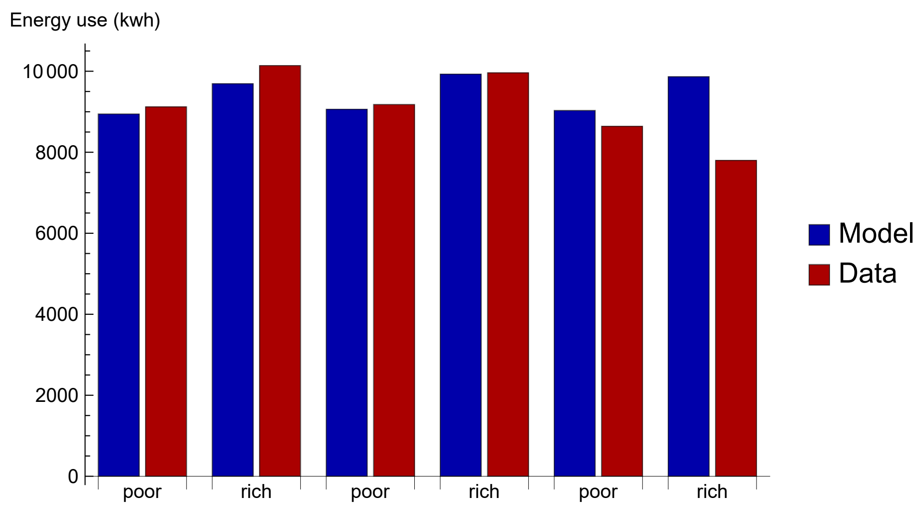
Our choice of counterfactuals is guided by the following principles. First, the policies should be easily implementable with our model and the data we use. Second, they should be reasonably close to policies that have actually been implemented or discussed in the context that we study (see Section 3 above).

In order to keep the analysis symmetric, we consider the same policies in our two cities. The only exception is the subsidy for electric scooters, which we do not consider in Maputo given its low share of motorcycles.

On the energy policy side, we run a counterfactual modeled on the existing subsidies to clean energy in Yogyakarta. As described above, we assume a subsidy to variable costs of 70%.

On the transport side, we consider the following policies. First, we introduce a tax on private transport. As described above, in Yogyakarta as in many other developing country cities, fuel is relatively heavily subsidized. Here, we run a counterfactual that reduces this subsidy. Based on an existing subsidy of 21%, we therefore increase the variable monetary

Figure 2: Energy use Maputo: Model v. data



Note: Modes from left to right: car, bus, motorcycle

costs of private transport by 33%. Second, to mimic the introduction of a BRT system, we reduce the time costs of formal public transport by 50%.

The last policy is a subsidy to electric scooters. We implement the existing subsidy in Indonesia of 33% on fixed an variable monetary costs of electric scooters, as well as a doubling of that to 67%.

In Appendix B, we describe another set of counterfactual policy simulations. There, the aim is to use different subsidies or taxes in order to meet the air quality guidelines provided by the WHO.

5.1 Yogyakarta

Our first counterfactual implements a subsidy on modern energy. As outlined above, this subsidy on LPG reduces the variable costs of the clean energy mode substantially, by 70%. Panel A of Tab. 2 shows the results from this counterfactual. As the panel shows, the policy leads to a strong reduction in the number of traditional energy users by 35% and an increase in modern energy users of 3.2%. This reduces emissions from residential energy use by 32%. Traffic emissions rise by 1%. The reason is that the reduction in energy costs increases utility most for private transport users. The total fall in emissions is again driven mostly by residential emissions, so aggregate emissions fall by 29%.

We next look at the effect of changing the costs of private transport. As described above, Yogyakarta has a history of subsidizing gasoline. In the counterfactual, we study

Table 2: Counterfactual results Yogyakarta

Residents		Transport mode			Energy mode		Emissions	Welfare	
A: decrease modern tech. cost by 70%									
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
-2.52	0.73	0.25	-6.86	0.79	3.16	-34.86	-29.06	7.92	3.05
B: increase private transport cost by 33%									
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
8.32	-2.41	-4.76	43.37	-4.48	-0.41	4.51	3.26	-5.96	-1.73
C: decrease time costs of public transport by 50%									
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
0.17	-0.05	-1.45	14.78	-1.56	-0.04	0.48	0.29	0.19	0.22

Note: For each outcome, the number shows the percentage change in the counterfactual relative to the baseline. Welfare is the ratio of compensating variation (CV) over income.

the effect of reducing this subsidy, which would increase the variable monetary costs of private transport (cars and motorcycles) by roughly 33%. Results are shown in Panel B of Tab. 2. As can be seen, the number of bus users increases by 43%, while private transport (car and motorcycle) use decreases by about 4.5%. Since public transport in Yogyakarta is much cleaner than private transport, this shift reduces commuting emissions. Since transport costs increase more with longer commute distance, households move from the suburb to the center, which also reduces traffic emissions. The combined reduction in emissions from commuting is 5.3%. However, the Panel shows that total emissions rise. This somewhat surprising result stems from the fact that traditional energy use increases by 4.5%. While transport mode and energy costs do not interact directly, the utility cost of increasing transport cost is proportional to $z_\ell^{-\gamma}$ and is therefore smaller for the cheaper traditional technology.[16] Since traditional energy is dirtier than modern energy, this increases emissions from residential energy use by 4%. Since residential emissions are much larger than traffic emissions at the baseline, this increases total emissions.

In our final counterfactual, we reduce the time costs of public transport. This counterfactual is modeled on the blueprint of the proposed BRT system in Maputo. As described, we estimate this kind of system to increase speed by 50%, hence reducing time costs by

[16]It is also proportional to Z_k, so the same argument holds with respect to the fixed costs of energy use.

the same 50%. The table shows that as expected, bus use strongly increases. The result is a fall in traffic emissions of 1.5%. However, similar to the first counterfactual, there is an offsetting increase in residential emissions of 0.5%. Again, since residential emissions outweigh traffic emissions at baseline, total emissions increase by 0.3%.

Table 3: Counterfactual results Yogyakarta: electric motorcyles

Residents		Transport mode				Energy mode		Emissions	Welfare	
A: subsidize electric motorcyles by 33%										
center	suburb	car	bus	comb. motorcycle	el. motorcycle	modern	trad.	PM	Poor	Rich
-0.03	0.01	-0.17	-0.28	-0.31	7.08	0.00	-0.03	-0.05	0.05	0.02
B: subsidize electric motorcyles by 100%										
center	suburb	car	bus	comb. motorcycle	el. motorcycle	modern	trad.	PM	Poor	Rich
-0.12	0.03	-0.53	-0.92	-0.99	22.83	0.01	-0.11	-0.17	0.16	0.07

Note: For each outcome, the number shows the percentage change in the counterfactual relative to the baseline. Welfare is the ratio of compensating variation (CV) over income.

Introducing electric motorcycles. In our final counterfactual for Yogyakarta, we introduce electric motorcycles. In order to do so, we change our baseline calibration and include a fourth mode, electric motorcycles, alongside cars, buses, and combustion motorcycles. Electric motorcycles have higher purchase prices but lower operating costs than combustion ones. Based on the available evidence, we set the fixed cost of electric motorcycles at 150% of that of combustion motorcycles and the variable cost at 15% of that of combustion motorcycles. We calibrate our new baseline to our data, assuming that 5% of all motorcycles in the baseline are electric.[17]

It is important to note that there is a low percentage of electric motorcycles even though *on purely financial terms*, electric motorcycles seem very competitive. In fact, if we were to assume that electric and combustion motorcycles were perfect substitutes, all households in our model, rich and poor, would drive electric ones based on the lower total costs, as the increased fixed cost is more than outweighed by the lower variable costs. The model therefore rationalizes the low baseline share of electric motorcycles through the idiosyncratic preference component captured by the Fréchet parameter $\mathcal{B}$, which determines the average utility for each combination of transport mode, cooking fuel, and residential

[17] This is probably an overestimate of the status quo, see IESR (2020). Intuitively, if we instead assume a baseline electric share of, say, 1%, the effect of the subsidy is even smaller than the effect we present here.

location. While the model is silent on what exactly drives this attractiveness, the most natural explanation would be poor access to electricity for home charging, coupled with relatively short driving ranges and a lack of public charging stations.

Panel A of Tab. 3 shows the result of subsidizing the variable and fixed costs of electric motorcycles at 33%. As the table shows, there is an increase in the use of electric motorcycles of 7% on average. The other three modes lose between 0.2% and 0.3% of their mode shares. On average, then, there is a substitution towards cleaner electric motorcycles. The net result is a decrease of pollution of 0.05%. Panel B shows that even if we raise the subsidy to 100%, the pollution decrease is less than 0.2%. Thus, according to our model, even giving away electric scooters and the electricity needed to charge them would have very little impact on air quality. The reason is that the heterogeneity of tastes implied by the baseline distribution across modes would render this policy rather ineffective. This suggests that subsidizing electric motorcycles on its own would not be able to do the trick of reducing the air pollution emanating from motorcycle use. Other interventions, such as changes in charging infrastructure, would be necessary to have a large effect on pollution, as long as the share of electric motorcycles is still low (see also IESR (2020)).

Mechanisms. In Tab. 4 and 5, we compare the baseline counterfactual results with those where one of the choice margins is taken away. That is, we recompute the baseline and counterfactual assuming that, one by one, one of the choice margins (location, transport mode, energy technology) is not available.[18]

The tables show effects which differ quite a bit by the policy. For the subsidy of modern energy, Tab. 5 shows that residential energy mode choice is responsible for the bulk of the emissions change. The reason is that energy costs don't vary across either locations or transport modes, so these choice margins do, by themselves, not change the outcome very much.

Things look different for the tax on private transport. Tab. 4 shows the baseline outcome in Panel A, and in Panels B–D the counterfactual outcomes shutting down, one at a time, location choice, transport mode choice, and energy mode choice.

Panel B shows that compared to the baseline results, without location choice the mode share of public transport increases slightly more. Moreover, the share of traditional energy users also increases a bit less than in the baseline. Together this implies that emissions do

[18]When computing the amended counterfactuals, we set all parameters equal to a population weighted average of the respective parameter values. Without location choice, we further assume that city housing supply equals the sum of the two city parts' supply functions.

not increase as much as in the baseline, but the effect is modest.

Surprisingly, Panel C shows that eliminating mode choice does not have a large effect on the change in pollution. On the one hand, the benign effect of switching towards the cleaner transport mode is shut down. On the other hand, the indirect effects on location and energy mode choice change slightly: more households relocate from the suburbs to the center, while fewer switch from modern to traditional energy, compared to the baseline. Since, again, residential energy is responsible for the bulk of emissions, total pollution increases a bit less than in the baseline.

Finally, Panel D shows that without residential energy mode choice, emissions fall by 3% instead of rising by 3%. This experiment in fact shuts down the switching from clean to dirty energy mode which is responsible for the increase of emissions in the baseline counterfactual. Hence, without energy mode choice, emissions decrease, since the strong switch from private to public transport decreases commuting emissions.

Table 4: Counterfactual results Yogyakarta: transport costs (channels)

Residents		Transport mode			Energy mode		Emissions	Welfare	
A: increase private transport cost by 33% (baseline)									
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
8.32	-2.41	-4.76	43.37	-4.48	-0.41	4.51	3.26	-5.96	-1.73
B: increase private transport cost by 33% (w/o location choice)									
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
–	–	-4.77	46.05	-4.81	-0.36	3.96	2.86	-5.82	-1.70
C: increase private transport cost by 33% (w/o mode choice)									
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
8.75	-2.53	–	–	–	-0.28	3.11	2.48	-6.14	-1.71
D: increase private transport cost by 33% (w/o energy mode choice)									
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
8.26	-2.39	-4.78	43.42	-4.48	–	–	-3.19	-5.85	-1.57

Note: For each outcome, the number shows the percentage change in the counterfactual relative to the baseline. Welfare is the ratio of compensating variation (CV) over income.

Tab. 5 shows the working of the mechanisms in the counterfactual where we subsidize

Table 5: Counterfactual results Yogyakarta: energy costs (channels)

A: decrease modern tech. cost by 70% (baseline)										
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
-2.50	0.72	0.24	-6.82	0.79	3.15	-34.67	-28.91	7.86	3.03
B: decrease modern tech. cost by 70% (w/o location choice)									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
–	–	0.17	-7.26	0.85	3.27	-36.08	-30.11	7.82	3.06
C: decrease modern tech. cost by 70% (w/o mode choice)									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
-2.47	0.72	–	–	–	3.14	-34.64	-29.05	7.87	3.04
D: decrease modern tech. cost by 70% (w/o energy mode choice)									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
-2.09	0.60	0.61	-6.13	0.64	–	–	2.56	7.57	2.12

Note: For each outcome, the number shows the percentage change in the counterfactual relative to the baseline. Welfare is the ratio of compensating variation (CV) over income.

modern energy. Here, shutting down location or transport mode choice does not have strong effects, as shown by Panels B and C. The lion's share of the fall in pollution is therefore explained by switching to modern residential energy. This can be seen in Panel D: if the choice of residential energy source is shut down, pollution *increases* instead of decreasing.

Redistribution and welfare. We now want to look at the welfare and redistributive effects of the different policies. Doing so reveals some interesting effects. We first compute, for each counterfactual, the compensating variation (CV) for households of both types. This is defined in the usual way as the amount of income a household would be willing to give up (or that they would need to receive) such that they are just indifferent between no policy and the policy after paying the CV.

Tab. 2 shows the CV as a share of income for each policy and both poor and rich. Note that all the policies are not neutral, in the sense that the CV share varies with income.

Consider our first counterfactual (subsidizing clean energy) first. Note that energy costs constitute a larger share of income for the poor.[19] Hence, subsidizing clean energy benefits the poor more than the rich. The CV values in Tab. 2 (8% for the poor, 3.2% for the rich) corroborate this.

The second counterfactual (taxing private transport), on the other hand, appears to be regressive, since the CV is -6% for the poor and -1.7% for the rich. This seems intuitive, since (monetary) transport costs are a larger share for poor than for rich households.

Last, making public transport faster benefits the poor slightly more than the rich. Since time costs are proportional to income, this small divergence seems to come from the fact that the poor rely more heavily on public transport.

Note that until now, we have not considered the financing of subsidies nor possible rebates of tax revenue. One simple way to put the numbers in perspective is to compare our welfare measures to the taxes that would be necessary to finance subsidies to modern energy, or the size of a lump-sum rebate of the revenue collected from taxing private transport.

Consider first the subsidy of modern energy. If this were to be financed by lump-sum taxes on all households, each poor household would have to pay about 15% and each rich household 4.1% of their income. Comparing this to the CV values in Panel B of Tab. 2, we see that tax financing (with lump-sum taxes) would turn these subsidies into a welfare loss for the poor and a small welfare gain for the rich.[20]

Next, let us look at the tax on private transport. Suppose we rebate the revenue from taxing private transport lump-sum to all households. This yields a lump-sum payment of less than 0.1% of income for both households, way below the compensating variation values shown in Panel A of Tab. 2. Hence, the tax decreases total welfare. Regardless of whether or not it is rebated to consumers, the welfare effect is more negative for poor households (assuming lump-sum rebating).

5.2 Maputo

We now describe the results of the counterfactual simulations for Maputo. We use the same counterfactuals as before. Results are in Tab. 6.

As before, the first counterfactual is a subsidy to modern technology, which mirrors the

[19] This follows necessarily from Stone-Geary utility, which gives rise to expenditure shares that decrease with income.

[20] This result could be overturned if the damage of pollution in the utility function were much larger. If we compute the necessary pollution damage, we find, however, that it would be about 30%, much larger than the 5% from the data we use for calibration.

Table 6: Counterfactual results Maputo

A: decrease modern tech. cost by 70%									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-2.67	1.05	-4.09	6.46	-1.06	23.24	-24.22	-23.29	6.66	1.55
B: increase private transport cost by 33%									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-0.91	0.36	-18.83	6.22	6.25	3.33	-3.47	-3.41	-0.68	-0.69
C: decrease time costs of public transport by 50%									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-3.21	1.26	-6.53	26.55	-9.40	1.11	-1.16	-1.11	1.13	0.91

Note: For each outcome, the number shows the percentage change in the counterfactual relative to the baseline. Welfare is the ratio of compensating variation (CV) over income.

33% subsidy on LPG in Yogyakarta. Panel A of Tab. 6 shows the results of implementing this policy in Maputo. As can be seen, modern technology use increases strongly by 24%, and traditional technology falls by a comparable amount. This leads to a strong reduction in emissions, since traditional technology is particularly polluting in terms of PM_{10}. We find that this increases bus use and leads to some relocation to the center. However, in the case of Maputo, these effects net each other out, so the total decrease in pollution is of similar magnitude as the fall in traditional technology use.

Panel B shows the counterfactual where we decrease subsidies to private transport, in effect taxing it by 33%. As the table shows, bus use increases by 26.5%, while car use decreases by 6.5% and minibus by 9.4%. Traditional technology use also decreases slightly, all of which reduces PM emissions. There is a small rebound effect, however, since residents relocate from the center to the suburbs. This increases total commuting distances by 0.5%, which slightly reduces the fall in emissions. The net effect is a reduction in PM emissions of 1.1%. Note that the results from this and the next counterfactual are not strictly comparable to the results in Yogyakarta, since the transport modes differ. In Yogyakarta, private transport consists of cars and motorcycles, whereas in Maputo, it consists of cars only. On the other hand, Maputo has traditional public transport plus minibuses, which Yogyakarta does not.

Lastly, we increase private transport costs by 33%. Whereas in Yogyakarta, we increased the variable monetary costs of cars and motorcycles, for Maputo, we increase the costs of cars and minibuses (the latter being a form of informal and little regulated public transport). Results are in Panel C of Tab. 6. As can be seen, this policy reduces car use by 17.8% and increases bus use by 15.7%, while minibus use also slightly increases by 1.3%. This can be explained by the fact that minibus fares are very low and a 33% tax is therefore also low in absolute value. Since modern energy use increases and households relocate to the center, there is a stronger emissions reduction of 5%.[21]

Redistribution and welfare. Here, we show the redistributive effects of the policies. As before, for each policy, we solve for both household types' compensating variation. The results are in the last two columns of Tab. 6.

First, subsidizing modern energy benefits both household types, and the poor's welfare gain of 6.9% is much larger than that of the rich (1.9%). Again, this is caused by the larger share of energy costs in the poors' income. In our Maputo sample, the share of modern energy users for rich and poor households is relatively similar by income. Therefore, a modern energy subsidy has a progressive impact here.

Increasing private transport costs decreases welfare for both groups. Interestingly, the welfare loss is the same (0.65%) in percentage terms for both groups. On the one hand, monetary transport costs are a larger share of the poor's income. While the share of rich households who drive their own car is much larger than for the poor (41.5% compared to 8.2%), the poor have a large share of minibus use (63% compared to 39%), so taxing cars and minibuses hits both rich and poor households.

Finally, the table shows that the increase in public transport speed produces a welfare gain of around 1% for both poor and rich households (which is only slightly larger for the poor). This is perhaps not surprising since time costs are proportional to income. The share of public transport users in our sample is a bit larger for poor than rich households (29% compared to 19%), which again accounts for the somewhat larger welfare gain for the poor.

In the same vein as before, we now briefly analyze the amount of taxes households would have to pay to finance subsidies, or the amount of lump-sum rebate out of the revenue from taxing private transport.

[21] We also compute the same analysis of mechanisms as for Yogyakarta. For reasons of space and compactness, results are shown in Appendix Tables A.4 and A.5.

Financing subsidies to modern energy (our third counterfactual) would require a lump-sum tax that amounts to roughly 24% of income for the poor and 4.7% for the rich. Comparing this to the CV values in Panel A of Tab. 6 shows that this turns the welfare gain into a loss for both groups of households.

The second counterfactual (taxing private transport) yields a lump-sum rebate which is, as in the case of Yogyakarta, less than 0.1% of income for both groups, way below the (negative) CV values in Tab. 6 Panel B. This means that taxing private transport leads to a welfare loss, even if the revenue is rebated to households.

5.3 Sensitivity

In this subsection, we briefly report the results of two sensitivity analyses, where we vary those parameters about which we have less information: the Fréchet parameter ϵ and housing elasticity θ. We report only the variation for the counterfactual for Yogyakarta where private transport costs are increased by 33%. The results for the same counterfactual with the same parameter variation for Maputo are in Appendix C.

Table 7: Counterfactual results Yogyakarta: sensitivity

A: increase private transport cost by 33% (baseline)									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
8.32	-2.41	-4.76	43.37	-4.48	-0.41	4.51	3.26	-5.96	-1.73
B: increase private transport cost by 33% ($\epsilon = 8.25$)									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
10.67	-3.09	-7.04	72.38	-7.63	-0.61	6.77	4.89	-5.91	-1.77
C: increase private transport cost by 33% ($\theta_1 = 0.4375, \theta_2 = 0.875$)									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	motorcycle	modern	trad.	PM	Poor	Rich
7.95	-2.30	-5.59	58.34	-6.17	-0.58	6.34	4.66	-5.84	-1.75

Note: For each outcome, the number shows the percentage change in the counterfactual relative to the baseline. Welfare is the ratio of compensating variation (CV) over income.

Results are reported in Tab. 7. In the first experiment, we increase the shape Parameter of the Fréchet distribution, ϵ, by 50% to 8.25. This implies a lower variance of the distribution of idiosyncratic preferences, which in turn implies that households are more responsive to policy changes. For comparison, Panel A shows our baseline results. Panel B shows that, as expected, there is now more switching between transport and energy modes as well as between locations. As a result, the emissions changes are more pronounced as well.

Panel C reports the results from a 50% decrease of the housing elasticity both in the center and suburb to 0.4375 and 0.875. As can be seen, the results are not hugely different from the baseline counterfactual. Relocation to the center is dampened by the stronger capitalization of policies into housing prices. This results in a smaller reduction of average commuting distance, so one would expect a smaller reduction of emissions. However, this is more than offset by a larger increase in traditional energy use, such that emissions rise even more than in the baseline.

6 Conclusion

We have studied the effect of energy policies on emissions in developing country cities. We use a quantitative equilibrium model calibrated to Yogyakarta, Indonesia and Maputo, Mozambique. Our model has several margins of adjustment, in particular housing and energy consumption, residential location, and mode choice in transport and energy technologies. Thus, it can be used to study various equilibrium policy impacts, including rebound effects that come from consumers increasing residential energy use or switching to high emission modes or locations.

We find, in general, that these rebound effects tend to be largest for subsidies to public transport or modern residential energy technology. For example, we find that subsidizing modern residential energy may induce some households to relocate to the suburbs and commute longer distances. Taxing private transport, on the other hand, may cause some households to switch from modern to traditional residential energy. The combination of choices of transport and energy modes and location choice thus seems to be important to gauge the equilibrium effects of energy policies on pollution.

In addition, based on the case of Yogyakarta our results suggest that urban emission reduction through electric motorcycle adoption is unlikely to be achieved by only changing the relative price of electric versus combustion motorcycles. We find that subsidizing electric motorcycles – even in effect giving away the motorcycles and electricity – only leads to a small absolute increase in the number of electric motorcycles, because the baseline share of electric motorcycles is very small. Hence, to speed up the adoption electric motorcycles, other interventions such as changes in charging infrastructure, seem to be needed.

While our model is reasonably rich by including various choice margins, our data does not allow a detailed spatial modeling of residential and work location (as in Ahlfeldt *et al.*, 2015; Monte *et al.*, 2018) More detailed data would allow for endogenous commuting choices that may provide additional insights into the effects of energy policies. Likewise, while we have tried to incorporate into our model features that are important in the context of developing country cities, we have ignored other aspects such as housing informality (Henderson *et al.*, 2020). Combining these aspects in a single model will surely lead to improved modeling of location choices and pollution in the future.

References

Ahlfeldt, G. M., Redding, S. J., Sturm, D. M., and Wolf, N. (2015). The economics of density: Evidence from the Berlin wall. *Econometrica*, **83**(6), 2127–2189.

Aldeco, L., Barrage, L., and Turner, M. A. (2019). Equilibrium particulate exposure. Working paper, IGC.

Allen, T. and Arkolakis, C. (2022). The welfare effects of transportation infrastructure improvements. *Review of Economic Studies*, **89**(6), 2911–2957.

Anas, A. (1990). Taste heterogeneity and urban spatial structure: The logit model and monocentric theory reconciled. *Journal of Urban Economics*, **28**(3), 318 – 335.

Andadari, R. K., Mulder, P., and Rietveld, P. (2014). Energy poverty reduction by fuel switching. impact evaluation of the lpg conversion program in indonesia. *Energy Policy*, **66**, 436–449.

Balboni, C., Bryan, G., Morten, M., and Siddiqi, B. (2020). Transportation, gentrification, and urban mobility: The inequality effects of place-based policies.

Bauernschuster, S., Hener, T., and Rainer, H. (2017). When labor disputes bring cities to a standstill: The impact of public transit strikes on traffic, accidents, air pollution, and health. *American Economic Journal: Economic Policy*, **9**(1), 1–37.

Bel, G. and Holst, M. (2018). Evaluation of the impact of bus rapid transit on air pollution in Mexico City. *Transport Policy*, **63**, 209–220.

Berkouwer, S. B. and Dean, J. T. (2022). Credit, attention, and externalities in the adoption of energy efficient technologies by low-income households. *American Economic Review*, **112**(10), 3291–3330.

Bird, J. and Venables, A. (2019). Growing a developing city: A computable spatial general equilibrium model applied to Dhaka. Policy Research Working Paper Series 8762, The World Bank.

Bird, J. and Venables, A. J. (2020). Land tenure and land-use in a developing city: A quantitative spatial model applied to Kampala, Uganda. *Journal of Urban Economics*, **119**, 103268.

Borck, R. (2019). Public transport and urban pollution. *Regional Science and Urban Economics*, **77**, 356 – 366.

Borck, R. and Brueckner, J. K. (2018). Optimal energy taxation in cities. *Journal of the Association of Environmental and Resource Economists*, **5**(2), 481–516.

Borck, R. and Pflüger, M. (2019). Green cities? Urbanization, trade, and the environment. *Journal of Regional Science*, **59**(4), 743–766.

Bryan, G. and Morten, M. (2019). The aggregate productivity effects of internal migration: Evidence from Indonesia. *Journal of Political Economy*, **127**(5), 2229–2268.

CE Delft (2023). Handboek milieuprijzen 2023 (Handbook on Environmental Pricing 2023). Delft.

Chafe, Z. A., Brauer, M., Klimont, Z., Dingenen, R. V., Mehta, S., Rao, S., Riahi, K., Dentener, F., and Smith, K. R. (2014). Household cooking with solid fuels contributes to ambient pm2.5 air pollution and the burden of disease. *Environmental Health Perspectives*, **122**, 1314–1320.

Colas, M. and Morehouse, J. M. (2022). The environmental cost of land-use restrictions. *Quantitative Economics*, **13**(1), 179–223.

Das, I., Jeuland, M., and Plutshack, V. (2022). The role of taxes and subsidies in the clean cooking transition: A review of relevant theoretical and empirical insights. Policy brief, Nicholas Institute for Environmental Policy Solutions.

Davis, L. (2008). The effect of driving restrictions on air quality in Mexico City. *Journal of Political Economy*, **116**(1), 38–81.

Gallego, F., Montero, J.-P., and Salas, C. (2013). The effect of transport policies on car use: Evidence from Latin American cities. *Journal of Public Economics*, **107**, 47 – 62.

Gendron-Carrier, N., Gonzalez-Navarro, M., Polloni, S., and Turner, M. A. (2022). Subways and urban air pollution. *American Economic Journal: Applied Economics*, **14**(1), 164–96.

Goel, D. and Gupta, S. (2015). The effect of metro expansions on air pollution in Delhi. *World Bank Economic Review*, **31**(1), 271–294.

Goldemberg, J., Martinez-Gomez, J., Sagar, A., and Smith, K. R. (2018). Household air pollution, health, and climate change: cleaning the air. *Environmental Research Letters*, **13**(3).

Heblich, S., Redding, S. J., and Sturm, D. M. (2020). The making of the modern metropolis: Evidence from London. *Quarterly Journal of Economics*, **135**(4), 2059–2133.

Henderson, J. V., Regan, T., and Venables, A. J. (2020). Building the City: From Slums to a Modern Metropolis. *The Review of Economic Studies*, **88**(3), 1157–1192.

IESR (2020). The role of electric vehicles in decarbonizing indonesia's road transport sector. Technical report, Institute for Essential Services Reform (IESR), Jakarta, Indonesia.

Imelda (2020). Cooking that kills: Cleaner energy access, indoor air pollution, and health. *Journal of Development Economics*, **147**, 102548.

Jeuland, M., Tan Soo, J.-S., and Shindell, D. (2018). The need for policies to reduce the costs of cleaner cooking in low income settings: Implications from systematic analysis of costs and benefits. *Energy Policy*, **121**, 275–285.

Larson, W., Liu, F., and Yezer, A. (2012). Energy footprint of the city: Effects of urban land use and transportation policies. *Journal of Urban Economics*, **72**(2-3), 147–159.

Li, S., Liu, Y., Purevjav, A.-O., and Yang, L. (2019). Does subway expansion improve air quality? *Journal of Environmental Economics and Management*, **96**, 213–235.

Lin, T., Yu, Y., Bai, X., Feng, L., and Wang, J. (2013). Greenhouse gas emissions accounting of urban residential consumption: A household survey based approach. *PLoS ONE*, **8**, 55642.

Martínez, J., Martí-Herrero, J., Villacís, S., Riofrio, A., and Vaca, D. (2017). Analysis of energy, co2 emissions and economy of the technological migration for clean cooking in ecuador. *Energy Policy*, **107**, 182–187.

McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics*, **3**(4), 303 – 328.

Monte, F., Redding, S. J., and Rossi-Hansberg, E. (2018). Commuting, migration, and local employment elasticities. *American Economic Review*, **108**(12), 3855–90.

Parry, I. W. H. and Small, K. A. (2009). Should urban transit subsidies be reduced? *American Economic Review*, **99**(3), 700–724.

Proost, S. and Van Dender, K. (2001). The welfare impacts of alternative policies to address atmospheric pollution in urban road transport. *Regional Science and Urban Economics*, **31**(4), 383 – 411.

Redding, S. J. and Rossi-Hansberg, E. A. (2017). Quantitative spatial economics. *Annual Review of Economics*, **9**, 21–58.

Saiz, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics*, **125**(3), 1253–1296.

Severen, C. (2023). Commuting, Labor, and Housing Market Effects of Mass Transportation: Welfare and Identification. *Review of Economics and Statistics*, **105**(5), 1073–1091.

Small, K. A. (1980). Energy scarcity and urban development patterns. *International Regional Science Review*, **5**(2), 97–117.

Small, K. A. (2012). Valuation of travel time. *Economics of Transportation*, **1**(1-2), 2–14.

Suharsono, A. and Lontoh, L. (2022). *Indonesia's Energy Policy Briefing*. Winnipeg, Canada.

Tscharaktschiew, S. and Hirte, G. (2012). Should subsidies to urban passenger transport be increased? A spatial CGE analysis for a German metropolitan area. *Transportation Research Part A: Policy and Practice*, **46**(2), 285 – 309.

Tsivanidis, N. (2023). Evaluating the impact of urban transit infrastructure: Evidence from Bogota's TransMilenio. Mimeo, UC Berkeley.

World Bank (2020). *The Global Health Cost of Ambient PM2.5 Air Pollution*. World Bank.

Zheng, S. and Kahn, M. E. (2017). A new era of pollution progress in urban China? *Journal of Economic Perspectives*, **31**(1), 71–92.

Zheng, S., Zhang, X., Sun, W., and Wang, J. (2019). The effect of a new subway line on local air quality: A case study in Changsha. *Transportation Research Part D: Transport and Environment*, **68**, 26–38.

Appendix

A Calibration of β

We calibrate β as follows. Define the social cost of pollution for a type-i, j, k, l household:

$$SCE_{i,j,k,l} = -\frac{\partial v_{i,j,k,l}/\partial E_k}{\partial v_{i,j,k,l}/\partial w_i} \tag{A.1}$$

Then, using a linear approximation, the total cost of pollution is

$$TCE \approx \sum n_{i,j,k,l} SCE_{ijkl} \tag{A.2}$$

We calibrate β to target a share of TCE in total wage income ($\sum n_{ijkl} w_i$) that we get from World Bank (2020) and CE Delft (2023). World Bank (2020) provides the health costs of $PM_{2.5}$ pollution for countries worldwide. For Indonesia, health costs are estimated to be 3% of income and for Mozambique 1.4%. We adjust these based on figures from CE Delft (2023) as follows: first, we account for the higher costs in urban areas compared to the average (Table 38 in the report). Second, we adjust for the fact that our pollution measure is PM_{10}, which has lower health costs than the smaller $PM_{2.5}$ particles. We base our adjustment on the (urban) ratio of PM_{10} to $PM_{2.5}$ health costs from (CE Delft, 2023, Tables 38, 66). Our final target cost shares are then 0.026 for Yogyakarta and 0.012 for Maputo. Solving for β gives $\beta^Y = 0.03, \beta^M = 0.014$, where superscript Y stands for Yogyakarta, and superscript M for Maputo.

B Meeting WHO pollution standards

Here, we ask whether certain policies can be used to meet pollution standards. In particular, we ask which policies could reduce pollution emissions enough to meet the 2005 standard for PM_{10}, namely 10 $\mu g/m^3$. These standards were published by the WHO to provide guidelines for individual air pollutants that cities should follow, based on scientific evidence of their health effects. In the benchmark, we assume pollution concentration in Yogyakarta and Maputo mirrors average concentration in Indonesia and Mozambique. Based on data from the World Bank, average concentrations in 2010-2016 were approximately $20\mu g/m^3$ in Indonesia and $24\mu g/m^3$ in Mozambique.[22] Therefore, meeting WHO

[22] https://databank.worldbank.org/source/world-development-indicators

Table A.1: Emission factors

Yogyakarta				
Cars (g/km)	Pub. transp. (g/km)	Motorcycles (g/km)	Modern tech. (g/kwh)	Trad. tech. (g/kwh)
0.027	0.0005	0.03	0.009	1.45
Maputo				
Priv. transp. (g/km)	Pub. transp. (g/km)	Minibus (g/km)	Modern tech. (g/kwh)	Trad. tech. (g/kwh)
0.03	0.0009	0.001	0.009	1.62

Sources: Various sources.

emissions standard would mean cutting emissions by roughly one half in both cities.

We first look at taxes on private and subsidies to public transport, taxes on traditional and subsidies on public transport.[23] For Yogyakarta, we find that only a tax on traditional energy achieves a 50% reduction. The implied tax rate is, however, very high, namely 217%. Subsidizing modern energy yields a maximum reduction of 34%, with a subsidy of 93%. Subsidizing public transport achieves a maximum reduction of less than 0.1%, with a 99% subsidy, while taxing private transport *increases* emissions for all positive tax rates.

For Maputo, we similarly find that a tax on traditional energy is able to achieve a 50% pollution reduction. In this case, the tax rate is 65%. Subsidizing modern energy achieves a maximum reduction of 31%, at a 97% subsidy rate. Subsidizing public transport achieves at most a 0.6% reduction with a 99% subsidy. Finally, taxing private transport is able to reduce emissions by 16% with a high 200% tax rate.

C Additional tables

[23]Here, taxes and subsidies apply both to fixed and variable costs.

Table A.2: Baseline distribution of residents (% of total)

Variable	Center poor	Center rich	Subcenter poor	Subcenter rich
Yogyakarta				
car & modern fuel	0.26%	4.09%	2.34%	17.44%
car & traditional fuel	0.26%	0.54%	0.26%	0.82%
bus & modern fuel	1.30%	2.45%	6.75%	6.27%
bus & traditional fuel	0.26%	0.27%	1.04%	0.54%
motorcycle & modern fuel	14.55%	18.26%	64.16%	45.50%
motorcycle & traditional fuel	2.08%	0.54%	6.75%	3.27%
Maputo				
% private transport & modern fuel	0.98%	7.79%	0.59%	6.86%
% private transport & traditional fuel	2.35%	16.51%	4.31%	10.39%
% bus & modern fuel	5.29%	3.34%	15.29%	8.35%
% bus & traditional fuel	0.20%	0.19%	8.04%	7.61%
% minibus & modern fuel	2.16%	3.71%	31.57%	16.14%
% minibus & traditional fuel	2.75%	11.13%	26.47%	7.98%

Source: Numbers from survey described in the main text.

Table A.3: Counterfactual results Maputo: sensitivity

Residents		Transport mode			Energy mode		Emissions	Welfare	
B: increase private transport cost by 33% (baseline)									
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-0.91	0.36	-18.83	6.22	6.25	3.33	-3.47	-3.41	-0.68	-0.69
B: increase private transport cost by 33% ($\epsilon = 8.25$)									
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-1.45	0.57	-22.70	7.53	7.52	3.72	-3.88	-3.82	-0.48	-0.67
C: increase private transport cost by 33% ($\theta_1 = 0.66, \theta_2 = 1.31$)									
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-0.91	0.36	-18.88	6.24	6.27	3.34	-3.48	-3.42	-0.67	-0.69

Note: For each outcome, the number shows the percentage change in the counterfactual relative to the baseline. Welfare is the ratio of compensating variation (CV) over income.

Table A.4: Counterfactual results Maputo: transport costs (mechanisms)

Residents		Transport mode			Energy mode		Emissions	Welfare	
A: increase private transport cost by 33% (baseline)									
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-0.91	0.36	-18.83	6.22	6.25	3.33	-3.47	-3.41	-0.68	-0.69
B: increase private transport cost by 33% (w/o location choice)									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
–	–	-23.50	7.76	7.80	4.05	-4.22	-4.16	-0.85	-0.88
C: increase private transport cost by 33% (w/o mode choice)									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
10.11	-3.97	–	–	–	5.04	-5.25	-5.03	-4.42	-0.69
D: increase private transport cost by 33% (w/o energy mode choice)									
Residents		Transport mode			Energy mode		Emissions	Welfare	
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-0.82	0.32	-18.56	6.13	6.16	–	–	-4.81	-0.65	-0.68

Note: For each outcome, the number shows the percentage change in the counterfactual relative to the baseline. Welfare is the ratio of compensating variation (CV) over income.

Table A.5: Counterfactual results Maputo: energy costs (mechanisms)

Residents		Transport mode			Energy mode		Emissions	Welfare	
A: decrease modern tech. cost by 70% (baseline)									
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-2.60	1.02	-4.05	6.36	-1.04	22.80	-23.77	-22.86	6.47	1.52
B: decrease modern tech. cost by 70% (w/o location choice)									
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
–	–	-2.88	7.02	-1.92	22.60	-23.56	-22.66	6.43	1.49
C: decrease modern tech. cost by 70% (w/o mode choice)									
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-4.08	1.60	–	–	–	24.43	-25.47	-24.19	6.68	1.55
D: decrease modern tech. cost by 70% (w/o energy mode choice)									
center	suburb	car	bus	minibus	modern	trad.	PM	Poor	Rich
-5.62	2.21	36.12	-12.76	-11.60	–	–	20.19	16.62	3.60

Note: For each outcome, the number shows the percentage change in the counterfactual relative to the baseline. Welfare is the ratio of compensating variation (CV) over income.