Policy portfolios can reduce GHG emissions in urban transport in 120 cities by 20% while improving welfare

Charlotte Liotta (charlotte.liotta@gmail.com)
CIRED https://orcid.org/0000-0003-1412-6694

Vincent Viguié
Centre International de recherche sur l'environnement et le développement (CIRED)
https://orcid.org/0000-0002-8994-2648

Felix Creutzig
Mercator Research Institute on Global Commons and Climate Change https://orcid.org/0000-0002-5710-3348

Article

Keywords:

Posted Date: November 21st, 2022

DOI: https://doi.org/10.21203/rs.3.rs-2131432/v1

Additional Declarations: There is **NO** Competing Interest.

Version of Record: A version of this preprint was published at Nature Sustainability on May 29th, 2023. See the published version at https://doi.org/10.1038/s41893-023-01138-0.

Policy portfolios can reduce GHG emissions in urban transport in 120 cities by 20% while improving welfare

Charlotte Liotta[1,2,*], **Vincent Viguié**[1], **and Felix Creutzig**[2,3]

[1]CIRED (Ecole des Ponts ParisTech), Nogent-sur-Marne, France
[2]Technische Universität Berlin, Berlin, Germany
[3]Mercator Research Institute on Global Commons and Climate Change, Berlin, Germany
[*]To whom correspondence should be addressed; E-mail: liotta@centre-cired.fr.

ABSTRACT

City-level policies are increasingly recognized as key components of strategies to reduce transport greenhouse gas emissions. However, at a global scale, their total efficiencies, costs, and practical feasibility remain unclear. Here, we use a spatially-explicit urban economic model, systematically calibrated on 120 cities worldwide, to analyze the impact of four representative policies aiming at mitigating transportation GHG emissions, also accounting for their economic welfare impacts and health co-benefits. Applying these policies in all cities, we find that total transportation GHG emissions can be reduced by 28% in 15 years, compared with the baseline scenario. However, the consequences of the same policies vary widely between cities, with specific effects depending on the policy considered, income level, population growth rate, spatial organization, and existing public transport supply. Impacts on transport emissions span from high to almost zero, and consequences in terms of welfare can either be positive or negative. Applying only welfare-increasing policies captures most of the emission reductions: overall, they reduce emissions by 20% in 15 years. Our results highlight that there is no one-size-fits-all optimal policy to mitigate urban transport emissions but that cities can match their specific situation with a selection of mitigation policies: hence, we call for global climate mitigation models to better represent heterogeneity across cities.

1 Introduction

Urban action could significantly help to close the gap between Nationally Determined Contributions (NDCs) and the reductions in emissions needed to keep the world within +1.5°C of warming[1–3]. This is especially true for urban transportation,

which accounts for about 8% of total emissions[4,5]. However, so far, the actual potential of such local policies to reduce emissions on a global scale remains largely unknown[6]. Correspondingly, NDCs largely neglect city policies, despite urban transport emissions being a critical factor in mitigating climate change[7]. These local policies are also crucial for wider sustainability goals. Decarbonizing urban transport can indeed bring significant benefits on a large array of issues such as cleaner air, noise and road accident reduction, or better health due to the shift to active transportation modes[8].

Global assessments of the environmental impacts of urban transport policies have been carried out either using descriptive approaches focusing on current situation and comparing cities, or using aggregated models aiming at simulating the potential of future policies. Comparing current emissions in 274 cities worldwide and using threshold regressions, a 2015 study by Creutzig et al. estimated that adequate urban planning policies could reduce emissions by about 25% in 2050 compared with a business-as-usual scenario[9]. Using a scenario-based approach and an aggregated model, the Coalition for Urban Transitions 2019 study estimated a decrease of 21% in urban transport emissions by 2050 compared to a business-as-usual scenario, via a reduction in travel demand and a shift to electric and more efficient vehicles[10]. Using six representative urban archetypes, the 2017 report by C40 and McKinsey estimated a 22% decrease via transit-oriented development, new infrastructures for mass transit, walking, cycling, next-generation vehicles, and commercial freight optimization[11]. Global assessments of transport policies, including urban and non-urban transport, have also been carried out using integrated assessment models (IAMs), studying changes in technologies, infrastructures, and behaviors[12–19].

However, urban scale policies are difficult to take into account in such studies because of the complexity to capture the spatial heterogeneity, inside and within cities, of the travel demand and mode choices of households[20–23]. The local characteristics of cities, especially their urban forms, significantly impact their transportation emissions, and the potential efficiency of possible policies[9,24]. For example, a high population density and the coexistence of spatially distinct job centers when cities are large enough are associated with lower emissions per capita[25]. A street-level analysis reveals that households' distances to the city center and subcenters are a key predictor of urban transport GHG emissions[22]. Hence, possible mitigation strategies for urban transportation depend on precise city characteristics, which are difficult to consider globally[26]. For instance, in sprawled cities, promoting electric vehicles may be more efficient than investing in mass rapid transit, while the contrary holds in dense cities[27,28]. Another difficulty

comes from the fact that there is an interplay between transport policies and the real estate market. Transport policies impact housing prices, with large consequences on households' welfare and, indirectly, on long-term changes in transport demand[13,29].

At the local scale, such mechanisms can be taken into account using city models, such as land-use transport interaction (LUTI) models simulating transport and land planning policies in cities[30]. Examples are numerous, with rich literature analyzing case studies in various cities[31–34]. However, generalization is difficult as this field is highly fragmented, with a large diversity of methods, frameworks, and indicators, and limited reference to previous works, which does not allow accumulating knowledge or doing comparisons[33,34]. What is missing is a scalable approach that provides an assessment for a large number of cities while taking urban idiosyncrasies into account.

Here, we use a spatially-explicit land-use transport interaction model to systematically assess and compare, on a collection of 120 cities worldwide (see figure 3), the consequences of four urban transport policies on public finance, transportation emission reduction, housing affordability, as well as health benefits due to variations in air pollution, noise, car accidents and exercise through active transportation modes. The cities cover all continents except Africa, due to data availability, and count in total 525 million inhabitants, or 13% of the global urban population (see supplementary section C for the city selection process).

The model combines a transport mode choice model with a residential location choice model derived from the standard urban economics framework[29,35]. It simulates, in each city, the residential and transportation choices of households as a function of detailed city characteristics, such as the location of employment centers, transportation costs, and the local land-use policies. The model is calibrated for each city individually, with parameters structurally estimated using databases of population densities, transport times, and rent levels within each city (see section 4 - Methods). Thus, our model enables to simulate city-level prospective scenarios downscaling global techno-economic scenarios[36].

The four policies that we analyze (Table 1, Supplementary Section E) are simplified representations of four broad types of city-level transport policies: a local fuel tax targeting polluting transportation modes, investments in "cleaner" transportation modes with the development of a bus rapid transit network, a land-use policy promoting urban density, and a "fuel efficiency" policy that makes the use of low-emission vehicles mandatory. These policies are simple enough to be applied to a large sample of cities, but remain representative of existing policies. We simulate their impact in 2035 in terms of transportation GHG emissions and social welfare and compare it with a Business-As-Usual scenario in which we

assume the continuation of current trends with no additional city-level policy (see supplementary section D).

Policy name	Description
Fuel tax	Fuel price increases by 30% compared to the business-as-usual scenario (broadly corresponding to a level of carbon pricing of US $50–100/tCO2, the level required to cost-effectively reduce emissions in line with the temperature goals of the Paris Agreement[37]). Local tax revenues are redistributed uniformly among inhabitants.
Bus Rapid Transit (BRT)	Construction of a Bus Rapid Transit (BRT) network on all main streets of the city (identified using OpenStreetMap). The new BRT has a uniform speed of 40km/h and a construction cost of 12.23 million USD per km, equally shared by households over 50 years with a 5% interest rate.
Urban Growth Boundary (UGB)	Urban Growth Boundary, strictly forbidding any new construction beyond places already built in 2020. To accommodate the growing population, cities have to become denser. The associated increase in housing prices can negatively impact inhabitants' welfare.[29]
Fuel efficiency	Fuel consumption of private cars decreases by - 3.7% per year, in line with the IEA "2°C Scenario".[38] In the business-as-usual scenario, the fuel consumption of private cars evolves in line with the business-as-usual Scenario of the same report (decrease by - 1% per year).

Table 1. Policies analyzed (see Supplementary Section E for a detailed description).

2 Results

2.1 Aggregated impacts of the four policies

Our analysis demonstrates that policies are effective but affect each city differently (Figures 1 and 3). Indeed, emission reductions typically stand between 19% and 29% (25th and 75th quantile) with a median reduction of 22%. The combined four policies could lead to a reduction in annual urban transport emissions of 28% compared to the baseline scenario over the sample by 2035.

This emission reduction is slightly higher than existing global assessments in the literature but of the same order of magnitude. A 2015 review of local scenarios

of low-carbon urban transport strategies estimated potential global emission reduction by 20–50% in 2050 compared to baseline scenarios[39]. Using machine learning to meta-analyze thousands of case studies of climate change mitigation in cities, the 2020 article by Sethi et al. estimated a possible decrease of 28% in 2050 through travel demand management, fuel shift, and intelligent transportation system (and potentially more, but with no clear quantification, with pan-city expansions of public transportation systems and more efficient vehicles)[33]. The two aggregated studies mentioned at the beginning of this paper estimated, in 2050 also, a possible decrease of 21% and 22% compared to a baseline scenario[10,11]. Our study suggests that mitigation can happen earlier than modeled in other studies. A key reason for this difference is that we model spatially explicit policies, thus broadening the portfolio of options and improving the resolution of effects.

The impact of the policies on households' welfare is complex (Figure 2). They increase households' financial burden due to the public investment required by the construction of the BRT system, the increased fuel cost for the fuel tax, or the increased housing prices, in particular for the urban growth boundary. However, this burden is counterbalanced by health benefits through decreases in air pollution, car accidents, and noise, together with an increase in active mode uses[40]. We find that, when expressed in monetary terms, these benefits do not seem to fully compensate for the financial losses, leading to an average decrease in welfare by 7% (figure 1). This decrease occurs in almost all cities: the median variation in welfare is -5.1% and only two cities in our sample experience a positive (but moderate) welfare increase by about 0.5%.

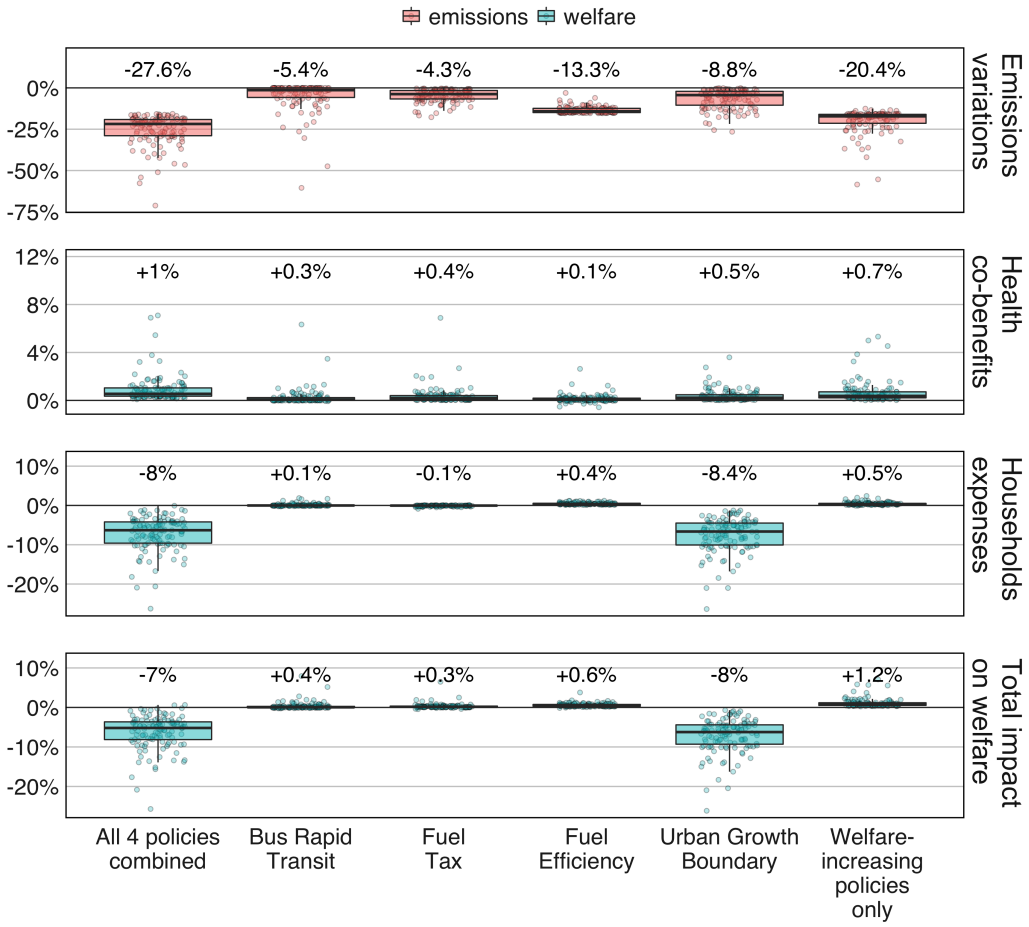


Figure 1. Impact of the four policies on annual transport emissions and average welfare in the 120 cities in 2035, compared with the business-as-usual scenario. *Each dot represents a city. The numbers above the box plots represent the aggregated mean of changes, accounting for cities' population sizes.*

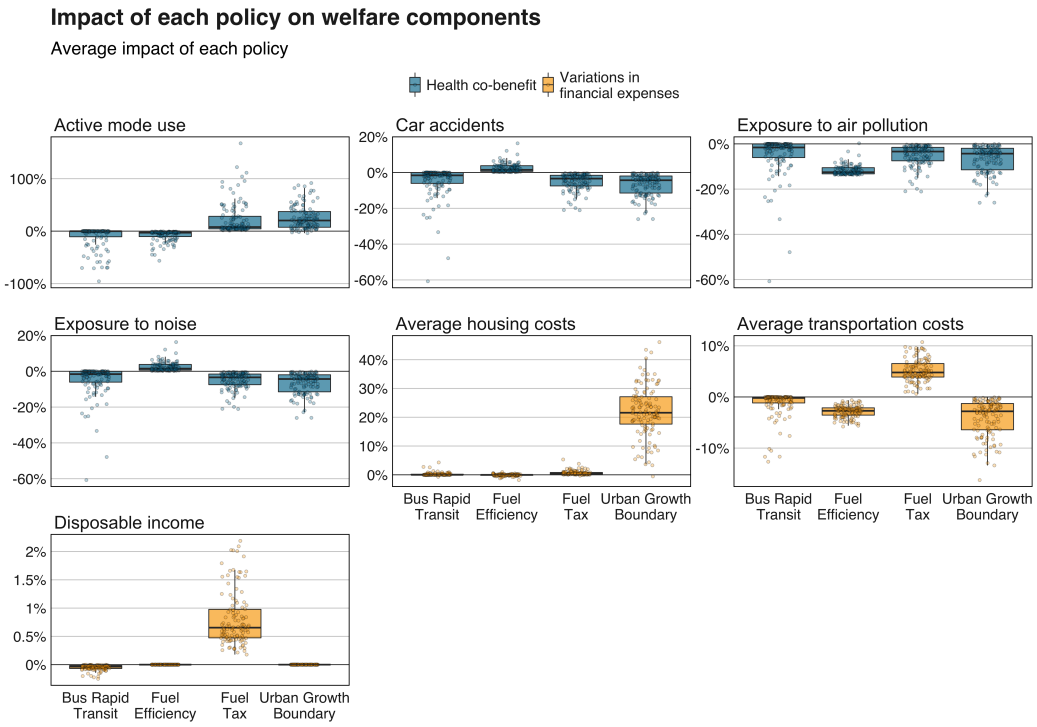


Figure 2. Decomposition of welfare variations between different drivers.
The figures represent the average variations over all cities in 2035, compared to the business-as-usual scenario. Disposable income is the variation of income due to local taxes (fuel tax revenues are redistributed uniformly among the inhabitants of each city, hence increasing disposable income, while the construction of the BRT is financed by households, hence decreasing their income).

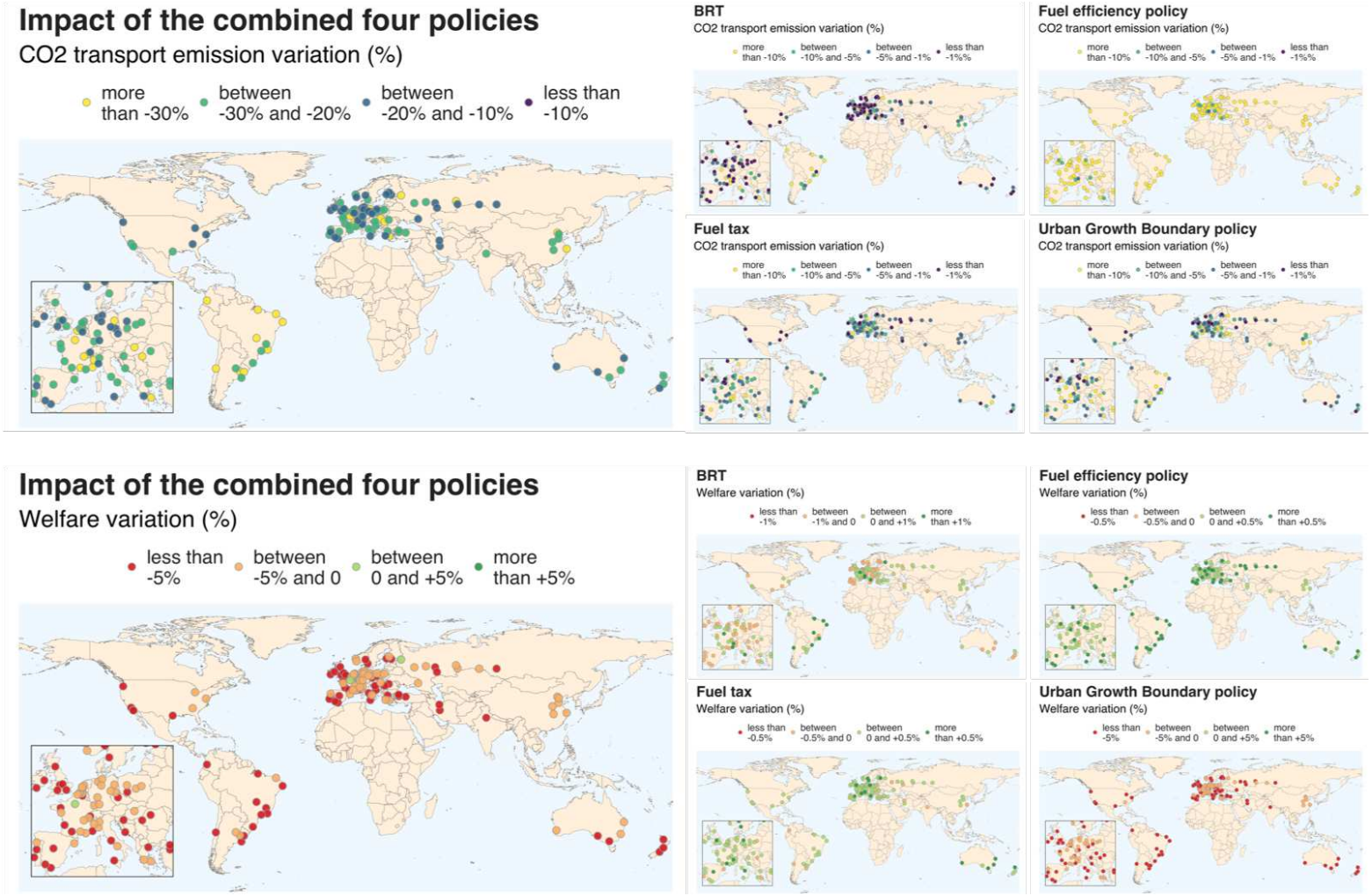


Figure 3. Effect of the four policies on urban transport emissions and on welfare (including direct and indirect financial cost of the policies and health co-benefits) in 2035, compared to the business-as-usual scenario.
See also supplementary figures S7 and S8.

2.2 Effectiveness of policy portfolio depend on city characteristics

The impacts of the four policies on transportation emissions and welfare are largely heterogeneous between cities (Figures 1 and 2). The level of emissions reduction ranges from very high to almost zero depending on cities. Regarding welfare, we notably observe that the BRT, the fuel tax, and the fuel efficiency policy increase inhabitants' welfare in some cities and decrease it in others.

Individually considering each policy, some geographical patterns emerge (Figure 3). Regarding emissions, the BRT achieves the largest mitigation in South America, while the fuel tax has the largest impact in Europe and South America. By contrast, the fuel efficiency policy has a similar impact in most cities, except for Europe where emissions' mitigation is of a lower magnitude. Finally, the UGB allows achieving large emissions mitigation in some cities in South America, Europe, and China. Regarding welfare, the BRT has a mostly positive impact in South America and Europe. The fuel efficiency policy increases the welfare in almost all cities, though of a lower magnitude in Europe. The fuel tax has a positive welfare impact in North America, Oceania, and most of Europe but can be harmful in South America, Eastern Europe, and Asia. Finally, the UGB is harmful in all cities as it largely increases rents.

However, geographical factors are insufficient to explain the heterogeneity of policies' impacts between cities, as we also observe heterogeneity within continents and countries. To understand the role that might play other city characteristics, we linearly regress emissions and welfare impacts of policies on some cities' characteristics that have been shown to impact urban forms, urban emissions, or policies' efficiency[9,25,27,41,42] (supplementary section F). We find that the availability of public transport, the level of income, or the population and income growth of cities affect the efficiency and welfare impact of policies. However, the characteristics that we listed are insufficient to fully explain the policies' impacts, as almost 50% of the variations remain unexplained (the R2s of the regressions are between 0.24 and 0.54, see supplementary tables S8 and S7 in supplementary section F). Moreover, for a given policy, the characteristics which significantly impact its consequences on emissions are generally not the same as those which impact its consequences on welfare. This highlights the utility of using a spatial model that explicitly accounts for cities' spatial characteristics and the interplay between them to properly capture mitigation policies' impacts.

2.3 A welfare-increasing policy portfolio catches most emission reductions

As policies' impacts are heterogeneous between cities, alternate policy portfolios designed in a context-adequate way may have higher efficiencies and fewer negative

side-effects than a policy portfolio made of the same policies for all cities. Here, we simulate a scenario in which we implement, in each city, the policies that locally increase inhabitants' welfare only. Depending on cities, this corresponds to at least one and up to three emission-reducing and welfare-increasing policies (see supplementary figure S14).

In such a scenario, the minimum decrease in urban transport emissions is 13% (the median is 17%, and the interquartile range is 16.0% to 21.4%), and welfare variation is always positive (Figure 1). Globally, urban transport emissions are reduced by 20%, and welfare increases on average by 1.2%.

Therefore, by designing policies adapted to each city's characteristics, it appears possible to systematically improve welfare while reducing emissions by more than two-thirds of the initial figure. These results are a priori underestimated, as the policy portfolio simulated in this paper is not optimal. The magnitude of emissions reduction could potentially be increased while keeping welfare variation positive by tailoring the policies to each city's characteristics, using, for instance, different tax levels, or designing different urban growth boundary policies.

3 Discussion and conclusion

The main message of this study is that the current increase in available urban data allows to model, although simply, the consequences of local policies in a large set of cities, explicitly accounting for their spatial characteristics. This enables to downscale global scenarios such as those produced by IAMs at the city scale and to quantitatively assess the consequences of local strategies involving land-planning or local transport infrastructure provision under such scenarios. Moreover, such spatially-explicit modeling also enables to capture the impact of these strategies on households' expenses related to housing and transport and on several side-effects of the policies, especially health co-benefits.

In line with existing studies, we find that urban forms and cities' spatial characteristics impact the mitigation policies' efficiency in a complex way, with no direct one-to-one mapping.[9,24,43] Even within the same continent or country, differences can be large, and city models can help to capture this heterogeneity. In line with the literature, we also find that the positive side-effects of urban transport policies can be high, especially regarding the financial cost of these policies.[40] It appears possible to reduce emissions in a welfare-increasing way in each city while keeping most of the global emission reductions. However, a context-adequate policy portfolio is required with strategies tailored to each city.

There are many limitations to the present study. If more and more city-level

data becomes available, data availability still heavily constrains our modeling and scenarios. We could not include in our analysis any African city, and there is a strong geographical bias in favor of developed countries, a common weakness of the literature on cities.[31] Our model is simple and did not consider, for instance, any mechanism relative to endogenous job locations or description of income inequalities inside cities. Recently, models capturing these dimensions have been proposed in the literature and could be used to reproduce our analysis in the future, when adequate data about the location of jobs and income groups within cities becomes available.[44] We also ignored cities characterized by high levels of informal settlements. Indeed, modeling such cities is still a research challenge, as is the identification of low-carbon and sustainable mobility policies in this context.[45]

Using more sophisticated models and additional data may enable to analyze important policies that we could not assess with our framework. The promotion of mixed land use, for instance, or the development of bicycle lane networks could not be evaluated here. We also could not capture the inequalities created by the policies, something which would require data about where richer and poorer inhabitants live within each city. The welfare variations and health co-benefits that we simulate therefore give an indication of the average effect of the policies, but should not be considered as a direct indication of the political feasibility of their implementation. With the current and continuous increase in available socio-economic, land-use, and transport data on cities, however, progresses on these issues may occur in the coming years.

4 Methods

4.1 Urban modeling

For each city individually, we run a spatially-explicit urban model based on the model NEDUM[36,46]. This model combines a simple transport allocation model with a land-use model based on the Standard Urban Model (SUM) of urban economics, or Alonso-Muth-Mills model[47–49], with inertia in city evolution. It allows spatially-explicit modeling of residential and transportation choices of households as a function of employment center locations, transportation costs, and land-use constraints, which enable the analysis of housing, transport, or land-use policies. This model is easily tractable so that it can be applied to a large number of cities. In addition, it relies on a limited number of inputs and hypotheses, which makes its outputs easily interpretable.

Models based on the SUM have often been used to analyze mitigation and transport policies: to cite a few recent examples, the construction of the Bus Rapid

Transit (BRT) system in Bogotá[50], London's Congestion Charge[51], or an urban growth boundary in Cape Town[52]. The SUM has been shown to capture well the spatial patterns of population density and housing prices in several cities across the world[53,54], and the recent rise of available urban data has allowed testing some predictions of the SUM on large numbers of cities, for instance in the US[55], in Europe[56], and in developing countries[57].

Our model is fully described in supplementary section A and summarized below. In a first step, we assume that, within a city, households trade-off between transportation costs to employment centers and rents per unit of dwelling, resulting in rents decreasing when transportation costs increase. In this paper, we assume that households select the transport mode with the lowest generalized transportation costs, choosing between private cars, public transport, and walking.

In a second step, private developers build the amount of housing that maximizes their profit, accounting for households' bid-rents and for land-use constraints. Under standard hypotheses on the construction function, this results in the construction of capital-intensive buildings near employment centers, where bid-rents per unit of housing are higher. Here, we use a dynamic version of the model, assuming housing depreciation and inertia in housing construction.

As a result, our urban model allows us to estimate population density, housing supply, transportation choices, and rents as a function of employment centers' location, transportation infrastructures, and land-use constraints.

4.2 Outputs of the model

Our model allows to estimate two main outputs at the city level: GHG transportation emissions and inhabitants' welfare. The computation of these outputs is detailed in supplementary section A.5 and described below.

Transportation emissions are derived from the transportation demand of each mode and the greenhouse gases intensity of each transportation mode, assuming that the level of emissions of private cars per unit of distance depends on their fuel consumption and that the level of emissions per unit of distance of public transport is fixed and exogenous.

Total social welfare is measured as the sum of individual utilities, derived in our framework from the consumption of housing and composite good, and from health co-benefits related to transportation. While the consumptions of housing and composite good are standard outputs of urban economics models, directly resulting from households' utility maximization, we also include four health co-benefits in our analysis: exposure to noise, air pollution, and car accidents, which negatively impact welfare, and the positive health impact of active transportation modes.

We compute the monetary equivalent of the impacts of air pollution, noise and car accidents, assuming that they linearly depend on the demand of transportation from private cars, as well as on the fuel consumption of private cars for air pollution. For health improvements through active transportation modes, we adapt the HEAT model of the WHO[58], assuming that walking or cycling to work brings reduced mortality, which translates into a monetary gain through the Value of Statistical Life. We include these co-benefits in the utility function as described in supplementary section A.2.

4.3 Data sources and parameters calibration

We individually calibrate the model's city-specific parameters on each city of the sample using spatially-explicit data on population densities, rents, transportation costs, land use, and dwelling sizes for the 120 cities for 2015 (see supplementary section A.6). Due to data availability, in each city, we only consider the city center as the main employment center. The validity of such an approximation was one of the constraints on the choice of the cities in our sample (see supplementary section C).

We use the dataset from Lepetit et al. (2022)[59], which provides spatially explicit data on population densities, rents, dwelling sizes, land use, and transportation costs for 191 cities on five continents at a 1km-resolution. Population density and land cover are from the GHS-POP[60] and the ESA CCI[61] databases respectively, while transportation and real estate data have been obtained from the Google Maps API and the web scraping of real estate websites. This dataset is the first including spatialized data on real estate and transportation in a large sample of cities covering both developed and developing countries and allowing an integrated analysis of density, real estate, transportation, and land use. In addition, we use city-level data on city characteristics, including incomes, the fuel consumption of private vehicles, fuel costs, and agricultural rents. All data sources are in supplementary section B.

We tried to assess the model's ability to reproduce urban structures in two ways. First, within each city, we compared simulated densities and rents with density and real estate data. Then, at the city level, we compared simulated modal shares and transportation emission levels with existing data. Results are in supplementary section A.7.

4.4 Scenarios

The baseline scenario is a business-as-usual (BAU) scenario, assuming the continuation of current trends with no additional city-level mitigation policies. It uses the population growth scenarios of the World Urbanization Prospects of the United

Nations, which provides population growth projections from 2015 to 2035 for cities with more than 300 000 inhabitants and for national urban populations. For income variatrions, it uses income per capita growth scenarios from the global integrated assessment model (IAM) IMACLIM-R[62]. More details about this BAU scenario are in supplementary section D.

We also run our four policy scenarios, designed to be representative of a wide spectrum of potential urban policies, yet simple enough to be generically applied to our sample of cities. We assume the same trends for population and income as in the BAU scenario, while transportation infrastructures and land-use constraints are impacted by the policies. Details about the policy scenarios are in supplementary section E.

4.5 Robustness checks

In supplementary section I, we carry out a robustness check of the results of this paper: we simulate an alternative version of each type of policy and check that the results remain qualitatively the same.

More precisely, we assume, starting in 2020, that the fuel tax increases fuel prices by 10% instead of 30%, that the fuel efficiency policy reduces the fuel consumption of new vehicles by 2% each year instead of 3.7%, and that the Urban Growth Boundary prevents new constructions in areas with a density below 400 inhabitants per km2 in 2020. For the BRT, instead of using OpenStreetMap street network data, we assume more simply that two new public transport lines, North-South and East-West, are opened in each city.

Results are qualitatively the same as with the main policies' specifications. The combined four policies allow mitigating transport emissions by 13.5% in 15 years, with large heterogeneity in policies' efficiencies between cities. However, city-specific policy portfolios that only implement welfare-increasing policies allow keeping most of the emissions mitigation (-11.8%) while increasing average welfare by 1.1%.

References

1. Prieur-Richard, A.-H. *et al.* *Extended version: Global Research and Action Agenda on Cities and Climate Change Science* (2018).

2. GCoM. Climate Emergency: Unlocking the Urban Opportunity Together. Tech. Rep., The Global Covenant of Mayors for Climate and Energy (GCoM), Brussels (2019). URL https://www.globalcovenantofmayors.org/wp-content/uploads/2019/12/2019-GCoM7Aggregation-Report.pdf.

3. C40, ARUP & {University of Leeds}. The future of urban consumption in a 1.5°C world. Tech. Rep. (2019).

4. Creutzig, F. *et al.* Urban infrastructure choices structure climate solutions. *Nature Climate Change* **6**, 1054–1056 (2016). URL https://www.nature.com/articles/nclimate3169. Bandiera_abtest: a Cg_type: Nature Research Journals Number: 12 Primary_atype: Comments & Opinion Publisher: Nature Publishing Group Subject_term: Climate-change mitigation;Economics;Engineering Subject_term_id: climate-change-mitigation;economics;engineering.

5. Minx, J. C. *et al.* A comprehensive and synthetic dataset for global, regional, and national greenhouse gas emissions by sector 1970–2018 with an extension to 2019. *Earth System Science Data* **13**, 5213–5252 (2021). URL https://essd.copernicus.org/articles/13/5213/2021/. Publisher: Copernicus GmbH.

6. Hale, T. N. *et al.* Sub- and non-state climate action: a framework to assess progress, implementation and impact. *Climate Policy* **21**, 406–420 (2021). URL https://doi.org/10.1080/14693062.2020.1828796. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/14693062.2020.1828796.

7. UN-Habitat. Sustainable Urbanization in the Paris Agreement. Tech. Rep., Nairobi (2017). URL https://unhabitat.org/sustainable-urbanization-in-the-paris-agreement.

8. Gössling, S., Nicolosi, J. & Litman, T. The Health Cost of Transport in Cities. *Current Environmental Health Reports* **8**, 196–201 (2021). URL https://doi.org/10.1007/s40572-021-00308-6.

9. Creutzig, F., Baiocchi, G., Bierkandt, R., Pichler, P.-P. & Seto, K. C. Global typology of urban energy use and potentials for an urbanization mitigation wedge. *Proceedings of the National Academy of Sciences* **112**, 6283–6288 (2015). URL http://www.pnas.org/lookup/doi/10.1073/pnas.1315545112.

10. Coalition for Urban Transitions, X. Climate Emergency, Urban Opportunity. Tech. Rep., C40 Cities Climate Leadership Group (C40) and World Resources Institute (WRI) Ross Center for Sustainable Cities, London and Washington, DC (2019). URL https://urbantransitions.global/urban-opportunity/.

11. McKinsey & Cities, C. Focused Acceleration: A Strategic Approach for Climate Action in Cities to 2030. Tech. Rep. (2017). URL https://www.c40.org/researches/mckinsey-center-for-business-and-environment.

12. Daly, H. E. *et al.* Incorporating travel behaviour and travel time into TIMES energy system models. *Applied Energy* **135**, 429–439 (2014). URL https://www.sciencedirect.com/science/article/pii/S0306261914008629.

13. Waisman, H.-D., Guivarch, C. & Lecocq, F. The transportation sector and low-carbon growth pathways: modelling urban, infrastructure, and spatial determinants of mobility. *Climate Policy* **13**, 106–129 (2013). URL https://doi.org/10.1080/14693062.2012.735916. Publisher: Taylor & Francis _eprint: https://doi.org/10.1080/14693062.2012.735916.

14. Ó Broin, E. & Guivarch, C. Transport infrastructure costs in low-carbon pathways. *Transportation Research Part D: Transport and Environment* **55**, 389–403 (2017). URL https://www.sciencedirect.com/science/article/pii/S1361920916301997.

15. Mittal, S., Dai, H., Fujimori, S., Hanaoka, T. & Zhang, R. Key factors influencing the global passenger transport dynamics using the AIM/transport model. *Transportation Research Part D: Transport and Environment* **55**, 373–388 (2017). URL https://www.sciencedirect.com/science/article/pii/S1361920916300451.

16. Rottoli, M. *et al.* Coupling a Detailed Transport Model to the Integrated Assessment Model REMIND. *Environmental Modeling & Assessment* **26**, 891–909 (2021). URL https://link.springer.com/10.1007/s10666-021-09760-y.

17. McCollum, D. L. *et al.* Improving the behavioral realism of global integrated assessment models: An application to consumers' vehicle choices. *Transportation Research Part D: Transport and Environment* **55**, 322–342 (2017). URL https://www.sciencedirect.com/science/article/pii/S1361920915300900.

18. Tattini, J. *et al.* Improving the representation of modal choice into bottom-up optimization energy system models – The MoCho-TIMES model. *Applied Energy* **212**, 265–282 (2018). URL https://linkinghub.elsevier.com/retrieve/pii/S030626191731766X.

19. Gurney, K. R. *et al.* Greenhouse gas emissions from global cities under SSP/RCP scenarios, 1990 to 2100. *Global Environmental Change* **73**, 102478 (2022).

20. Edelenbosch, O. Y. *et al.* Decomposing passenger transport futures: Comparing results of global integrated assessment models. *Transportation Research Part D: Transport and Environment* **55**, 281–293 (2017). URL https://www.sciencedirect.com/science/article/pii/S1361920916301304.

21. Muratori, M. *et al.* Future integrated mobility-energy systems: A modeling perspective. *Renewable and Sustainable Energy Reviews* **119**, 109541 (2020). URL https://www.sciencedirect.com/science/article/pii/S136403211930749X.

22. Wagner, F. *et al.* A novel machine learning framework to identify location-specific relevance of built environment for urban motorised travel .

23. Javaid, A., Creutzig, F. & Bamberg, S. Determinants of low-carbon transport mode adoption: systematic review of reviews. *Environmental Research Letters* **15**, 103002 (2020).

24. Creutzig, F. How fuel prices determine public transport infrastructure, modal shares and urban form. *Urban Climate* **10**, 63–76 (2014). URL https://linkinghub.elsevier.com/retrieve/pii/S2212095514000674.

25. Castells-Quintana, D., Dienesch, E. & Krause, M. Air pollution in an urban world: A global view on density, cities and emissions. *Ecological Economics* **189**, 107153 (2021). URL https://www.sciencedirect.com/science/article/pii/S0921800921002111.

26. Creutzig, F., Bai, X., Khosla, R., Viguie, V. & Yamagata, Y. Systematizing and upscaling urban climate change mitigation. *Environmental Research Letters* **15**, 100202 (2020). URL https://doi.org/10.1088/1748-9326/abb0b2. Publisher: IOP Publishing.

27. Kennedy, C. A., Ibrahim, N. & Hoornweg, D. Low-carbon infrastructure strategies for cities. *Nature Climate Change* **4**, 343–346 (2014). URL https://www.nature.com/articles/nclimate2160. Number: 5 Publisher: Nature Publishing Group.

28. Gouldson, A. *et al.* Exploring the economic case for climate action in cities. *Global Environmental Change* **35**, 93–105 (2015). URL https://www.sciencedirect.com/science/article/pii/S0959378015300169.

29. Viguié, V. & Hallegatte, S. Trade-offs and synergies in urban climate policies. *Nature Climate Change* **2**, 334–337 (2012).

30. Köhler, J., Ristimäki, M., Viguié, V. & et al. A review and analysis of quantitative integrated environmental assessment methods for urban areas. In *Understanding Cities: Advances in Integrated Assessment of Urban Sustainability* (Centre For Earth Systems Engineering Research, 2014).

31. Lamb, W. F., Creutzig, F., Callaghan, M. W. & Minx, J. C. Learning about urban climate solutions from case studies. *Nature Climate Change* **9**, 279–287 (2019). URL https://www.nature.com/articles/s41558-019-0440-x.

32. Creutzig, F. *et al.* Upscaling urban data science for global climate solutions. *Global Sustainability* **2** (2019). URL https://www.cambridge.org/core/journals/global-sustainability/article/upscaling-urban-data-science-for-global-climate-solutions/D2D622B43CD50A9B2FD5DF855BCC0F18. Publisher: Cambridge University Press.

33. Sethi, M., Lamb, W., Minx, J. & Creutzig, F. Climate change mitigation in cities: a systematic scoping of case studies. *Environmental Research Letters* **15**, 093008 (2020). URL https://doi.org/10.1088/1748-9326/ab99ff. Publisher: IOP Publishing.

34. Karjalainen, L. E. & Juhola, S. Urban transportation sustainability assessments: a systematic review of literature. *Transport Reviews* **41**, 659–684 (2021). URL https://www.tandfonline.com/doi/full/10.1080/01441647.2021.1879309.

35. Duranton, G. & Puga, D. Chapter 8 - Urban Land Use. In Duranton, G., Henderson, J. V. & Strange, W. C. (eds.) *Handbook of Regional and Urban Economics*, vol. 5 of *Handbook of Regional and Urban Economics*, 467–560 (Elsevier, 2015).

36. Viguié, V., Hallegatte, S. & Rozenberg, J. Downscaling long term socio-economic scenarios at city scale: A case study on Paris. *Technological Forecasting and Social Change* **87**, 305–324 (2014). URL https://www.sciencedirect.com/science/article/pii/S0040162514000092.

37. Bank, W. State and trends of carbon pricing 2020. Tech. Rep., World Bank, Washington, DC (2020). URL https://openknowledge.worldbank.org/bitstream/handle/10986/33809/9781464815867.pdf?sequence=4&isAllowed=y. OCLC: 1276916149.

38. IEA & OECD. Energy Technology Perspectives 2017. Tech. Rep., International Energy Agency (IEA), Paris (2017).

39. Creutzig, F. Evolving Narratives of Low-Carbon Futures in Transportation. *Transport Reviews* **36**, 341–360 (2016). URL https://doi.org/10.1080/01441647.2015.1079277. Publisher: Routledge _eprint: https://doi.org/10.1080/01441647.2015.1079277.

40. Creutzig, F., Mühlhoff, R. & Römer, J. Decarbonizing urban transport in European cities: four cases show possibly high co-benefits. *Environmental Research Letters* **7**, 044042 (2012). URL https://iopscience.iop.org/article/10.1088/1748-9326/7/4/044042.

41. Ürge Vorsatz, D. *et al.* Locking in positive climate responses in cities. *Nature Climate Change* **8**, 174–177 (2018). URL https://www.nature.com/articles/s41558-018-0100-6. Number: 3 Publisher: Nature Publishing Group.

42. Avner, P., Rentschler, J. & Hallegatte, S. *Carbon Price Efficiency: Lock-in and Path Dependence in Urban Forms and Transport Infrastructure*. Policy Research Working Papers (The World Bank, 2014). URL http://elibrary.worldbank.org/doi/book/10.1596/1813-9450-6941.

43. Borck, R. & Brueckner, J. K. Optimal Energy Taxation in Cities. *Journal of the Association of Environmental and Resource Economists* **5**, 481–516 (2018). URL https://www.journals.uchicago.edu/doi/abs/10.1086/695614. Publisher: The University of Chicago Press.

44. Gaigné, C., Koster, H. R., Moizeau, F. & Thisse, J.-F. Who lives where in the city? Amenities, commuting and income sorting. *Journal of Urban Economics* **128**, 103394 (2022).

45. Bryan, G., Glaeser, E. & Tsivanidis, N. Cities in the Developing World. *Annual Review of Economics* **12**, 273–297 (2020). URL https://doi.org/10.1146/annurev-economics-080218-030303. _eprint: https://doi.org/10.1146/annurev-economics-080218-030303.

46. Viguié, V. & Hallegatte, S. Trade-offs and synergies in urban climate policies. *Nature Climate Change* **2**, 334–337 (2012). URL http://www.nature.com/articles/nclimate1434.

47. Alonso, W. Location and land use. Toward a general theory of land rent. *Location and land use. Toward a general theory of land rent.* (1964). URL https://www.cabdirect.org/cabdirect/abstract/19641802976.

48. Muth, R. F. Cities and housing. (1969). URL https://trid.trb.org/view/545388.

49. Mills, E. S. An Aggregative Model of Resource Allocation in a Metropolitan Area. *The American Economic Review* **57**, 197–210 (1967). URL https://www.jstor.org/stable/1821621.

50. Tsivanidis, N. Evaluating the Impact of Urban Transit Infrastructure: Evidence from Bogotá's TransMilenio (2019).

51. Herzog, I. The City-Wide E ects of Tolling Downtown Drivers: Evidence from London's Congestion Charge. 120 (2021).

52. Pfeiffer, B., Rabe, C., Selod, H. & Viguie, V. *Assessing Urban Policies Using a Simulation Model with Formal and Informal Housing: Application to Cape Town, South Africa* (World Bank, Washington, DC, 2019). URL http://hdl.handle.net/10986/31987.

53. Duranton, G. & Puga, D. Chapter 8 - Urban Land Use. In Duranton, G., Henderson, J. V. & Strange, W. C. (eds.) *Handbook of Regional and Urban Economics*, vol. 5 of *Handbook of Regional and Urban Economics*, 467–560 (Elsevier, 2015). URL https://www.sciencedirect.com/science/article/pii/B9780444595171000088.

54. Liotta, C., Viguié, V. & Lepetit, Q. Testing the monocentric standard urban model in a global sample of cities. *Regional Science and Urban Economics* **97**, 103832 (2022). URL https://www.sciencedirect.com/science/article/pii/S0166046222000710.

55. Paulsen, K. Yet even more evidence on the spatial size of cities: Urban spatial expansion in the US, 1980–2000. *Regional Science and Urban Economics* **42**, 561–568 (2012). URL https://www.sciencedirect.com/science/article/pii/S0166046212000087.

56. Oueslati, W., Alvanides, S. & Garrod, G. Determinants of urban sprawl in European cities. *Urban Studies* **52**, 1594–1614 (2015). URL https://doi.org/10.1177/0042098015577773. Publisher: SAGE Publications Ltd.

57. Jedwab, R., Loungani, P. & Yezer, A. Comparing cities in developed and developing countries: Population, land area, building height and crowding. *Regional Science and Urban Economics* **86**, 103609 (2021). URL https://www.sciencedirect.com/science/article/pii/S0166046220302945.

58. Kahlmeier, S. *et al.* Health economic assessment tool (HEAT) for walking and for cycling. methods and user guide on physical activity, air pollution, injuries and carbon impact assessments (2017). URL https://www.zora.uzh.ch/id/eprint/151107. Publisher: World Health Organization, Regional Office for Europe.

59. Lepetit, Q., Viguie, V. & Liotta, C. A gridded dataset on densities, real estate prices, transport, and land use inside 192 worldwide urban areas. SSRN Scholarly Paper 4105575, Social Science Research Network, Rochester, NY (2022). URL https://papers.ssrn.com/abstract=4105575.

60. Schiavina, M., Freire, S. & MacManus, K. GHS population grid multitemporal (1975, 1990, 2000, 2015) R2019A (2019). URL http://data.europa.eu/89h/0c6b9751-a71f-4062-830b-43c9f432370f. European Commission, Joint Research Centre (JRC).

61. ESA. Land Cover CCI Product User Guide Version 2. Tech. Rep. (2017). URL maps.elie.ucl.ac.be/CCI/viewer/download/ESACCI-LC-Ph2-PUGv2_2.0.pdf.

62. Lefèvre, J. *et al.* Global socio-economic and climate change mitigation scenarios through the lens of structural change. *Global Environmental Change* **74**, 102510 (2022). URL https://www.sciencedirect.com/science/article/pii/S0959378022000486.

63. Fujita, M. *Urban Economic Theory: Land Use and City Size* (Cambridge University Press, 1989). Google-Books-ID: 5xbZvxyhpEcC.

64. Ahlfeldt, G. If Alonso Was Right: Modeling Accessibility and Explaining the Residential Land Gradient. *Journal of Regional Science* **51**, 318–338 (2011).

65. Ahlfeldt, G. M. & Wendland, N. Fifty years of urban accessibility: The impact of the urban railway network on the land gradient in Berlin 1890–1936. *Regional Science and Urban Economics* **41**, 77–88 (2011). URL https://www.sciencedirect.com/science/article/pii/S0166046210000736.

66. Lemoy, R. & Caruso, G. Scaling evidence of the homothetic nature of cities. *arXiv:1704.06508 [physics, q-fin]* (2017). URL http://arxiv.org/abs/1704.06508. ArXiv: 1704.06508.

67. Sims, R. *et al.* Transport. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (2014).

68. van Essen, H. *et al.* External costs of transport in Europe. Tech. Rep., CE Delft, INFRAS and Fraunhofer ISI (2011).

69. Ayaragarnchanakul, E. & Creutzig, F. Bangkok's locked-in traffic jam: Price congestion or regulate parking? *Case Studies on Transport Policy* (2021). URL https://www.sciencedirect.com/science/article/pii/S2213624X21002157.

70. Dixon, S., Irshad, H., Pankratz, D. M. & Bornstein, J. The 2019 Deloitte City Mobility Index. Tech. Rep., Deloitte (2019).

71. Moran, D. *et al.* Carbon footprints of 13 000 cities. *Environmental Research Letters* **13**, 064041 (2018). URL https://iopscience.iop.org/article/10.1088/1748-9326/aac72a.

72. Nangini, C. *et al.* A global dataset of CO 2 emissions and ancillary data related to emissions for 343 cities. *Scientific Data* **6**, 180280 (2019). URL https://www.nature.com/articles/sdata2018280. Number: 1 Publisher: Nature Publishing Group.

73. Kona, A. *et al.* Global Covenant of Mayors, a dataset of GHG emissions for 6,200 cities in Europe and the Southern Mediterranean. *Earth System Science Data Discussions* 1–17 (2021). URL https://essd.copernicus.org/preprints/essd-2021-67/. Publisher: Copernicus GmbH.

74. IEA. Fuel Consumption of Cars and Vans – Analysis. Tech. Rep. (2021). URL https://www.iea.org/reports/fuel-consumption-of-cars-and-vans.

75. Trujillo, J. Redefining Global Cities. Tech. Rep., Brookings Institution, Washington, DC (2016). URL https://www.brookings.edu/wp-content/uploads/2016/09/metro_20160928_gcitypes.pdf.

76. Liotta, C., Viguié, V. & Lepetit, Q. Is the Monocentric Urban Economic Model Still Empirically Relevant? Assessing Urban Econometric Predictions in 192 Cities on Five Continents. *arXiv:2111.02112 [econ, q-fin]* (2021). ArXiv: 2111.02112.

77. United Nations, Department of Economic and Social Affairs & Population Division. *World urbanization prospects: the 2018 revision* (2019).

78. Tian, S., Guo, B., Sun, J. & Sun, C. Brief Analysis of Urban Passenger Transport Development in China. In *2020 5th International Conference on Electromechanical Control Technology and Transportation (ICECTT)*, 465–468 (2020).

79. Gurney, K. R. *et al.* Greenhouse Gas Emissions from Global Cities Under SSP/RCP Scenarios, 1990 to 2100 (2021). URL https://eartharxiv.org/repository/view/2802/. Publisher: EarthArXiv.

80. World Bank, Ecofys & Vivid Economics. State and Trends of Carbon Pricing 2016 (2016). URL https://openknowledge.worldbank.org/bitstream/handle/10986/25160/9781464810015.pdf?sequence=7&isAllowed=y.

81. OECD. *Rethinking Urban Sprawl: Moving Towards Sustainable Cities* (OECD, 2018). URL https://www.oecd-ilibrary.org/environment/rethinking-urban-sprawl_9789264189881-en.

82. Anguelovski, I., Irazábal-Zurita, C. & Connolly, J. J. T. Grabbed Urban Landscapes: Socio-spatial Tensions in Green Infrastructure Planning in Medellín. *International Journal of Urban and Regional Research* **43**, 133–156 (2019). URL https://onlinelibrary.wiley.com/doi/abs/10.1111/1468-2427.12725. _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/1468-2427.12725.

83. Song, Y. & Zenou, Y. Property tax and urban sprawl: Theory and implications for US cities. *Journal of Urban Economics* **60**, 519–534 (2006). URL https://www.sciencedirect.com/science/article/pii/S0094119006000556.

84. {C40 Cities Climate Leadership Group}. Good Practice Guide: Low Emission Vehicles. Tech. Rep. (2016). URL https://c40-production-images.s3.amazonaws.com/good_practice_briefings/images/7_C40_GPG_LEV.original.pdf?1456788962.

85. Tiezzi, S. & Verde, S. F. Differential demand response to gasoline taxes and gasoline prices in the U.S. *Resource and Energy Economics* **44**, 71–91 (2016). URL https://www.sciencedirect.com/science/article/pii/S0928765516000208.

86. CPLC. Report of the High-Level Commission on Carbon Prices. Tech. Rep. (2017). URL https://static1.squarespace.com/static/54ff9c5ce4b0a53decccfb4c/t/59b7f2409f8dce5316811916/1505227332748/CarbonPricing_FullReport.pdf.

87. Gusdorf, F. & Hallegatte, S. Compact or spread-out cities: Urban planning, taxation, and the vulnerability to transportation shocks. *Energy Policy* **35**, 4826–4838 (2007). URL https://www.sciencedirect.com/science/article/pii/S030142150700167X.

88. Wheaton, W. C. A comparative static analysis of urban spatial structure. *Journal of Economic Theory* **9**, 223–237 (1974). URL https://www.sciencedirect.com/science/article/pii/0022053174900684.

89. Brueckner, J. K. *The Structure of Urban Equilibria: A Unified Treatment of the Muth-Mills Model*, vol. Handbook of Regional and Urban Economics (North Holland, 1987), edwin s. mills edn.

90. Newman, P. W. G. & Kenworthy, J. R. Gasoline Consumption and Cities. *Journal of the American Planning Association* **55**, 24–37 (1989). URL https://doi.org/10.1080/01944368908975398. Publisher: Routledge _eprint: https://doi.org/10.1080/01944368908975398.

91. Creutzig, F. & He, D. Climate change mitigation and co-benefits of feasible transport demand policies in Beijing. *Transportation Research Part D: Transport and Environment* **14**, 120–131 (2009). URL https://linkinghub.elsevier.com/retrieve/pii/S1361920908001478.

Supplementary information

A NEDUM-2D model

A.1 Overview

Our urban model, NEDUM, is based on the Standard Urban Model (SUM) of urban economics[35,63]. The SUM allows in-depth modeling of residential and transportation choices of households as a function of employment center locations, transportation costs, and land-use constraints, which enable the analysis of housing, transport, or land-use policies. This model is easily tractable so that it can be applied to a large number of cities. In addition, it relies on a limited number of inputs and hypotheses, which makes its outputs easily interpretable. Finally, it allows estimating both transportation emissions in cities, from households' housing and transportation choices, and social welfare, from households' consumption of housing, transportation, and other (composite) goods.

Models based on the same framework have been used a large number of times to analyze mitigation and transport policies: to cite a few recent examples, the construction of the Bus Rapid Transit (BRT) system in Bogotá[50], London England's Congestion Charge[51] or an urban growth boundary in Cape Town[52].

The SUM has been shown to capture well the spatial patterns of population density and housing prices in several cities across the world[53,54]. For instance, in Berlin, employment accessibility is a determinant of urban land prices, and the evolution of public transport supply explains the urban sprawl[64,65]. The recent rise of available urban data has allowed testing some predictions of the SUM on large numbers of cities, for instance on urban sprawl in 329 US cities[55], on urban sprawl and urban fragmentation in 282 European cities[56], and on population density and land use in 300 European cities[66]. The SUM can also account for the difference

between city structures (population density, city size, building heights) in rich and poor countries[57].

A.2 Housing demand

In a city composed of I discrete locations indexed i, households' utility is given by

$$U^{health}(z,q) = (z + health)^{1-\beta} q^{\beta} \tag{1}$$

with q the size of the dwellings, R the yearly rent, T the yearly transportation cost to the city center (where we assume for simplicity that all jobs are located), z the consumption of a composite good and $health$ the monetary value of health co-benefits related to transportation. We assume that households do not account for health co-benefits of transportation in their utility maximization as these co-benefits arise from the aggregation of individual behaviors and that they seek to maximize their perceived utility:

$$max \quad U(z,q) = z^{1-\beta} q^{\beta} \qquad\qquad s.t. \quad z + qR + T \leq Y \tag{2}$$

Y notes the yearly income. From equation 2, we find that:

$$\begin{aligned} q_i &= \beta(Y - T_i)/R_i \\ z_i &= (1-\beta)(Y - T_i) \end{aligned} \tag{3}$$

Writing u the uniform utility at equilibrium, we find:

$$R_i = R_0 (1 - \frac{T_i}{Y})^{1/\beta} \qquad with \qquad R_0 = (\frac{(1-\beta)^{(1-\beta)} \beta^{\beta} Y}{u})^{1/\beta} \tag{4}$$

R_0, therefore, represents the rent in the city center.

A.3 Transport mode choice

The city inhabitants choose between 3 modes of transport: car, public transport, and walking. We suppose that at each location i within the city, they choose the transport mode with the lowest generalized cost:

$$T_i = min(t_i^c, t_i^p, t_i^w)$$

with t^c the generalized transportation cost by car, t^p the generalized transportation cost by public transport, and t^w the generalized transportation cost by walking.

These costs take into account the monetary cost of the trip, and the cost associated to travel times. We note D^c the duration of the trip to the city center by car, D^p the duration of the trip to the city center by public transport, and D^w the duration of the trip to the city center by walking. We suppose that D^w is proportional to the distance to the city center by walking, $Dist^w : D^w = Dist^w * walking\_speed$.

We suppose that the monetary cost of walking is equal to 0, and we assume for simplicity that public transport is priced at a flat fare $COST^p$ and that the cost of travel by car is proportional to the trip distance $Dist^c$. More precisely, this cost is equal to $fuel\_conso * fuel\_cost$ where *fuel_conso* is the consumption of fuel and *fuel_cost* the unitary cost of fuel, with *fuel_conso* and *fuel_cost* being constant within cities and varying between cities. If *cost_time* is the monetary cost of time, we have:

$$\begin{aligned} t^c &= D^c * cost\_time + Dist^c * fuel\_conso * fuel\_cost \\ t^p &= D^p * cost\_time + COST^p \\ t^w &= Dist^w / walking\_speed * cost\_time \end{aligned} \tag{5}$$

Due to data availability, in each city, we only consider the city center as the main employment center. The transport times and costs that we consider are therefore the transport times and costs from each location i towards this center (the validity of such an approximation was one of the constraints on the choice of the cities in our sample, see supplementary section C). In each city, the city center was defined by a compromise between five qualitative criteria: the geographical center of the data, the historical center of the cities, the location of the public transport hub, the official central business district, and the city hall location (see supplementary section B).

A.4 Housing supply

Absentee private developers produce housing from capital K and land L with the following production function:

$$H(K, L_i) = \kappa L^{1-b} K^b \tag{6}$$

With k = K/L (capital intensity per land surface) and h = H/L (housing density, i.e. number of m2 built per m2 on the ground), equation 6 can be rewritten:

$$h(k) = \kappa k^b \tag{7}$$

Developers seek to maximize their profit per land surface $\pi = Rh(k) - \rho k$ considering a capital cost (interest rate, for instance) ρ. Thus, housing supply and

population write:

$$H_i = \kappa^{1/(1-b)}(bRi/\rho)^{b/(1-b)}L_i \tag{8}$$

and

$$n_i = H_i/q_i = \kappa^{1/(1-b)}(bRi/\rho)^{b/(1-b)}L_i/q_i \tag{9}$$

with L_i accounting for natural constraints at location i.

We assume that the housing supply adjusts with inertia. First, private developers form their expectations on the equilibrium at t+1: $h^{eq}_{t+1}(i)$ such that $h^{eq}_{t+1}(i) \geq h_t(i) - \frac{h_t(i)}{\theta}$ with θ the depreciation time of buildings, assumed constant within and between cities.

Then, we assume that building takes time. Writing τ the construction time:

$$\begin{aligned} h_{t+1}(i) - h_t(i) &= \frac{h^{eq}_{t+1}(i) - h_t(i)}{\tau} - \frac{h_t(i)}{\theta} \qquad if \qquad h_t(i) < h^{eq}_{t+1}(i) \\ h_{t+1}(i) - h_t(i) &= -\frac{h_t(i)}{\theta} \qquad otherwise \end{aligned} \tag{10}$$

Given the housing supply at t+1, rents and dwelling sizes adjust instantaneously. It is worth noting that, with this setup, there is hysteresis in cities' evolution: increasing housing supply at any location takes less time than decreasing housing supply. This captures the somewhat irreversibility of constructing buildings.

A.5 Outputs of the model: emissions, welfare and health co-benefits

We measure policies' impacts on 2 outcomes: emissions per capita variation compared with the BAU scenario, 15 years after policy implementation, and total social welfare variation compared with the BAU scenario, 15 years after policy implementation.

Aggregated emissions are computed as a function of the number of passenger-km and of the GHG intensity of each transportation mode: $E = \sum(n_i(T = t^c) * Dist^c * E_c) + \sum(n_i(T = t^p) * Dist^p * E_p)$, writing respectively E_c and E_p the emissions per passenger per km by car and by public transport. We assume that E_p is equal to 15 gCO2 / pkm (GHG emissions typically vary between 20 and 300 gCO2/pkm, depending on the transportation mode[67]), and that E_c is proportional to the city's average fuel consumption of cars (data sources can be found in Appendix B), with 1L of gasoline burning approximately 2.3 kg of CO2.

Total social welfare is measured as the sum of individual utilities, given by equation 1. In this equation, z and q are given by the model. The monetary value

of health co-benefits *health* is computed as the sum of 4 components: impacts of air pollution, noise, and car accidents on health, which are negative, and impact of active transportation modes on health, which is positive.

We assume that the monetary equivalent of the impacts of air pollution, noise and car accidents linearly depends on the number of passenger-km for private cars and that the monetary equivalent of the impacts of air pollution also linearly depends on the fuel consumption of private cars. Assuming proportionality to GDP per capita, marginal costs (in euros per passenger-km) are derived from the report *External costs of transport in Europe*[68] and adjusted for each country and to 2015 using GDP per capita growth[69].

For health improvements through active transportation modes, we adapt the HEAT model of the WHO[58], assuming that walking or cycling to work brings reduced mortality, which translates into a monetary gain through VSL (value of statistical life). Mortality and VSL for each country are taken from the parameters of HEAT.

A.6 Calibration and parameters

We calibrate the city-specific parameters β, b, κ, and R_0 for the 120 cities of the final sample using the 2015 data. Denoting R_i, q_i, and n_i the estimated rents, dwellings sizes and densities, $\hat{R}_i$, $\hat{q}_i$, and $\hat{n}_i$ the actual rents, dwellings sizes, and densities from 2015 data, and $\varepsilon_{R,i}$, $\varepsilon_{q,i}$, and $\varepsilon_{n,i}$, the error terms on rents, dwellings sizes, and densities, we have:

$$\begin{aligned} log(\hat{R}_i) &= log(R_i) + log(\varepsilon_{R,i}) \\ log(\hat{q}_i) &= log(q_i) + log(\varepsilon_{q,i}) \\ log(\hat{n}_i) &= log(n_i) + log(\varepsilon_{n,i}) \end{aligned} \tag{11}$$

From equations 3, 4, and 9, we compute $log(R_i)$, $log(q_i)$, and $log(n_i)$ as:

$$\begin{aligned} log(R_i) &= log(R_0) + \tfrac{1}{\beta} log(1 - \tfrac{T_i}{Y}) \\ log(q_i) &= log(\beta) + log(Y - T_i) - log(R_i) \\ log(n_i) &= \tfrac{1}{1-b} log(\kappa) + \tfrac{b}{1-b} log(\tfrac{bR_i}{\rho}) + log(L_i) - log(q_i) \end{aligned} \tag{12}$$

We assume that error terms on densities, rents, and dwelling sizes are idiosyncratic variables whose values follow a normal distribution centered on 0. We proceed by minimizing the sum of the log-likelihoods of $\varepsilon_{n,i}$, $\varepsilon_{R,i}$ and $\varepsilon_{q,i}$, using the scipy.optimize python package, with $[0.1, 0.99]$, $[0.001, 0.95]$, $[0.000001, +\infty)$, and $[0.001, +\infty)$ as boundaries for β, b, κ, and R_0.

As there exists no consistent definition of urban boundaries across countries, we restrict our calibration to the discrete locations i where more than 50% of the area is urbanized according to the data. We carried out a sensitivity analysis, considering the discrete locations i where more than 20% and more than 80% of the area is urbanized, without major changes in the results.

A.7 Validation

First, we checked that the model allows fitting rents and densities data. For each city, we computed the correlation coefficient between simulated densities and densities data and between simulated rents and rent data. Fig S2 shows examples comparing simulated rent and real estate data and simulated densities and densities data, and the distribution of these coefficients is in Table S1 and Figure S1. For densities, the fit between the model and the data is generally good, with a minimum correlation coefficient of 0.31, a median of 0.63 and a maximum of 0.89. For rents, the fit is good for most cities (median of the correlation coefficients of 0.46, maximum of 0.84) but is low for some cities (the correlation coefficient is below 0.32 for 25% of the cities). From Figure S1, the fit between the model and density data is the best for Europe and South America and the lowest for North America, with heterogeneity within continents as well. Liotta et al. (2022)[54] highlights some city characteristics that might explain the low fit of the Standard Urban Model, including polycentricity, informal housing, and local amenities.

	Minimum	Quartile 1	Median	Quartile 3	Maximum	N
Density	0.31	0.56	0.63	0.75	0.89	120
Rent	0.02	0.32	0.46	0.59	0.84	120

Table S1. Densities and rents.
Distribution of the correlation coefficients between data and our estimations of densities and rents in 2015.

Then, we aimed at checking that the model allows estimating the modal shares of cities. We compared the outputs of the model in 2015 with external databases on modal shares: CDP data (`https://data.cdp.net`), Deloitte data[70], EPOMM data (`https://epomm.eu`), or a combination of these three (prioritizing Deloitte and CDP data, and using EPOMM data instead when they are not available).

However, the relevance of the comparison between the external databases and the model outputs is limited for some reasons. First, none of the external databases

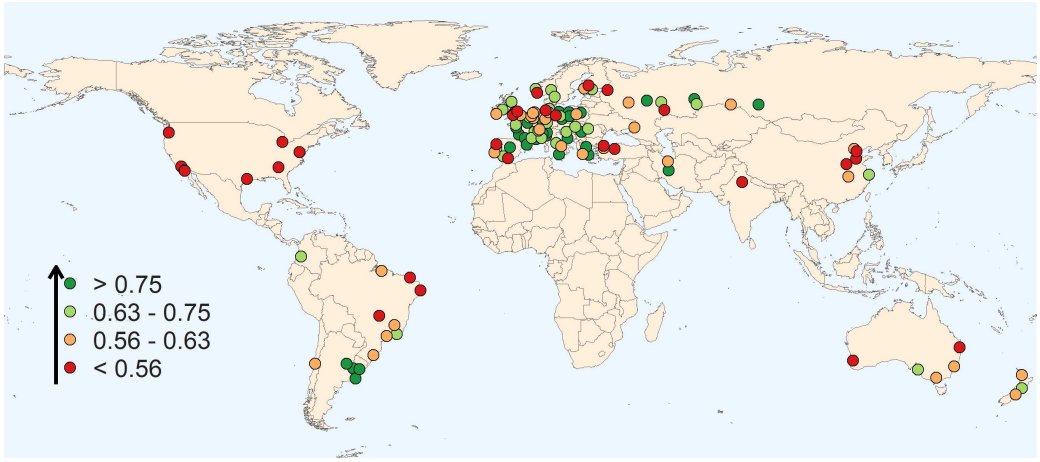
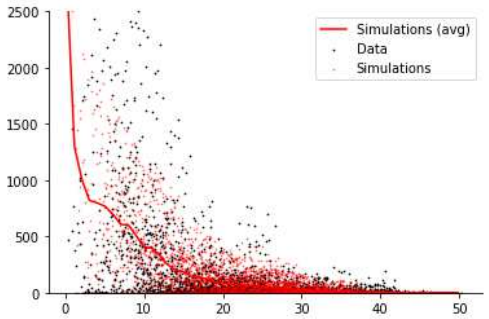


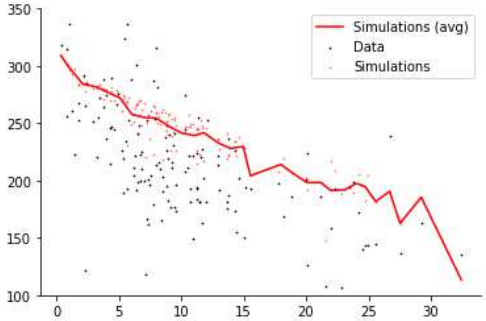
Figure S1. Correlation coefficients between density data and our estimations of densities in 2015.

contains all the cities of our sample: combining the three databases, we have data for only 76 cities out of 120. Second, the CDP and the EPOMM databases are composed of data reported by the cities themselves, and the Deloitte data are composed of the aggregation of a variety of sources (governments' statistical databases, third-party reports, private vendors, nongovernmental organizations, expert judgments), which doesn't guarantee the validity of the comparison between cities. Third, there are some methodological differences between external databases and our model, in particular in terms of urban boundaries definitions. In our model, we adopt a wider delineation of cities than for most cities of the external databases, as external databases often rely on administrative boundaries whereas we consider the whole urban area.

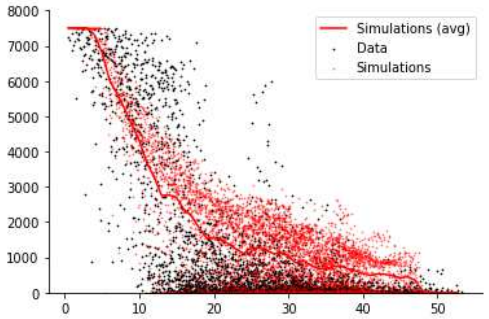
We find a good fit between our model and external databases regarding the modal share of private cars and public transportation (table S2). The coefficient of correlation between the combination of the three external databases and the outputs of the model is 0.35 for private cars and 0.63 for public transport. However, the fit is less good for active modes. An explanation is that, as external databases often have narrower definitions of urban boundaries, usually limited to administrative boundaries, they tend to overestimate the modal share of walking and cycling compared to our model.



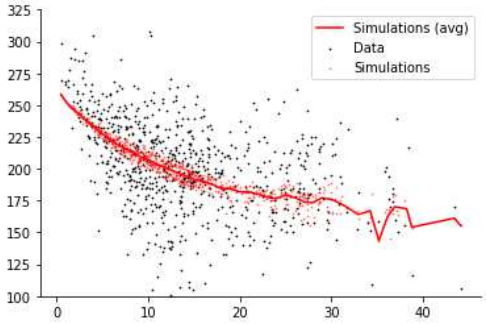
(a) Densities (pers./km2) - Bergen



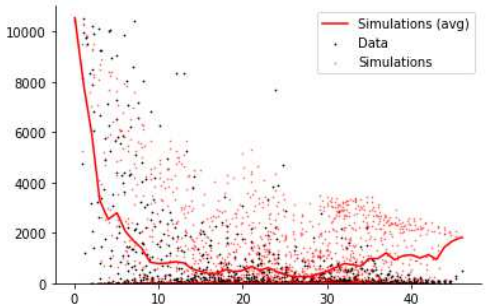
(b) Rents (USD per m2 per year) - Bergen



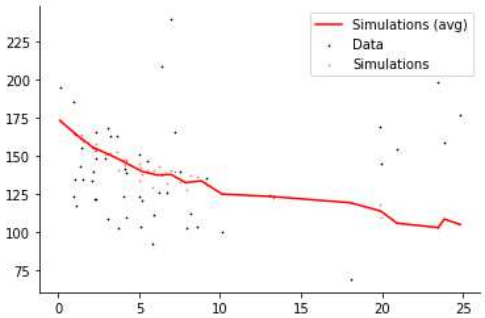
(c) Densities (pers./km2) - Berlin



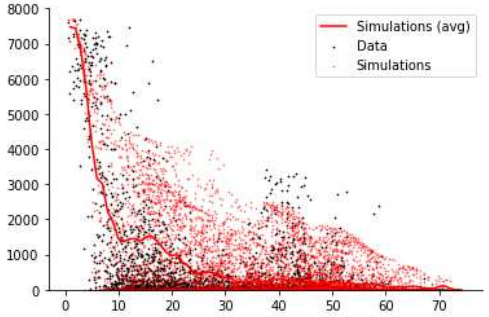
(d) Rents (USD per m2 per year) - Berlin



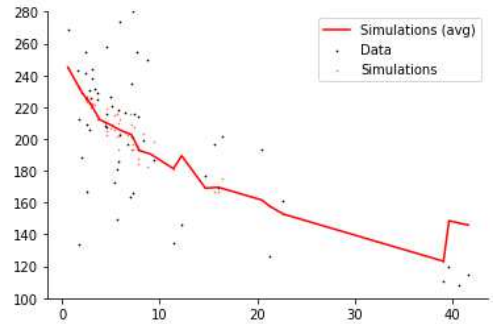
(e) Rents (USD per m2 per year) - Genoa



(f) Rents (USD per m2 per year) - Genoa



(g) Densities (pers./km2) - Yekaterinburg



(h) Rents (USD per m2 per year) - Yekaterinburg

Figure S2. Comparisons between simulated rents and real estate data, and simulated densities and density data, for the cities of Bergen, Berlin, Genoa and Yekaterinburg

	Cars	Public transport	Active modes
Deloitte (N=15)	0.42	0.60**	0.21
CDP (N=29)	0.45**	0.47**	0.17
EPOMM (N=57)	0.33**	0.62***	-0.13
All (N=76)	0.36***	0.63***	0.05

Table S2. Modal shares. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Coefficient of correlation between the modal shares derived from the model for 2015 and external databases.

Finally, we aimed at checking that the model allows estimating urban transportation emissions. We compared the outputs of the model in 2015 with external databases on urban emissions: Moran et al. (2018)[71], Nangini et al. (2019)[72], and Kona et al. (2021)[73]. However, two elements question the relevance of the comparison. First, Moran et al. and Nangini et al. do not report transportation emissions but only total emissions, whereas our estimates are for transport emissions only. Second, the data themselves are not fully consistent: comparing the databases on the cities they have in common, we find a correlation coefficient of 0.41 (p-value of 0.000) between Nangini et al.'s and Moran et al.'s data, a correlation coefficient of 0.16 (p-value of 0.573) between Nangini et al.'s and Kona et al.'s data, and a correlation coefficient of 0.04 (p-value of 0.843) between Moran et al.'s and Kona et al.'s data. Indeed, the methodologies of the three databases differ: Nangini et al. and Kona et al. use a bottom-up approach, with cities reporting their emissions, whereas Moran et al. use a top-down approach, downscaling national or subnational emissions at the city scale; Nangini et al. report Scope 1 emissions, Kona et al. report direct transport emissions and Moran et al. Scope 3 emissions.

Comparing the model's estimations of transportation emissions per capita with external datasets (table S3), we find a correlation coefficient of 0.45 with Nangini et al., of 0.32 with Kona et al., and of 0.53 with Moran et al.

Nangini et al. (2019)	Moran et al. (2018)	Kona et al. (2021)
0.45** (N=24)	0.53*** (N=68)	0.32* (N=38)

Table S3. Emissions per capita. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$
Coefficient of correlation between the transportation emissions per capita derived from the model for 2015 and external databases.

B Data sources

B.1 Spatially-explicit data

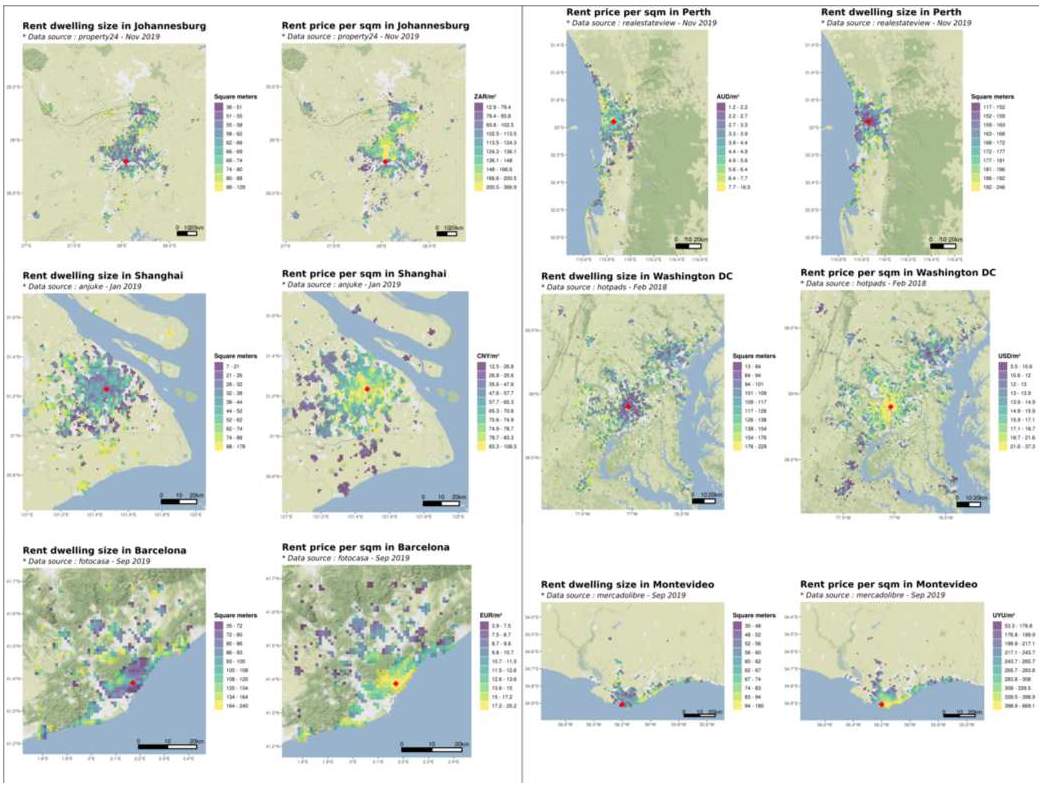
Our main data source is the dataset from Lepetit et al. (2022)[59], which provides spatially explicit data on population densities, rents, dwelling sizes, and transportation costs for 191 cities on 5 continents (see also section C). This dataset allows calibrating the model (parameters β, b, and κ) and thus is essential to our analysis.

For population density, Lepetit et al. used the GHSL data of the European Commission, available for 1975, 1990, 2000, and 2015 at a 250m resolution[60]. For land use, they used the European Space Agency (ESA) land cover data, available worldwide at a 300m spatial resolution on an annual basis from 1992 to 2015[61]. Land cover data are reclassified as "urbanizable" or "with natural constraints" areas.

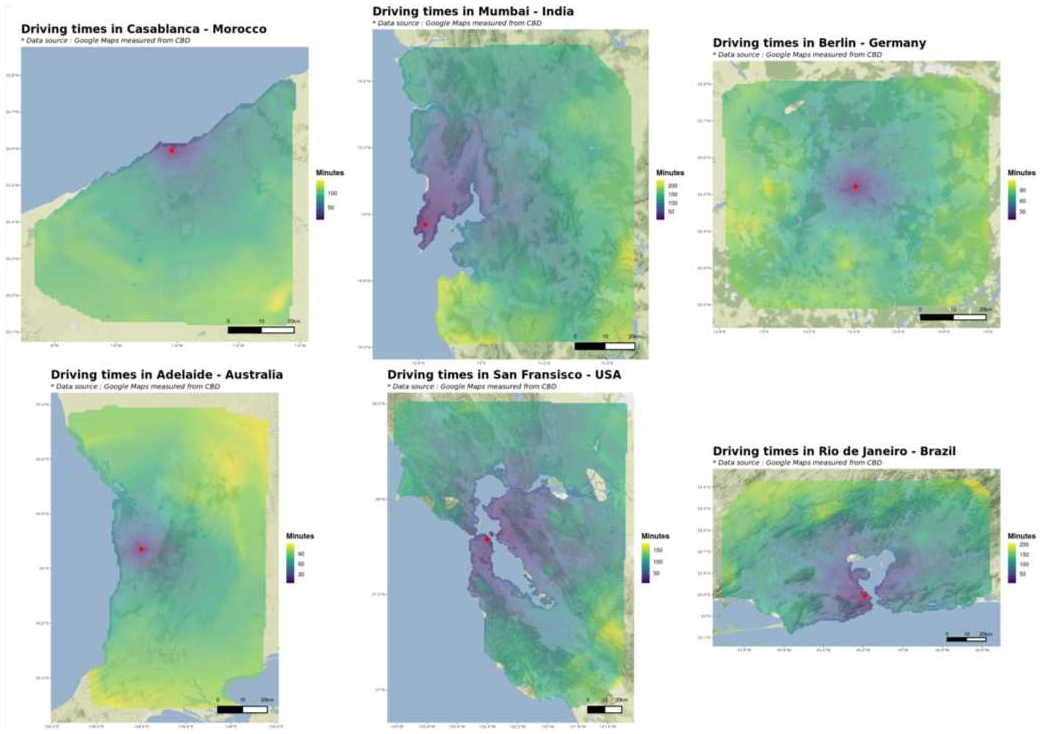
Lepetit et al. obtained real estate data on rents and dwelling sizes from the web scraping of real estate websites from 2017 to 2020. The real estate websites have been selected following four criteria: the website must have nationwide coverage to ensure consistent results in a given country, it must geolocalize the dwellings, have values for both rent or sale prices and dwelling size, and read in local languages and propose prices in local currency to limit real estate ads targeting expatriates.

Finally, the authors collected transport distances and durations to the city center using Google Maps and Baidu Maps APIs (Application Programming Interfaces). Different definitions of city centers exist in the urban economics literature. Most rely on job density data, which are unfortunately not available consistently in the cities of the database. Therefore, the authors defined city centers by a compromise between five qualitative criteria: the geographical center of the data, the historical center of the cities, the location of the public transport hub, the official central business district, and the city hall location. They conducted transport data collection from the centers defined above to each grid cell, and during typical afternoon rush hours. They collected, when available, both driving and public transport data. It was not possible to collect transport data from each grid cell, so they collected data from 10% of all cells and interpolated them.

Population density data, real estate data, transportation data, and land cover data have then been aggregated on 1km2-resolution grids encompassing urban areas. Examples of these grids can be found in Figure S3.



(a) Real estate data



(b) Driving times data

Figure S3. Examples of real estate and transportation data for a few cities

B.2 Other data sources and parameters

We gathered additional data on city characteristics.

Transport Regarding transportation costs, we used World bank data on gasoline prices (https://data.worldbank.org/indicator/EP.PMP.SGAS.CD) and data on average car fuel efficiency per country from the International Energy Agency[74]. We collected data on the fixed monetary cost of public transport (fare for a one-way ticket) from various sources: our preferred source is Numbeo (https://www.numbeo.com/cost-of-living/country_price_rankings?itemId=18), a crowd-sourced global database of quality of life data, and, in case of missing data for some cities, we used two additional sources, kiwi.fr (https://www.kiwi.com/stories/cheapest-and-most-expensive-public-transport-revealed/) and Wordatlas (https://www.worldatlas.com/articles/cost-of-public-transportation-around-
html).

Income For average income per city, we combined three datasets: OECD GDP per capita at the city scale data (https://stats.oecd.org/Index.aspx?DataSetCode=CITIES), Brookings GDP per capita at the city scale data[75], and World Bank GDP per capita at the country scale data (https://data.worldbank.org/indicator/NY.GDP.PCAP.PP.CD).

Population We compute the total population as the sum of densities over the grid.

Agricultural rent We used agricultural rent data from the FAO (https://www.fao.org/faostat/en/#home), dividing agricultural GDP by the total agricultural area in the country.

Other parameters Finally, some parameters are assumed as being constant, both within and between cities. We assume that the cost of time is equal to the hourly wage and that the walking speed is 5 km/h, regardless of, e.g., walkability or weather. We assume that the emissions of public transports are equal to 15 gCO2 / pkm, as GHG emissions typically vary between 20 and 300 gCO2/pkm, depending on the transportation mode[67]. Based on a case study in Paris[36], we consider a uniform time lag for housing construction of 2 years and a depreciation time of buildings of 100 years. One limitation of this study is that we do not account for the fact that buildings' lifetimes vary with cities. However, urban forms might adapt faster to the policies, for instance by becoming denser when a fuel tax is implemented if buildings' lifetimes are shorter.

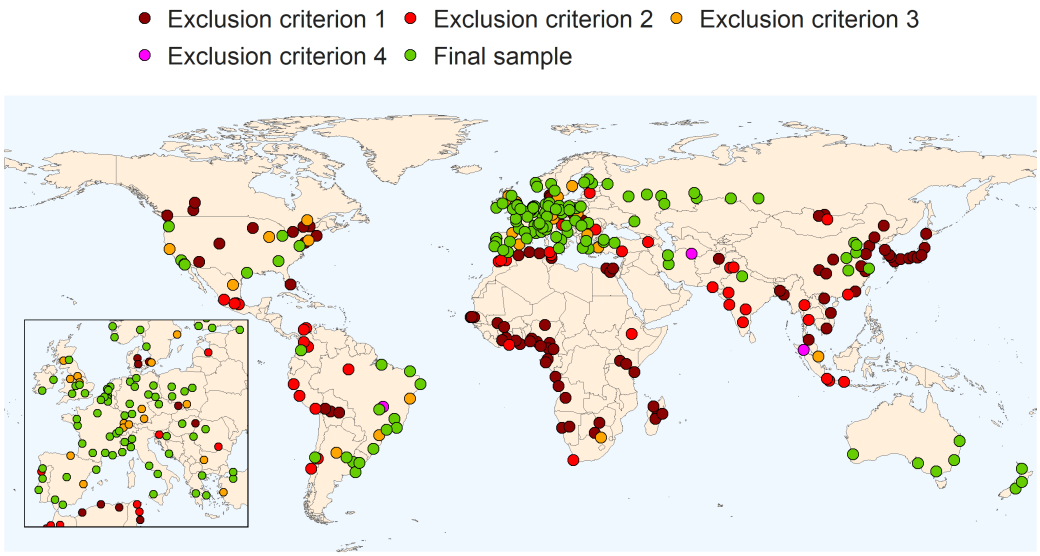


Figure S4. Cities that have been excluded from the analysis and final sample.

C City sample selection

From the initial sample of 281 cities of Lepetit et al. (2022)[59], we have restricted our analysis to 120 cities (figure S4) following a selection process described below (see Table S4).

Lepetit, Liotta and Viguié initially selected a sample of 281 cities following two criteria: cities had to have more than 300 000 inhabitants in 2015 so that the sample contains a large share of the global urban population, and cities had to be on different continents and with different cultural, political, and historical backgrounds, to maximize the heterogeneity between the cities. Among these 281 cities, the authors identified geolocalized real estate data for 191 cities. Such data being needed to calibrate the model, we restricted our sample to these 191 cities.

We also removed from the sample 42 cities in which the real estate data from the database and our income proxy did not appear consistent. More precisely, we removed the cities in which, for more than 80% of the population, the yearly housing budget (computed using average rents and average dwelling sizes from the database) appeared higher than the GDP per capita. An explanation for these discrepancies between income and real estate data is that, as data on average income is often not available at the city level, we used the GDP per capita data at the country level (source: World Bank) as a proxy. Such an approach is likely to underestimate average incomes in cities as incomes are generally higher in big

Initial sample	281 cities	
Exclusion criterion 1: Real estate data availability	-90 cities	Lack of real estate data, mainly in Africa and Asia.
Exclusion criterion 2: Real estate data consistent with income data	-42 cities	Lack of data on income at the city level. Lack of data on informal housing.
Exclusion criterion 3: Transportation data quality	-26 cities	Insufficient quality of the data on public transportation.
Exclusion criterion 4: Reasonable fit of the model	-3 cities	Lack of data on informality, local regulation, and amenities[76].
Final sample	120 cities	

Table S4. Sample selection process.

cities than in the rest of the country. Discrepancies between income data and real estate data might also be due to high levels of informality: informal settlements are not accounted for in our real estate data, while the low-income households living in these informal settlements pull down average income data. Another explanation might be the parents subsidizing their children or relatives, for instance in Asia[1].

In another step, we removed 26 more cities because we found large discrepancies between the modal share of public transport computed by a simple minimization of transport generalized costs across the city, and external data sources (a combination of CDP data (https://data.cdp.net, accessed on 10.1.2022), Deloitte data[70], or EPOMM data if none if the previous two is available). This likely indicates a lack of quality of the data on public transportation (due for instance to the inclusion of only part of the network in Google Maps and Baidu Maps).

Lastly, we removed 3 additional cities (Brasilia, Mashhad, and Medan) in which the model that we use performed poorly. More precisely, the correlation coefficient between the densities simulated by the model and density data was negative, or the correlation coefficient between the rents simulated by the model and rent data was negative. Explanations for these low correlation coefficients may be low data qualities or the fact that the standard framework of urban economics is not valid in cities with high levels of informality, local regulations, or amenities that are not properly accounted for in the model[76].

The final sample includes 120 cities representing 525 million inhabitants, or 13% of the global urban population. Due to the sample selection process largely

[1] https://www.echinacities.com/china-news/Survey-Most-Chinese-Parents-Willing-to-Support-Childre

driven by data availability, the final sample is unbalanced. Europe is overrepresented, with 78 cities. In North America, the USA are also well represented (7 cities) although Canada is absent from the sample. South America (15 cities) and Oceania (8 cities) are also well represented in the sample, whereas South-East Asia and India (with 12 cities in total in Asia) are underrepresented. There is no African city in the final sample. Overall, cities included in the sample are richer and have fewer informal settlements than the cities that are not included in the sample (table S5).

	Cities included (N = 120)	Cities excluded (N = 161)
Average income (mean)	33,529 USD per year	18,574 USD per year
Average income (median)	34,616 USD per year	7,957 USD per year
Share of slums (mean)	4.7%	20.5%
Share of slums (median)	0.0%	16.0%
Gini index (mean)	0.36	0.39
Gini index (median)	0.35	0.39

Table S5. Characteristics of the cities included or not in the sample.

D Baseline scenario

D.1 Data source

The baseline scenario is a business-as-usual (BAU) scenario, assuming the continuation of current trends with no additional city-level mitigation policies. Our population growth scenarios are based on the World Urbanization Prospects of the United Nations[77], which provides population growth projections from 2015 to 2035 for cities with more than 300 000 inhabitants and for national urban populations.

Income per capita growth scenarios are derived from the integrated assessment model (IAM) IMACLIM-R[62]. In particular, the scenario that we retain is a baseline scenario, based on the "middle of the road" SSP2: it is quite standard in the IAM community, and corresponds to a central scenario.

Finally, we assume that there is no change in public transports infrastructures and that the fuel consumption of new private cars decreases by 1.0% per year, in line with current trends for light-duty vehicles[38], assuming a vehicle lifespan of 15 years: it means that, each year, the oldest vehicles (corresponding to 1/15th of

all vehicles) are replaced by new ones, and are assigned the fuel consumption of new vehicles, which decreases by 1.0% per year, while the fuel consumption of the remaining 14/15th of the vehicle fleet remains unchanged. This improvement in the fuel efficiency of private vehicles can also be interpreted as an increase in the share of electric vehicles.

D.2 Description of the scenario

Figure S5 shows the distribution of emissions per capita variations in the cities of the sample between 2015 and 2035 in the BAU scenario. Overall, urban transport emissions per capita tend to decrease, largely because of fuel efficiency improvements, or to moderately increase. For a few cities, the growth in urban transportation emissions per capita is very large. It exceeds +50% for 2 of them, Beijing and Shanghai, which are experiencing large population growths, a fast urban sprawl and development of subcenters in peripheries, an increase in transportation demand, and insufficient, though rapidly developing, public transport[78].

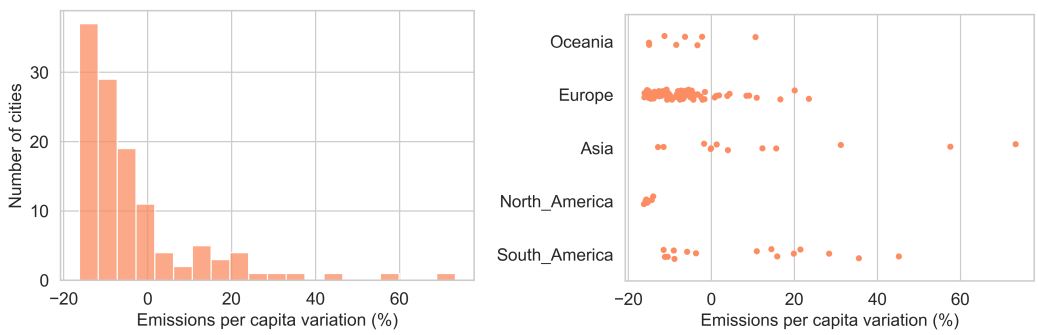


Figure S5. Transportation emissions per capita increase between 2015 and 2035, over the 120 cities of the sample.

The distribution per continent shows that, in North American and Oceanian cities, transportation emissions per capita generally decrease in the BAU scenario, which can be explained by high initial levels. European cities will have decreasing or moderately increasing transportation emissions per capita. South American and Asian cities are highly heterogeneous, with transportation emissions growth up to +45% for South America and +73% for Asia. However, our sample of cities is not representative by continent: we do not have any Canadian cities for North America, and we do not have any Japanese cities for Asia for instance.

These baseline results are in line with the literature. The road transportation sector emissions have grown by about 2% per year since 1970[5]. Urban emissions per capita (non necessarily related to the transportation sector) have increased by 11.8% globally between 2000 and 2015, ranging from -6.5% in developed countries to 71.7% in Asia and developing Pacific[79]. IAMs also provide various projections of non-specifically urban passenger transportation emissions evolution, reviewed in Edelenbosch et al. (2017)[20]: they forecast an increase of total transportation emissions between 2010 and 2050, with a large heterogeneity between IAM, but the result for emissions per capita is not explicitly displayed, preventing direct comparisons with our results.

E Policies simulated

E.1 Overview

To assess the impact of urban transport policies on transportation emissions and inhabitants' welfare in cities, we designed four policy scenarios representative of a wide spectrum of potential policies. These policy scenarios had to be simple enough to be generically applied to a large sample of cities, yet to be representative of existing urban policies. Therefore, we choose 4 policies which are simplified representations of four broad types of city-level transportation mitigation policies (summarized in Table S6):

- Taxes and tolls targeting polluting transportation modes: congestion tolls[51], carbon taxes[80], "flat" taxes proportional to the distance traveled in the city center[81].
- Investments in "cleaner" transportation modes: an increase in public transport speed[50], a decrease in public transport cost (see the example of Vienna, https://www.theguardian.com/world/2019/jul/09/vienna-euro-a-day-public-transport-berlin-365-annual-ticket, accessed March 26, 2021), construction of new public transport infrastructures.
- Land-use policies: Transit-oriented development, policies aiming at limiting urban sprawl (e.g. greenbelts)[82], property taxes[83].
- Technological improvements and regulations: requirement of low-emission vehicles (LEV), mandatory increase in the uptake of LEV[84].

We simulate the evolution of each city between 2015 and 2035, assuming that policies are implemented in 2020.

Policy type	Scenario name	Modeling
-	BAU	No mitigation policy.
Taxes and tolls	Fuel tax	Fuel price increases by 30%.
Investments in "cleaner" transportation modes	BRT	BRT on the main streets of the city.
Land-use policies	UGB	Constructions beyond 2020 area forbidden.
Technological improvements and regulations	Fuel efficiency	Fuel consumption of private car - 3.7% per year.

Table S6. Policy scenarios.

E.2 Taxes and tolls

Description of the policy We accounted for the first category of city-level policies by simulating a fuel tax which increases fuel cost by 30%. This level broadly corresponds to a level of carbon pricing of US \$50–100/tCO2 (for instance, in the United States, between 2007 and 2010, a carbon tax of \$92/tCO2 would have translated into a 30%-increase in gasoline prices[85]) required to be implemented in 2030 to cost-effectively reduce emissions in line with the target of the Paris Agreement to limit global warming to 2°C[37,86], with tax revenues being redistributed uniformly among households.

Impacts on emissions The fuel tax makes car use more expensive, and impacts transportation emissions by inducing a modal shift toward public transport or active modes, and by incentivizing shorter commuting distances.

Impact on welfare The fuel tax increases transportation costs, but tax revenues are redistributed among households, with ambiguous effects on welfare[87]. However, the fuel tax and the modal shift toward clean transport modes it induces have positive impacts on health through reduced air pollution, noise, car accidents, and increased physical activity.

E.3 Investments in "cleaner" transportation modes

Description of the policy For the second category of policies, we simulated a policy that consists in the implementation of a network of Bus Rapid Transit (BRT) on the main streets of the city. The main streets of the city have been identified using OpenStreetMap, and we assume a speed of 40km/h and a capital cost of

12.23 million USD per km that is equally shared by households over 50 years with a 5% interest rate[50].

Impacts on emissions The BRT enriches the available public transportation options and thus can reduce emissions by leading to a modal shift toward public transportation. It is also an incentive to densify housing near the new BRT lines, with an unclear effect on average distances to the city center.

Impact on welfare BRT has ambiguous effects on welfare: it provides households with a new mode of transport, potentially reducing transportation costs, but it is also financed by households in the model, hence decreasing their available income. However, BRT also has positive health impacts through reduced pollution, noise and car accidents.

E.4 Land-use policies

Description of the policy We accounted for the third category of city-level policies in our study by simulating an urban growth boundary (UGB), assuming that the city cannot expand beyond its 2020 limits, i.e. beyond the areas that were urbanized in 2020. Areas are considered "urbanized" if they are qualified as "urban" in ESA 2015 global land cover database, and if population density in 2015 GHSL data is not zero (these databases are presented in supplementary section B).

Impacts on emissions The UGB reduces transportation emissions by largely reducing commuting distances to the city center. As households live closer to the city center, a larger share of the population tend to have access to public transportation, generally decreasing the modal share of private car and reducing transportation emissions.

Impact on welfare By imposing large land-use constraints, the UGB largely increases housing costs, with negative welfare impacts. This is partially mitigated by the decrease in transportation cost, the increase in active mode use, and the decrease in car accidents, exposure to air pollution, and noise due to the decrease in the modal share of private cars.

E.5 Technological improvements and regulations

Description of the policy For the fourth category of policies, we simulate that the fuel efficiency of private vehicles improves faster than in the BAU scenario. More precisely, in the BAU scenario, vehicles have a 15-year life span, and the fuel consumption of the new vehicles that replace old vehicles in the fleet decreases by 1% each year, in line with current trends[38] (see section D). In the fuel efficiency

scenario, we keep assuming that vehicles have a 15-year life span, but we assume that the fuel consumption of the new vehicles decreases by 3.7% each year, in line with the IEA "2°C Scenario"[38]. This improvement in the fuel efficiency of private vehicles can also be interpreted as an increase in the share of electric vehicles.

Impacts on emissions in the simulations For the fuel efficiency policy, emissions reduction is due to the fact that private cars become less polluting, but there is a rebound effect because transportation using private cars is less expensive as cars consume less fuel.

Impact on welfare The large positive welfare impact through reduced transportation costs is partially attenuated by the negative health impact related to the increase in transportation demand by private cars, such as increased noise and car accidents, or reduced physical activity. In addition, the costs of investments in this new technology are not accounted for in the model.

F Impact of city characteristics on the policies consequences

F.1 Methods

To understand which factors influence emissions and welfare variations in cities, we linearly regress them on some cities' characteristics that have been shown to impact urban forms, urban emissions, or policies' efficiency.[9,25,27,41,42].

These characteristics are: urban population in 2015, average income in 2015, agricultural land rent in 2015, modal shift potential (defined as the share of the population that has a public transport option to go to the city center that is less than 40% longer than the private cars' option), population growth rate from 2015 to 2035, income growth rate from 2015 to 2035, total urban area in 2015, a variable controlling for the monocentric urban model's ability to explain the spatial distribution of populations in cities (the share of the variance in population spatial distribution explained by the model in 2015), and length of the BRT network simulated per capita (i.e. length of the primary road network per capita). See supplementary sections B and D for the list of the databases that we used to compute these variables.

Then, as our data on city characteristics suffer from multicollinearity, we perform a Principal Component Regression. The city characteristics on which the Principal Component Analysis is performed are urban population in 2015, average income in 2015, modal shift potential, population growth rate from 2015 to 2035, income growth rate from 2015 to 2035, and density in 2015.

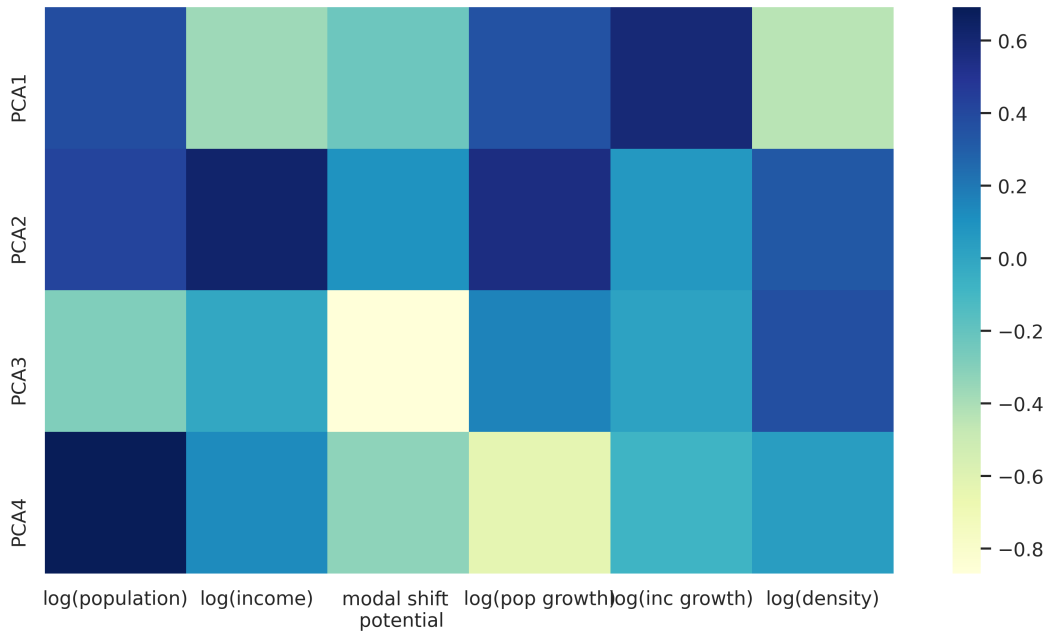


Figure S6. PCA components and features

We use four principal components, displayed in figure S6, and explaining 91% of the variation in the dependent variable. Highly populated and poor cities, with few modal shift potential, rapidly growing in terms of population and income, and spread out, have a high score along principal component 1. Highly populated, rich and dense cities with many public transport have a high score along principal component 2. Small cities with few public transports have a high score along principal component 3. Highly populated cities that are not growing in terms of population have a high score along principal component 4.

F.2 Linear regression - Welfare

The Fuel Tax increases more (or decreases less) inhabitants' welfare in cities with a large modal shift potential: indeed, it means that commuters can, in some cases, switch to public transport instead of paying the full cost of the fuel tax. The fuel tax also tends to improve more (or decrease less) the welfare in cities that are growing in terms of population but not of income. The Fuel Efficiency policy tends to improve welfare more in sprawled and low-income cities where income is slowly growing. The Urban Growth boundary has the largest negative impact on welfare in low-income cities that are growing rapidly in terms of population, but not of

income. Finally, the BRT policy has the largest positive impact on welfare in large and poor cities. Its impact on welfare also depends on the length of the network in a parabolic way: increasing the length of the network starts by increasing welfare, but an inefficiently long network might also be too costly.

	Dependent variable: welfare variation			
	Fuel tax	Fuel efficiency	Urban growth boundary	Bus rapid transit
log(population)	0.119	-0.032	-0.614	**0.271****
	(0.083)	(0.056)	(0.705)	(0.109)
log(income)	-0.262	**-0.519*****	**7.476*****	**-1.016****
	(0.208)	(0.120)	(1.498)	(0.426)
log(farmland rent)	-0.101	**-0.141****	0.144	-0.011
	(0.126)	(0.069)	(0.379)	(0.068)
modal shift potential	**0.532****	-0.115	-2.032	0.550
	(0.241)	(0.104)	(1.750)	(0.422)
log(population growth)	**1.763*****	0.343	**-13.167*****	0.377
	(0.689)	(0.437)	(3.684)	(0.446)
log(income growth)	**-1.430*****	**-0.616***	**9.169****	-0.233
	(0.554)	(0.335)	(4.138)	(0.561)
urban area	4.786e-11	**1.685e-10*****	9.499e-11	-1.056e-10
	(1.1e-10)	(5.79e-11)	(7e-10)	(8.5e-11)
model's performance	-0.040	**-0.306*****	3.786	-0.350
	(0.130)	(0.099)	(2.310)	(0.315)
BRT network / capita				**3.173***
				(1.671)
(BRT network / capita) ^{2}				**-2.510***
				(1.321)
Intercept	1.521	**6.560*****	**-80.611*****	6.468
	(2.254)	(1.306)	(17.277)	(4.494)
Observations	120	120	120	120
R^2	0.247	0.379	0.380	0.236
Adjusted R^2	0.192	0.335	0.336	0.166

Note:
*p<0.1; **p<0.05; ***p<0.01

Table S7. Impact of cities' characteristics on the welfare variation due to the policies, compared with the BAU scenario, 15 years after implementation. *Dependent variable: welfare compared with BAU in 2035. For instance, for the fuel tax policy, welfare tends to increase more when the substitution potential is larger. Non-significant coefficients at the 10% level are not shown here.*

F.3 Linear regression - Emissions

The Fuel Tax allows to largely mitigate transportation GHG emissions in large, poor cities, with a high modal shift potential, in line with previous findings that

demonstrate that the price elasticity of GHG emissions is twice as high in the short run if public transport options exist. The Fuel Efficiency policy is more efficient at mitigating emissions in rich cities with little public transport. The Urban Growth Boundary is more efficient at mitigating emissions in cities with a high farmland rent, i.e. cities that tend to be compact anyway. However, it seems surprising that an urban growth boundary is not more efficient in rapidly growing cities (in terms of population), even though it is more harmful in these cities. An explanation might be that the efficiency of the urban growth boundary does not simply linearly depend on population growth, but on how this population growth translates spatially and on whether it leads to urban sprawl. Finally, the BRT is more efficient in terms of emissions mitigation in large and poor cities.

	Dependent variable: variation in emissions			
	Fuel tax	Fuel efficiency	Urban growth boundary	Bus rapid transit
log(population)	**-0.750***	0.427	-0.556	**-2.387****
	(0.449)	(0.271)	(0.965)	(1.153)
log(income)	**1.902***	**-1.344****	1.525	**7.548****
	(0.997)	(0.558)	(1.789)	(3.354)
log(farmland rent)	**-0.962*****	**0.524*****	**-1.285****	0.044
	(0.322)	(0.188)	(0.564)	(0.687)
modal shift potential	**-7.008*****	**3.969*****	-0.966	-3.896
	(1.033)	(0.593)	(1.872)	(3.706)
log(population growth)	0.610	0.242	-2.215	0.886
	(2.243)	(1.145)	(4.582)	(4.904)
log(income growth)	2.943	-1.786	-2.241	-2.236
	(2.553)	(1.235)	(4.332)	(5.506)
urban area	-2.771e-10	3.913e-10	-4.522e-10	1.401e-09
	(4.49e-10)	(4.24e-10)	(6.89e-10)	(9.21e-10)
model's performance	**-4.213*****	**1.796*****	**-9.503*****	-0.369
	(0.966)	(0.504)	(2.813)	(2.884)
BRT network / capita				**-30.302****
				(13.094)
(BRT network / capita) ^{2}				**24.016****
				(10.651)
Intercept	-13.194	-5.876	-11.275	-40.967
	(10.600)	(7.145)	(19.829)	(36.193)
Observations	120	120	120	120
R^2	0.535	0.534	0.228	0.235
Adjusted R^2	0.501	0.500	0.173	0.165

Note:
*p<0.1; **p<0.05; ***p<0.01

Table S8. Impact of cities' characteristics on the emissions variation due to the policies, compared with the BAU scenario, 15 years after implementation. *Dependent variable: emissions compared with BAU in 2035. For instance, for the fuel tax policy, emissions tend to decrease more when the population is larger and when the city is poorer. Non-significant coefficients at the 10% level are not shown here.*

F.4 PCA - Welfare

Table S10 shows that the fuel tax has the largest negative impact on welfare alongside PC1 and PC3, i.e. for highly populated and poor cities and small cities with little public transport. The fuel efficiency policy tends to increase welfare more in small cities with little public transport. The UGB is more harmful in highly populated, poor, growing, and sprawling cities, and less harmful in highly populated cities that are not growing in terms of population. Finally, the BRT tends to increase welfare in large, poor, and rapidly growing cities with little public transport, and less welfare-increasing in small cities.

	Dependent variable: welfare variation			
	Fuel tax	Fuel efficiency	UGB	BRT
PC1	**-0.058****	0.028	**-0.680****	**0.245****
	(0.024)	(0.023)	(0.330)	(0.098)
PC2	**0.171***	-0.035	**0.706***	-0.178
	(0.087)	(0.049)	(0.373)	(0.113)
PC3	**-0.113****	**0.078****	0.463	**-0.274****
	(0.050)	(0.036)	(0.440)	(0.132)
PC4	-0.080	0.057	**1.367*****	-0.019
	(0.059)	(0.055)	(0.481)	(0.111)
model's performance	0.020	**-0.238****	2.597	-0.045
	(0.125)	(0.102)	(3.000)	(0.343)
BRT network / capita				**3.794***
				(2.028)
(BRT network / capita) ^{2}				**-2.804***
				(1.609)
Intercept	**0.584*****	**0.659*****	**-7.996*****	0.274
	(0.076)	(0.058)	(1.182)	(0.243)
Observations	120	120	120	120
R^2	0.129	0.075	0.216	0.227
Adjusted R^2	0.091	0.034	0.181	0.179

Note:
*p<0.1; **p<0.05; ***p<0.01

Table S9. Impact of cities' characteristics on the welfare variation due to the policies (PCR analysis).
For instance, the fuel tax has a larger negative impact on inhabitants' welfare in cities that perform well along PC1, i.e. large, poor, and growing cities.

F.5 PCA - Emissions

Table S10 shows that the fuel tax mitigates less emissions in highly populated, poor, and sprawling cities, and in small cities with few public transportation. By contrast, the fuel efficiency policy is more efficient in mitigating emissions in these

cities. The UGB is more efficient to reduce emissions in large, poor, growing, and sprawling cities. Finally, the BRT is more efficient in reducing emissions in large, poor, growing, and sprawling cities and less efficient in small cities with little public transport.

	Dependent variable: emission variation			
	Fuel tax	Fuel efficiency	UGB	BRT
PC1	**0.394****	**-0.150*****	**-0.885*****	**-2.414*****
	(0.161)	(0.077)	(0.316)	(0.817)
PC2	-0.104	0.184	-0.250	**1.864****
	(0.219)	(0.126)	(0.428)	(0.881)
PC3	**2.198*****	**-1.198*****	0.631	**2.384****
	(0.287)	(0.171)	(0.555)	(1.137)
PC4	0.048	0.059	-0.116	-0.004
	(0.271)	(0.171)	(0.694)	(0.982)
model's performance	**-4.378*****	**1.959*****	**-9.147*****	-3.108
	(0.917)	(0.465)	(2.544)	(2.419)
BRT network / capita				**-35.917****
				(15.556)
(BRT network / capita) ^{2}				**26.796****
				(13.057)
Intercept	**-3.176*****	**-14.022*****	**-3.706*****	2.286
	(0.381)	(0.196)	(0.837)	(1.759)
Observations	120	120	120	120
R^2	0.491	0.462	0.207	0.262
Adjusted R^2	0.469	0.438	0.172	0.216

Note:
*p<0.1; **p<0.05; ***p<0.01

Table S10. Impact of cities' characteristics on the emission variation due to the policies (PCR analysis).
For instance, the fuel tax is less efficient in mitigating emissions in cities that perform well along PC1, i.e. large, poor, and growing cities.

G Impact of city characteristics on the welfare-effectiveness

G.1 Methods

In this section, we aim at understanding the impact of cities' characteristics on the welfare-effectiveness of the 4 urban mitigation policies in the 120 cities of the sample, compared with the BAU scenario, 15 years after implementation. Welfare-effectiveness is the ratio between relative change in welfare and relative change in emissions under the policies, compared with the BAU scenario. A high welfare-effectiveness (for a policy, in a given city) means that the policy allows to increase

welfare while decreasing emissions by a large amount. A low welfare-effectiveness means that the policy decreases welfare and/or has a small impact on emissions.

Welfare-effectiveness is computed as :

$$\frac{\frac{WELFARE_{p,2035}}{WELFARE_{BAU,2035}}}{\frac{EMISSIONS_{p,2035}}{EMISSIONS_{BAU,2035}}}$$

As in the previous section (see section F.1), we run linearly regress the welfare-effectiveness of the policies on city characteristics, and then perform a Principal Component Analysis.

G.2 Linear regression

The regression of the welfare-effectiveness of policies on city characteristics (Table S11) reveals that modal shift potential is a key variable influencing the welfare-effectiveness of public policies. In particular, a fuel tax is more welfare-efficient in cities where a modal shift is easy, in line with previous findings that demonstrate that the price elasticity of GHG emissions is twice as high in the short run if public transport options exist[42]. The fuel efficiency policy, in contrast, is more efficient in cities where there is little public transportation. Indeed, in these cities, people are constrained to use private cars, and efficient cars translate into cost savings and decrease the emissions of the car-dependent majority.

For the fuel tax, in addition to the modal shift potential, farmland rents, incomes, and urban areas also impact the welfare-effectiveness of the policy. The fuel tax is more welfare-efficient in cities with high farmlands rents, as urban economic theory predicts that these cities will spread out less and spare farmland[88,89]. Higher fuel prices also matter in poor cities as low-income households are more sensitive to changes in transportation prices, and they matter in large cities that typically boost competitive public transportation supported by sufficient ridership density[24].

Farmland rents also impact the fuel efficiency policy's welfare-efficiency. The fuel efficiency policy is more welfare-effective in cities where the farmland rents are lower: an explanation might be that the urban economics theory[88,89] predicts that, everything else being equal, lower farmland rents lead to more spread-out cities, where the modal share of private cars tend to be higher[90].

The UGB policy is more welfare-efficient in cities that are growing in terms of income but not in terms of population. Indeed, urban economics predicts that, everything else being equal, higher incomes will lead to more spread-out cities[88,89]: the UGB might thus have the potential to prevent the city from sprawling too much. Regarding population growth, an explanation might be that, in cities that are

growing too much, the UGB might be too harmful in terms of welfare by leading to very small housing sizes. In these cities, other policies might be more welfare-efficient than a UGB, such as a transit-oriented development policy allowing the city to keep sprawling while shaping it to increase its density and reduce the modal share of private cars.

Finally, the BRT policy is more welfare-efficient in low-income cities, probably because low-income households are more likely to use it as its monetary cost is often lower than the monetary cost of commuting by private cars. Its welfare-efficiency also depends on the length of the network implemented in a parabolic way: increasing the length of the network starts by increasing the welfare-efficiency of the policy, but a network that is inefficiently long might be also too costly. However, BRT and other expansions of public transit are predicted to be a fitting complement for rising fuel taxes or congestion charges, reducing the opportunity costs of car drivers choosing to restrain from driving[91], an issue to model in further studies.

The variable controlling for the model's ability to explain the spatial distribution of populations in cities has an ambivalent status. It can be seen as a control variable of the quality of the model, or as a variable indicating whether structures of cities can be explained by the monocentric Standard Urban Model (SUM), i.e. whether the city is monocentric and whether inhabitants' locational and modal choices are based on transportation costs to the city center and land-use constraints. For instance, the fuel efficiency policy is more welfare-efficient in North American cities, where the SUM has little explanatory power as cities are sprawled.

Cities' characteristics appear alone insufficient to explain policies' welfare-effectiveness, as more than 50% remains unexplained. A spatial model that explicitly accounts for cities' spatial characteristics and the interplay between them is needed to properly capture the impacts of the policies on welfare and emissions.

	Dependent variable: welfare-effectiveness			
	Fuel tax	Fuel efficiency	Urban growth boundary	Bus rapid transit
log(population)	**0.010***	-0.006	2.024e-05	0.032
	(0.006)	(0.004)	(0.016)	(0.020)
log(income)	**-0.025****	0.011	**0.067****	**-0.166***
	(0.013)	(0.008)	(0.028)	(0.089)
log(farmland rent)	**0.010****	**-0.008*****	**0.016***	0.001
	(0.005)	(0.003)	(0.009)	(0.013)
modal shift potential	**0.086*****	**-0.053*****	-0.009	0.110
	(0.014)	(0.008)	(0.034)	(0.087)
log(population growth)	0.012	0.000	**-0.118***	-0.006
	(0.030)	(0.017)	(0.071)	(0.087)
log(income growth)	-0.052	0.015	0.125	0.044
	(0.034)	(0.017)	(0.077)	(0.101)
urban area	3.641e-12	-2.883e-12	4.977e-12	-1.757e-11
	(6.19e-12)	(5.69e-12)	(1.31e-11)	(1.67e-11)
model's performance	**0.046*****	**-0.028*****	**0.150*****	-0.045
	(0.012)	(0.007)	(0.054)	(0.068)
BRT network / capita				**0.623***
				(0.360)
(BRT network / capita) ^{2}				**-0.483***
				(0.277)
Intercept	**1.169*****	**1.137*****	0.215	**2.170****
	(0.137)	(0.098)	(0.330)	(0.955)
Observations	120	120	120	120
R^2	0.491	0.533	0.261	0.186
Adjusted R^2	0.454	0.499	0.208	0.111

Note:
*p<0.1; **p<0.05; ***p<0.01

Table S11. Impact of cities' characteristics on the welfare-effectiveness of the 4 urban mitigation policies.
Lecture: A fuel tax is more welfare-effective in cities with a high modal shift potential, meaning that it can reduce emissions while maintaining a high level of welfare in these cities.

G.3 PCA Analysis

	Dependent variable: welfare-effectiveness			
	Fuel tax	Fuel efficiency	UGB	BRT
PC1	**-0.005*****	0.002	0.001	**0.043****
	(0.002)	(0.001)	(0.006)	(0.019)
PC2	0.004	0.002	0.015	**-0.040***
	(0.003)	(0.005)	(0.009)	(0.024)
PC3	**-0.027*****	**0.019*****	-0.003	**-0.050***
	(0.004)	(0.003)	(0.012)	(0.027)
PC4	9.712e-05	0.001	**0.030***	-0.011
	(0.004)	(0.004)	(0.017)	(0.022)
model's performance	**0.049*****	**-0.031*****	**0.127***	0.007
	(0.012)	(0.009)	(0.065)	(0.065)
BRT network / capita				0.742*
				(0.433)
(BRT network / capita) ^{2}				-0.544
				(0.333)
Intercept	**1.038*****	**1.176*****	**0.964*****	**0.944*****
	(0.005)	(0.005)	(0.024)	(0.048)
Observations	120	120	120	120
R^2	0.440	0.240	0.173	0.205
Adjusted R^2	0.415	0.207	0.137	0.155

Note:
*p<0.1; **p<0.05; ***p<0.01

Table S12. Impact of cities' characteristics on the welfare-effectiveness of policies (PCR analysis).
For instance, the fuel tax is less welfare-effective in cities that perform well along PC1, i.e. large, poor, and growing cities.

Then, we perform a Principal Component Regression (table S12), following the components described in section F.1. The fuel tax is less welfare-effective for big, poor, spread out and developing cities with few public transports and for small cities with few public transports. The fuel efficiency policy is more welfare-effective for small cities with few public transport. The UGB is more welfare-effective for big cities that are not growing in terms of population. Finally, the BRT is more welfare-effective for big, poor, spread out and developing cities.

H Supplementary graphs

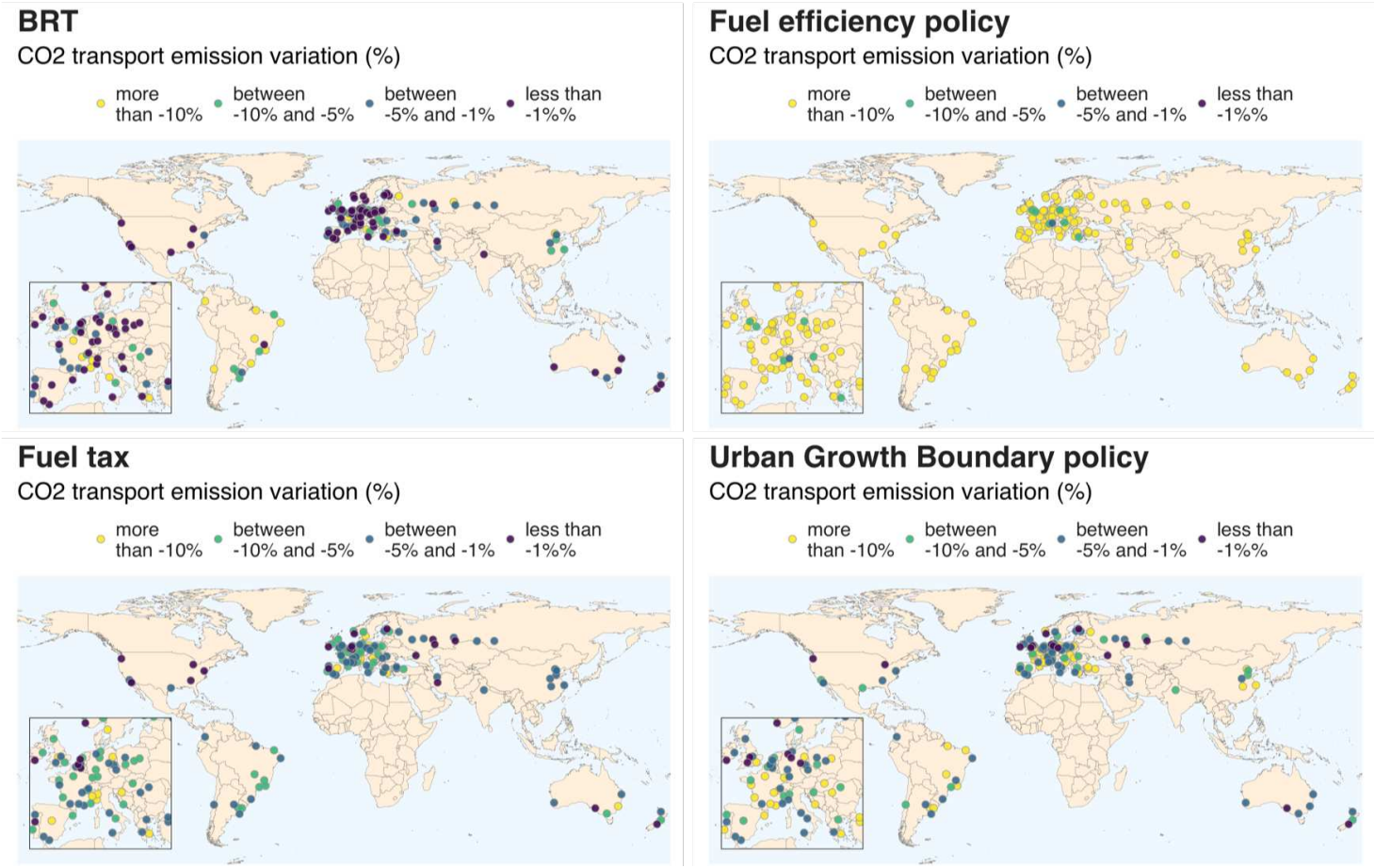


Figure S7. Emission variations in each city, in 2035, compared to the business as usual scenario, for each policy considered separately. These maps appear also in figure 3.

Policy's have heterogeneous impacts with cities. The BRT achieves the largest emissions mitigation in South America, while the fuel tax has the largest impact in Europe and SoUth America. By contrast, the fuel efficiency policy has a similar impact in most of the cities, except for Europe where the emissions mitigation is of a lower magnitude. Finally, the urban growth boundary allows to achieve large emissions mitigation in some cities in South America, Europe and China.

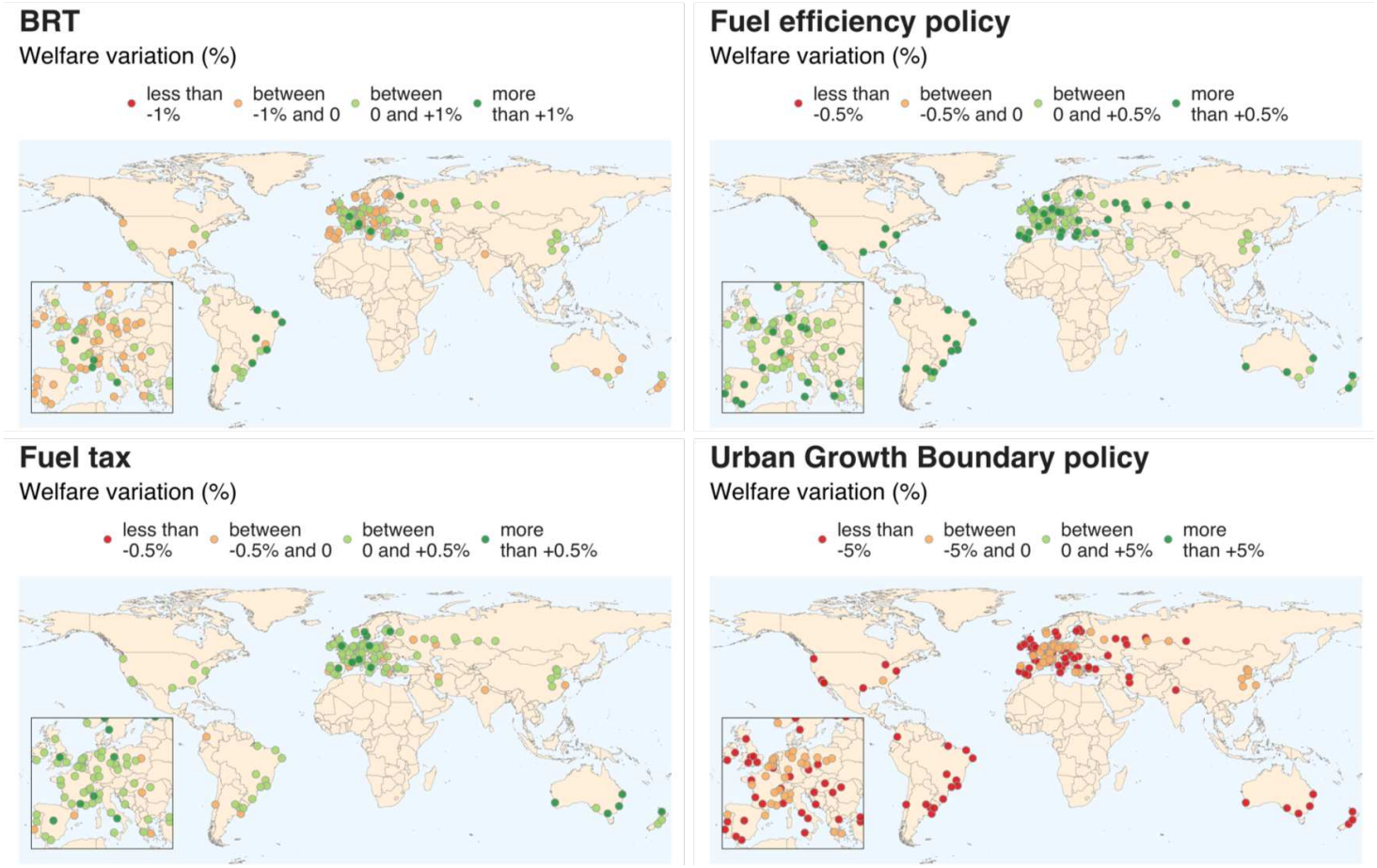


Figure S8. Welfare variations in each city, in 2035, compared to the business as usual scenario, for each policy considered separately. These maps appear also in figure 3.

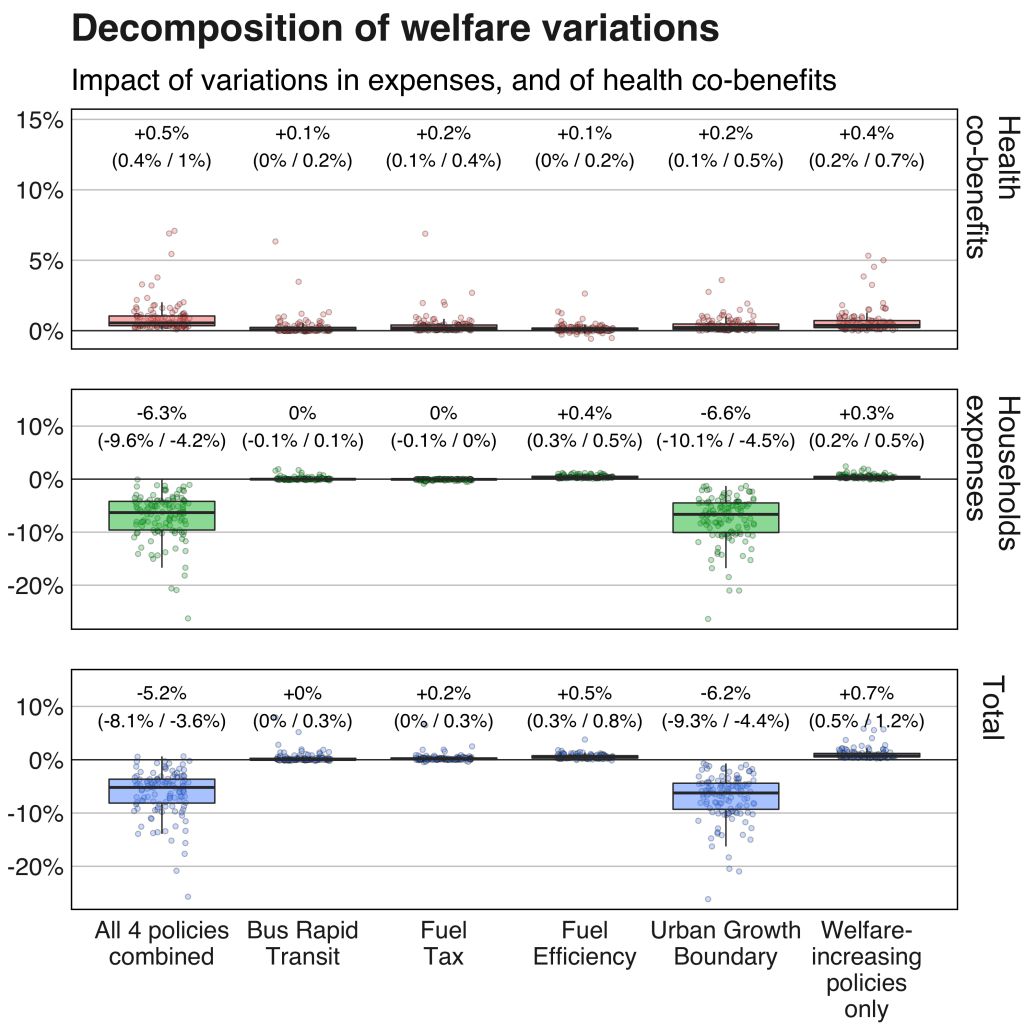


Figure S9. Decomposition of welfare variations between variations in households expenses and income, and variations in monetized health co-benefits. The number above the box plots represent the median, and in brackets, the 25th and the 75th quartiles.

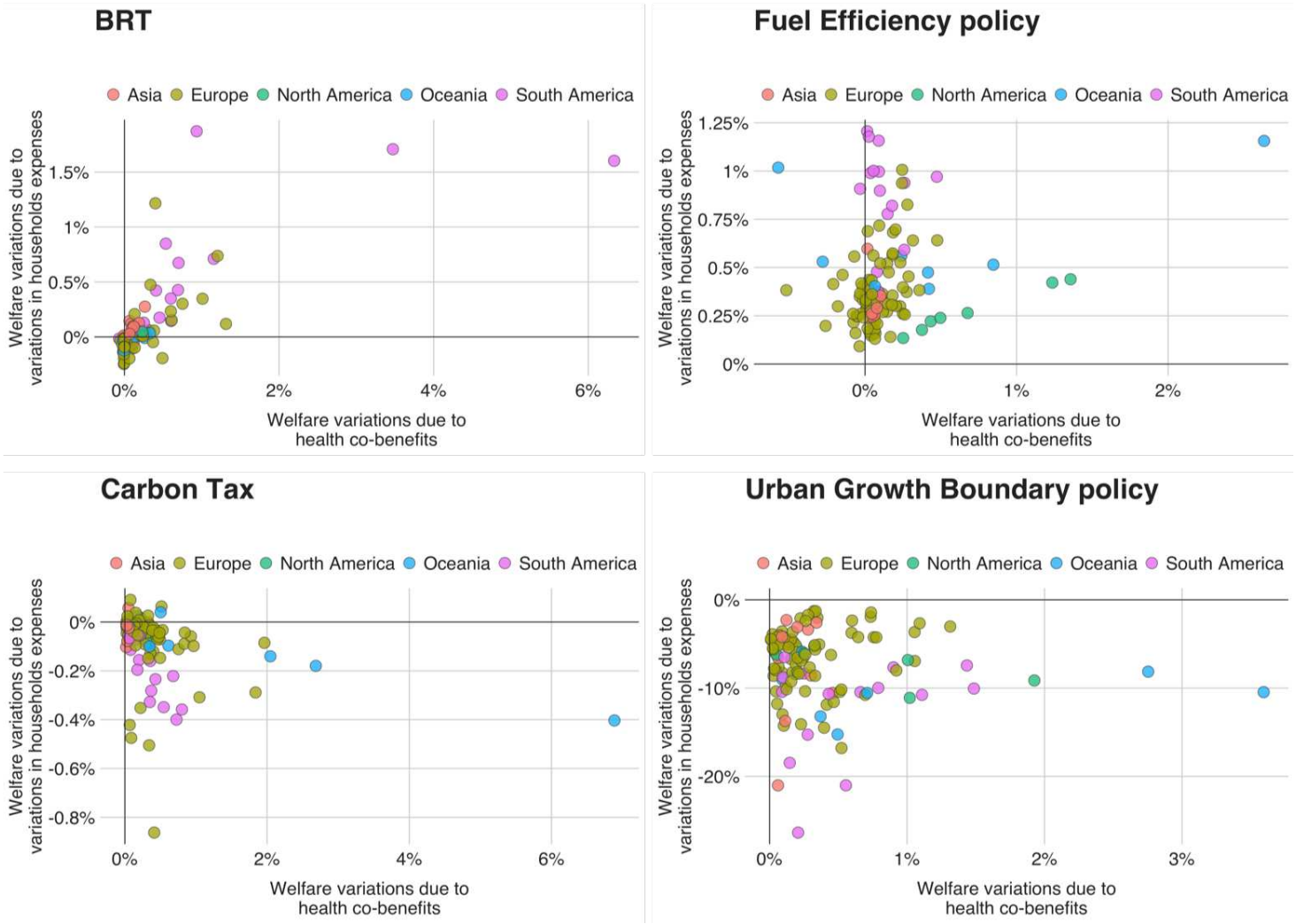


Figure S10. Decomposition of welfare variations: variations in households expenses and income as a function of variations in monetized health co-benefits.

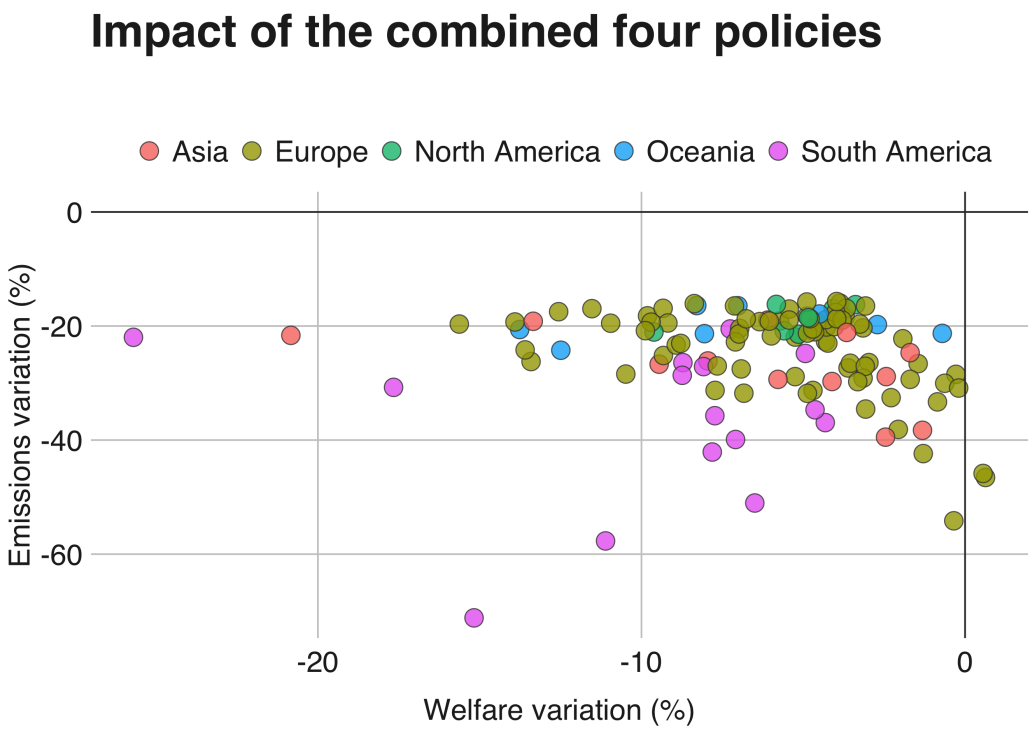


Figure S11. Emission and welfare variations in each city, in 2035, compared to the business as usual scenario.

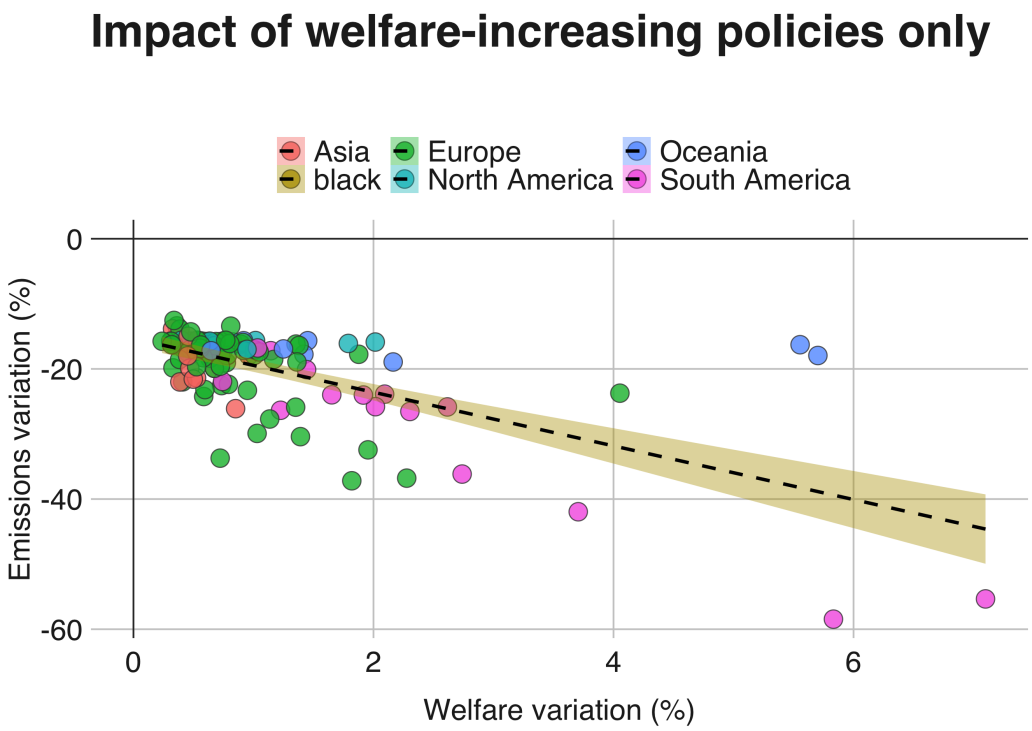


Figure S12. Emission reductions as a function of variations in welfare in all cities, when applying in each city welfare-increasing policies only. The dotted line represents the regression line. Welfare increases are significantly associated to emission decreases (p-value lower than 0.1%).

Figure S13. Emission and welfare variations in each city, in 2035, compared to the business as usual scenario, for each policy considered separately.

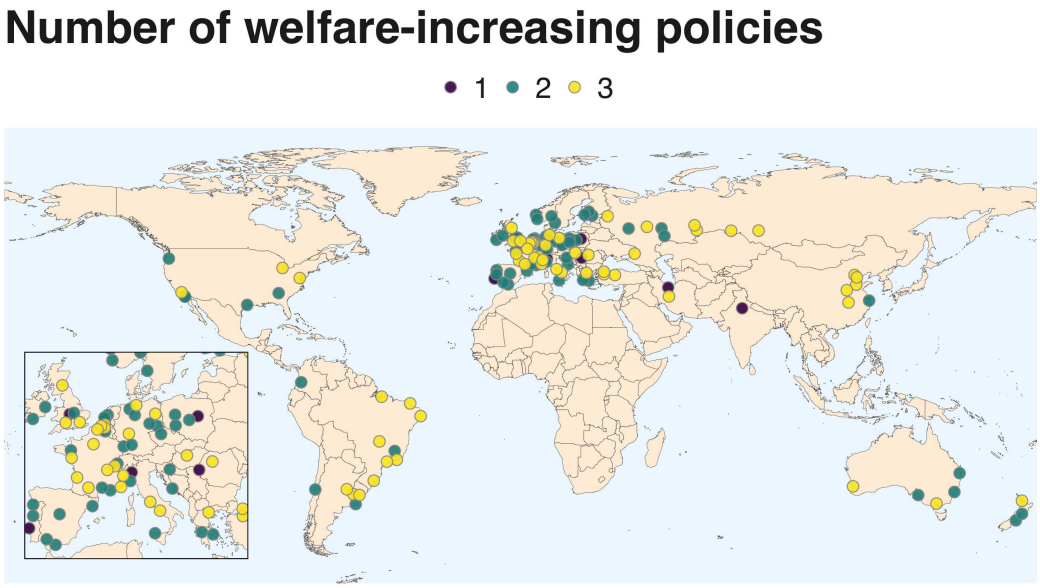


Figure S14. Number of policies which increase welfare, among the four policies that we simulate.

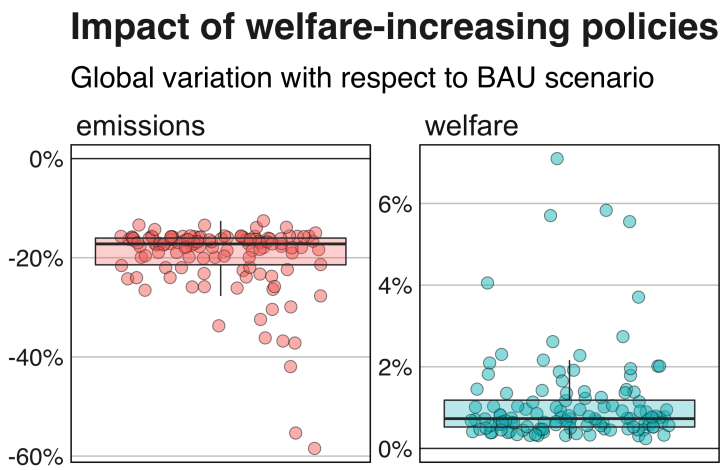


Figure S15. Impacts, in each city, of the only policies which increase welfare. The box plot represents the median, the 25th and the 75th percentile of each indicator. The emission decrease is typically between 16.0% and 21.4% (interquartile range, median is 17.2%), and the welfare increase between 0.53% and 1.18% (interquartile range, median is 0 0.73%).

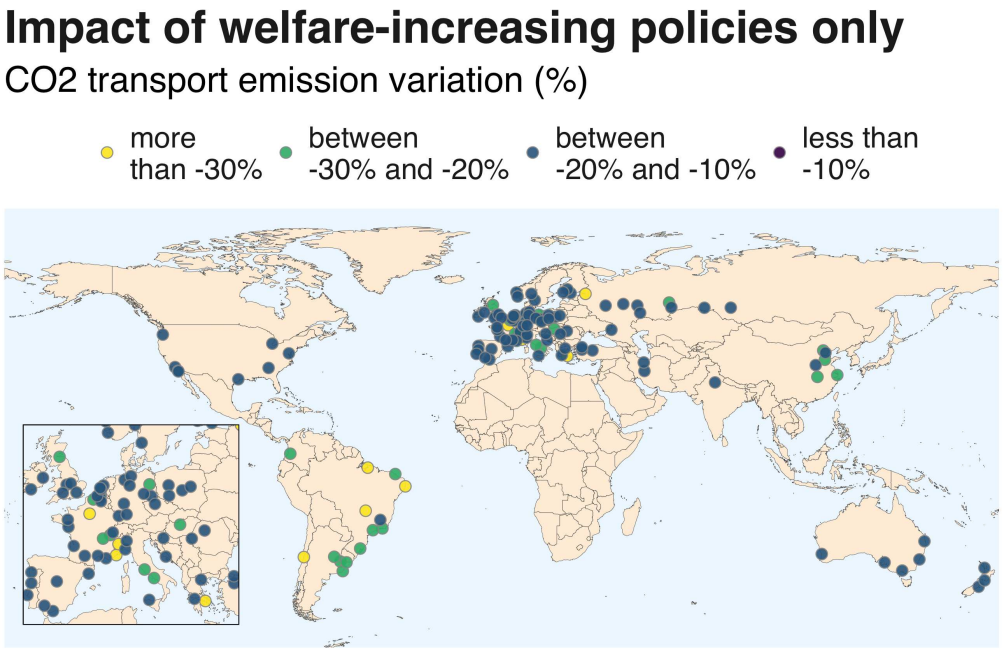


Figure S16. Impact on emissions of the policies which increase welfare, among the four policies that we simulate.

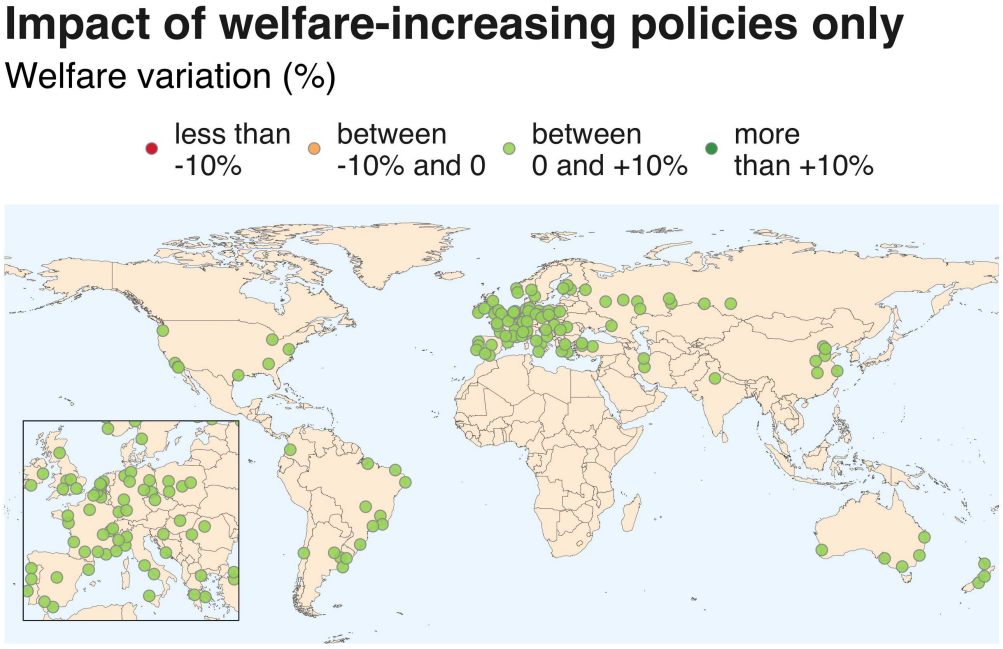


Figure S17. Impact on welfare of the policies which increase welfare, among the four policies that we simulate.

I Robustness checks

As a robustness check, we implement a slightly different version of each policy and check that the results are qualitatively the same. For the fuel price and the fuel efficiency policies, we change the parameters: for the fuel tax, we assume that fuel prices increase by 10% in 2020, and for the fuel efficiency policy, we assume that the fuel consumption of new private vehicles decreases by 2% per year starting in 2020. For the BRT policy, we assume that 2 new public transport lines (North-South and East-West) are built in each city, abstracting from the street network. Finally, for the UGB, we assume that constructions beyond the areas that have a density lower than 400 inhabitants per km2 in 2020 are forbidden.

Policy	Modeling
BAU	No mitigation policy.
Fuel tax	Fuel price increases by 10%.
Fuel efficiency	Fuel consumption of private car - 2% per year.
BRT	2 new public transport lines (North-South and East-West), speed of 25km/h.
UGB	Constructions beyond 2020 area with a density lower than 400 inhabitants per km2 forbidden.

Table S13. Policy scenarios considered in this robustness check.

Here are the results:

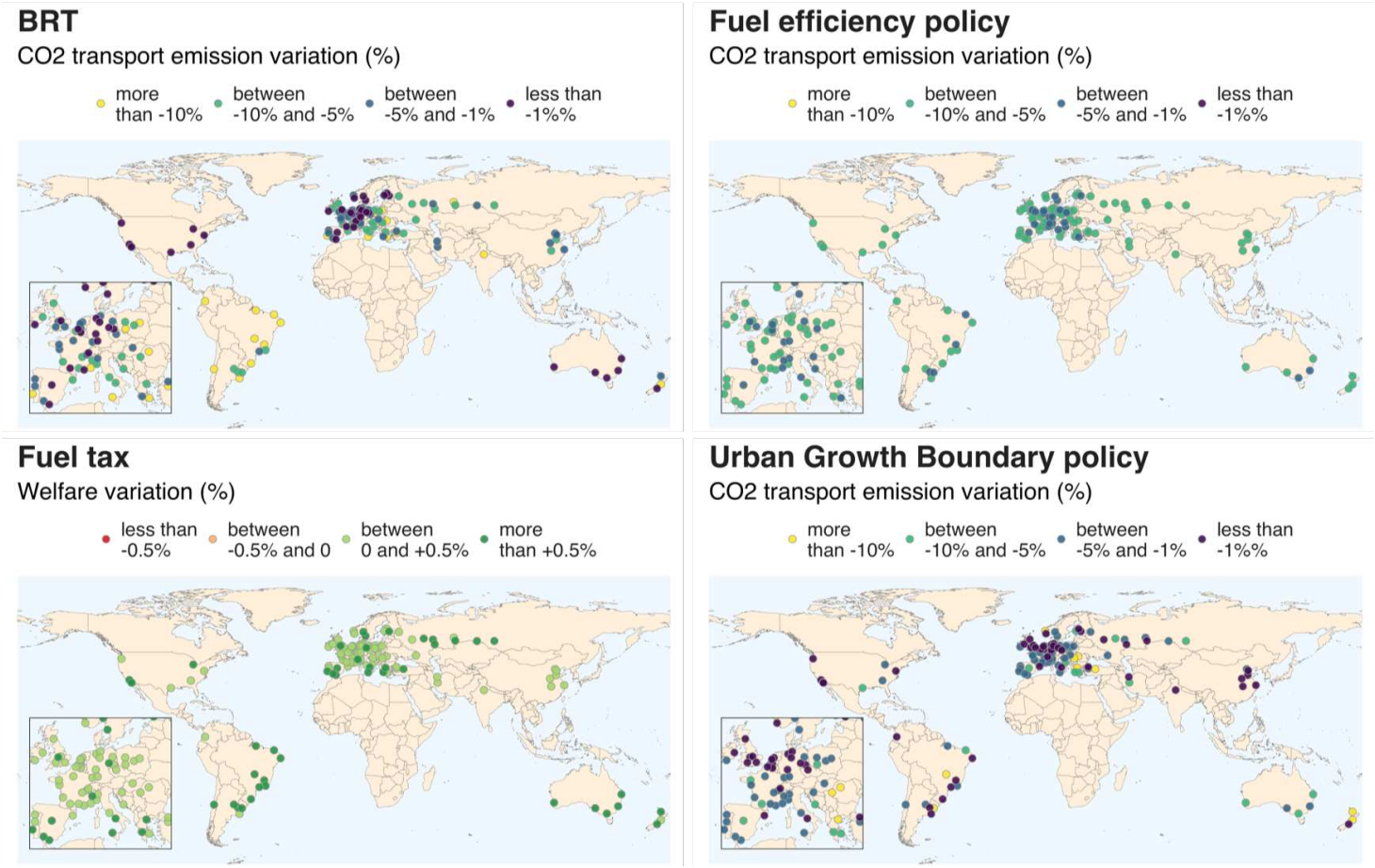


Figure S18. Emission variations in each city, in 2035, compared to the business as usual scenario, for each policy considered separately.[robustnesss check]

Policy's have heterogeneous impacts with cities. The BRT achieves the largest emissions mitigation in South America, while the fuel tax has the largest impact in Europe and SoUth America. By contrast, the fuel efficiency policy has a similar impact in most of the cities, except for Europe where the emissions mitigation is of a lower magnitude. Finally, the urban growth boundary allows to achieve large emissions mitigation in some cities in South America, Europe and China.[robustness check]

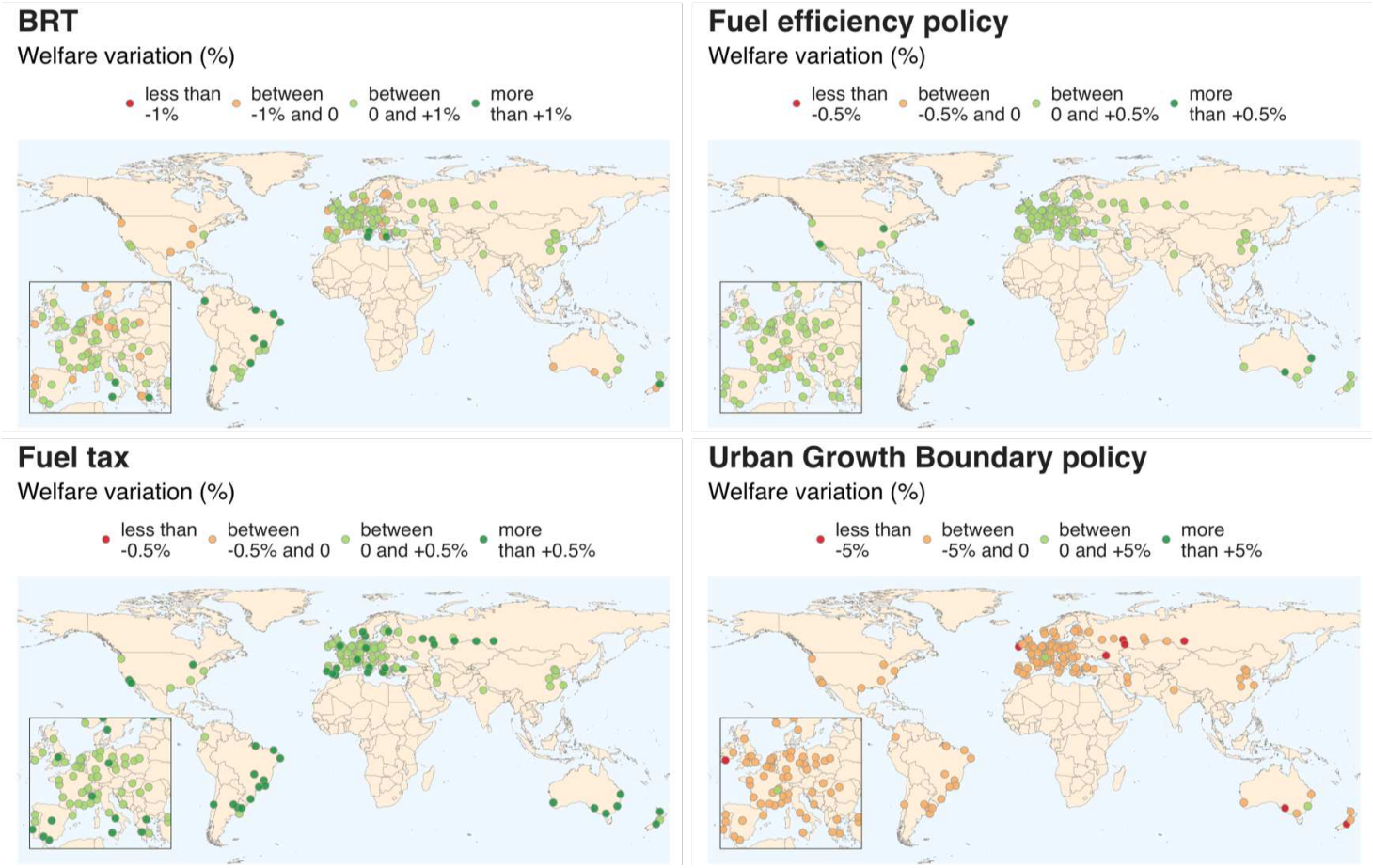


Figure S19. Welfare variations in each city, in 2035, compared to the business as usual scenario, for each policy considered separately.[robustness check]

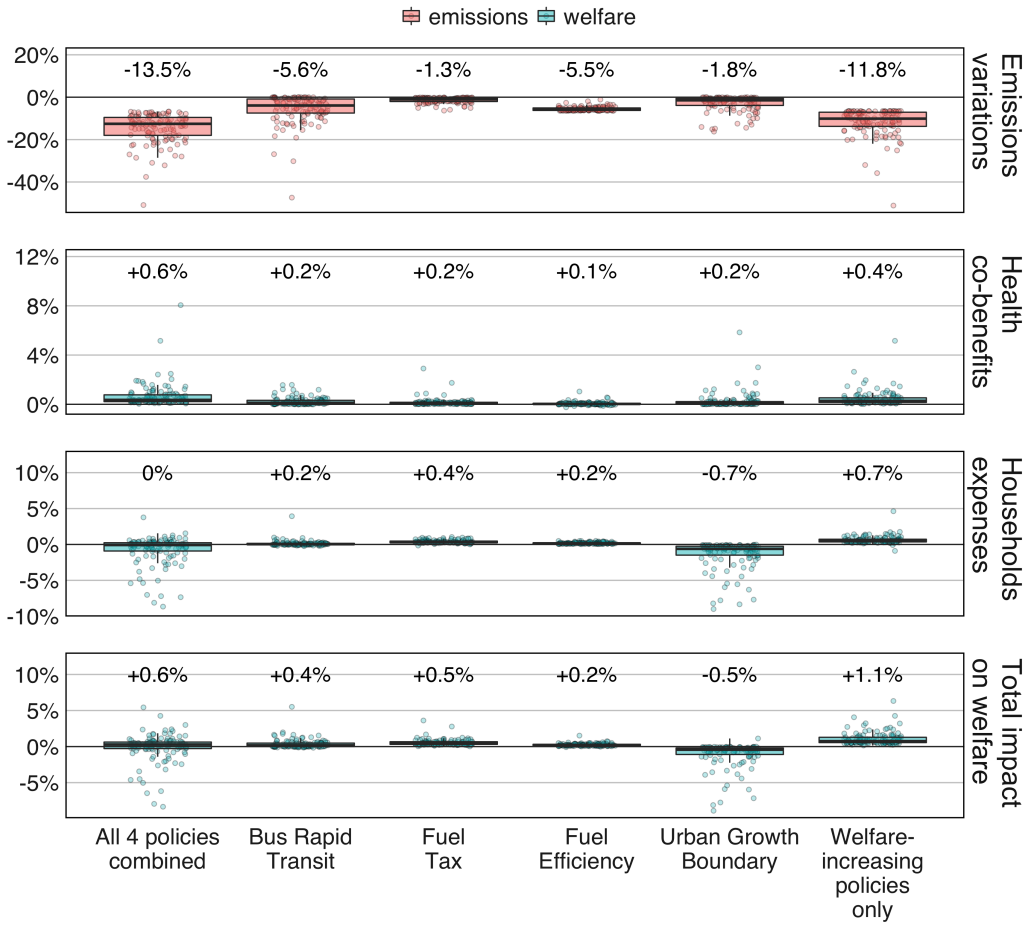


Figure S20. Impact of the four policies on annual transport emissions and average welfare in the 120 cities, in 2035, compared with the business-as-usual scenario. Each dot represents a city. The numbers above the box plots represent the aggregated mean of the changes, when taking into account cities population sizes. [robustness check]

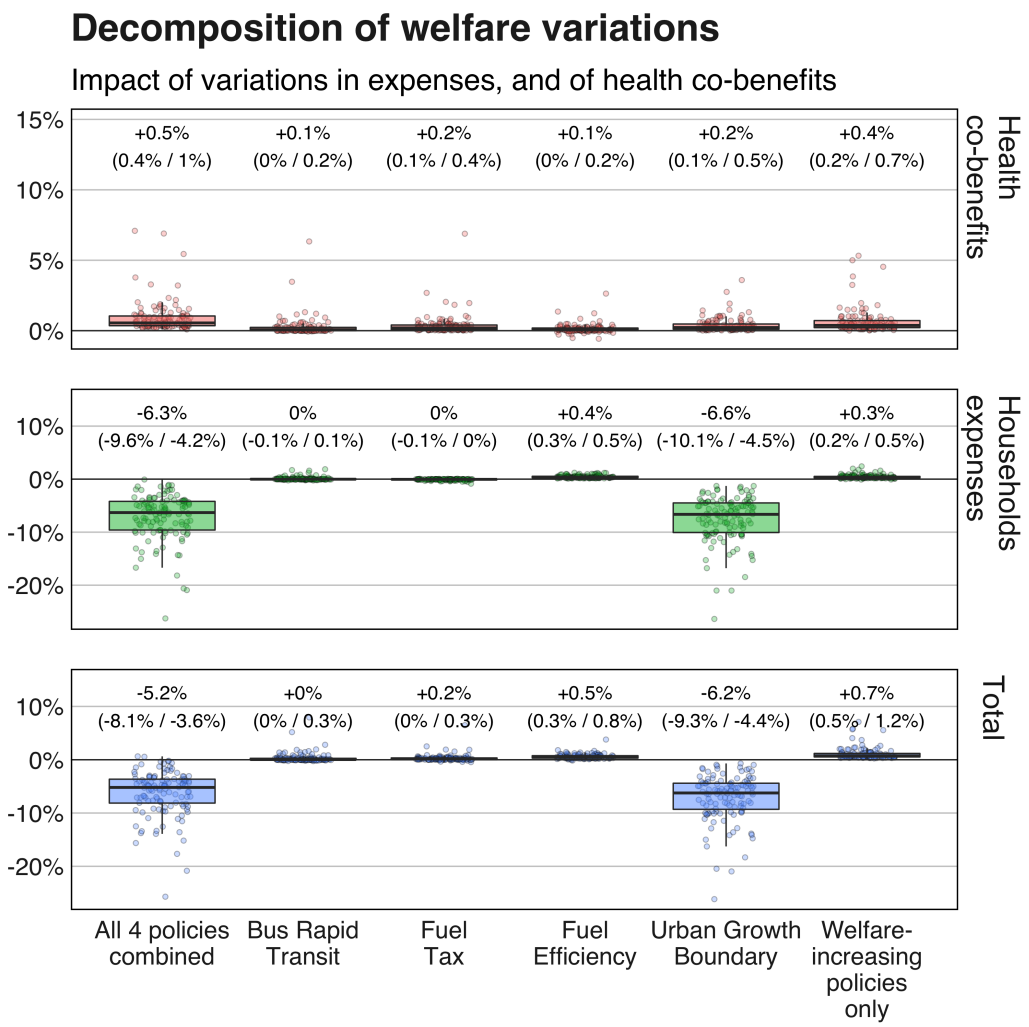


Figure S21. Decomposition of welfare variations between variations in households expenses and income, and variations in monetized health co-benefits. The number above the box plots represent the median, and in brackets, the 25th and the 75th quartiles.[robustness check]

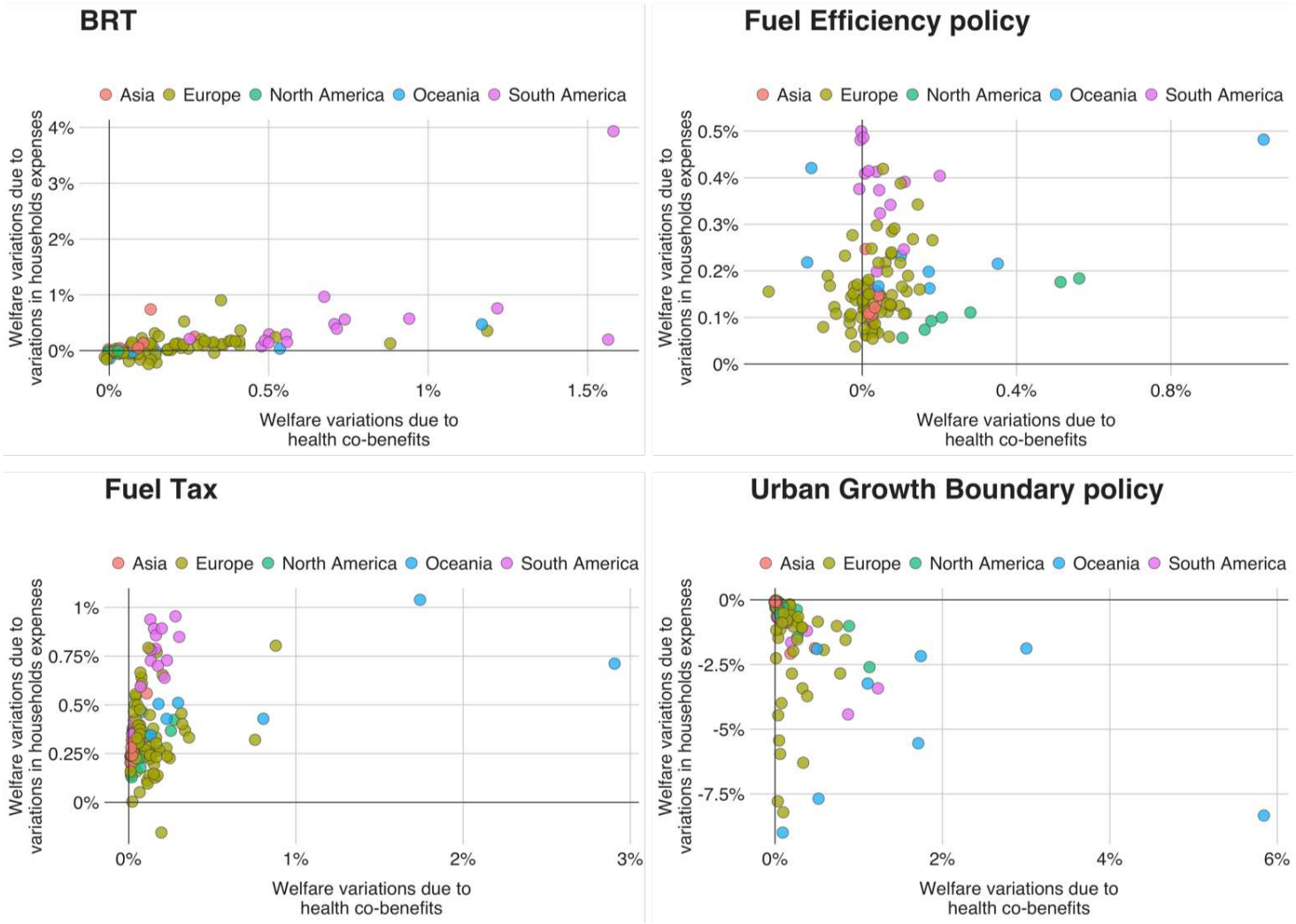


Figure S22. Decomposition of welfare variations: variations in households expenses and income as a function of variations in monetized health co-benefits.[robustness check]

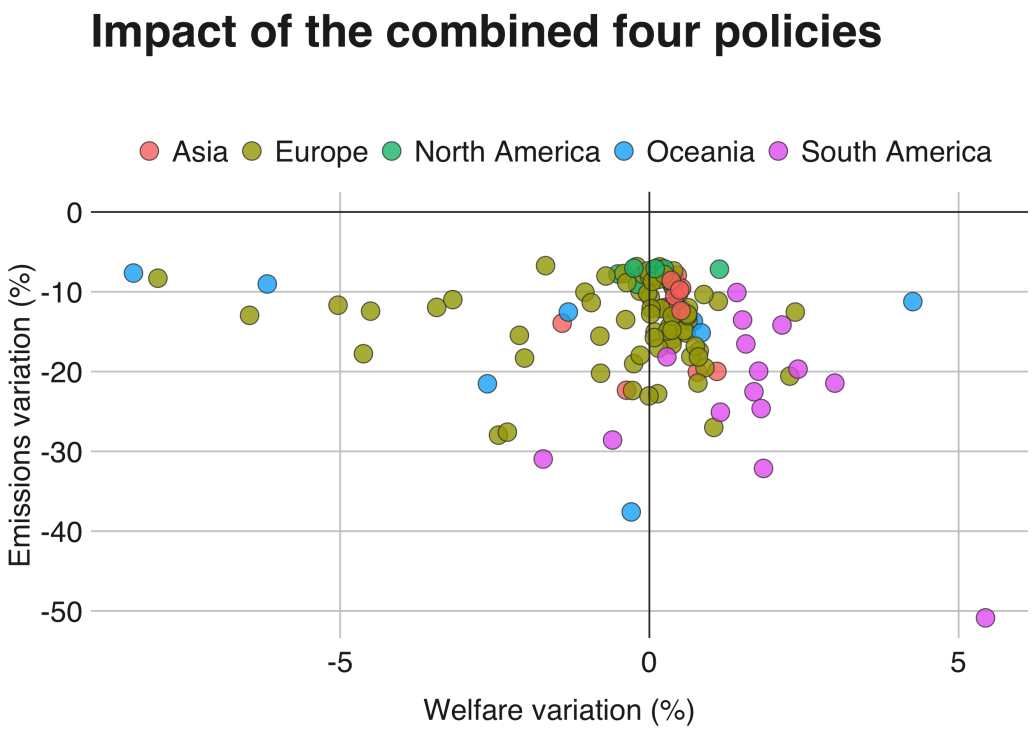


Figure S23. Emission and welfare variations in each city, in 2035, compared to the business as usual scenario. [robustness check]

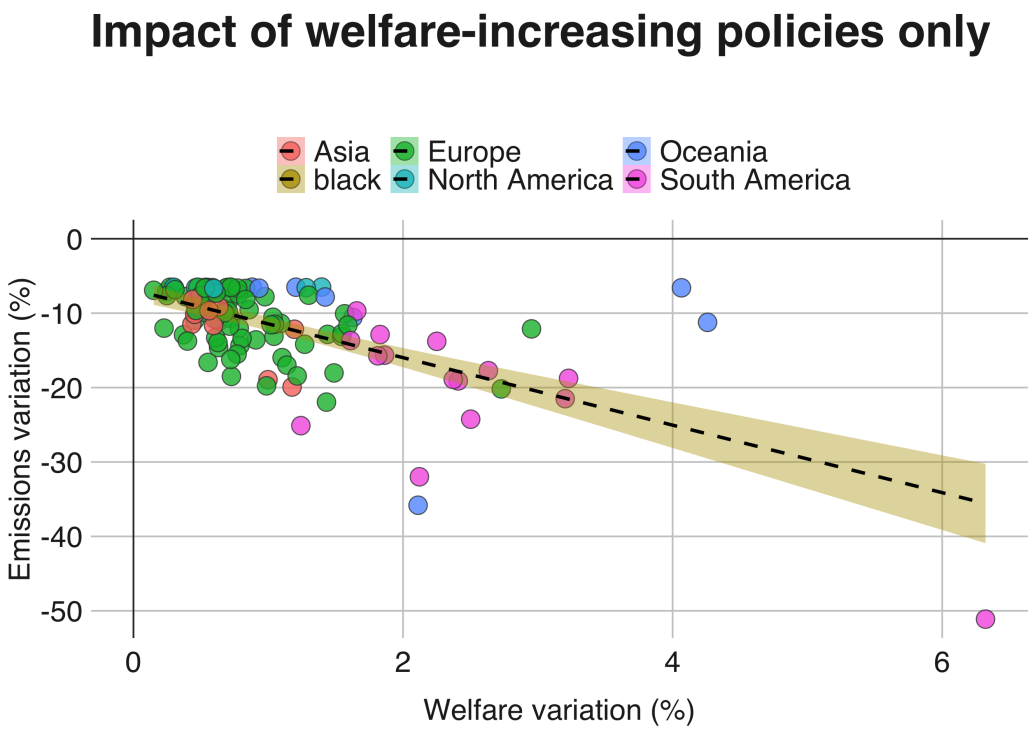


Figure S24. Emission reductions as a function of variations in welfare in all cities, when applying in each city welfare-increasing policies only. The dotted line represents the regression line. Welfare increases are significantly associated to emission decreases (p-value lower than 0.1%).

Figure S25. Emission and welfare variations in each city, in 2035, compared to the business as usual scenario, for each policy considered separately. [robustness check]

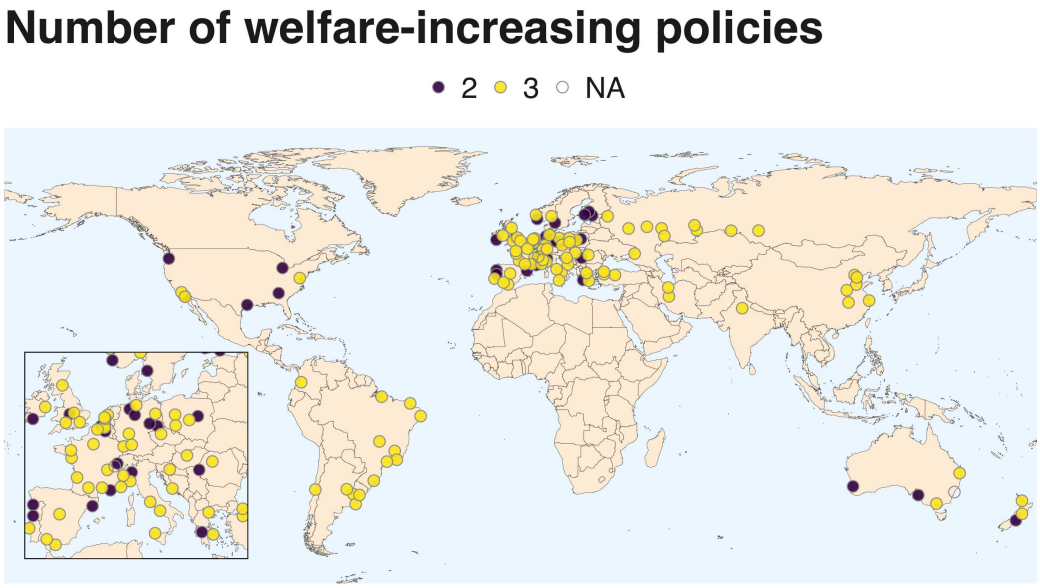


Figure S26. Number of policies which increase welfare, among the four policies that we simulate. [robustness check]

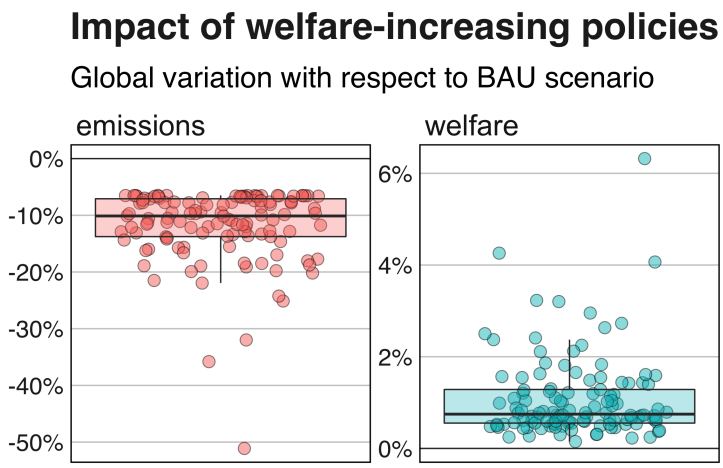


Figure S27. Impacts, in each city, of the only policies which increase welfare. The box plot represents the median, the 25th and the 75th percentile of each indicator. The emission decrease is typically between 16.0% and 21.4% (interquartile range, median is 17.2%), and the welfare increase between 0.53% and 1.18% (interquartile range, median is 0 0.73%).[robustness check]

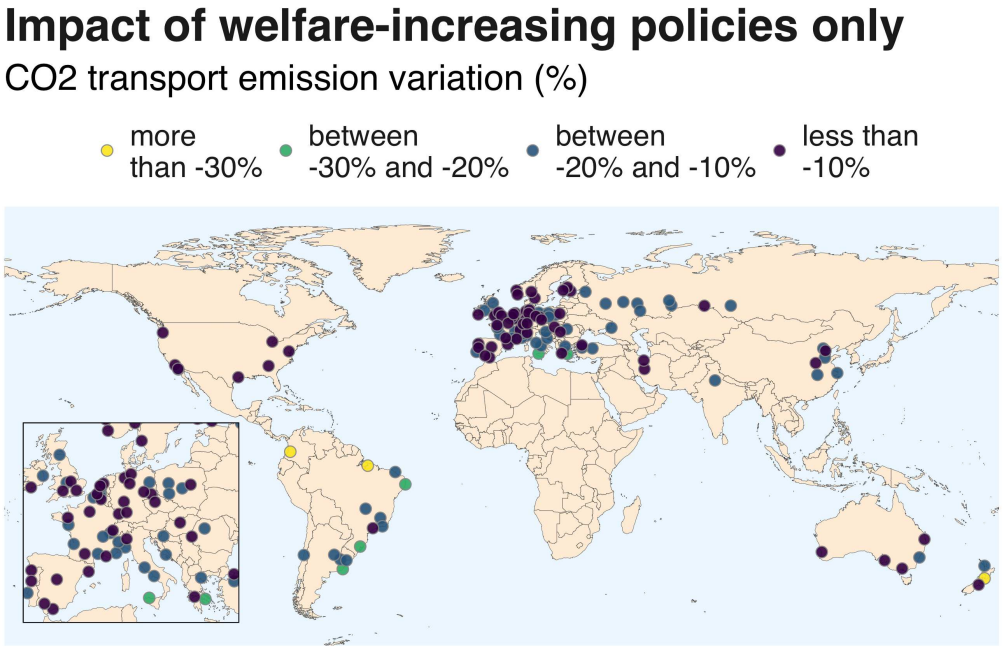


Figure S28. Impact on emissions of the policies which increase welfare, among the four policies that we simulate. [robustness check]

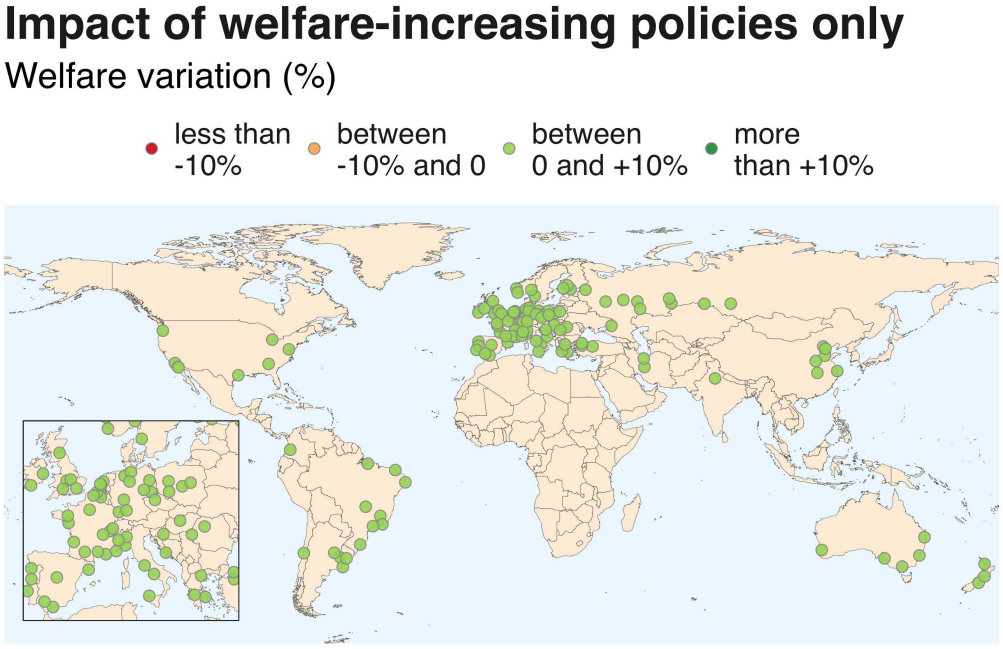


Figure S29. Impact on welfare of the policies which increase welfare, among the four policies that we simulate. [robustness check]