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Abstract

Policy action to avoid the impending societal costs of climate change is particularly warranted in transport sector, which is responsible for 30% of greenhouse gas emissions in OECD countries. To design appropriate interventions in this sector, policy makers should account for the recent emergence of shared mobility services in urban areas and their potential advantages in terms of emissions mitigation. These services offer a similar degree of flexibility as private car travel, as well as the capacity to transport many passengers simultaneously, similar to public transport services. This combination of characteristics could render shared mobility as a viable alternative not only to private car use, but also to public transport. The degree to which shared mobility constitutes constitute a cost-effective alternative to conventional private and public modes of transport, from a social point of view, is unknown. Consequently, the environmental impacts of shared mobility should be explored before considering how to encourage the adoption of these services.

This study estimates the impact that the widespread uptake of shared mobility services could have on the carbon footprint of urban transport. To this end, it simulates the share of each transport mode and aggregate emissions from passenger transport in 247 cities across 29 OECD countries between 2015 and 2050. The simulations make use of econometric estimates obtained from a unique cross-city survey on individual preferences regarding transport modes, including shared mobility.

Once mainstreamed, shared mobility services are found to offer a significant environmental benefit. The analysis indicates that they have the potential to eliminate, on average, 6.3% of passenger transport emissions. This mitigation potential varies widely across cities and depends in large part on current modal splits in cities. The analysis shows that such services will not easily thrive in car dependent environments, where the cost of their provision is going to be higher and preferences for using shared modes of transport are weaker. Cities in which public transport delivers almost all mobility will not see emissions reductions from the uptake of shared mobility services either, as in these cases shared mobility is expected to reduce public transport ridership. However, almost all of the urban areas examined in the analysis fall outside of these polar cases. In the majority of cities, the environmental benefits of shared mobility uptake are positive and, in many cases, considerable.

These findings have a number of policy implications. In cities that stand to benefit from the uptake of shared mobility services, these results may call for a relaxation of the various barriers that hamper this uptake. This holds especially in cases in which their removal does not contradict other policy objectives, such as those related to job security and fair competition. To this end, the analysis points to several policies that could effectively influence the penetration rate of shared mobility services. These include pricing instruments that increase the generalised cost of car use, *vis-à-vis* that of shared mobility. Such policies are justified especially in urban areas where neither private car nor public transport are the dominant modes of travel. Reducing the relative cost of shared mobility is one of the most effective levers. These findings also highlight the limits of shared mobility as a strategy for decarbonising urban transport. According to these results, shared mobility can play a complementary role in efforts to reach carbon neutrality by 2050.

Résumé

Une action politique visant à éviter les coûts sociétaux imminents du changement climatique est particulièrement justifiée dans le secteur des transports, qui est responsable de 30% des émissions de gaz à effet de serre dans les pays de l'OCDE. Pour concevoir des interventions appropriées dans ce secteur, les décideurs devraient tenir compte de l'émergence récente de services de mobilité partagée dans les zones urbaines et de leurs avantages potentiels en termes d'atténuation des émissions. Ces services offrent un degré de flexibilité similaire à celui des déplacements en voiture privée, ainsi que la capacité de transporter de nombreux passagers simultanément, à l'instar des services de transport public. Cette combinaison de caractéristiques pourrait faire de la mobilité partagée une alternative viable non seulement à l'utilisation de la voiture privée, mais aussi aux transports publics. Le degré auquel la mobilité partagée constitue une alternative rentable aux modes de transport privés et publics conventionnels, d'un point de vue social, est inconnu. Par conséquent, les impacts environnementaux de la mobilité partagée doivent être explorés avant d'envisager comment encourager l'adoption de ces services.

Cette étude évalue l'impact que l'adoption généralisée des services de mobilité partagée pourrait avoir sur l'empreinte carbone des transports urbains. À cette fin, elle simule la part de chaque mode de transport et les émissions agrégées du transport de passagers dans 247 villes de 29 pays de l'OCDE entre 2015 et 2050. Les simulations utilisent des estimations économétriques obtenues à partir d'une enquête interurbaine unique sur les préférences individuelles en matière de modes de transport, y compris la mobilité partagée.

Une fois intégrés, les services de mobilité partagée offrent un avantage environnemental significatif. L'analyse indique qu'ils ont le potentiel d'éliminer, en moyenne, 6,3% des émissions du transport de passagers. Ce potentiel d'atténuation varie considérablement d'une ville à l'autre et dépend en grande partie des répartitions modales actuelles dans les villes. L'analyse montre que ces services ne prospéreront pas facilement dans des environnements dépendant de la voiture, où le coût de leur fourniture sera plus élevé et les préférences pour l'utilisation de modes de transport partagés sont plus faibles. Les villes dans lesquelles les transports publics assurent la quasi-totalité de la mobilité ne verront pas non plus de réduction des émissions grâce à l'utilisation de services de mobilité partagée, car dans ce cas, la mobilité partagée devrait réduire l'utilisation des transports publics. Cependant, presque toutes les zones urbaines examinées dans l'analyse se situent en dehors de ces cas polaires. Dans la majorité des villes, les avantages environnementaux de l'adoption de la mobilité partagée sont positifs et, dans de nombreux cas, considérables.

Ces résultats ont un certain nombre d'implications politiques. Dans les villes susceptibles de bénéficier de l'adoption de services de mobilité partagés, ces résultats peuvent exiger un assouplissement des divers obstacles qui entravent cette adoption. Cela vaut en particulier dans les cas où leur suppression ne contredit pas d'autres objectifs politiques, tels que ceux liés à la sécurité de l'emploi et à une concurrence loyale. À cette fin, l'analyse met en évidence plusieurs politiques qui pourraient effectivement influencer le taux de pénétration des services de mobilité partagée. Il s'agit notamment d'instruments de tarification qui augmentent le coût généralisé de l'utilisation de la voiture, par rapport à celui de la mobilité partagée. De telles politiques se justifient en particulier dans les zones urbaines où ni la voiture privée ni les transports publics ne sont les modes de déplacement dominants. La réduction du coût relatif de la mobilité partagée est l'un des leviers les plus efficaces. Ces résultats mettent également en évidence les limites de la mobilité partagée en tant que stratégie de décarbonation des transports urbains. Selon ces résultats, la mobilité partagée peut jouer un rôle complémentaire dans les efforts pour atteindre la neutralité carbone d'ici 2050.

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1. Introduction

The latest scientific evidence suggests that allowing the global average temperature to reach 1.5 °C higher than its pre-industrial level will heighten the risk of extreme weather events and threaten human welfare in diverse ways (IPCC, 2018[1]). The most recent analyses show that global average temperature has already reached 1.1°C above pre-industrial levels, and that the commitments outlined in the current Nationally Determined Contributions to the Paris Agreement will fall short of climate goals.[1] Limiting temperature rise to 1.5 °C will require a fivefold increase in targeted emissions reductions (WMO, 2019[2]), necessitating the mobilisation of a large number of policy levers across multiple sectors.

The transport sector constitutes one of the areas of economic activity in which technological change and policy action is most urgently needed to address climate change. Transport-related activity accounts for 23% of annual emissions worldwide, and 30% of emissions in OECD countries (IEA, 2018[3]). Although OECD countries comprised only 17% of the world's population in 2015, they were responsible for an estimated 50% of domestically-emitted CO_2 emissions from transport that year (ITF, 2019[4]). Moreover, while emissions from the industry and energy sectors have begun to decline in recent years, emissions from transport have continued to rise despite the implementation of mitigation policies and improvements in fuel efficiency (IEA, 2018[3]).

Policy interventions and technological developments that affect mobility at the urban level are more relevant than ever before. Without substantial policy interventions or a major green technological disruption, transport-related emissions in urban areas are not expected to fall substantially below their current levels in 2050.[2] The continued increase in transport emissions is due in part to growing populations and rising *per capita* income, which drive demand for travel. The proportion of global population residing in urban areas is expected to increase from 54% in 2018 to 68% in 2050 (UN, 2018[5]), a number that rises to 80% for OECD countries. Technology- and policy-driven decarbonisation efforts must therefore be intensified in urban areas if emissions reductions are to be accelerated in the face of increasing travel demand.

Shared mobility, which can be broadly defined as the common use of a vehicle by multiple users, has been recently identified as a way to reduce transport-related emissions, especially in urban areas. A wide array of shared mobility services currently offer various types of shared mobility to their users. These services differ with respect to the temporal pattern under which passengers share a vehicle owned by an individual or company. In many cases, these services are provided to a single party, i.e. to an individual or a group of individuals that have *ex-ante* agreed to use the service jointly. For instance, *car sharing* services provide the right to rent a car for a short period of time, possibly a single trip, to a single party. Similarly, *ride-sourcing* services use digital applications to employ drivers using personal or company-owned vehicles for taxi type of services to a single party. Despite these services enable some type of shared mobility, their long-run impact on transport-

[1] The currently projected global average temperature rise lies between 2.9°C and 3.4°C by 2100 (WMO, 2019[2]),.

[2] Recent studies indicate that, under a business-as-usual path, the total emissions of urban transport in 2050 are expected to be higher in 2050, compared to their levels in 2018 (e.g. OECD, 2019, for a city-specific case study and ITF, 2019, for a global level projection).

related emissions is potentially limited, and could even be negative. This is because they are characterised by low occupancy ratios, i.e. a small number of passenger kilometres are served for each vehicle kilometre materialised.

This study focuses exclusively on the environmental impacts of *ride-sharing*. These services enable the simultaneous use of any type of vehicle during a given trip by multiple parties. Each party may be composed by one or more passengers and has a different trip origin and destination. The matching of parties to be served by a given vehicle, the pick-up and drop-off locations and the route of the vehicle are all variables to be determined by algorithms on a real time fashion. Therefore, ride-sharing refers to an algorithm-based common use of a given vehicle stock which, in contrast to traditional public transport, does not preclude fixed routes and periodicity in the provision of service. Importantly, the provided definition does not preclude any assumption about the ownership regime of these services, as the underlying operator can be private or public. Throughout the paper, shared mobility will therefore be used to refer to ride-sharing with these characteristics.

High-occupancy ride-sharing is attracting attention as a strategy for reducing overall vehicle-kilometres travelled and thus transport-related emissions in urban areas (Fulton, 2018[6]; Greenblatt and Shaheen, 2015[7]; Santos, 2018[8]). The promising nature of these services stems from the fact that they are able to transport more people per vehicle-kilometre than private cars. Notably, such services can be provided using vehicles with a range of capacities, e.g. conventional cars, mini-shuttles, taxi-busses and eventually conventional busses. Relative to traditional public transport systems, shared mobility services also offer greater flexibility in terms of their scheduling and the extent of their physical network. The considerable versatility in terms of capacity, schedule, and geographic coverage of these shared mobility systems combines characteristics of travelling by car with characteristics of travelling by public transport. In this way, the shared mobility services considered in this study can be thought of as a form of versatile, on-demand public transport.

The study estimates the impact of a widespread deployment of ride-sharing services on the total carbon emissions of urban transport in the period 2015-2050. To this end, it econometrically estimates the preference parameters governing travellers' choices between transport modes, including shared mobility. Using these estimates, it then projects the adoption rate of shared mobility services and the impact that their uptake will have on the share of car and public transport in the modal split. Finally, it translates changes in the modal shares over this period into changes in the resulting greenhouse-gas emissions. This exercise is repeated for different sample years, cities and trip types. Across them, various trip characteristics that are key to transport mode choice, e.g. travel cost, travel time, are allowed to vary. Furthermore, the simulation exercise explicitly accounts for the cross-city variation of traffic conditions, the cross-country variation of carbon-intensity of electricity generation and the car fleet, as well as their intertemporal evolution.

The analysis is largely based on two unique data sets. The first one comprises the characteristics of approximately 12000 synthetic trips in 247 cities across 29 OECD countries. These trips are simulated using actual geographic, transport, population and employment data encapsulated in the Global Urban Model developed by the ITF. The second dataset contains stated responses from a consumer survey, which was tailored to identify the drivers behind the potential adoption of a ride-sharing type of shared mobility service and was carried out in Auckland, Dublin and Helsinki. The study also utilises secondary data sources that contain current or projected information, such as that for the current and future emission intensity of the power generation sector (IEA, 2018[9]).

Based on the above methodology, the study provides a comparative analysis of two scenarios. In a reference scenario, the current low level of uptake of shared mobility persists to 2050. In this scenario, low uptake through 2050 reflects existing technological and institutional barriers. A counterfactual scenario simulates the gradual removal of these barriers. This simulation isolates the impact of mainstreaming shared mobility services *per se* from other factors that evolve across over time in each scenario, e.g. emission factors.

The paper exhibits a wide array of findings. Once mainstreamed, shared mobility services are found to offer a significant environmental benefit. The analysis reveals that they have the potential to eliminate, on average, 6.3% of passenger transport emissions. The mitigation capacity of shared mobility services is shown to vary widely across cities and to depend largely on the current mode shares in cities. The analysis shows that such services are not likely to thrive in car dependent environments, highlighting the fact that their successful deployment depends on user willingness to adopt these services. On the other hand, cities in which public transport supplies the dominant share of travel, do not stand to benefit from such services, as they are expected to reduce public transport ridership, implying a net increases in emissions per passenger-kilometre travelled. However, more than 95% of urban areas examined in the analysis do not fall into these extreme cases. In these cities, the environmental impact of shared mobility services is positive and, in some cases, considerable.

These findings have a number of policy implications. In cities that stand to benefit from the uptake of shared mobility services, these results may call for a relaxation of the various barriers that hamper their uptake. This holds especially in cases in which such a removal does not contradict other policy objectives, in particular those related to job security and fair competition. To this end, the analysis points to a number of specific policies that could effectively influence the penetration rate of shared mobility services, key among which is reducing the relative cost of these services. These policies are justified especially with respect to urban areas where public transport is not the dominant mode of travel. Reducing the costs of shared mobility services, and increasing the costs of their alternatives, are shown to be among the most effective levers, pointing to potential interventions that modify these relative costs.

The findings also indicate, however, the limits of shared mobility as a means to decarbonise urban transport. The results suggest that shared mobility services will play a complementary, rather than central, role in efforts to reach carbon neutrality by 2050. They also underline the urgency of core policies that seek to better align the private cost of private car use with its social cost. Many such policies could also serve to increase the uptake of shared mobility services, and the successful deployment of the latter could help facilitate a shift away from car use. However, more explicit support measures to shared mobility, such as subsidies, should be evaluated according to the social costs and benefits they are expected to yield.

The structure of the paper is as follows. **Section 2** provides an analytic description of the data sources used in the study. **Section 3** lays out the complete methodology of the study, describing the specification and the properties of the econometric and simulation models used in the analysis. **Section 4** summarises the findings from the econometric analysis and their importance for designing instruments that could encourage the adoption of shared mobility services. **Section 5** exhibits the simulation results and provides a discussion on the potential environmental impact of shared mobility on various cities and countries.

2. Data

This section describes the data sources employed in the study. The first part of the section introduces the survey data used to estimate the effect of transport attributes and socio-demographic characteristics on an individual's choice of transport mode. The survey contains a choice experiment in which respondents make a series of choices among four transport modes: non-motorised modes, public transport, shared mobility or car. Respondents are also asked questions about their personal characteristics. The data generated from this choice experiment enables the estimation of underlying drivers behind the share of each transport mode in the modal split.

The second part of this section describes the data sources employed in simulating the impact of shared mobility uptake on greenhouse gas emissions. This part summarizes the synthetic dataset generated using the global urban passenger transport model developed by the ITF. This dataset contains plausible simulated trips whose characteristics vary across cities and depend on the mode used to make them. Trip attributes (travel costs, times, and conditions) also vary with departure times and location, as well as with the type of shared mobility proposed. Other key data used in the simulation pertain the projected total travel demand in each city, the emission factors of each transport mode and the carbon intensity of electricity generation in each country.

Survey data

The data used for the estimation of individuals' utility parameters were gathered through surveys conducted in three cities: Auckland, Dublin and Helsinki. The questionnaire collected respondents' stated preferences on transport mode *via* a choice experiment, along with their socio-demographic characteristics.

Questionnaire design

Survey respondents first received information regarding the nature of shared mobility services. This included information about the effect that shared mobility services could have on traffic congestion and air pollution, as well as on overall accessibility and the comfort of urban travel. Specific information was also provided on the characteristics of the vehicles that would provide hypothetical shared mobility services in the choice experiment, namely shared taxis and taxi-busses.

The hypothetical services provided by the two types of vehicles differ substantially. *Shared taxis* are requested in real time and provide a door-to-door service. Shared taxis make small detours to pick up and drop off other passengers. As a result, travel *via* shared taxi is designed to be 25-30% cheaper than travel *via* their conventional counterparts. Waiting times for shared taxis are short, i.e. 5-10 minutes. In contrast to shared taxis, *taxi-busses* are requested 15-30 minutes in advance, have a maximum capacity of 8 to 16 passengers and stop at pre-programmed locations that are close (within 400 metres) of riders' departure points and destinations. Taxi-bus services are designed to be around 75% cheaper than conventional taxis, and therefore cheaper than shared taxi services.

The survey also collected information on a number of relevant socio-demographic characteristics. Respondents were asked to indicate the proximity of their residence to the city centre, their gender, age, occupation, and their typical use of smartphones, tablets and apps. They were also asked to characterise their current mobility habits: the transport mode they use, the number of weekly trips and their average trip duration for various trip purposes.

The choice experiment consisted of a sequence of four choices between transport options (see Table 2.1). Respondents were asked to choose from among four modes: private car, non-motorised transport (i.e. walking or biking), public transport and one of the forms of shared mobility described above (i.e. shared taxi or taxi-bus). Each option was described in terms of several attributes, e.g. travel time and cost, the value of which varied across subsequent rounds of the experiment. This variation generated the heterogeneity in the data needed to estimate the choice model described in **Section 3** and elucidate the role of each attribute on respondents' utilities. Participants could drop out of the survey at any time, resulting in some limited attrition: about 83.6% of the participants completed all four rounds of the experiment. To ensure the panel dataset is balanced, the analysis employed in this study retains only the observations from subjects who completed all four rounds. The set of attributes and their levels can be found in **Annex A** Table A A.1.

Table 2.1. Example of a choice set

Choose the option below that best suits your preferred mode of travel. Compare current transport options and shared mobility options.	
Public Transport On board time: **40mins** Fare: **NZ$2.5** Walking time (from/to stop or station): **20 mins** Waiting time: **20 mins** Number of transfers: **1** Mode: **Bus**	**Shared Mobility** On board time: **15 mins** Fare: **NZ$8** Walking to and from the stop: **10 mins** Lost time (waiting + detour time): **15 mins** Passengers on board: **4**
Private Car Travel time: **30 mins** Fuel / energy cost: **NZ$2** Parking cost: **No cost** Congestion level: **Less than 20% of time stopped in traffic** Congestion charge / tolls: **NZ$5**	**Other (non-motorised)** Travel time: **45 mins** Availability of cyclepath: **Good** Ease of crossing in traffic: **Pedestrian crossing** Mode: **Walk**

Source: ITF survey.

Descriptive statistics

Shared mobility adoption can depend on geographic location, gender, age and the number of private vehicles a household owns. This part of the section explores the extent to which the collected data align with existing evidence from literature to date.

Geographic location appears to be one of the main determinants of modal preferences. Table 2.2 shows that the usual transport mode is bus for most respondents in Helsinki. Figure 2.1 displays mode choice patterns in conjunction with other important socio-economic variables (i.e. gender, age, and number of cars). The panel referring to cities in Figure 2.1 illustrates that respondents from Helsinki tend to prefer shared mobility over the other modes. This panel also shows that respondents in Auckland prefer cars over public transport. The distribution of mode choice among respondents from Dublin indicates more equal preferences among modes. The estimated econometric models, presented in Section 3 and Section 4, reflect these patterns. The panel corresponding to location in Figure 2.1 illustrates that respondents living in the city centre are equally likely to opt for a car or a shared mobility ride, and exhibit a higher propensity to choose non-motorised modes. In contrast, respondents far from the city centre appear to prefer private car over shared and non-motorised forms of transport.

Table 2.2. Mean and standard deviation of social demographic variables by city

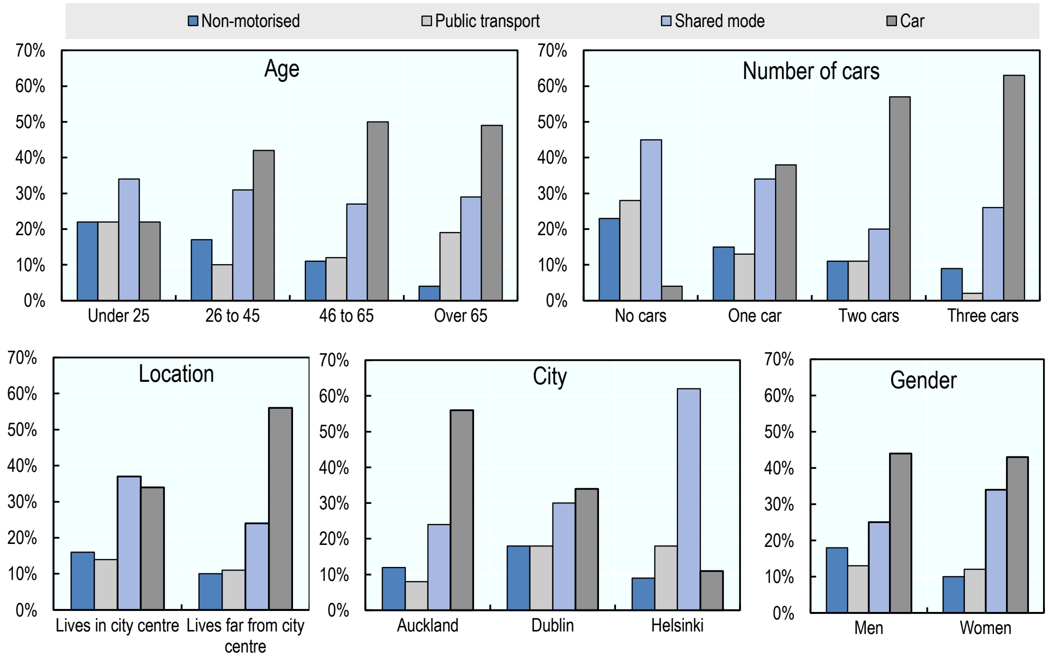
	Helsinki	Dublin	Auckland
Age			
	43	42.93	45.74
	(14.62)	(13.37)	(15.11)
Number of cars in the household			
	0.55	1.13	1.88
	(0.50)	(0.76)	(0.74)
Share of women			
	0.5	0.49	0.52
	(0.50)	(0.50)	(0.50)
Employment status			
Full time	0.35	0.57	0.54
	(0.48)	(0.50)	(0.50)
Part time	0.15	0.23	0.15
	(0.36)	(0.42)	(0.36)
Student	0.25	0.07	0.08
	(0.43)	(0.25)	(0.27)
Unemployed	0.25	0.13	0.23
	(0.43)	(0.34)	(0.42)
Usual transport mode			
Bus	0.45	0.20	0.10
	(0.50)	(0.40)	(0.29)
Car	0.2	0.57	0.82
	(0.40)	(0.50)	(0.39)
Rail	0.1	0.07	0.03
	(0.30)	(0.25)	(0.16)
Walk	0.25	0.16	0.06
	(0.43)	(0.37)	(0.24)

Note: Standard deviations are in parenthesis.
Source: Authors' elaboration of ITF survey data.

Another insight issuing from Figure 2.1 is that women appear to have a weaker preference for non-motorised modes and stronger preference for shared mobility compared to men. These tendencies are also present in the literature, which indicates that women are generally less prone to consider cycling as a convenient transport mode (Garrard, Rose and Lo, 2008[10]). Spurlock et al. (2019[11]) also find that women are more likely to adopt shared mobility than men.

Mode choice patterns also appear to cohere with the literature regarding the impact of other socioeconomic variables. The strength of preferences for shared mobility and non-motorised modes decrease with age, and the number of cars in the household is strongly correlated with stated preferences for private car travel. Respondents reporting having no cars in the household are more open to shared mobility.

Figure 2.1. Share of mode choice by socio-demographic characteristics



Source: ITF Survey data

Data used in simulations

The simulation exercise presented in the paper uses input data generated by the ITF's Global Urban Model. The model focuses on 1692 cities that, according to the UN Habitat, had over 300000 inhabitants in 2015. An extended version of the model incorporates 9660 cities with populations of between 50000 and 300000 inhabitants around the world. The model uses aggregate land-use, transport supply and socioeconomic data collected for each of these cities to predict overall travel demand and vehicle ownership. A more detailed description of the global urban passenger transport model is provided in the **Annex C** of the paper. This study uses a subsample of 247 cities in 29 OECD countries.

The simulations carried out in the study make use of synthetic trips generated using the output of the global urban model. The characteristics of these synthetic trips, such as cost and travel time, also vary between similar trips, whenever these are undertaken in different cities or by different transport modes. Trip origin, distance, and time of the day can also differentiate trips. For instance, a 5 km trip originating from a suburban area at peak hour, is characterised by different travel time and cost compared to a 5 km trip originating from the inner core of the city that is taken during an off-peak hour. The specification of the simulation model, as well as the exact way in which the characteristics of simulated trips enter it, is presented in detail in the second part of **Section 3**.

The attributes of synthetic car trips largely depend on the characteristics of the city in which they are generated. Larger cities imply longer average trips. The time and the cost of these trips depends on a series of parameters. Cities with higher overall road capacity, higher speed limits and lower car ownership rates give rise to faster car trips than cities characterised by the opposite features. The cost of car trips is computed using the distance of a trip and energy costs, where the latter are approximated from national values. If present, road tolls are incorporated in the simulated cost. Parking costs are also added, assuming an average duration of 3.0 hours of parking.

The attributes of synthetic public transport trips are generated using city specific-characteristics as well as existing development plans of local authorities, operators or other providers. The average speed of a trip undertaken by public transport decreases with the overall mode share of busses in a city's public transport supply. This implies that in cities where most of the passenger kilometres are carried out by rail and metro, a trip undertaken by public transport will generally take less time than the *same* trip in a city where all public transport is provided by busses. A similar rationale is used for waiting times. The average time needed to access a node of the public transport system is also factored in. This is approximated using the overall density of public transport stops in the city, i.e. number of stops per square kilometre. Public transport fares are statistically predicted using information on the GDP *per capita*, on whether the payment of trip fares is integrated across public transport modes in the city and by controlling for regional fixed effects. The level of comfort of public transport is approximated using the ratio between the overall capacity of the public transport system and the population of the city.

The attributes of synthetic trips carried out by non-motorised transport, i.e. walk and bike, are estimated using an assumed speed of 5 km/h for walking and 13 km/h for biking. Non-motorised modes are assumed to entail no pecuniary costs.

The attributes of synthetic shared mobility trips are generated using the corresponding attributes of travel by private car and the estimated size of the shared mobility vehicle fleet in the city. The travel time is calculated based on the time that would be needed had the same trip been made with a private car. That time is increased by an additional detour time, which depends on population density in the city. The rationale is that in areas of relatively lower density, the probability that a passenger will be matched to a suitable shared taxi bus vehicle within a given time interval is lower. This also implies that the detour and waiting times for synthetic trips are greater in low density areas. The fares of synthetic shared mobility trips depend on distance, as well as on the fuel and electricity costs of each city. Since lower population density decreases the probability of matching riders, it increases detour times and thus the corresponding simulated fares. In all cases, the simulated shared mobility fares are assumed to be at least as high as those of public transport.

The simulation exercise generates a set of 48 trips for each city. These trips differ from each other with respect to at least one of the following: (i) trip distance, (ii) the time of the day in which the trip is generated (i.e. peak or non-peak hour), (iii) the departure location of the trip (i.e. suburban or urban area) and (iv) the type of vehicle used when shared mobility services are chosen (i.e. shared taxi or taxi-bus). Six distance intervals are considered: less than 1.0 km, 1.0-2.5 km, 2.5-5.0 km, 5.0-10.0 km, 10.0-20.0 km and 20.0-40.0 km. Eight combinations of departure time, location and type of shared mobility service, shown in Table 2.3, correspond to each trip in each of these six categories, giving rise to a synthetic sample of 48 trips per city. For each such trip, the general rules outlined above are used to generate its corresponding attributes.

Table 2.3. Definition of a trip

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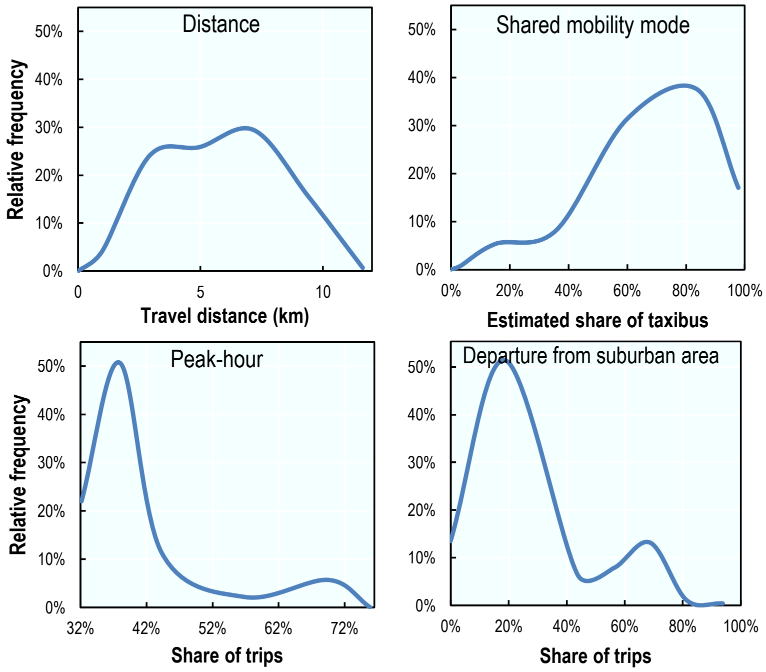
	Distance segment							
Origin: suburban	Yes	Yes	Yes	Yes	No	No	No	No
Hour: peak	Yes	Yes	No	No	Yes	Yes	No	No
Shared mode: Taxibus	Yes	No	Yes	No	Yes	No	Yes	No

Source: Authors' elaboration.

Figure 2.2. Probability distributions of trip conditions



Notes: All panels refer to cross-city distributions of city-specific means; Upper left panel: distance of trips; Upper right panel: estimated share of trips offered by taxi-bus, if they are made with a shared mobility mode; Lower left panel: share of trips undertaken during the peak hour; Lower right panel: share of trips originating from a suburban location.
Source: Authors' elaboration of ITF urban model data.

Not all synthetic trips are equally likely to occur in a given city. Cities with large suburban surfaces and population generate a higher frequency of long, suburban trips. Furthermore, the bigger the footprint of a city is, the higher the relative frequency of longer trips. A direct outcome of the above is that an identical synthetic trip occurs with different relative frequencies across different cities. The *distance* panel in Figure 2.2 shows the distribution of the expected trip distances across the cities of the sample. The distribution is bimodal: the first peak corresponds to short distance trips of approximately 2 km and the second peak to trips of 7-8 km. The *peak-hour* panel in the same figure illustrates that in most cities around 30-35% of trips are generated during peak hours. Regarding the *departure location*, in most cities the share of trips originating in suburban areas lies below 40%. The *shared mobility mode* panel in Figure 2.2 displays the expected share that taxi-busses would have over shared taxis in a hypothetical scenario in which shared mobility services are widely used. This is approximated using the current amount of travel carried out by conventional buses as a portion of travel carried out by all modes that currently resemble shared mobility, essentially conventional taxis, and public busses.

Other key data used in the simulation include the projected total travel demand in each city between 2015 and 2050, the projected emission factors of each transport mode and the carbon intensity of electricity generation in each country. The exact role that these variables play in the simulation is detailed in **Section 3**.

Table 2.4. Average attributes' distribution over cities

	Min.	Percentile			Max.	Mean	Standard deviation
		25th	50th	75th			
Non-motorised							
Bike	0.03	0.10	0.17	0.27	0.47	0.19	0.10
Sidewalk / Cyclepath	0.16	0.23	0.26	0.33	0.68	0.29	0.10
Priority crossing	0.20	0.25	0.30	0.38	0.75	0.34	0.12
Travel time	11.16	32.90	44.21	62.62	147.46	48.70	24.98
Car							
> 50% travel time stopped	0.00	0.00	0.00	0.00	0.29	0.02	0.07
20 to 50% travel time stopped	0.00	0.00	0.00	0.00	0.58	0.04	0.14
Fuel cost	0.07	0.24	0.39	0.70	1.96	0.51	0.35
Parking cost	0.00	0.30	0.67	1.14	7.38	0.83	0.81
Toll	0.00	0.27	0.65	1.04	3.16	0.74	0.60
Travel time	2.18	10.93	16.21	24.46	108.27	19.17	13.40
Public transport							
Accessing time	0.05	3.27	7.33	20.29	74.76	13.41	14.25
Very crowded	0.00	0.29	0.32	0.41	0.64	0.35	0.11
Crowded	0.17	0.48	0.51	0.52	0.56	0.49	0.06
Fare	0.37	1.25	2.12	2.82	6.36	2.18	1.14
Number of transfers	0.38	1.29	1.78	1.84	2.12	1.59	0.40
Travel time	5.25	20.15	29.14	40.57	113.51	32.70	17.80
Waiting time	2.17	9.17	13.87	14.48	16.20	12.06	3.49
Shared mobility							
Accessing time	0.02	2.89	6.14	10.29	14.32	6.57	4.23
Fare	1.16	4.14	5.82	8.36	30.93	6.80	4.26
Lost time	2.24	12.60	17.75	24.88	45.77	19.11	8.53
Number of passengers	0.68	3.08	4.85	6.53	20.46	5.22	2.75
Travel time	2.95	20.98	31.98	49.07	148.79	37.11	24.83

Source: Authors' elaboration of ITF urban model data.

3. Methodology

Overview

This section documents the methods and assumptions employed in this study. It is composed of two parts. The first part describes the econometric model used to evaluate the role of several key variables in determining an individual's choice of transport mode. These variables include the standard modal attributes, such as travel time and cost, as well as socioeconomic factors that could favour or hamper the use of different transport modes, such as age and gender. The econometric model is estimated using stated preference data based on a hypothetical setting where individuals choose between a shared mobility service and other, traditional transport mode options, such as bike, walk, car and bus. These data are described in detail in the first part of Section 4.

The second part utilises the estimated preference parameters of the econometric model to project the impact of a widespread deployment of shared mobility services on the amount of CO_2 emissions generated by urban passenger transport. The projections use a large sample of synthetic trips generated for 247 OECD cities using the International Transport Forum's Global Urban Model. The present analysis computes the expected carbon footprint of each of these trips in a reference situation, in which shared mobility services enjoy limited popularity or are completely absent from a city. Then, it repeats the calculation for a counterfactual future situation, in which the underlying barriers responsible for the current limited uptake of these services are substantially weakened. The corresponding synthetic cross-city data are described in the second part of **Section 2**.

Econometric model

Evaluating consumer proclivity to adopt shared mobility services requires the estimation of the parameters that govern the mode choices made by transport users. The focus is on the preference parameters that underlie the sensitivity of transport mode choice to variables that differ across the various alternatives, such as car, public transport, shared mobility and soft mobility. The larger the magnitude of these parameters, the more prone consumers are to switching transport mode following a change in relative travel times, costs and other important modal characteristics. Obtaining numerical values of these impacts requires specifying and estimating a parametric statistical model.

The analysis in this paper is based on a random utility model (RUM). In such a model, the personal level of well-being or satisfaction individual n obtains from a hypothetical trip r with transport mode i is given by:

$$U_{nri} = \underbrace{A_{ni} + \mathbf{X}_{ri}\boldsymbol{\beta}_i + \mathbf{S}_n\boldsymbol{\alpha}_i}_{\textbf{systematic utility } (V_{nri})} + \underbrace{\varepsilon_{nri}}_{\substack{\textbf{random}\\ \textbf{utility}}} . \quad (1)$$

In equation (1), X_{ri} denotes a series of variables that vary across trips and modes, such as the travel time and cost; S_n denotes a set of socio-demographic variables, which differ across individuals but are constant across all trip and mode combinations (r,i) a given individual n faces. In the same equation, ε_{nri} denotes a random term, which varies across individuals, trips and transport modes. That term represents omitted factors that can influence the choice of transport mode. For example, it could embody the presence of a shopping mall, which is accessible if the hypothetical trip r is realised with a car. It could also encapsulate any other unobserved characteristic of mode i or individual n that is important for transport mode choice. Although such factors could potentially play a role in mode choice, they are not observed and are therefore excluded from the systematic part of utility V_{nri}. Finally, equation (1) contains a transport mode-specific term, A_{ni}, which represents the average utility from unobserved factors in transport mode i relative to the reference mode. This utility is differentiated by several socioeconomic factors that vary across individuals.

Table 3.1. Control variables in the econometric model

Variable	Included in the compact model?
Travel time in soft mobility: the time to carry out the trip with bike or walk	Yes
In-vehicle travel time: in public transport, private car and shared mobility modes	Yes
Access and waiting time in public transport: the time needed to access the public transport stop and the average waiting time	Yes
Lost time in shared mobility modes: Time lost due to the detours of vehicles delivering ride-sharing services.	Yes
Travel cost of trip if taken by car: (i) fuel and toll cost, (ii) parking cost	Yes
Travel cost of trip if taken by public transport: inferred public transport fare	Yes
Travel cost of trip if taken by shared mobility: assumed service fare	Yes
Travel conditions of trip if taken by soft mobility: presence of bike lanes and priority crossing.	Yes
Travel conditions of trip if taken by car: presence of moderate or severe congestion.	Yes
Travel conditions of trip if taken by public transport: (i) standing for a part of the trip (ii) number of transfers	Yes
Travel conditions of trip if taken by shared mobility: (i) number of co-passengers	Yes
Socioeconomic variables interacting with soft mobility:(i) senior or not, (ii) gender	No
Socioeconomic variables interacting with car: (i) adult or not, (ii) young or not (iii) household possesses no cars, (iv) household possesses multiple cars, (v) household located far from the centre.	No
Socioeconomic variables interacting with public transport: (i) unemployed or not, (ii) household possesses no cars	No
Socioeconomic variables interacting with soft mobility:(i) gender, (ii) unemployed or not	No

Note: The compact model is used for the simulation projecting the uptake of shared mobility in future years.

The control variables included in the econometric model are presented in Table 3.1. These include different components of the travel time, costs, and conditions of a trip taken by mode i. They also incorporate the sociodemographic characteristics of individual n that play a role in the choice of transport mode. For public transport and shared mobility modes, components of travel time include waiting time, in-vehicle time and the time needed to access a public transport stop or a ride-sharing pick up point. For car and soft mobility, i.e. walking and biking, travel time consists only of in-vehicle and active travelling time, respectively. Lost time due to detours and route re-optimization is integral to any ride-sharing service, as such services will almost always deviate from the shortest or fastest path in order to ensure a high occupancy rate by serving multiple passengers simultaneously. The latter is a prerequisite for these services to break even, i.e. to make profits rather than deficits. However, the environmentally relevant goal of a minimum occupancy rate could hypothetically be imposed by policy-makers aiming to ensure a large number of passenger kilometres per vehicle kilometre travelled.

Regarding costs, public transport and shared mobility travel entail only a trip fare, whereas car travel entails fuel, toll and parking costs. Walking and biking do not entail any pecuniary costs. In addition to travel time and costs, the model controls for various qualitative aspects. Qualitative controls include the level of congestion for car travel, as well the presence of bike lanes and priority crosswalks for biking and walking. They also incorporate the possibility that a passenger needs to stand during a trip, the number of transfers for public transport and the number of other passengers in the vehicle for shared mobility.

The econometric model in (1) attempts to predict transport mode choice by exploiting the variation of observed factors, which are summarised in Table 3.1 and are embodied in V_{nri}. It also exploits the variation of unobserved factors, which are captured in the term ε_{nri}. It can be shown that if the unobserved factors in ε_{nri} are distributed identically and independently across individuals and transport modes, the probability that individual n chooses to make the hypothetical trip r with mode i is:

$$P_{nri} = \frac{exp\left(A_{ni} + \mathbf{X}_{ri}\boldsymbol{\beta}_i + \mathbf{S}_n\boldsymbol{\alpha}_i\right)}{\sum_j \left(exp\left(A_{nj} + \mathbf{X}_{rj}\boldsymbol{\beta}_j + \mathbf{S}_n\boldsymbol{\alpha}_j\right)\right)} = \frac{exp\left(V_{nri}\right)}{\sum_{j\in\mathcal{C}} \left(exp\left(V_{nrj}\right)\right)}. \tag{2}$$

where j indexes an arbitrary transport mode in the choice set $\mathcal{C}$. The latter set contains all possible options considered in the model: car, public transport, soft mobility (i.e. walking, biking) and shared mobility. The choice probability of any of these options (e.g. i) increases with the utility that option provides the user, represented by the numerator of equation (2), relative to the general utility gained from all available options. This general utility is represented by the denominator of equation (2).

The estimation technique adjusts the parameters corresponding to the control variables in (1) so that the logit choice probabilities predicted by the econometric model shown in (2), are well-aligned with the observed choices individuals make in the survey data. This technique, known as *maximum likelihood estimation*, is elaborated in the **Annex B** of the paper. The corresponding estimation results are presented in **Section 4** and **Annex A**.

Based on the estimation results of this model, **Section 4** identifies how public policies could accelerate the uptake of shared mobility services. That analysis is based on how equation (2) is affected by changes in the explanatory variables it contains. The rationale behind this is that several of the control variables in Table 3.1 can be affected by policies. For instance, car travel times can be affected by congestion management and road pricing measures. Similarly, the public transport costs incurred by an individual can be affected through public transport fare subsidies. Changes in policy instruments that change the levels of the variables included in $\mathbf{X}_{ri}$ induce changes in the probability with which each transport mode is chosen. The formulas describing the elasticities, i.e. the sensitivity of these choice probabilities to changes in mode and trip-specific variables, such as travel time and cost, are presented in the **Annex B** of the paper.

The econometric analysis provides insights regarding why the penetration rate of shared mobility services is currently low and how it could be accelerated by policies. However, it does not provide information on the environmental impact of a transition to shared mobility services. The simulation model documented in the next sub-section builds upon the results of the econometric model to project the impact of such transition to CO_2 emissions.

Simulation model

The estimated values of the parameters entering equations (1) and (2) can be used to simulate the change in the greenhouse gas emissions caused by a widespread deployment of shared mobility services. To this end, the study uses the following formula to approximate the carbon footprint of passenger transport in a given city c at year t:

$$E_{ct} = T_{ct} \sum_{r} \left(\pi_{rct} \sum_{j} \left(\underbrace{\mathrm{D}_r \, P_{crjt}\left(\mathbf{x}_{rjc}; \hat{\boldsymbol{\beta}}_j, \Omega_{jct}\right) \frac{\mathrm{e}_{cjt}}{\mathrm{L}_{cjt}}}_{\substack{\textbf{carbon footprint of trip } r \\ \textbf{with mode } j \textbf{ in city } c \textbf{ at year } t}} \right) \right). \tag{3}$$

The variables and indexes entering equation (3) are described in detail in Table 3.2.

Table 3.2. Variables and indexes used in the simulation model.

Variable or index	Description
r	A type of simulated trip, differentiated by its length, the time of the day at which it is initiated (on peak or off-peak), the place from which the traveller departs (suburban or urban location), the available transport mode if the trip is undertaken with public transport (bus or rail) and the available transport mode if the trip is undertaken with shared mobility (shared taxi or taxi-bus).
D_r	The distance category at which trip *r* belongs to. Categories are: less than 1.0 km, 1.0-2.5 km, 2.5-5.0 km, 5.0-10.0 km, 10.0-20.0 km, 20.0-40.0 km.
t	The time between the benchmark year (2015) and a future year (e.g. in 2020, *t* = 5).
c	Indexes a city of an OECD country included in the simulation study (247 cities).
j	Indexes a transport mode out of: soft mobility (bike, walk), public transport (bus or light rail), car and shared mobility (shared taxi or shared minibus).
T_{ct}	Travel demand in city *c* in year *t*, expressed relative to the total travel demand of a reference city *c*, in the benchmark year (2015).
π_{rct}	Relative frequency of trip type *r* in the trips materialising in city *c* during in year *t*.
$\mathbf{x}_{rjc}$	The set of attributes (e.g. travel time, cost) of trip type *r*, when that is materialised in city *c* by transport mode *j*.
$\hat{\boldsymbol{\beta}}_j$	Estimated parameters.
$\boldsymbol{\Omega}_{ct}$	Alternative specific constants. In the benchmark year, $\boldsymbol{\Omega}_{c0}$ replicate the market share of each transport mode (modal split) in each city *c*.
E_{cjt}	CO_2 per vehicle kilometre travelled by transport mode *j* in city *c* during year *t*.
L_{cjt}	Load factor, i.e. the average number of passenger kilometres for each vehicle kilometre travelled by transport mode *j* in city *c* during year *t*

Source: Generated by the authors.

Some of the variables entering equation (3) require specific attention. Variable L_{cjt} denotes the *load factor*, i.e. the average number of passenger kilometres served for each kilometre traversed with a vehicle of transport mode j. The term e_{jt} is the emission factor, i.e. the amount of CO_2 released for each kilometre traversed with a vehicle of transport mode j. Both terms vary across cities and can evolve over time. The subscript r denotes a synthetic trip which is simulated using the global urban model developed by the ITF. This trip, whose total distance is D_r, has a set of attributes which are denoted by $\mathbf{x}_{rjc}$ and therefore differ across modes, trip types, and cities. These attributes are enumerated in Table 3.1. **Section 2** provided an overview of how these attributes are generated in the model from known variables. The probability that trip r is taken by a specific transport mode i in city c during year t is assumed to be expressed through a logit model:

$$P_{crit}\left(\mathbf{x}_{rc}; \hat{\boldsymbol{\beta}}_j, \Omega_{ict}\right) = \frac{exp\left(\Omega_{ict} + \mathbf{x}_{rci}\hat{\boldsymbol{\beta}}_i\right)}{\sum_j \left(exp\left(\Omega_{jct} + \mathbf{x}_{rcj}\hat{\boldsymbol{\beta}}_j\right)\right)}. \quad (4)$$

The parameters $\hat{\boldsymbol{\beta}}$ are imported to equations (3) and (4) by re-estimating the econometric model in (1) and (2) with a subset of the control variables used in the full specification. These are the variables included in the *compact version* of the econometric model, enumerated in Table 3.1. This subset contains the explanatory variables that vary across combinations of trips and modes, such as travel times, travel costs and travel conditions. The subset is denoted by $\mathbf{x}_{rci}$ in equation (4). The compact version of the econometric model excludes the socioeconomic characteristics mentioned in Table 3.1, which were denoted by $\mathbf{S}_n$ in (1) and (2). These include, among others, age, gender and unemployment status. The reason for excluding these socioeconomic variables is that the available cross-city data do not contain socioeconomic information that matches $\mathbf{S}_n$ in the same way that travel times, costs and conditions are matched across $\mathbf{x}_{rci}$ and $\mathbf{X}_{ri}$.

The simulation model utilises a set of trips that differ with respect to distance, departure time, i.e. on peak or off-peak, and departure location, i.e. suburban versus central. Thus, each combination of distance, departure time and location gives rise to a different trip r. **Section 2** and **Annex C** briefly explain how the ITF Global Urban Model simulates the corresponding attributes of the trip, such as travel time, cost, and conditions, for each transport mode i and city c.

In addition to mode choice, the simulated emissions in equation (3) depend on total travel demand, which is denoted by T_{ct}. Not all sample trips generated for a given city are equally likely to occur. The higher the relative frequency of longer, more emission-intensive trips, the higher the total emissions generated by urban transport are. The relative frequency of a trip r in city c at year t is denoted by π_{rct} in equation (3) and is computed using the ITF global urban transport model.

The constant terms of the simulation model, i.e. Ω_{cit}, are calibrated such that the predicted choice probabilities for each transport mode in a given city fit the best guesses for the corresponding actual modal split for the benchmark year. The **Annex B** of the paper provides more information about the calibration exercise.

In summary, the simulation model allows the emissions to vary with the overall travel demand, the relative frequency of distant trips, the share of carbon-intensive modes in the various trip categories, the occupancy rate of various transport modes and their carbon intensity. **Section 5** provides the results from the various simulation exercises and highlights the corresponding policy implications of it.

4. Econometric results and policy analysis

Overview

This section presents the results of the econometric analysis using choice experiment data collected in Auckland, Dublin, and Helsinki. The aim of this section is twofold. First, it explores traveller preferences for the different transport modes available to them in the choice experiment. Specifically, the analysis sheds light on the value that people place on the various attributes of each of these modes, e.g. travel cost and travel time. It also provides insights regarding how changes in these attributes induce subsequent changes in the propensity to choose these modes and their alternatives. The results point to policy levers that will likely be effective in encouraging the uptake of shared mobility. The econometric estimates are also used to project the future uptake of shared mobility services and to simulate their environmental impacts. That simulation is presented in **Section 5**.

The section consists of three parts. First, it provides a brief qualitative review of the estimation results of the multinomial logit regression. Second, it reports the elasticities calculated from these parameter estimates. Finally, it draws a number of implications for the design of policies that aim to increase the uptake of shared mobility services in cases where such an increase is expected to have net social benefits.

Estimation results

The parameter estimates of the multinomial logit model (see **Annex A**) reflect how each of the variables included in the model impact the probability of choosing a particular transport mode. Three models are estimated. The first is a complete model that includes variables distinguishing between different types of pecuniary costs associated with car use. The second model is tailored to estimate willingness-to-pay (WTP), in which the impact of all of the pecuniary costs of car use are estimated jointly. The third is a compact model that includes only variables that correspond to those used in the simulation exercise presented in **Section 5**. The parameter estimates of these models are reported in Table A A.2 in **Annex A**.[3] The results reviewed in this section reflect the complete model.

Regarding travel by private car, most of the estimates are qualitatively aligned with theoretical underpinnings and earlier empirical evidence. As expected, travel time has a negative impact on the probability of choosing to travel by car. The cost coefficients indicate that fuel costs and parking prices also have a negative impact on the likelihood of choosing car travel. However, parking prices appear to constitute a stronger disincentive than fuel costs and tolls together.[4] Congestion also affects mode choice, a finding that

[3] Private car is chosen as the reference mode in all estimations. Although the choice of reference mode can be arbitrary, car is used in this case because it is the current preferred mode of most individuals in our sample, as indicated by self-reports gathered in the survey. Additionally, evaluating preferences for alternative modes relative to those for private car use yields insights readily suited to policies seeking to shift travel away from private car use as the dominant mode.

[4] This is likely due to the fact that in this stated preference survey people do not have the opportunity to repeat their choices and learn from possible mistakes as they would in a repeated daily routine. However, there may indeed be a behavioural bias that makes people more sensitive to parking costs than to fuel and toll costs, even in real life situations.

corroborates earlier contributions (Wardman and Nicolás Ibáñez, 2012[12]). The results show that a moderate amount of congestion, here defined as a situation in which vehicles are stopped between 20% and 50% of the travel time, reduces the probability of choosing to travel by car. This may arise from the uncertainty that congestion introduces with respect to travel time, as well as the fact that the amount of time saved in congested situations may be more valuable. Young people and those with no cars in the household are also less likely to choose private car as a mode of transport. In contrast, residing far from the city centre and owning more than one vehicle increase the likelihood of choosing to travel by private car.

In-vehicle travel time, the time required to access a public transport stop and waiting time reduce the likelihood of travelling by public transport. As it has been found in literature (Wardman and Whelan, 2011[13]), walking and waiting time are considered twice as costly as in-vehicle time. The same holds for public transport fares, the degree to which the public transport mode is crowded during a trip (Haywood and Koning, 2015[14]; Wardman and Whelan, 2011[13]) and the number of transfers (Schakenbos et al., 2016[15]; Garcia-Martinez et al., 2018[16]). In terms of the role of individual-specific characteristics, adults are less likely to use public transport, while the opposite is true for those with no cars in the household and those who are not currently employed. The latter group includes those unemployed, voluntarily unemployed and retired.

Regarding non-motorised transport modes, the estimation results indicate that women are less likely to travel by bike and that seniors are less likely to choose either walking or biking. The provision of infrastructure for non-motorised modes of travel, namely bike lanes and priority crossings for pedestrians, does not appear to affect the likelihood of choosing to travel *via* these modes significantly.

As it is the case with other modes, the likelihood of choosing shared mobility decreases with a higher fare and longer in-vehicle and out-of-vehicle times. Respondents also prefer having fewer co-passengers in the vehicle. Women and those who are unemployed tend to favour shared mobility over private car transport, whereas those who live in Dublin appear to be less likely to choose shared mobility versus private car travel, all else equal.

Elasticities

In contrast to parameter estimates, the resulting elasticity values, which are shown in Table 4.1, have a direct interpretation. These values reflect the degree to which the estimated probability of choosing shared mobility responds to changes in the independent variables. These changes could occur in attributes of the shared mobility service itself, in attributes of alternative modes, as well as in socio-demographic characteristics. As detailed in **Annex B**, elasticities reflect the ratio of the percentage change in one variable to the percentage change in another, based on the estimated coefficients in the utility function. For instance, an elasticity of 0.5 implies that increasing the underlying attribute by 10% will induce a 5% increase in the value of the examined probability.[5] Beyond the qualitative information provided by the coefficient estimates from the multinomial logit model, these values provide information about how people are willing to make trade-offs between attributes.

[5] This means that if the probability was initially 20%, it will have to increase to 21%. This is not to be confused with a probability increase of 5.0 percentage points, which would lift the above probability to 25%.

Table 4.1. Elasticities and cross-elasticities for probability to choose shared mobility

	Mode and attribute affected			
Attribute changing	**SM**	**PT**	**C**	**BW**
Mode-specific characteristics				
Trip cost	-0.37224	0.060905		
Travel time	-0.19361	0.060587	0.351132	0.304922
Accessing/waiting/lost time	-0.11898	0.076986		
Number of passengers in the vehicle	-0.11265			
Need to stand for at least part of the trip		0.062049		
Vehicle is a bus		-0.05232		
Number of transfers		0.033293		
Fuel and toll costs			0.171142	
Parking cost			0.12118	
City- and individual-specific characteristics				
20 to 50% travel time stopped			0.029102	
Age < 26			0.025276	
Residing far from the city centre			0.064574	
Having more than one car in the household			-0.09751	
Having no cars in the household		-0.00761	0.067471	
Age 26-45		0.02505		
Being unemployed	0.05214	-0.01772		
Residing in Dublin	-0.10122			
Being female	0.092736			
Being female and using a bike				0.032387
Bike lanes and pedestrian priority measures in place				-0.00334
Age > 65				0.015287

Note: All elasticities computed from estimated coefficients with a 10% level of significance. Medium amount of congestion reflects the fact that, when taking a car, the traveller should expect to be stopped for 20-50% of the total travel time.
Source: Authors' elaboration from the econometric results and ITF survey data.

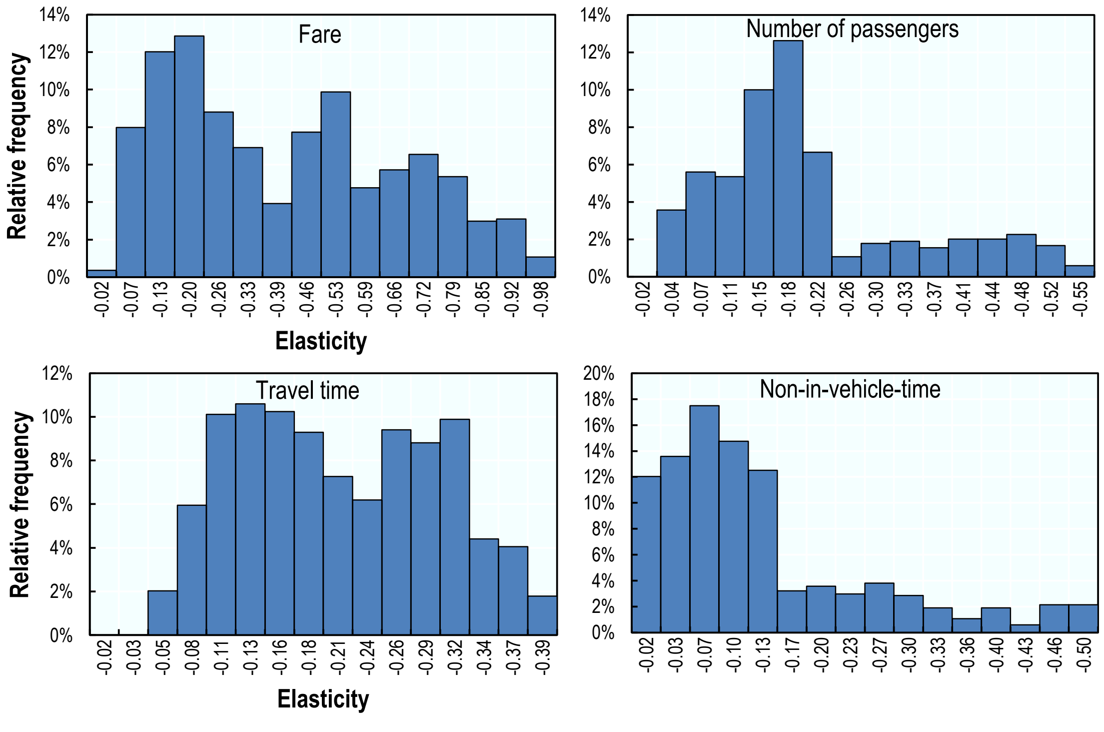
The elasticities referring to the likelihood of choosing shared mobility are reported in Table 4.1. In this table, the row indicates the attribute that changes, while the four columns entitled SM, PT, C and BW refer to the mode whose attribute is affected. Positive values indicate that an increase in the attribute of the underlying mode is associated with an increase in the probability *of choosing shared mobility*. A negative value indicates that an increase in this mode's attribute is associated with a decrease in the probability of choosing shared mobility, and *vice versa*. For example, a one percent increase in the fuel and toll costs of private car use increases the probability of choosing shared mobility by 0.17%. Low absolute values represent a relatively inelastic relationship, meaning that the probability of adopting a shared mobility service is not very responsive to the change in underlying attribute of the mode considered. All absolute values found in this study are less than one, indicating that a change in the considered mode attribute is associated with a less than proportional change in the probability of choosing shared mobility.

The potential behavioural responses captured by these elasticities provide insights into the conditions that are likely to increase the probability of shared mobility uptake. The responses can be divided into three broad categories, namely responses stemming from: (i) changes in the characteristics of the shared mobility service itself, (ii) changes in the characteristics of alternative transport modes, (iii) changes in city- and individual-specific characteristics.

The elasticities reported in Table 4.1 are point-elasticities, which are evaluated at the sample mean. As such, they can mask significant heterogeneity in the range of elasticities that can be obtained by examining the entire sample. Therefore, examining the distribution of key elasticities across the entire sample can provide a basis for much richer policy analysis. These distributions are shown in Figure 4.1.

Figure 4.1 shows the distribution of elasticities for shared mobility attributes across the entire sample. The own-elasticities indicate that the propensity to choose shared mobility is sensitive to the characteristics of the shared mobility service itself. The more expensive a ride is, the longer the in-vehicle and out-of-vehicle times are, and the larger the number of passengers sharing the vehicle with the respondent, the lower the likelihood that this respondent will choose shared mobility. The probability of choosing shared mobility is most sensitive to changes in the fare price of a shared mobility trip.

Figure 4.1. Distribution of the elasticities of shared mobility attributes



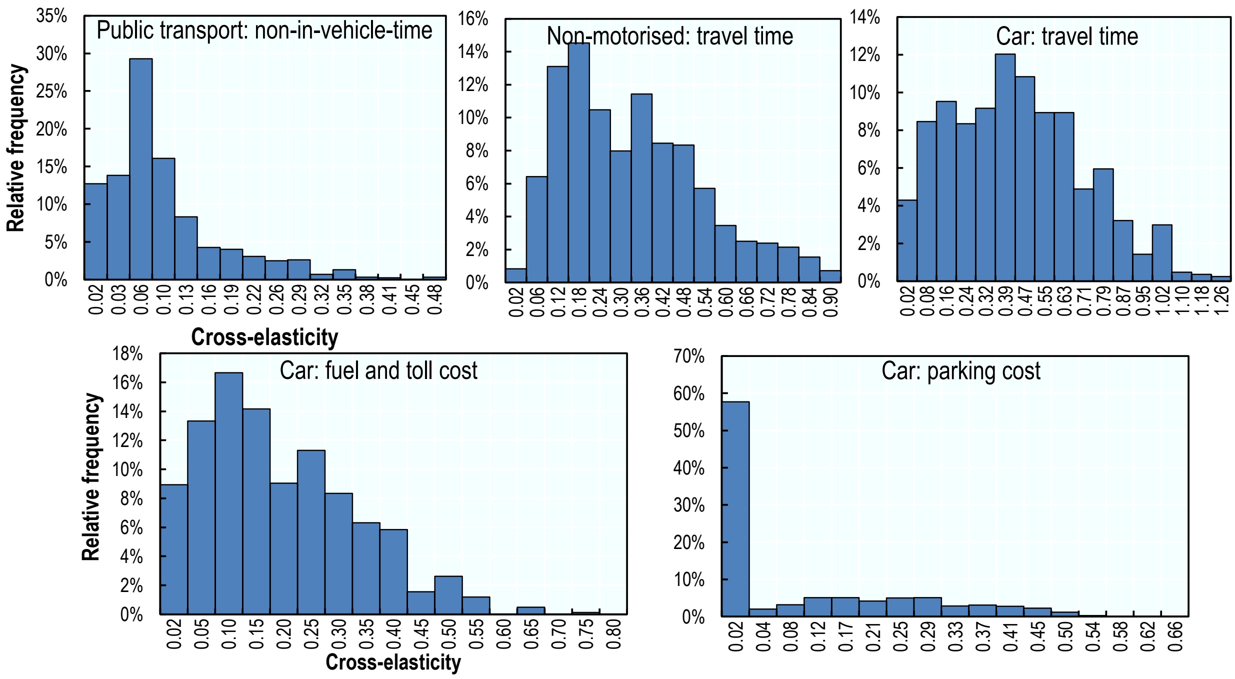
Source: Authors’ elaboration from the econometric results and ITF survey data.

Shared mobility elasticities display specific patterns that matter for policymaking. First, the elasticity with respect to the fare indicates that a non-negligible portion of respondents in the choice experiment demonstrate greater responsiveness to changes in fare price. Second, the elasticity with respect to the travel time indicates that while a portion of observations exhibit a very low sensitivity to changes in the travel time of shared mobility, another contingent of observations indicates relatively higher sensitivity to these changes.

The cross-elasticities in Table 4.1 indicate that choosing shared mobility is most sensitive to changes in the travel times and costs of alternative modes. A 1% increase in the travel time for private car and non-motorised modes increases the propensity to choose shared mobility by an average of 0.35% and 0.30%, respectively. Similarly, a 1% increase in fuel or toll costs and in parking costs for private cars increases the probability of choosing shared mobility by an average of 0.17% and 0.12%, respectively.

Figure 4.2 shows the distribution of cross-elasticities with respect to the attributes of alternative modes across the entire sample. The range of cross-elasticities is greatest for car travel time, with a maximum of 1.26, indicating that some people in the sample are quite sensitive to car travel time and would be prone to switch to shared mobility if car travel times become long. Other attributes, such as the non-in-vehicle time spend travelling by public transport, and the parking costs for private cars, have smaller ranges, indicating that people are less sensitive to changes in these attributes when it comes to the propensity to adopt to shared mobility.

Figure 4.2. Cross-elasticities with respect to alternative mode attributes



Source: Authors' elaboration from the econometric results and ITF survey data.

Table 4.1 indicates that while higher parking prices may induce some people to consider shared mobility, this is not the case for most. This is evident insofar as the average cross-elasticity with respect to parking costs masks a skewed distribution in which the propensity to choose shared mobility is insensitive to parking costs for private cars for a large portion of the observations. Additionally, the distribution of elasticities differs across attributes, meaning that public responses to these policies will differ from the average response in different ways for different attributes.

The values reported for the variables gender and place of residence (i.e. Dublin versus other cities) represent changes in the probability of choosing shared mobility. Women may be more likely to choose shared mobility than men if they are less likely to own a car and have lower time valuations relative to men. The impact of gender on the likelihood of choosing shared mobility can be further investigated. For example, the model predicts that if all users were male shared mobility services would supply 40% of total travel demand. In contrast, if all users were female, the share of shared mobility services in the modal split would rise to 49%.[6] A similar exercise comparing the place of residence finds that if all users are assumed to live in Dublin, the mode share of shared mobility services is 35%, which rise to 49% if no users are assumed to live in Dublin.

Policy implications

A number of policy-relevant insights can be drawn from the results of the econometric analysis, notably from the resulting elasticities and cross-elasticities reported in the previous section. First, the calculated elasticities point to certain measures that would be effective in encouraging the uptake of shared mobility. Second, the uptake of these services should not come at the expense of public transport and non-motorised modes (walking and biking), as long as they are associated with greater social benefits than shared mobility. When this is the case, shared mobility services should be designed so as to complement existing public transport services and non-motorised transport infrastructure.

Case-by-case analyses will be useful in identifying the optimal policies to support shared mobility uptake without attracting users from public transport and non-motorised modes. Case-by-case analyses will also enable policymakers to identify situations in which shared mobility is associated with higher net social benefits than public transport. In these cases, shared mobility services could be promoted even at the expense of public transport. Promoting shared mobility over public transit may be justified, for instance, in sparsely populated areas where heavy public transit infrastructure is not cost-effective or in areas where providing this infrastructure is not feasible, e.g. for geographic reasons. Ensuring net gains in social welfare with the introduction of shared mobility services could be accomplished, for example, through regulations regarding occupancy rates, fare structures, integration with public transport or the way in which shared mobility services are dispatched and routes optimised. The possibility that shared mobility could exacerbate urban sprawl by increasing accessibility for those living in low density peripheral areas should also be considered.

Negative elasticities with respect to the trip cost, travel time, accessing time and waiting times of shared mobility services indicate that these attributes should be minimised in order to encourage the uptake of these services. Policies designed according to average elasticities are likely to generate behavioural responses that are not uniform across the population, which may lead to unexpected outcomes. For this reason, the potential for heterogeneous preferences should be investigated during feasibility studies for new shared mobility services in order to gauge the viability of uptake in a given city.

The results suggest that measures aiming to increase the generalised cost of car use will increase the probability of adopting shared mobility. This can be illustrated through estimations of the market shares. Assuming that all attributes are at their average levels, the market share of shared mobility in the survey is 44%. If the average cost of a car trip increases by $1.00, the market share of shared mobility rises to 47%. Parking costs could potentially be more effective in changing market shares. A $1 increase in the average parking cost results in a shared mobility market share of 50%. The implementation of distance-based charges and cordon tolls that offer an exemption for shared mobility

[6] These calculations set the rest of the attributes at their survey sample mean.

vehicles exceeding a minimum occupancy level could possibly generate a double dividend. That is, it could encourage the uptake of high-occupancy shared mobility services, while decreasing the use of private vehicles. Insofar this policy mix aligns with other policy objectives, such as reducing congestion, it can be generalised to any mix that combines disincentives for car use and incentives for shared mobility use.

Efficient routing algorithms and access to fast lanes will contribute to reducing accessing, waiting, and travel times of shared mobility trips. Moreover, access to fast lanes could be conditioned on a minimum number of passengers in shared mobility vehicles. Such a minimum occupancy requirement could further augment time savings, insofar as it could ease congestion. In the long term, trip fares could be significantly reduced with the penetration of autonomous vehicles in shared mobility fleets.

Some of the findings highlight the ultimate limitations of shared mobility. While the potential environmental benefits of shared mobility stem from its high-occupancy nature, the analysis suggests that the adoption rate of these services will decrease with occupancy rate. This is evidenced by calculating the effect that a change in the number of passengers has on the expected market share of these services. With a unique passenger, the expected market share of shared mobility is 48%. With sixteen passengers in a taxi-bus, the market share falls to 25%. This finding suggests that shared taxis may be more readily adopted in the immediate term than shared taxi-busses and shuttles. In turn, that introduces a ceiling in the potential of shared mobility to reduce the carbon footprint of urban transport, a limitation that is reflected in the results of **Section 5**.

Policy makers should keep in mind, however, that any incentives provided to encourage the uptake of shared mobility should not undermine the relative attractiveness of public transport services. Given that travel undertaken *via* shared mobility will typically have a higher emissions-intensity than travel undertaken *via* public transport, it is unlikely that the net environmental benefits of shared mobility use will be positive for travellers who switch from public transport. This will also hold true when travel *via* shared mobility replaces travel *via* non-motorised transport modes, as non-motorised modes generate zero emissions. Measures to promote shared mobility should therefore be designed so as not to draw riders away from public transport, walking and biking.

In contexts where efficient high capacity public transport networks already exist, shared mobility services can serve as a useful complement to public transport. Policies that seek to coordinate shared mobility with public transport networks can constitute part of a general strategy that harnesses the synergies between emerging shared mobility services and existing transport systems. The greater flexibility that characterises both the occupancy rates and geographical network of shared mobility services could establish them as a potential complementary mode to public transport in many areas. That is, by providing these "feeder" services, shared mobility could facilitate the transport of people to and from public transit stations. That would increase the access to and ridership on public transit systems.

Taken together, the results presented here show that the presence and magnitude of environmental benefits from shared mobility services depend on a number city-specific characteristics. These include the extent and the quality of the existing public transport supply, as well as the habits and preferences of its population. Furthermore, the potential environmental benefits depend on the specific operational characteristics of the implemented service (e.g. occupancy rates, emissions-intensity per vehicle-kilometre). The following section explores the potential of shared mobility systems to reduce greenhouse gas emissions in more than 200 cities worldwide.

5. The impact of shared mobility on greenhouse gas emissions

Overview

This section provides the results and the associated policy implications from the application of the simulation model exhibited in the second part of **Section 3**. The simulation exercise focuses on the differential impact that shared mobility services could have on the greenhouse gas emissions of urban transport. To this end, the section examines the extent to which a widespread deployment of shared mobility services could give rise to additional emission reductions. These reductions come on top of those stemming from overall technological progress, which encompasses increased fuel efficiency of conventional vehicles and less carbon-intensive electricity generation. However, such reductions are far from guaranteed and depend on the context of each specific city, region, and the country it belongs to. In fact, it has been proposed that ride sharing may even increase miles travelled for a variety of reasons. These include the additional distances travelled between clients, i.e. the pick-up detours, or the displacement of the use of public transportation. Recent research such as Henao and Marshall (2019[17]) shows that miles travelled and associated emissions may *increase* with the use of these services, or that the impacts of these services on miles travelled is uncertain (Circella et al., 2018[18]), though these results could change in the longer term.

Whenever present, the additional emissions reductions originate from the fact that shared mobility may cause a shift away from conventional private car use, which is characterised by a low passenger-to-vehicle kilometre ratio. In contrast, shared mobility enables multiple passengers to be simultaneously served with every traversed vehicle kilometre. As such, high-occupancy forms of shared mobility can also constitute an alternative to public transport. If the carbon footprint of the latter is relatively low, however, a shift toward shared mobility and public transport could generate a considerable rebound effect that would eliminate part of the gains obtained from the shift away from conventional cars.

The simulation exercise presented in this section accounts for this dynamic. That is, it allows scenarios to have different impacts on the relative attractiveness of each transport mode, which gives rise to a different evolving market share (modal split) for each of them. To calculate the change in emissions resulting from the change in modal split, the study accounts for a number of relevant variables that evolve between 2015 and 2050. Specifically, the simulation factors in each city's expected increase in total travel demand, which is an outcome of population and income growth. It also accounts for expected improvements in the emission factors (CO_2/vkm) of all modes and in the carbon intensity of electricity generation (CO_2/kWh).

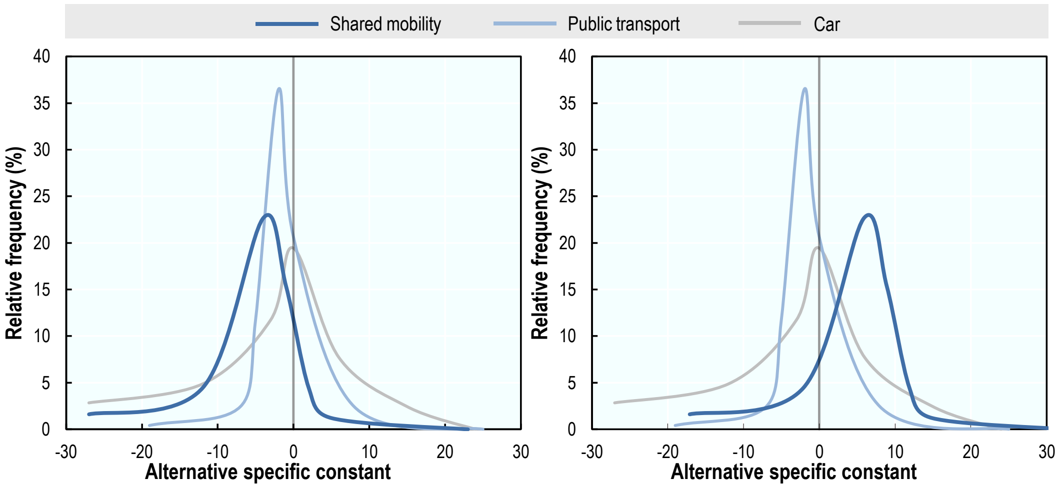
The analysis uses a sample that covers 247 cities in 29 OECD countries and contains synthetic trips of various distances, departure times and departure locations within each city. It imports the preference parameters for the impact of travel time, cost and other important attributes on the choice of transport mode. As shown in **Section 3**, these parameters are estimated using survey data from Auckland, Dublin and Helsinki, hence they are not able to accurately reproduce the travel patterns in the remaining 244 cities. To correct for this, a set of fixed effects that vary across cities and transport modes are calibrated to approximate the share of each mode in each of the 247 urban areas in 2015.

The study compares two scenarios. In a *reference scenario*, all unobserved factors that are responsible for the fact that shared mobility services currently possess a small fraction of the modal split in urban areas remain fixed throughout the period 2015-2050. In contrast, a *counterfactual scenario* allows the aforementioned unobserved factors to improve within the same period substantially. The findings indicate that such an improvement has an important impact on the aggregate urban transport emissions. The former scenario predicts a 10.6% reduction in CO_2 emissions from urban transport. In the latter scenario, total emissions are reduced by 16.9%. The city-by-city analysis indicates that the effect is also present at the city level, as improving the underlying conditions at which shared mobility services are provided is associated with lower emissions in almost all cities in the sample. The accompanying policy implications are elaborated.

The section is organised in three parts. The first part describes the reference and counterfactual scenario, respectively. The second part displays the findings from the simulations. The third part discusses the accompanying policy implications. The **Annex B** of the paper offers a series of technical details related to the calibration and forward simulation of the model.

Figure 5.1. Distribution of the unobserved factors

Overall quantified advantages of each mode in the benchmark year (left), terminal year under the reference scenario (left) and terminal year under the counterfactual scenario (right)



Note: The **left panel** displays the cross-city distributions of fixed effects in the benchmark year, i.e. 2015. For the reference scenario, these distributions remain fixed across the entire time window of the study (2015-2050). The **right panel** displays the cross-city distributions of fixed effects in the terminal year, i.e. 2050, under the counterfactual scenario. The mean shared mobility fixed effect increases by approximately one standard deviation. In both panels, the distributed values of fixed effects are expressed as differences from the underlying effects associated with soft mobility (bike, walk), which are set to zero. *Source*: Graph generated by the authors.

Scenarios

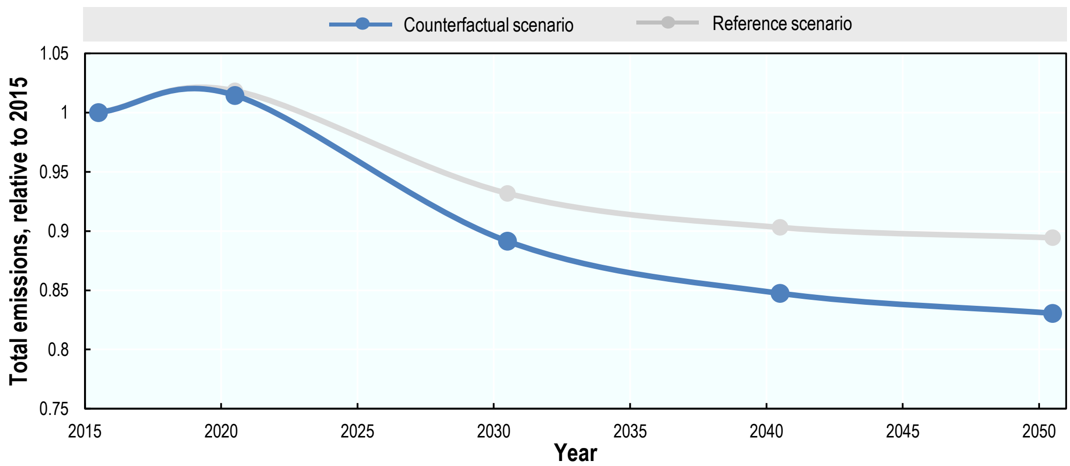
The study examines two scenarios that differ with respect to the assumptions they make about the intertemporal evolution of unobserved factors that affect choice of transport mode. These factors reflect considerations beyond the standard characteristics of travel modes such as travel cost, time and comfort. For shared mobility, the factors reflect technological and institutional *barriers* that are currently responsible for the low prevalence of these services in cities. In the reference scenario, all unobserved factors that determine mode choice remain fixed to their values in the benchmark year, i.e. 2015. Thus, their cross-city distribution remains intact between 2015 and 2050. The left panel of Figure 5.1 displays these distributions, which are obtained by calibrating the model to fit the observed market shares of each transport mode in each of the 247 cities in year 2015.

In the counterfactual scenario, the unobserved factors that are currently responsible for the low market share of shared mobility are allowed to evolve across time in each city. The right panel of Figure 5.1 displays the cross-city distribution of the fixed-effect values in 2050 under the counterfactual scenario. A visual comparison with the left panel reveals that the counterfactual scenario keeps the unobserved factors that govern the choice of car and public transport fixed, while the shared mobility fixed effects increase by one standard deviation from their initial position. This shift takes place between 2015 and 2050 in a continuous manner. An intuitive way to interpret the counterfactual scenario is to consider a pair of cities, e.g. A and B, with the latter city lying one standard deviation ahead of the former in 2015. The scenario assumes that in 2050, shared mobility services in city A will resemble those offered in city B back in 2015.

Simulation results

The results indicate that a widespread deployment of shared mobility services could have a significant effect on the overall emissions of urban passenger transport. Figure 5.2 displays the evolution of total CO_2 emissions, i.e. the aggregate emissions from transport in the sample of 247 cities, relative to their initial value in 2015. The difference between the two curves represents the isolated impact of overcoming remaining technological constraints and institutional barriers that currently hamper a widespread adoption of shared mobility. This difference is substantial: while the reference scenario predicts a 10.6% reduction in CO_2 emissions from urban transport, that reduction is 16.9% in the counterfactual scenario.

Figure 5.2. Evolution of total CO_2 emissions from urban transport

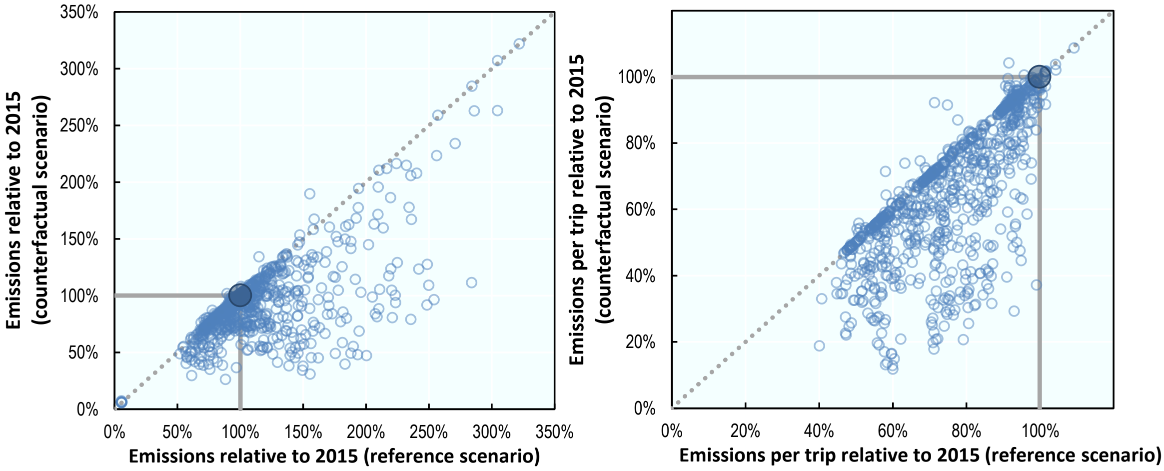


Note: The emissions at any time point are expressed relative to the total emissions at year 2015.
Source: Generated by the authors.

The contribution of shared mobility services could be even higher if a series of factors not modelled explicitly in this exercise are taken into account. The most important of them is that, upon becoming the dominant form of urban transport, shared mobility could also have a feedback effect on car ownership. That is, a much sparser use of private cars could potentially induce a substantial share of the population to reconsider car ownership. Second, a switch to shared mobility would increase the passenger-to-vehicle kilometre ratio, as it would allow the utilisation of larger shuttles that deliver more passenger kilometres to be undertaken per vehicle kilometre travelled. Finally, the large scale adoption of shared mobility services has the potential to reduce congestion, increasing average vehicle speeds, reducing gasoline consumption, and reducing travel times.

Figure 5.3. The impact of mainstreaming shared mobility on CO_2 emissions across cities

Mainstreaming shared mobility could reduce total emissions (left) and average emissions per trip (right) in almost every city.

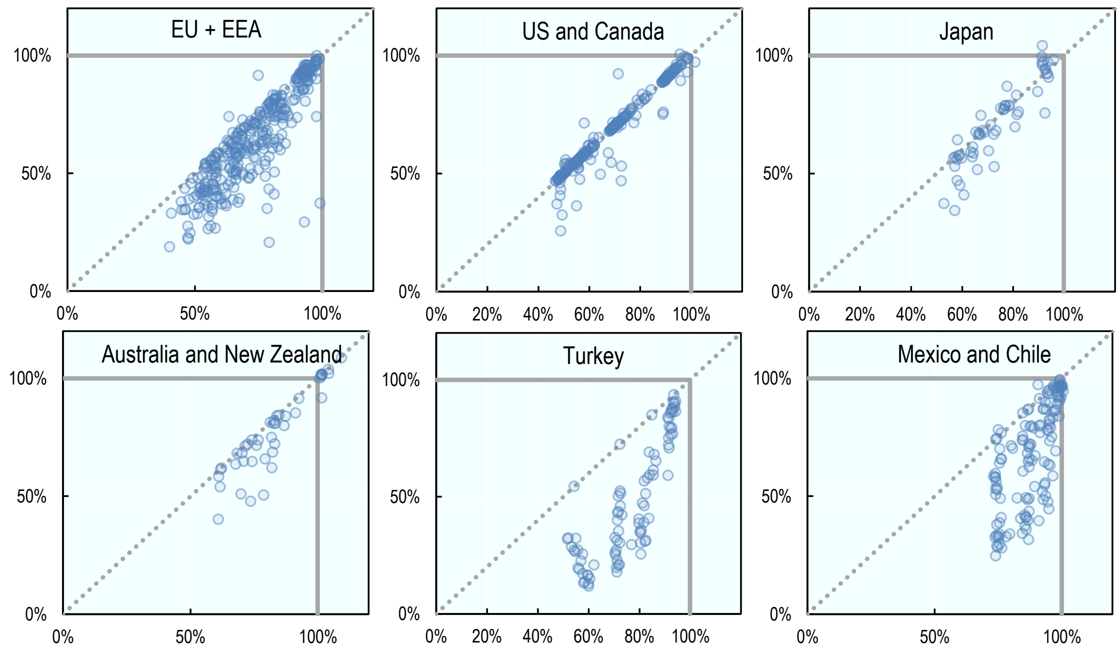


Note: The left (respectively, right) panel displays the change in total CO_2 emissions (respectively, average CO_2 emissions per trip) predicted by the reference scenario relative to the corresponding change predicted by the counterfactual scenario. Dots below the diagonal 45° line represent cities in which the *per se* mainstreaming of shared mobility services will reduce emissions. Dots within the inner boxes represent cities in which total CO_2 emissions (left panel) or average CO_2 emissions per trip (right panel) will be reduced in both scenarios.
Source: Generated by the authors.

The impact of mainstreaming shared mobility services may vary substantially across cities and countries. Figure 5.3 visualises this variation. In both panels of the figure, each circle represents a city in any of the sample years used in the simulation, i.e. 2015, 2020, 2030, 2040 and 2050. The horizontal position of each point reflects the total CO_2 emissions (left panel) or average CO_2 emissions per trip (right panel) relative to their respective values in 2015, under the reference scenario. Thus, points whose horizontal axis values exceed 100% represent cities in which emissions compared to their benchmark levels are expected to increase over time. Similarly, the vertical position of each dot embodies the total CO_2 emissions (left panel) or average CO_2 emissions per trip (right panel) relative to the respective values in 2015, under the counterfactual scenario. Therefore, points that lie below the diagonal line represent cities in which mainstreaming of shared mobility services *per se* will have positive impact in reducing the total CO_2 emissions (left panel) or average CO_2 emissions per trip (right panel). The opposite holds for points lying above the diagonal line. Points lying on the diagonal represent cities in which the mainstreaming of shared mobility will have an insignificant impact on their CO_2 emission profile. Finally, points falling within the inner boxes of the two panels represent cities in which total CO_2 emissions (left panel) or average CO_2 emissions per trip (right panel) are expected to decrease compared to their values in 2015. Further inspection of the figures provides a series of important insights.

Figure 5.4. The impact of mainstreaming shared mobility on average CO_2 per trip

Impacts displayed by region



Note: Panels display the change in the average CO_2 emissions per trip predicted by the reference scenario relative to the corresponding change predicted by the counterfactual scenario. Dots below the diagonal 45° line represent cities in which the per se mainstreaming of shared mobility services, i.e. the counterfactual scenario, will reduce emissions. Points within the inner boxes represent cities in which the average CO_2 emissions per trip will be reduced in both scenarios.
Source: Generated by the authors.

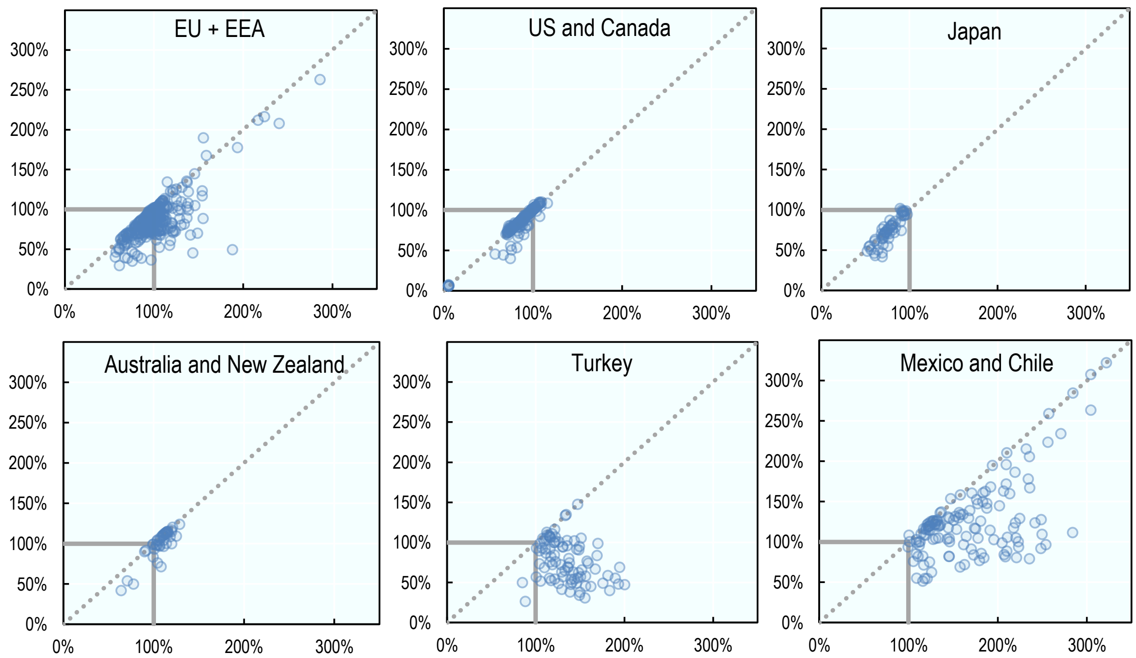
In almost all of the cities in the sample, the average CO_2 footprint of a given trip decreases under both scenarios. This can be observed in the right panel of Figure 5.3, in which the vast majority of the cities fall within the inner box. The result is robust across regions, as the accompanying visual inspection of Figure 5.4 suggests. That figure breaks down the effect in six different regions. The temporal disaggregation of the analysis indicates that the aforementioned reduction is reinforced over time, as the lower panels of Figure 5.6 suggest. The falling carbon intensity of the average trip can be primarily attributed to three factors: the increasing fuel efficiency of vehicles, the expected electrification of a part of the private vehicle fleet and the decreasing carbon intensity of electricity generation, which powers part of public transport services.

While the average carbon intensity of a trip has a clear decreasing trend in almost all urban areas, the same is not true for the total CO_2 emissions from urban transport. The left panel of Figure 5.3 shows that in a large number of cities, total CO_2 emissions from urban transport are expected to continue increasing to 2050. Furthermore, this occurs under both the reference and counterfactual scenarios. Figure 5.5 provides further insights on the regional character of this finding. In particular, the cross-region analysis reveals that the pattern is relatively stronger in Mexico, Chile and Turkey. A possible explanation is that the overall travel demand in urban areas of these countries is expected to increase faster than the pace at which an average urban trip is decarbonised. This could be attributed to a series of drivers that underlie the growth in travel demand, such as population and income growth, which are expected to be high in these countries during the time window of the study. The upper panels of Figure 5.6 indicate that the effect does not diminish over time (further detail can be found in Figure A C.1. in **Annex C**).

Although the mainstreaming of shared mobility does not seem to provide a solution to increasing CO_2 patterns, it should be part of the effort to decarbonise transport in most of the urban areas. This is indicated in all panels of Figure 5.3-Figure 5.5, which indicate that shared mobility could assist almost all cities to reduce the CO_2 emissions from an average trip, as well as their total carbon footprint from passenger transport. Most importantly, that holds even in the vast majority of cities in which total transport-related CO_2 emissions are expected to increase. In line with this, Figure 5.5 shows that almost all of the cities whose total transport-related CO_2 emissions display an upward trend could benefit from shared mobility and substantially curb that trend. In some of the cases, the widespread deployment of shared mobility could reverse the trend. That holds particularly for Turkish cities, as well as a considerable fraction of European, Chilean and Mexican cities.

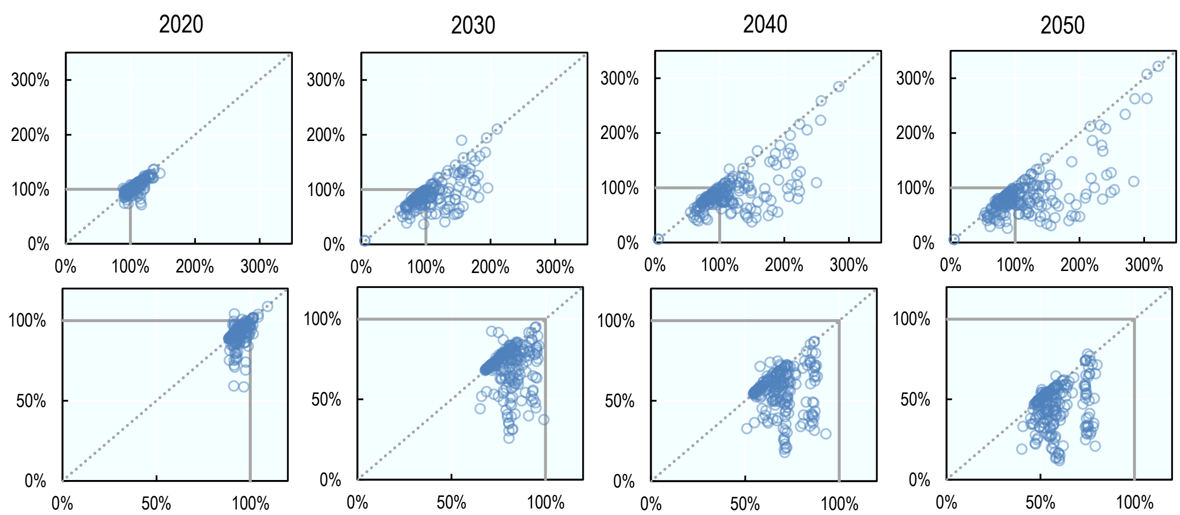
Figure 5.5. The impact of mainstreaming shared mobility on average CO_2 per trip

Impacts displayed by region



Note: All panels display the change in total CO_2 emissions predicted by the reference scenario (x-axis) relative to the corresponding change predicted by the counterfactual scenario (y-axis). Points below the diagonal represent cities in which the per se mainstreaming of shared mobility services will reduce emissions. Dots within the inner boxes represent cities in which total CO_2 emissions will be reduced in both scenarios
Source: Generated by the authors.

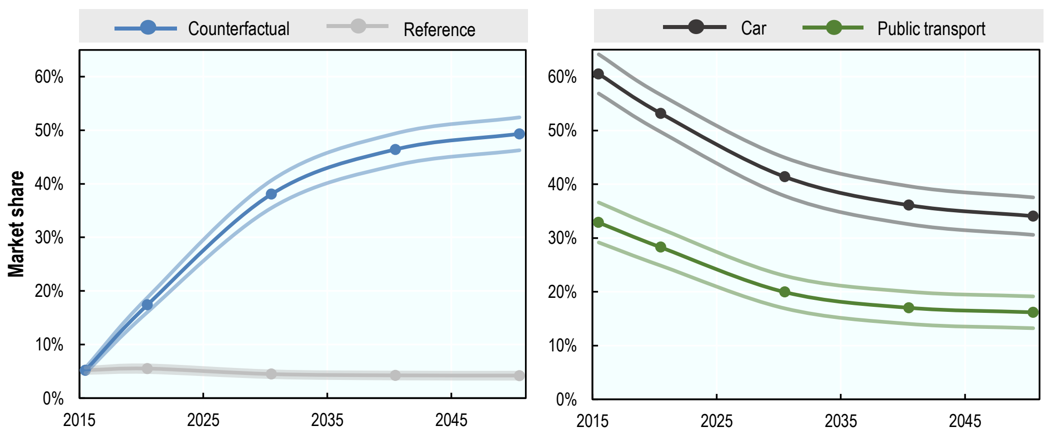
Figure 5.6. The impact of mainstreaming shared mobility on CO_2 emissions across time



Note: Upper (respectively, lower) panels display the change in total CO_2 emissions (respectively, average CO_2 emissions per trip) predicted by the reference scenario (x-axis) relative to the corresponding change predicted by the counterfactual scenario (y-axis). Points below the diagonal represent cities in which the *per se* mainstreaming of shared mobility services will reduce emissions. Points within the inner boxes represent cities in which total CO_2 emissions (upper panels) or average CO_2 emissions per trip (lower panels) will be reduced in both scenarios.
Source: Generated by the authors.

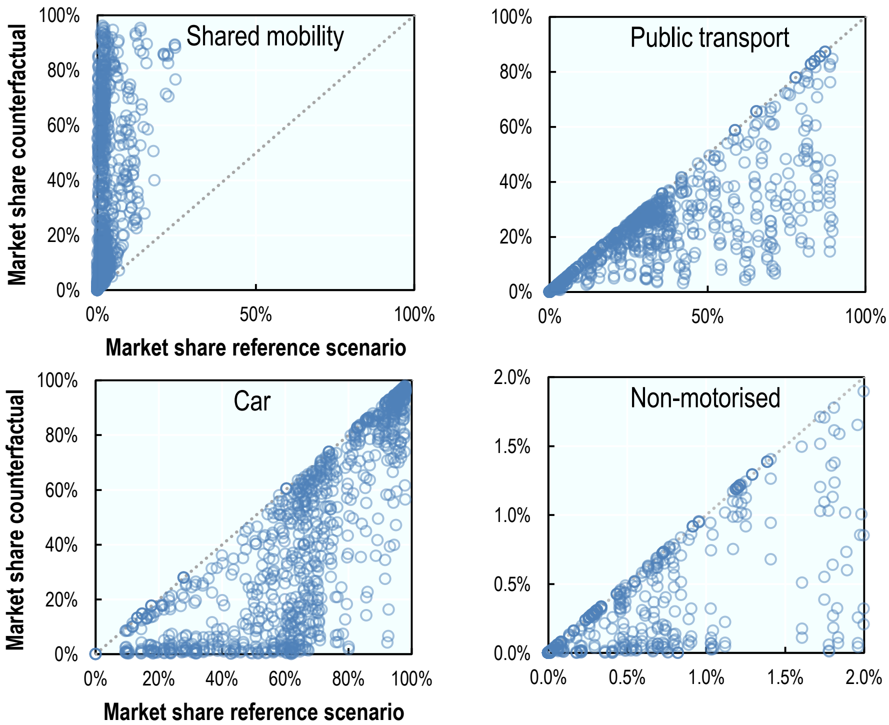
The difference in CO_2 emissions between the reference and counterfactual scenarios stems primarily from a change in modal splits. Figure 5.7 displays the evolution of the modal splits under the counterfactual scenario over time. The mode share of cars and public transport fall with the increased uptake of shared mobility services.

Figure 5.7. Evolution of the city average modal split over time



Note: The average is obtained by weighting the estimated modal split for each city by the share of passenger kilometres of that city over the total passenger kilometres in the given year.
Source: Generated by the authors.

Figure 5.8. Market shares over the counterfactual scenario



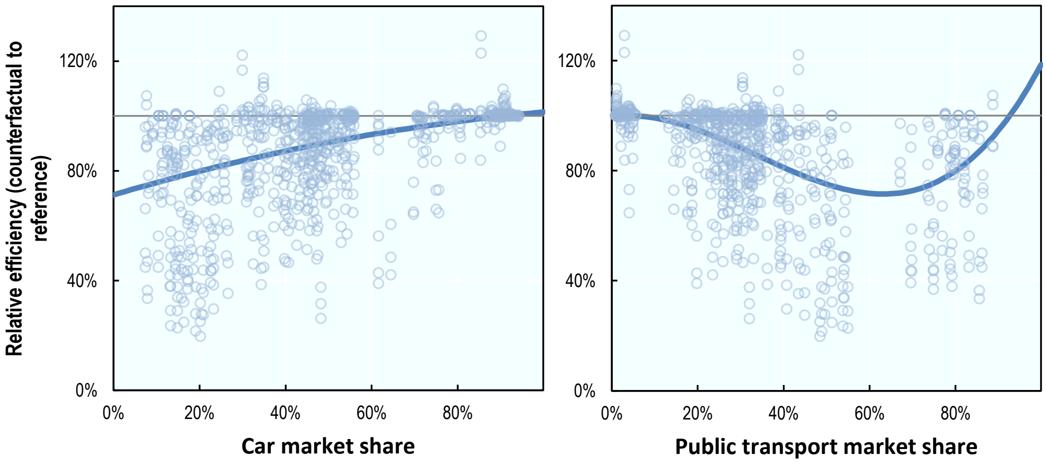
Note: Each observation represents one city in one given year. When the dot lie on the diagonal, the market shares are identical in both scenarios. If the dot is above the diagonal, the market share of the mode is larger in the counterfactual scenario. Otherwise, the market is smaller in the counterfactual scenario.
Source: Generated by the authors.

Shared mobility replaces a larger number of trips from cars than from public transport. Figure 5.8 shows that this average effect holds in most cities. This can be seen by the considerable number of cities in which the mode share of cars lies between 20% and 60% in the reference scenario, but falls to zero in the counterfactual scenario. In contrast, the vast majority of points in the "public transport" panel of the figure are concentrated around the diagonal line. This implies that in a large fraction of the cities in the sample, the market share of public transport is relatively stable across scenarios.

The initial share of car and public transport in the modal split is an important predictor of the emission reductions that shared mobility can generate. Figure 5.9 displays the results of a regression conducted to explore the relationship between the initial modal split (in 2015) and the efficiency ratio of the two scenarios (further detail can be found in Figure A C.2. in **Annex C**). The efficiency ratio expresses CO_2 emissions in the counterfactual as a fraction of the corresponding emissions in the reference scenario. Thus, values close to zero indicate that shared mobility brings relatively large emission reductions. Similarly, values close to one indicate that shared mobility does not have significant mitigation potential. Finally, values exceeding one indicate that the widespread adoption of shared mobility services increases CO_2 emissions.

The results highlight two aspects that are important when it comes to introducing shared mobility services. First, cities in which the mode share of public transport is already high do not stand to benefit from shared mobility services. This is because the share of public transport in the modal split will fall with the uptake of these services. That will be followed by an increase in the carbon footprint of these cities, as the carbon intensity of a passenger-kilometre undertaken with shared mobility is higher than a corresponding passenger-kilometre undertaken by public transport. Second, although cities with a high level of private car stand to see substantial emissions reductions from shared mobility uptake, car dependency itself appears to pose a significant barrier to the uptake of these services in these cities. This is indicated by the small efficiency ratio values in cities where the share of public transport in the modal split is very low. The exact nature of this apparent inertia in mode splits cannot be identified in the context of this study and should be examined on a case-by-case basis.

Figure 5.9. Predicting the relative efficiency of scenarios with the initial modal split.



Note: Each observation represents one city in one given year. The relative efficiency (in the vertical axis) is the result of dividing the total CO_2 emissions in the reference scenario over the total CO_2 emissions in the counterfactual. The observations above the grey horizontal line imply that the emissions are larger in the counterfactual than in the reference scenario.
Source: Generated by the authors.

Policy implications

The study yields a series of important policy implications. These are related to whether shared mobility constitutes, from a social point of view, a cost-effective alternative to conventional private and public modes of transport. The implications pertain also the degree to which future leverage of relevant urban transport decarbonisation policies should rely to these services.

The finding that a widespread deployment of shared mobility services leads, in almost all cases, to a decrease in transport-related CO_2 emissions has certain policy implications. The most clear of them is that long-run institutional barriers to that deployment that are not justified from an economic viewpoint, or contradict other policy objectives, should be relaxed or removed altogether. The results indicate that mainstreaming shared mobility is highly likely to reduce the use of private car much more than the use of public transport. The net environmental effect of shared mobility will therefore be positive, not only in terms of greenhouse gas emissions, but also in the form of reduced tailpipe emissions of air pollutants. In addition, these positive effects could extend to other urban externalities that result from the excess use of private cars, such as congestion, noise and traffic accidents.

Furthermore, all findings indicate that shared mobility cannot be considered a stand-alone strategy for decarbonising urban transport. The analysis shows that while these services have the potential to enhance urban transport decarbonisation, alone they cannot be expected to deliver emissions reductions on a massive scale. Perhaps the most striking finding of the study is that, despite being significant, the *per se* contribution of shared mobility to reductions of urban transport emissions does not exceed 6.5%. An immediate outcome of this finding is that core policies, such as taxes and subsidies, should also target other, possibly more effective ways to decarbonise urban transport.

This holds true particularly for the cities that are highly car-dependent. Most of these cities are located in the US, Canada, Australia, and New Zealand, but the findings indicate that such areas can also be found in Europe. In these cities, the uptake of shared mobility is limited, likely due to strong established preferences for travel by private car. Cities with high mode shares of public transit also do not see strong emissions reductions from an increased uptake of shared mobility either. The mechanism behind the weak mitigation potential of shared mobility in these cities is, however, different than that of cities with high private car use. Shared mobility in these contexts is ineffective not because it is not adopted, but because it draws users from public transport, which is generally less emissions-intensive per passenger-kilometre than travel *via* shared mobility services. That is, in areas that are well-served by public transport, shared mobility services will inevitably attract a considerable share of public transport users, neutralising most of the gains resulting from reduced private car use. In both of these cases, policy support for shared mobility that bears a non-negligible social cost is not warranted.

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Annex A. Econometric estimation and results

Annex A contains additional information concerning the ITF survey data and the results from the econometric models.

Survey data: attribute levels

Table A A.1. summarizes the attribute levels that could be faced by the individuals during the completion of the survey. At the beginning of the survey each individual chose a number from 1 to 4, corresponding to a randomization of the survey that leads to a specific combination of the attribute levels presented below for each of the four rounds.

Table A A.1. Attribute levels

Variable	Mode	Levels
Travel time	Car	30, 20
	Shared Mobility	15, 25
	Non-motorised	20, 45
	Public transport	10, 40
Fuel Cost	Car	1.02, 1.06 1.25, 3.11 3.56, 3.70
Parking Cost	Car	0, 2.18, 3.05, 3.17
Toll Cost	Car	0, 1.25, 3.11, 5.08, 12.20, 12.67
Fare	Shared mobility	1.52, 1.58, 1.87, 3.56, 3.70, 4.98
	Public transport	1.02, 1.06, 1.56, 3.05, 3.17, 3.74
Waiting time	Public transport	5, 20
Lost time (waiting + detour time)	Shared mobility	0, 2, 3, 5, 10, 15
Accessing time	Shared mobility	0, 2, 5, 10, 15
	Public transport	10, 20
Number of Passengers	Shared mobility	0, 3, 4, 10
Number of transfers	Public transport	0, 1, 3
Availability of cycle path or sidewalk	Non-motorised	None available, good.
Ease of crossing in traffic	Non-motorised	Pedestrian crossing (regular priority crossing), traffic light crossing with pedestrian/bicycle priority button (protected and prioritised).
Congestion level	Car	Greater than 50% or less than 20% of time stopped in traffic, 20% to 50% of time stopped in traffic.
Crowding on board	Public transport	Part of trip standing, able to choose a seat and standing and difficult to move.

Note: The time is expressed in minutes and the monetary values in $US PPP 2017.
Source: Authors' elaboration of ITF survey data.

Econometric models estimated coefficients

Table A A.2. Econometric models estimated coefficients

	Complete model	Complete model WTP	Reduced model Simulations
Non-motorised	-0.622	-0.329	-1.4*
	(0.681)	(0.775)	(0.729)
Bike			-0.434*
			(0.222)
Travel time	-0.721***	-0.788***	-0.715***
	(0.122)	(0.11)	(0.108)
Priority crossing + Sidewalk / Cyclepath	0.102	-0.127	0.00427
	(0.285)	(0.309)	(0.305)
Age > 65	-1.34**	-1.38	
	(0.591)	(0.596)	
Female X Bike	-1.07***	-1.16***	
	(0.325)	(0.321)	
Public transport and Shared mobility			
Travel time	-0.177**	-0.185**	-0.184**
	(0.0759)	(0.0763)	(0.0726)
Non-in-vehicle time	-0.228**	-0.294***	-0.275***
	(0.11)	(0.109)	(0.106)
Fare	-0.222***	-0.214***	-0.232***
	(0.0688)	(0.0691)	(0.0656)
Public transport	-1.62**	-1.55**	-2.07***
	(0.752)	(0.772)	(0.675)
Bus	0.673**	0.678**	0.467*
	(0.286)	(0.283)	(0.259)
Need to stand for at least part of the trip	-0.926***	-0.942***	-0.839***
	(0.309)	(0.315)	(0.293)
Number of transfers	-0.303*	-0.261	-0.223
	(0.165)	(0.165)	(0.157)
Age 26-45	-0.449*	-0.453*	
	(0.235)	(0.234)	
Unemployed	0.755***	0.709**	
	(0.29)	(0.288)	
No car in the household	0.568*	0.573*	
	(0.293)	(0.293)	
Shared mobility	-0.638	-0.537	-1.16**
	(0.576)	(0.593)	(0.54)
Number of passengers	-0.0696***	-0.0691***	-0.0528**
	(0.0235)	(0.0233)	(0.0225)
Dublin	-0.587***	-0.57***	
	(0.178)	(0.177)	
Female	0.377**	0.365**	
	(0.165)	(0.164)	
Unemployed	0.54**	0.509**	
	(0.215)	(0.213)	
Car			
Travel time	-0.562***	-0.605***	-0.607***
	(0.196)	(0.197)	(0.183)
Fuel cost + Tolls	-0.175***		
	(0.0404)		
Parking cost	-0.405***		
	(0.0682)		
Fuel + Parking + Tolls cost		-0.227***	-0.274***
		(0.0406)	(0.0378)
20 to 50% travel time stopped	-0.461**	-0.394*	-0.397**
	(0.218)	(0.211)	(0.19)
Age < 26	-1.32***	-1.27	
	(0.344)	(0.332)	
More than 1 car in the household	0.822***	0.797***	
	(0.168)	(0.166)	
No car in the household	-2.35***	-2.3***	
	(0.534)	(0.532)	
Far from the city centre	0.701***	0.669***	
	(0.172)	(0.17)	

Note: *, **, and *** represent significance levels of p < 0.10, p < 0.05, and p < 0.01, respectively.
Source: Authors' estimations from ITF data.

Willingness to pay

The willingness-to-pay (WTP) is a measure of the monetary value individuals assign to an additional unit of a particular attribute.[7] Negative estimates could be interpreted as willingness-to-accept and reflect the amount that people would require to accept an increase in the unit of the attribute being evaluated.

Table A A.3 reports WTP estimates using the coefficients estimated by the WTP model, i.e. the model that estimates a joint parameter to reflect the impact of fuel, toll and parking costs on the utility obtained from choosing car travel.

Table A A.3. Estimates of the willingness to pay.

	Car	Public transit	Shared mobility
Travel time (EUR/hour)	16.01764	5.17099	5.17099
Accessing time (EUR/hour)	-	8.23843	8.23842
Number of transfers		1.21798	
Number of other passengers	-	-	0.32274
Standing (at least part of the time)	-	4.3986	-
Medium congestion (stopped for 20-50% of in-vehicle time)	1.7360	-	-

Note: WTP estimates are denominated in EUR PPP 2018. Estimates of the travel time and accessing time for public transport and shared mobility the same because the coefficients for these variables are assumed to be the same as long as the differing factors are included in the model.

The valuation of accessing time is, however, significantly higher than the valuation of travel time for public transit and shared mobility. This implies that respondents prefer a longer amount of in-vehicle time over spending more time accessing the vehicle. The latter finding is in line with earlier contributions (Abrantes and Wardman, 2011[19]) (Wardman and Whelan, 2011[20]). Respondents are also willing to pay at least one extra euro per trip in order to avoid having to make an additional transfer in public transport. Finally, crowdedness appears less desirable in public transport than in shared modes, as the need to stand during the travel time makes public transport significantly less appealing.

[7] Willingness-to-pay is calculated by dividing the coefficient of the attribute of interest for a particular mode by the cost coefficient for that mode. Hence the need to estimate a single cost coefficient for the costs of car use in the WTP model.

Annex B. Technical notes

Annex B contains technical information complementing **Section 3**.

Derivatives and elasticities used in the study

The policy analysis in **Section 4** relies on own- and cross-elasticities regarding the probability of choosing shared mobility. The derivative of the choice probability of mode i with respect to a change in an explanatory variable entering its own utility in (1), i.e. x_{ri}, is given by:

$$\frac{\partial P_{nri}}{\partial x_{ri}} = \beta_{ix}\, P_{nri}\, (1 - P_{nri}). \tag{TA.1}$$

Since equation (1) is linear in parameters and control variables, β_{ix} reflects the additional utility derived from a marginal increase of the explanatory variable x_{ti}. For example, (TA.1) can be used to compute the change in the probability of choosing shared mobility if the cost of it (x_{ti}) increases by a small amount. Similarly, equation (2) can be used to calculate the derivative of the choice probability of mode i with respect to a change in an explanatory variable entering the utility of another transport mode in (1), i.e. x_{rj}. That is:

$$\frac{\partial P_{nri}}{\partial x_{rj}} = -\beta_{jx}\, P_{nri}\, P_{nrj}. \tag{TA.2}$$

For example, (TA.2) could yield the change in the probability of choosing shared mobility if the cost of another mode (x_{ti}) increases by a small amount. Equations (TA.1) and (TA.2) can be used to calculate the associated *point* own- and cross-elasticities of the choice probabilities. For a given observation (n, t), these elasticities with respect to the mode of interest i and alternative mode j are, respectively:

$$\mathcal{E}_{i,x_{ti}} = \beta_{ix}\, x_{ti}\, (1 - P_{nti}), \tag{TA.3}$$

and

$$\mathcal{E}_{i,x_{tj}} = -\beta_{jx}\, x_{tj}\, P_{ntj}. \tag{TA.4}$$

The study reports the *average own and cross elasticities*, which are given, respectively, by:

$$\overline{\mathcal{E}_{\iota,x_{t\iota}}} = \frac{1}{N_S}\beta_{ix} \sum_{n} \left(\sum_{t} x_{ti}\, (1 - P_{nti}) \right), \tag{TA.5}$$

and

$$\overline{\mathcal{E}_{\iota,x_{tj}}} = -\frac{1}{N_S}\beta_{jx} \sum_{n} \left(\sum_{t} x_{tj}\, P_{ntj} \right). \tag{TA.6}$$

In equations (TA.5) and (TA.6), N_S denotes the size of the survey sample, which is 840 observations. This number is the product of the 210 individuals participating in the survey and the four responses each individual provides. The study also reports the *own and cross elasticity at the sample mean*. Denoting the average value of variables x_{ri} and x_{rj} by $\overline{x_{ri}}$ and $\overline{x_{rj}}$ respectively, these elasticities are:

$$\mathcal{E}^M_{i,x_{ti}} = \beta_{ix}\overline{x_{ti}}\,\widehat{P_{nti}}\,, \tag{TA.7}$$

and

$$\mathcal{E}^M_{i,x_{ti}} = -\beta_{jx}\,\overline{x_{tj}}\,\widehat{P_{ntj}}\,, \tag{TA.8}$$

respectively, where $\widehat{P_{nti}}$ and $\widehat{P_{ntj}}$ are the choice probabilities of mode i and j calculated at the sample mean.

Maximum likelihood estimation

The parameters in the choice model in equations (1) and (2) i.e. the vectors $\boldsymbol{\alpha}, \boldsymbol{\beta}$, and A_n are estimated using maximum likelihood estimation (MLE). The likelihood function is:

$$\ell = \prod_n \left(\prod_r \left(\prod_i \left(P_{nri}{}^{y_{nri}} \right) \right) \right), \tag{TA.11}$$

where y_{nri} equals one if the respondent n chooses transport mode i for hypothetical trip r and zero otherwise. Taking the logarithm of ℓ yields the log-likelihood function:

$$L(\boldsymbol{\alpha}, \boldsymbol{\beta}, A_n) = \sum_n \left(\sum_r \left(\sum_i \left(y_{nri}\, log\left(P_{nri}(\mathbf{X}_r, \mathbf{S}_n | \boldsymbol{\alpha}, \boldsymbol{\beta}, A_n) \right) \right) \right) \right). \tag{TA.12}$$

Maximum likelihood estimation adjusts the values of the parameter vectors $\boldsymbol{\alpha}$ and $\boldsymbol{\beta}$ so as to maximise the expression in (TA.12) given the observations $(\mathbf{X}_r, \mathbf{S}_n, y_{nri})$.

From estimation to cross-city simulation: practical considerations

The underlying transport mode choice model that corresponds to the choice probability (of choosing mode i in city c for trip r in year t) in equation (4) is:

$$U_{crit} = \Omega_{ict} + \mathbf{x}_{rci}\widehat{\boldsymbol{\beta}}_i + \omega_{ictr}, \tag{TA.13}$$

where $\widehat{\boldsymbol{\beta}}$ is the econometrically estimated vector of parameters corresponding to travel time, travel cost and trip conditions. Unlike equation (1), the expression in (TA.13) does not contain socioeconomic control variables. Furthermore, equation (TA.13) is computed for cities that are different than the three cities in which survey data are collected to estimate vector $\boldsymbol{\beta}$, i.e. Auckland, Dublin and Helsinki. As a result, the estimated fixed effects in that model, $\widehat{\boldsymbol{A}}$, do not capture the average utility of unobserved factors in the sample of cities used in the simulation exercise. As such, the estimated $\widehat{\boldsymbol{A}}$ will not be sufficient to reproduce the market share of each transport mode in each city. To overcome these limitations, the simulation model replaces $\widehat{\boldsymbol{A}}$, which vary only across modes and socioeconomic groups, with the term Ω_{ict}. The latter is calibrated so that in the benchmark year the expected probability of choosing transport mode i in city c, weighted by the relative frequency of trips, is equal to the modal share. That is:

$$\underbrace{\sum_r \left(\pi_{rc0} \frac{exp(\hat{\Omega}_{ic0} + \mathbf{x}_{rci}\widehat{\boldsymbol{\beta}}_i)}{\sum_j \left(exp(\hat{\Omega}_{jc0} + \mathbf{x}_{rcj}\widehat{\boldsymbol{\beta}}_j) \right)} \right)}_{\substack{\textbf{weighted probability of mode } i \textbf{ in city } c \\ \textbf{at the benchmark year } t\,=\,0}} = \hat{P}_{ic0}, \tag{TA.14}$$

where i.e. $t = 0$ denotes the benchmark year and π_{rc0} is the relative frequency of trip r in city c. In (TA.14), $\hat{\Omega}_{ic0}$ is the calibrated specific constant (i.e. fixed effect) for mode i and city c at $t = 0$ and $\hat{P}_{ic0}$ is the target choice probability. This probability is provided *via* the ITF global urban transport model and is used as the best available proxy for the actual share of transport mode i in city c at the benchmark year.

Calibration

The model used to project emissions, presented in detail in **Section 3**, is:

$$E_{ct} = T_{ct} \underbrace{\sum_r \left(\underbrace{\pi_{rct} \sum_j \left(\underbrace{\mathrm{D}_r\, P_{crjt}(\mathbf{x}_{rjc}; \widehat{\boldsymbol{\beta}}_j, \Omega_{jct}) \frac{\mathrm{e}_{cjt}}{\mathrm{L}_{cjt}}}_{\substack{\textbf{carbon footprint of trip } r \\ \textbf{with mode } j \textbf{ in city } c \textbf{ at year } t}} \right)}_{\textbf{carbon footprint of trip } r \textbf{ in city } c \textbf{ at year } t} \right)}_{\textbf{carbon footprint for the average trip in city } c \textbf{ at year } t}. \tag{TA.15}$$

The model contains a series of parameters $(\widehat{\boldsymbol{\beta}}, \boldsymbol{\Omega})$ that govern individual behaviour, in particular the probability that a transport mode is selected in any given year and city for a given type of trip. The latter probability is given by the formula:

$$P_{crit}(\mathbf{x}_{rc}; \widehat{\boldsymbol{\beta}}_j, \Omega_{ict}) = \frac{exp(\Omega_{ict} + \mathbf{x}_{rci}\widehat{\boldsymbol{\beta}}_i)}{\sum_j \left(exp(\Omega_{jct} + \mathbf{x}_{rcj}\widehat{\boldsymbol{\beta}}_j) \right)}, \tag{TA.16}$$

where $\widehat{\boldsymbol{\beta}}_j$ is the vector of individual behaviour parameters that determine the systematic utility of using mode j to make a trip r in city c. The latest trip has a set of characteristics that are quantified in the vector $\mathbf{x}_{rcj}$. Parameters $\widehat{\boldsymbol{\beta}}$ are directly imported using the econometric estimates obtained with survey data for Auckland, Dublin and Helsinki. The methods used to estimate these parameters are described in detail above.

Parameters $\boldsymbol{\Omega}$ represent fixed effects that vary by year, city and transport mode. In the context of this study, Ω_{ict} is the average utility from unobserved factors that are specific to the transport mode, but vary across cities and years. Importing the estimated alternative-specific constants reported in **Annex A** is not legitimate, since those values are confined to Auckland, Dublin and Helsinki. Instead, parameters $\boldsymbol{\Omega}$ are calibrated in order to reproduce the observed market share of each transport mode, in each city in the benchmark year of the study. Denoting that by $t = 0$, the calibration exercise computes the values of the alternative-specific vector $\boldsymbol{\Omega}_{c0}$ that minimizes the following objective function, separately for each city:

$$F_{c0}(\boldsymbol{\Omega}_{c0}) = \sqrt[2]{\sum_i \left(P^M_{ci0}(\boldsymbol{\Omega}_{c0}) - P^D_{ci0}\right)^2}. \tag{TA.17}$$

In equation (TA.17) P^D_{ci0} denotes the observed share of transport mode i in city c at the benchmark year, while $P^M_{ci0}(\boldsymbol{\Omega}_{c0})$ is the corresponding share predicted by the model for a set of mode-specific constants $\boldsymbol{\Omega}_{c0} = (\Omega_{BWc0}, \Omega_{Cc0}, \Omega_{PTc0}, \Omega_{SMc0})$. This model prediction is given by:

$$P^M_{ci0}(\boldsymbol{\Omega}_{c0}) = \underbrace{\sum_r \left(\pi_{rc0} \quad \underbrace{\frac{exp\left(\Omega_{ic0} + \mathbf{x}_{rci}\widehat{\boldsymbol{\beta}}_i\right)}{\sum_j \left(exp\left(\Omega_{jc0} + \mathbf{x}_{rcj}\widehat{\boldsymbol{\beta}}_j\right)\right)}}_{\substack{\textbf{probability that mode } i \textbf{ is chosen} \\ \textbf{for trip } r \textbf{ in city } c \textbf{ at benchmark year}}} \right)}_{\substack{\textbf{weighted choice probability of mode } i \textbf{ in city } c \\ \textbf{at benchmark year}}}. \tag{TA.18}$$

The optimal values for each city are rescaled in the standard way applying to discrete choice models, i.e. as:

$$\boldsymbol{\Omega}^*_{c0} = \left(0, \Omega^*_{C,c0} - \Omega^*_{BW,c0}, \Omega^*_{PT,c0} - \Omega^*_{BW,c0}, \Omega^*_{SM,c0} - \Omega^*_{BW,c0}\right). \tag{TA.19}$$

The cross-city distribution of the above parameters is displayed in Figure 5.1.

Annex C. Supplementary information

Additional notes on the ITF Global Urban Passenger Model framework

The ITF global urban passenger transport model is designed as a Systems Dynamic model (stock and flow model). It can be used to project urban mobility in all cities of over 50000 inhabitants around the world. The model focuses on 1692 cities that UN Habitat classified as having over 300000 inhabitants in 2015. It also incorporates 9660 cities with populations between 50000 and 300000 inhabitants.

The model contains a detailed classification of transport modes that range from conventional private cars, public transport and new emerging alternatives of shared mobility. The availability of these modes, fleet sizes, and pricing levels in each city are surveyed for the base year. A rule-based procedure is then used to simulate how new transport modes evolve given the local context. The main variables informing these rules are the geographic region in which the city is located, its population, and the income level of its inhabitants. Therefore, the projected values of population and income are indirectly used to project important attributes of transport modes.

Cross-city variation in such socio-economic characteristics, e.g. income and population, are exogenous to the model. Projections of GDP are obtained at the national level separately for each country, using OECD data. GDP growth is assumed to be uniform within cities in each country. The model uses data from the UN World Urbanization Prospects 2014 to project urban population.

The rest of the model's key input variables evolve every five years. The evolution of these variables varies by region and follows specific rules, which are based on the following assumptions. Land use evolves according to scenarios. These range from a business-as-usual scenario, in which population density is fixed, to scenarios that increase sprawl or generate densification. For the two last scenarios, the 25th percentile and 75th percentiles of the region's population density are use as density thresholds. The analysis presented in this paper relies on a business-as-usual land use scenario. The size of the private vehicle fleet, which contains cars, motorbikes and bicycles is projected for each city using a calibrated ownership model. Road and public transport infrastructure and supply of transport services evolve according to country-specific scenarios. This paper considers a business-as-usual scenario for the development of roads and public transport infrastructure. Vehicle load factors, energy prices and fuel efficiency evolve in each country according to the Mobility Model developed by the IEA.

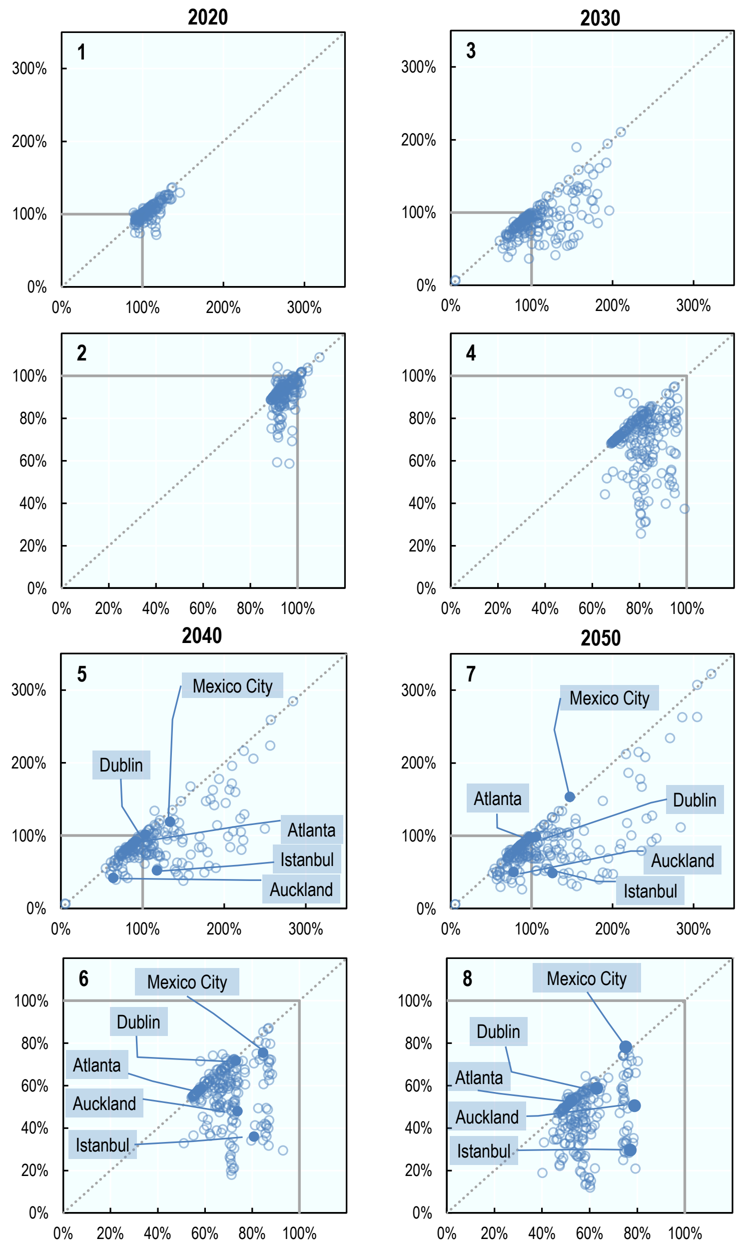
Table A C.1. Summary of data sources used in the calibration of the ITF global urban passenger model

Name	Description	Source
City List		
	Full list of cities with population above 300k by 2014	UN Habitat, WUP2014
Mode Shares		
	Percentage of trips (all purposes) by different type of modes	Various sources
	Main Source	The EPOMM Modal Split Tool - http://www.epomm.eu/tems/result_cities.phtml?more=1
	Other miscellaneous sources	National Household Travel Survey
		Statistic year books
		Reports from local transport authorities
		Reports from different research institutes and organizations
		UITP, Mobility in Cities Database
Transport Supply		
	Global road network	OpenStreetMap, https://www.openstreetmap.org/
	Global public transport network	OpenStreetMap, https://www.openstreetmap.org/
	Mobility in Cities Database	UITP
	World metro database	http://mic-ro.com/metro/table.html
	Rapid transit database	ITDP
Urban Built-up Areas		
	BUREF - Global Built-up Reference Layer (BUREF2010) is a spatial raster dataset containing an estimation of the distribution and density of built-up areas using publicly available global spatial data related to the year 2010	European Commission, Joint Research Centre, http://publications.jrc.ec.europa.eu/repository/handle/JRC90459
	LANDSAT - Landsat represents the world's longest continuously acquired collection of space-based moderate-resolution land remote sensing data.	A joint initiative between the U.S. Geological Survey (USGS) and NASA, http://landsat.usgs.gov//about_project_descriptions.php
Population		
	Total population, urban population by country, cities with population above 300K	UN Habitat, WUP2014
GDP		
	GDP, GDP per capita projection by country	OECD ECO department
	GDP by cell grid in 2010	LANDSAT
Car Ownership		
	Passenger Cars per 1000 inhabitant by country	World Bank, http://data.worldbank.org/indicator/IS.VEH.NVEH.P3, accessed on 2015-03-12
Transport Prices		
	Transportation prices by city, e.g. gasoline per litre, monthly pass, one-way transit ticket, taxi per hour etc.	NUMBEO, open source, http://www.numbeo.com/cost-of-living/prices_by_city.jsp

Source: ITF.

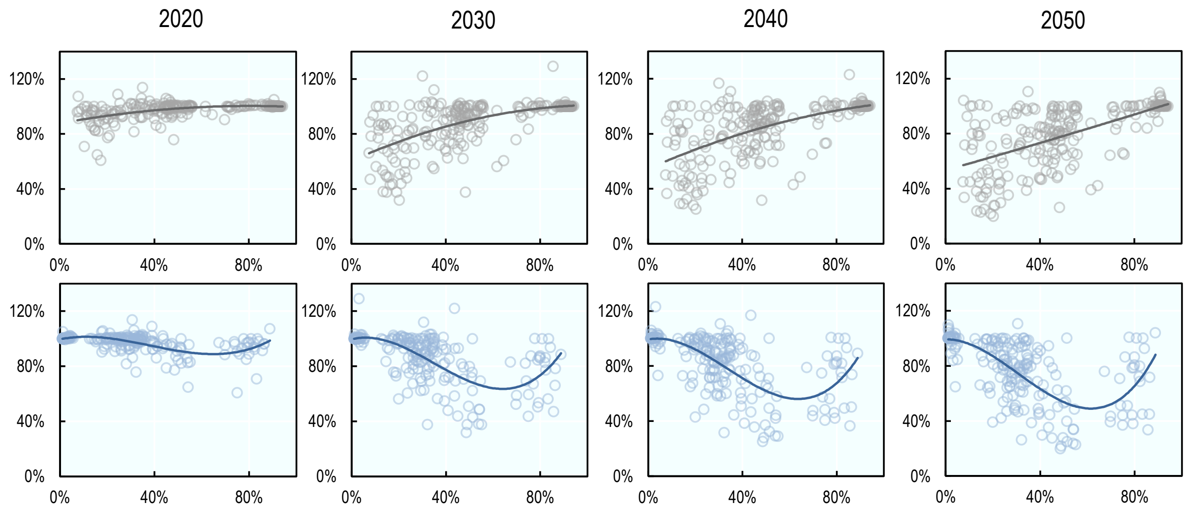
Simulation results: supplementary figures

Figure A C.1. The impact of mainstreaming shared mobility on CO_2 emissions across time – City examples



Note: Panels 1-2 correspond to the year 2020, 3-4 to 2030, 5- 6 to 2040, and 7-8 to 2050. Odd (respectively, even) panels display the change in total CO_2 emissions (respectively, average CO_2 emissions per trip) predicted by the reference scenario (x-axis) relative to the corresponding change predicted by the counterfactual scenario (y-axis). Points below the diagonal represent cities in which the *per se* mainstreaming of shared mobility services will reduce emissions. Points within the inner boxes represent cities in which total CO_2 emissions (upper panels) or average CO_2 emissions per trip (lower panels) will be reduced in both scenarios.
Source: Generated by the authors.

Figure A C.2. Predicting the relative efficiency of scenarios with the initial modal split - Evolution over time



Source: Generated by the authors.