Tackling car emissions in urban areas: Shift, Avoid, Improve

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Abstract

The environmental externalities associated with car use represent a significant cost to society. Using a representative transport survey from the Paris area, we investigate to what extent car use could be i)shifted to low-emission modes, ii)avoided via teleworking, or iii)improved via a transition to electric vehicles, in the context of daily mobility. According to our scenario analysis based on counterfactual travel time data for 45,000 observed car trips, 46% of car users could shift to e-bike – mostly – or public transit – in a few cases – with an increase in daily travel time below ten minutes. 25% would experience a decrease in daily travel time. Such modal shift would reduce CO_2 and local pollutant emissions from daily mobility by around 15%, generating climate and health benefits worth €125 million per year. Inability to undertake a modal shift is associated with living in the outer suburbs, being a man, living far from a public transport stop and having a high income. Teleworking two days a week could save an additional 5% of total emissions. Holding demand for mobility and public transport infrastructure fixed, achieving greater emission reductions would require improving the environmental performance of car use via a transition to electric vehicles.

Keywords: pollution, cities, sustainable transport, modal shift, scenario analysis
JEL Codes: R40, Q52, Q53

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1 Introduction

Car use is responsible for several environmental externalities representing a cost for society (Parry et al., 2007). Traditional combustion-engine cars emit both CO_2, contributing to climate change, and local pollutants that have detrimental health effects (WHO, 2014). These external costs are not reflected in market prices, which justifies government intervention in the form of emission taxes, road pricing or non-price regulations such as driving restrictions. Such interventions may be less costly in cities than in other areas, both because low-emission substitutes are more available in dense areas and because the benefits from avoided local pollution are likely to be greater (Carozzi and Roth, 2023; Creutzig et al., 2020). Nevertheless, policy proposals aiming at restricting the use of polluting cars in cities, whether motivated by air quality concerns or climate objectives, are controversial (Viegas, 2001; Delhaes and Kersting, 2019; Isaksen and Johansen, 2020; Bremner, 2021).

One concern is that some of the current car users might not have low-emission alternatives. Increasing the cost of driving could thus merely increase transport expenditure for a "car-dependent group". Assuming no compensation, distributional concerns might be worse if emissions from car use are particularly concentrated, as observed in several European cities (Bel and Rosell, 2017; Leroutier and Quirion, 2022), if low-income individuals are over-represented among "car-dependent" individuals, or if unobserved heterogeneity in the policy costs makes it hard to target compensation (Douenne, 2020). Despite these concerns, there is little evidence examining what precise alternatives current car users have in cities based on their observed travel patterns.

In this paper, we take Paris as a case study and investigate the options urban residents have to reduce car use, how much these alternatives would reduce emissions, and who the car-dependent individuals are. Our analysis focuses on urban daily mobility and disregards long-distance car trips. We embed our analysis in the"Avoid-Shift-Improve" (ASI) framework. This framework was first used in a German Parliamentarian report in 1994, as a way to categorize policy options aimed at reducing the environmental impact of transport. It classifies emission-reduction measures into three categories: 1)those avoiding the need to travel and reducing total distances 2)those shifting travel from high- to low-emission modes and 3)those improving vehicles to be more energy-efficient and fuels less carbon-intensive. The approach was then adopted more widely by sustainable transport practitioners, NGOs and transport scholars (see for example Dalkmann and Brannigan (2007); Hidalgo and Huizenga (2013)), but also extended to other domains (see for example the chapter on demand-side climate policies in the 2022 IPCC report, by Creutzig et al. (2022)). In this paper, we broaden the initial focus of the ASI framework on greenhouse gas emissions to also include local pollutant emissions, which cause significant health damage in urban contexts.

We use the latest available wave of a large representative transport survey of weekday mobility conducted in the Paris area. The data was collected in 2010-2011 and includes 12,000 car users completing 45,000 car trips. We verified that the observed transport patterns, dating back 13 years, are still relevant to understand today's mobility in the Paris area. We follow an approach in two steps. We first quantify the climate-related cost – in terms of CO_2 emissions – and the health-related cost – in terms of local pollutant emissions – associated with residents' daily mobility in the status-quo, using the rich information on modal choices and vehicles used from the survey. Second, we investigate the extent to which current car users may be able to shift to low-emission modes, avoid traveling by teleworking, or improve the environmental performance of car use by switching to electric vehicles.

We are able to investigate the "shift" component in greater depth thanks to rich counterfactual travel time data from a transport Application Programming Interface (API). That lever seems particularly suited to achieving quick emission reductions, since shifting to existing public transit or active modes does not necessarily require new infrastructure, while many "avoid" options imply changes in urban planning (Creutzig et al., 2022) and renewing the vehicle fleet with "improved" vehicles also takes time. Such quick emission reductions are required to respect climate and air quality objectives, in the light of the European "Fit for 55" strategy requiring a 55% greenhouse gas emission reduction by 2030 compared to 1990 levels, and the threat of financial sanctions for France if air pollution thresholds continue to be exceeded. Indeed, in August 2021, France was already fined €10 million for failing to meet air quality objectives in the first half of 2021 (Conseil d'État, 2021).

We build scenarios of modal shift potential based on three criteria: i)the purpose of the trip, having in mind that for some types of trips a car is particularly useful ii)the age of the individual, which may limit her ability to shift to an active transport mode, iii)the change in daily travel time implied by a shift from driving to either public transport or e-bike. The change in daily travel time is inferred from the trip-level travel times returned by the API for different transport modes, for each single car trip observed in the survey.

We characterize a "car-dependent" group by investigating individual and household characteristics associated with being unable to entirely shift away from car use under a median scenario. We finally examine the extent to which car-dependent individuals could reduce emissions by "avoiding" travel via teleworking, an uncommon practice in France before the Covid-19 epidemic, but now increasingly widespread, and by "improving" their car via a shift to an electric vehicle.

The primary contribution of our paper is to the literature examining the potential for emission reductions from transport, including both carbon emissions and local pollutant emissions. There is a large literature quantifying the potential for carbon emission reduction (Creutzig et al., 2021), with two complementary approaches. One approach relies on top-down integrated assessment models at a large scale, and the other approach aggregates country- or city-level studies in a "bottom-up" way. Our study falls in the second category to the extent that it relies on micro-level data and quantifies emissions reduction options at the individual level. However, in contrast to some bottom-up models, we do not model interactions between agents.

Given our focus on the modal shift potential, our paper also relates to the literature examining this option in particular (Javaid et al., 2020; Yang et al., 2018). In contrast to Yang et al. (2018), who also use counterfactual travel time data and estimate modal shift potential in Beijing, our scenarios are based on a large transport survey with 45,000 car trips made by a representative sample of residents from the Paris area. This enables us to extrapolate our results to the entire Paris area and quantify the monetary benefits associated with emission savings. We also examine the substitution potential of electric bicycles, an under-investigated but increasingly popular transport mode, which enables most of the modal shift in our case. The literature looking specifically at the modal shift potential of e-bikes (for example Mason et al. (2015); Bucher et al. (2019); McQueen et al. (2020); Philips et al. (2022)) mostly focuses on the associated savings in terms of carbon emissions and energy. In contrast, we also quantify the expected decrease in local air pollution emissions. Compared to de Nazelle et al. (2010) who examine the potential air pollution reduction from substituting short car trips to active modes, thanks to the richness of our data we are able to include trips of any distance in our analysis and to precisely quantify the monetary benefits associated with pollution reduction.

Our approach based on the ASI framework departs from a number of other approaches used in the economic and urban planning literature: first, in contrast to studies analysing the impact of past or existing transport policies on emissions, we look at emission reduction *potential*. We argue that such an *ex-ante* approach is particularly relevant to examine the potential for substitution to recently developed low-transport modes such as e-bike and recent phenomena such as teleworking, which are not well captured in historical survey data. For the same reason, our scenario analysis is not based on elasticity parameters estimated in a structural modal choice model, as done for example by Durrmeyer and Martinez (2022): the use of electric vehicles, e-bike and teleworking is too rare in the data to provide reliable estimates. Finally, throughout the analysis we take residential locations as fixed. This is in contrast to models of equilibrium sorting used to estimate the medium- to long-term effects of transport policies, where these variables are endogenous to policies. Our approach is suited to a short- to medium-term time horizon which we think is relevant given the urgent need to decarbonise transport and improve air quality in cities.

Second, our paper is related to the literature examining inequalities in the incidence of environmental policy costs, although we do not examine one policy in particular. Recent papers examining the distributional consequences of carbon taxation have documented a large heterogeneity of tax burden within a given income decile, which raises concerns about horizontal equity (Sallee, 2019; Douenne, 2020; Berry, 2019). While the factors underlying such heterogeneity are generally not well understood (Drupp et al., 2021), demand for car/fuel use has been found to be less elastic in areas with a lower availability of public transport (Gillingham and Munk-Nielsen, 2019). This explains why households in rural areas generally bear a higher carbon tax policy burden (Beck et al., 2016). By analysing modal shift potential among residents *within* a given urban area, our analysis underlines the individual heterogeneity in the ability to shift away from cars at the very local level. It also highlights the characteristics associated with car-dependency beyond the proximity to public transport.

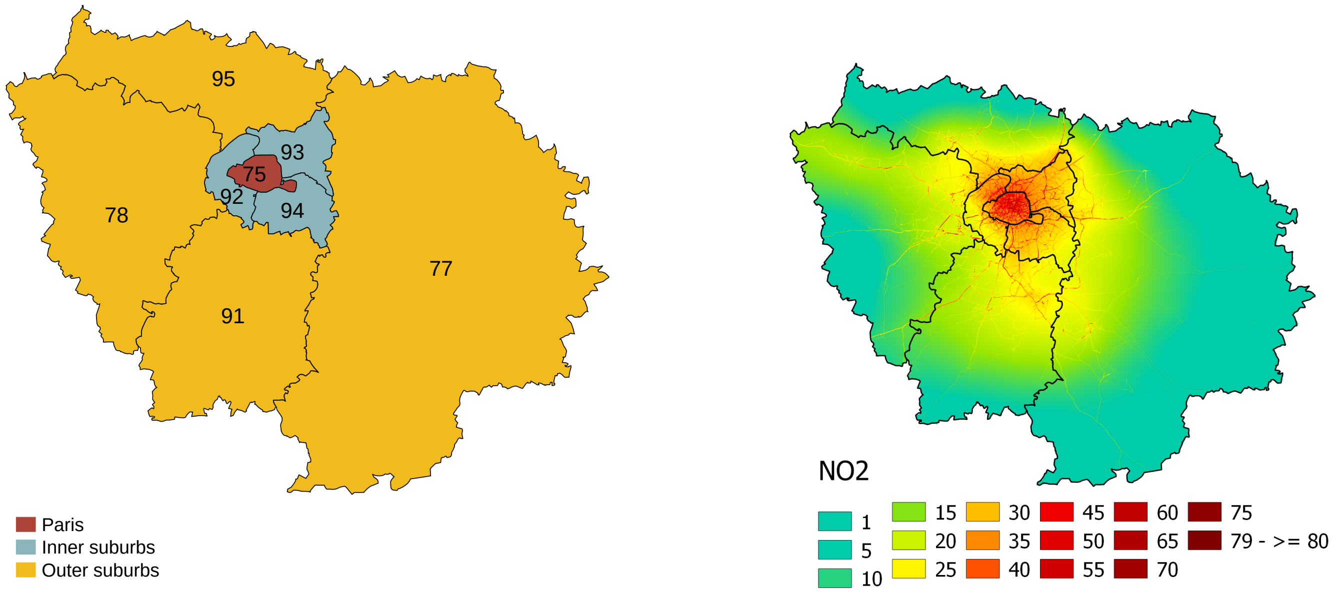
Finally, our paper adds to the literature examining the potential for teleworking and its environmental impact. Our contribution is to quantify the potential benefits of teleworking in terms of avoided local air pollutant emissions, whereas the existing literature has mostly focused on impacts in terms of carbon emissions (see e.g. Bachelet et al. (2021) for Germany, Crowley et al. (2021) for Ireland).

Section 2 presents the local context; section 3 presents the data; section 4 presents the methods; section 5 presents the results; section 6 discusses the results; section 7 concludes.

2 Background: the Paris area

The Paris area is defined here as the administrative *région* of Ile de France (IdF). It had a population of 12.2 million inhabitants in 2020 and consists of three concentric bands from the center to the periphery: the dense city center (red on figure 1a), the inner suburbs (blue on figure 1a) and the outer suburbs (yellow on figure 1a).

Local air quality is quite poor in Paris compared to recommended standards, especially



(a) The Paris Metropolitan Area

(b) NO_2 in 2015, µg/m^3

Figure 1: Background on the study area

Note: The black line shows the division of the *région* Ile de France into *départements*. The numbers are the administrative identifiers for each *département*: 75-Paris; 92-Hauts-de-Seine; 93-Seine-Saint-Denis; 94-Val-de-Marne; 77-Seine-et-Marne; 78-Yvelines; 91-Essonne; 95-Val d'Oise.

in the centre: For NO_2, a pollutant associated with respiratory diseases such as asthma (World Health Organization, 2016), the legal threshold of 40µg/m^3 was exceeded in Paris and the majority of the suburbs in 2015, as can be seen on figure 1b. The recently updated threshold recommended by the WHO for annual NO_2 exposure, 10µg/m^3, was exceeded in almost the whole area. This is despite a decrease in pollution levels over the past 10 years. Similarly, $PM_{2.5}$ concentrations - exposure to which increases mortality risk in the short- (Deryugina et al., 2019) and long-term (Lepeule et al., 2012) - still exceed the threshold of 5µg/m^3 recommended by the World Health Organization (Airparif, 2021b). Road traffic is responsible for 53% of NOx emissions and 19% of primary $PM_{2.5}$ emissions. Finally, road traffic contributes to climate change, being responsible for 29% of the region's CO_2 emissions.

Regional and local policies implemented to tackle emissions from cars include short-term driving restrictions during pollution peaks, new public transport and cycling infrastructure projects, support for the adoption of clean vehicles and for car-pooling, and speed reductions on the main ring road (Région Ile de France, 2016). A low-emission zone banning polluting cars from the city centre and inner suburbs - based on the age and fuel of the vehicle - was supposed to be progressively rolled out between 2017 and 2024. However, its implementation has been slowed down by the Covid-19 pandemic and by the reluctance of some municipalities to join the zone. In the longer-term, diesel cars should be completely banned from the city centre and parts of the inner suburbs (inside A86 freeway, the outer ring road) from 2024 on, and gasoline cars from 2030 on (Le Monde, 2018).

3 Data

3.1 Main Data sources

3.1.1 Transport survey

We use transport data from the 2010 wave of the EGT (*Enquête générale des transports* - EGT 2010-STIF-OMNIL-DRIEA), a survey conducted every 8 to 10 years in the Paris area. The 2010 wave was conducted between October 2009 and May 2010, and between October 2010 and May 2011. It is the latest available survey with a large enough sample size to carry out our analysis. The 2020 wave of the survey was supposed to be carried out between 2018 and 2022 and to collect data on 19,000 households. In the end, only 4,800 households have been surveyed between January 2018 and March 2020. After that, the data collection has been interrupted due to the Covid-19 epidemics.

Our data thus reflect the travel patterns and emission intensity of the vehicle fleet in 2010. They may not accurately reflect the environmental cost of today's mobility patterns if the three components entering the emission calculations – the distances travelled, modal shares and mode-specific emission intensities – changed in the last ten years. Data on a subsample of the 2020 survey wave suggest that distances travelled and modal shares have not changed much since 2010 (Omnil-Ile de France Mobilites, 2019): distances are stable and the car modal share decreased only slightly, from 38% to 34% of trips, compensated for by an increase in active modes and public transport. On the other hand, the emission intensity of the car fleet has been decreasing due to the increasing stringency of European emission standards and technological improvement. We will take this into account when we estimate trip-level emissions.

The survey contains detailed, geocoded information on the transport choices of 35,175 individuals from 14,885 households on a representative weekday (there was no survey during the school holidays). The geolocation is at a fine level, based on 100 meter x 100 meter grid cells. The survey is described in detail in Leroutier and Quirion (2022). The sample is representative of the Paris area population in 2008 in terms of household size, type of housing and individual socio-economic and demographic profiles. We use the subsample of adults having made at least one trip during the weekday (N=23,690), representing a total of 101,950 trips. A trip is characterized by an origin and a destination goal and may involve several transport modes. Table A.1 shows descriptive statistics for this subsample. We add three variables not readily available in the raw EGT data, as described in Leroutier and Quirion (2022): actual distances travelled, annual household income per consumption unit – which we derive from self-declared income brackets using an interval regression imputation method – and an indicator variable for whether the household lives within one kilometre of a public transport stop (including subway, regional train and streetcar).

3.1.2 Emission factors

We use emission factor data by transport mode and by vehicle type for personal vehicles. The data processing steps are summarized in the next section and described in detail in Appendix A.1 and in Leroutier and Quirion (2022).

3.1.3 Counterfactual travel time data

We used the Google Console Directions API to retrieve travel time information with different modes for all the non-walking trips reported in the EGT data. This represents 68,110 trips made by 20,725 individuals. The next section details the data request and quality checks.

3.2 Data processing

3.2.1 Retrieving counterfactual transport time with the Google API

For each of the EGT trips for which the main mode is not walking (N=68,110), we used the Google Console Directions API to predict how long that trip would take by public transport, cycling, and driving. The API outputs are similar to using Google Maps to enquire about an itinerary. For public transport, it takes into account the entire public transport network of the Paris area, which is organized by a regional organization, Ile de France Mobilités. To retrieve travel times, we first identified each trip's departure and arrival points with the latitude and longitude of the centroid of the origin and destination grid cells. To reduce the computational burden, we then pooled together the trips expected to have the same travel time with a given mode, based on how Google's prediction algorithm works:

- for cycling, the direction of the trip and the time where it starts does not influence travel time. In our cycling time request, we pooled together all the trips observed in the EGT having the same departure and arrival point, irrespective of the time at which they are made. We requested travel time as if those trips were made on a Tuesday morning.

- for public transport, travel times differ between day-trips and night-trips due to the lower train frequency at night. For all the EGT trips taking place between 6am and 9:59pm, we pooled together the trips having the same departure and arrival point. As for cycling, we requested travel time for trips made on a Tuesday morning. For all the EGT trips taking place at night between 10pm and 5:59am, we pooled together trips by hour of departure, point of departure and point of arrival. We requested the API to provide travel time by public transport if those trips were made on a Monday night, at the time when they took place according to the EGT.

- for driving, average traffic conditions are integrated into the algorithm, such that the hour of the trip and the direction of the flow can influence the trip duration. We pooled together trips by hour of departure, point of departure and point of arrival. We requested driving time for trips made on a Tuesday, at the actual time when they took place according to the EGT.

We obtained counterfactual travel times by car and cycling for 99.9% of the requests and counterfactual travel time by public transport for 85% of the requests - including some for which walking turned out to be the fastest option. For the remaining 15%, no public transit route existed between the departure and arrival point. We used cycling travel times - based on regular bikes - to infer e-bike travel times. We assumed an average cycling speed of 15km per hour and an average e-bike speed of 19km per hour, as estimated in a 2015 survey (6t, 2015). We applied this constant speed factor of 15/19 to the API's cycling times.

We compared the API's travel times with the self-reported travel times from the EGT for trips made with the same mode. Figure A.4 shows the distribution of travel time differences for trips actually made by (a) car, (b) public transport and (c) bicycle (a much smaller sample than car or public transport trips). The API's travel times are lower for all the three modes: excluding the top and bottom 5% values – where we find some outliers with unrealistic self-reported travel times – the API's travel times are shorter by 5 minutes on average (26%) for driving, by 8 minutes on average (17%) for public transport, and by 6 minutes on average (38%) for cycling.

There are many reasons why the API's travel times might differ from self-reported travel times with the same mode: first, self-reported durations are subject to recall bias and other biases specific to travel time estimation (Tenenboim and Shiftan, 2018); second, Google travel times do not take into account the time required to park, while individuals would likely account for this time in the self-reported measures; third, there is a ten-year gap between the API request (2020) and the EGT data (2010). Over that period, the driving and cycling conditions as well as the public transport schedule may have changed. But these differences between the two data sources are not that important for our scenario analysis, because we only rely on the travel time differences between modes as reported in the API data. What matters is that the relative time difference derived from the API's predictions should correctly reflect the true relative time difference. Given the higher discrepancy for cycling compared to driving and the lower discrepancy for public transport compared to driving in the API data, we may underestimate the facility with which individuals could switch from car to public transport and overestimate the facility with which they could switch from car to cycling.

3.2.2 Estimating trip-level emissions

We estimate individual- and trip-level contributions to CO_2 emissions and local pollutant emissions based on the detailed information contained in the EGT transport survey. For local pollutants, we consider both NOx and $PM_{2.5}$ emissions. The steps used to estimate emissions are detailed in Leroutier and Quirion (2022). In short, we first calculate emissions at the journey stage level – a trip can be made of several journey stages, where each stage is characterised by a unique transport mode. We do this based on the information on the transport mode used in each stage, the distance travelled and a per kilometre emission intensity. As explained in Leroutier and Quirion (2022), we use on-road emission factors for NOx and $PM_{2.5}$, and type-approval emission factors for CO_2.

For the journey stages by public transport, the emission intensity is specific to that transport mode and constant across trips. For the journey stages by car, light-commercial vehicle or two-wheeler, the emission intensity is the vehicle-specific emission factor divided by the number of passengers. The vehicle-specific emission factor is estimated on the basis of the vehicle's characteristics such as age or fuel type reported in the EGT. In the few cases where the vehicle used does not belong to the household, we do not know the vehicle's characteristics and we instead impute a constant emission factor.

Compared to Leroutier and Quirion (2022), we make three changes to calculate emissions. First, for car trips we apply different NOx and $PM_{2.5}$ emission factors for the first few minutes of each trip, to reflect cold starts. When the car starts and the engine is cold, cold starts contribute to additional exhaust emissions for a certain distance and duration, irrespective of the trip's total distance (Frank et al., 2000). Failing to take this into account would lead us to underestimate emissions from short trips. This matters when we estimate emission savings from modal shift, because modal shift is more feasible for short car trips. Appendix A.1 details the methodology used to calculate cold-start emissions.

Second, for the CO_2 emission factor of electric public transport, we take into account the emissions from the electricity used instead of a zero emission factor. The reason is that in this study we want to assess the total climate externality from daily mobility in the Paris area. In contrast to NOx and $PM_{2.5}$ emissions which cause a local pollution externality, the climate externality associated with CO_2 is global. Therefore, it is logical to include in the CO_2 footprint calculation any CO_2 emissions from the electricity used to run these transport modes. We use emission factors produced by the local transport authority (Transilien, 2019).

Third, we adjust each mode's emission factor so that total emissions reflect what can be expected from the fleet in circulation in 2020 rather than 2010, the time of the EGT survey. While distances travelled and modal shares have not changed much between 2010 and 2020, the emission intensity of the car fleet has been decreasing due to the increasing stringency of European emission standards and technological improvement. The average first registration year of vehicles owned by households in the survey is 2002. In that year, the average CO_2 emission intensity of new cars sold in France was 155g/km (Ademe, 2022), their average NOx emission intensity was 573mg/km and their average $PM_{2.5}$ emission intensity was 55mg/km[1].

[1]This is calculated combining information about the NOx and $PM_{2.5}$ emission intensity of diesel and gasoline vehicles from the Paris air quality agency: http://www.airparif.fr/calculateur-emissions/ with data on the proportion of diesel vs gasoline vehicles from ADEME: https://carlabelling.ademe.fr/chiffrescles/r/evolutionDiesel

We assume that the average car age has not changed since 2010 and was still eight years in 2020. It means that the first registration year was 2012 on average. The average emission intensity of new cars sold in France was 20% lower in 2012 than in 2002 for CO_2, 31% lower for NOx, and 48% lower for $PM_{2.5}$. To reflect this improvement in the emission intensity of the car fleet, we scale down the emission intensity of all car trips in the survey by these factors.

Table 1 summarises the emission factors that we use for each transport mode. Active modes have a zero emission factor for all three pollutants. The train and subway have a zero emission factor for NOx, but not for $PM_{2.5}$ and CO_2, due to the emissions from train brakes and electricity generation respectively. Car emission factors vary according to vehicle characteristics. The table only shows the assumed emission factors for vehicles not owned by the household. Figures A.1, A.2 and A.3 show the large variation in the observed emission intensity of car trips, which reflects the variation in vehicle characteristics and occupancy rate across trips.

Once we have emissions at the journey stage level, we simply aggregate them at the trip and individual level. Given the scope of the EGT survey, the individual emissions only include emissions from trips made within the metropolitan area for a representative weekday.

Table 1: Emission factors by mode

	Unit	NOx (mg)	$PM_{2.5}$ (mg)	CO_2 (g)
Type of emission value		Real-world	Real-world	Type-approval
Walking	per passenger-km	0	0	0
Cycling	per passenger-km	0	0	0
Street-car	per passenger-km	0	7	3
Metro	per passenger-km	0	7	4
Train	per passenger-km	0	7	6
Bus	per passenger-km	181	4	104
Taxi	per passenger-km	813	66	266
Car not owned by the household	per vehicle-km	406	33	133
Two-wheeler not owned by the household	per vehicle-km	59	11	52

Note: NOx and $PM_{2.5}$ emission factors reflect on-road emissions and CO_2 emission factors reflect type-approval values. All the assumptions are explained in Appendix A.1 The factors shown for car and taxi are those imputed when an individual travels with a car that she does not own or a taxi, for which we do not have vehicle characteristics. We then impute a constant emission value from a representative car (a 2008 diesel car of 7 hp). For taxis, we multiply the emission factor by two to reflect empty journeys, as suggested in (Ministère de la Transition écologique et solidaire, 2018).

3.3 Descriptive statistics

Figure 2 shows the contribution of the different transport modes to the total number of trips, total distances, and total emissions. While private cars are used as the main mode for only 40% of the trips, these trips represent 52% of the distances travelled and about 85% of transport emissions on a typical weekday (86% of the CO_2 emissions, 93% of the NOx emissions and 79% of the $PM_{2.5}$ emissions). The disproportionate impact of car trips on emissions justifies our decision to focus the analysis on car trips.

Trip purpose is likely to influence modal choice and the ability to avoid, shift or improve car travel. Figure 3 shows the distribution of trip purposes for car trips (on the left) in contrast to other modes (on the right). The biggest difference is for escorting trips, which represent 27% of car trips versus only 19% of trips made with other modes. In our scenarios, we will take into account the fact that substituting away from cars may be difficult when several people are in the car, as in escorting trips.

We focus the scenario analysis on the 12,595 individuals who use a car for a trip within

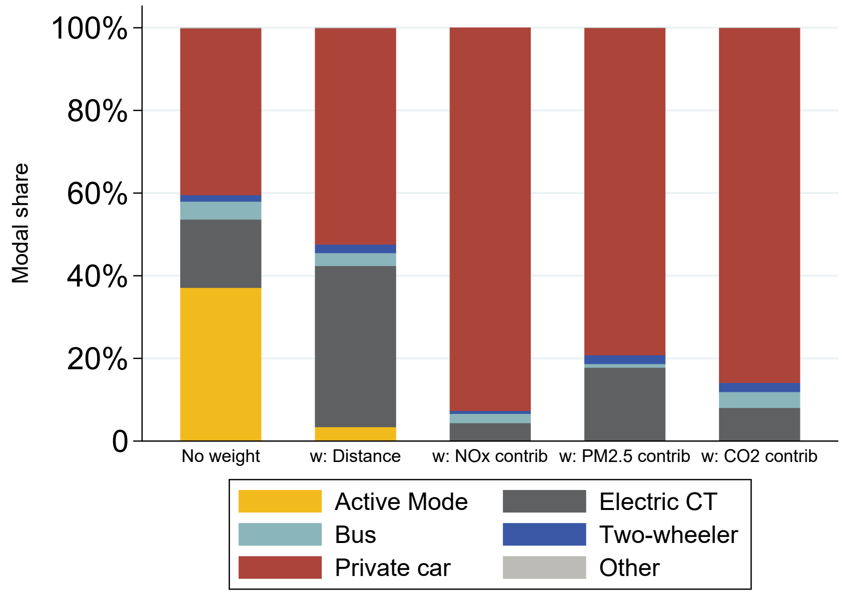


Figure 2: Modal shares in the number of trips, distances travelled and emissions

Note: the first bar chart shows the proportion of each mode in the number of trips, the second shows the proportion as a share of total distances driven, the third as a share of NOx emissions, the fourth as a share of $PM_{2.5}$ emissions, and the fifth as a share of CO_2 emissions. Source: EGT data. Sample: all trips made by individuals aged 18 and over. Individual sample weights included.

the Paris area at least once during the day, either as passenger or driver. They complete 45,897 car trips taking place within the Paris area in total. The few trips that start or finish outside the Paris area – 0.8% of all the trips recorded – are not geolocated and do not have a distance recorded. We exclude these trips from the analysis. Figure 4 shows that the proportion of car users is higher in the outer suburbs than in central Paris or the inner suburbs.

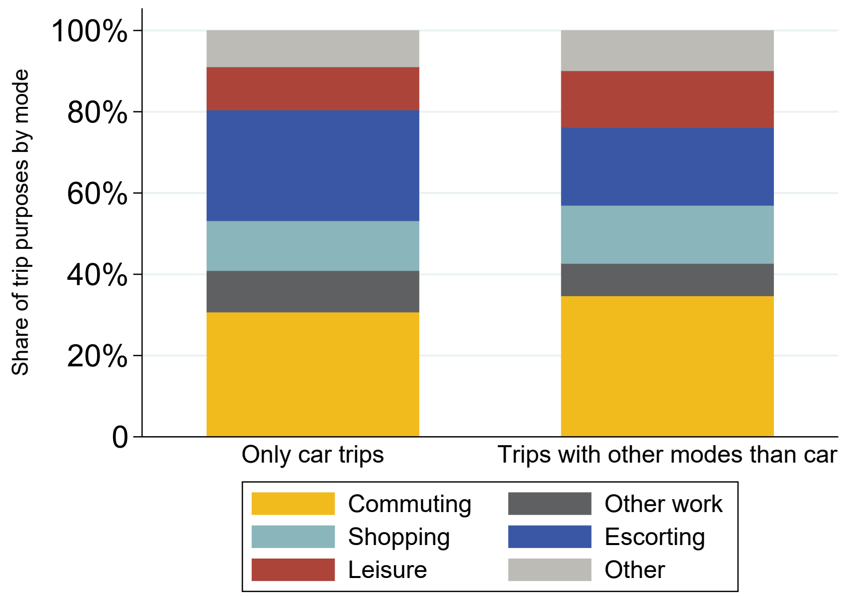


Figure 3: Proportion of trip purposes for car and non-car trips

Source: EGT data. Sample: all trips made by individuals aged 18 and above. The six purposes are allocated based on the survey information on the origin and destination motive of each trip. Commuting trips are those starting or finishing at the work or study place and finishing or starting at another place, except a work-related place. Other work trips are trips where the origin or destination motive is "Work other", and the other motive is home, the workplace or the study place, as well as trips between a workplace and study place. Shopping trips are trips where the destination motive is shopping, or the origin motive is shopping and the destination is home or work-related. Leisure trips are trips where the destination motive is leisure, or the origin motive is leisure and the destination is home or work-related. Escort trips are trips where the destination motive is escorting, or the origin motive is escorting and the destination is home or work-related. "Other trips" are all trips not covered by the previous purposes.

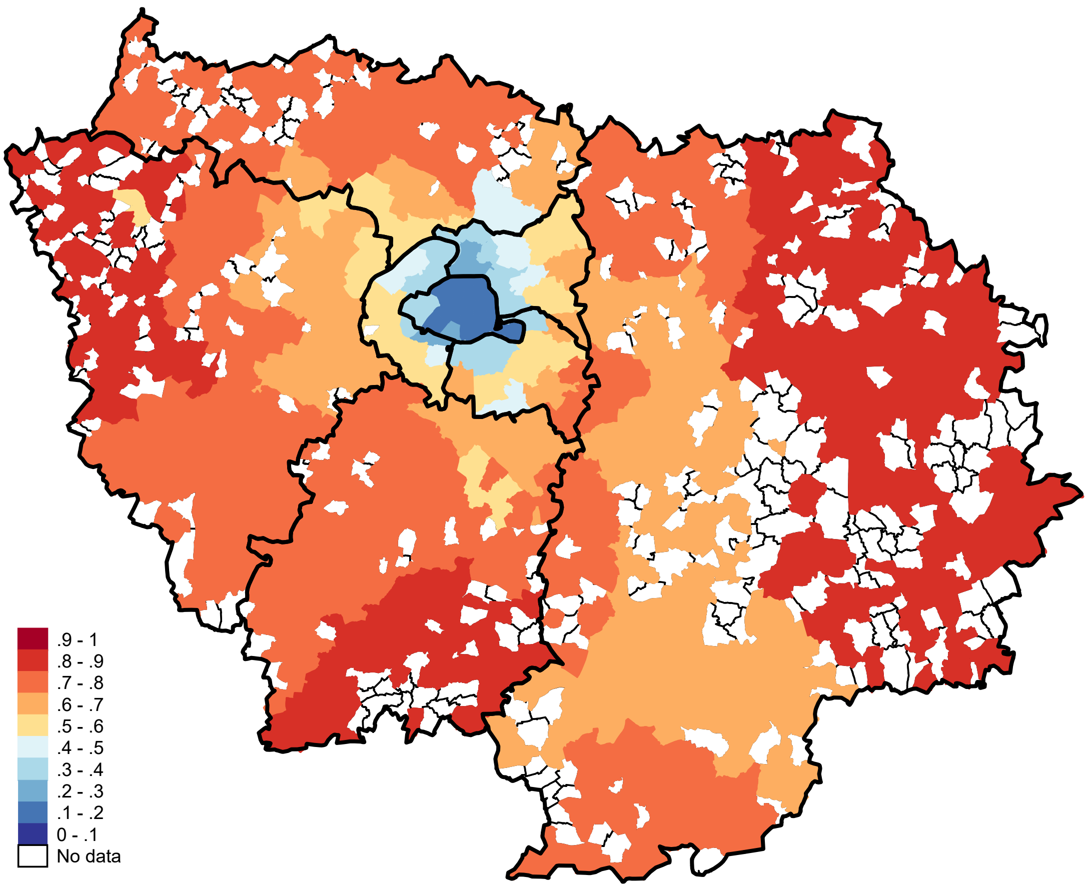


Figure 4: Share of car users by sampling zone (weighted average using individual sample weights)

Source: EGT data. Sample: all individuals 18 and above making at least one trip during the day.

4 Methods

4.1 Calculating the environmental cost of today's daily mobility

To calculate the environmental cost of daily mobility in the status-quo situation, we first estimate how much individuals emit given the modal choices observed in the EGT. Then we combine this quantity of emissions with the unit costs of CO_2 emissions, NOx and $PM_{2.5}$ from the literature.

For the unit cost of CO_2 emissions, we use the official French value for the social cost of carbon for 2020 (France Stratégie, 2019), of €84.5 per ton of CO_2 (after adjustment to euros 2020). For NOx and $PM_{2.5}$ emissions, we use monetary values from the European Commission report on the external costs of transport (EU Commission, 2020), dating back to 2016. These values include the costs of air pollution in terms of individual health, crop losses, material and building damages, and biodiversity losses. We use the "city" estimate for NOx – a pollutant for which there are only two values, one for rural areas and one for cities – and the "metropolis" value for $PM_{2.5}$ – a pollutant for which there are three values, including "metropolis" for cities with more than 0.5 million inhabitants. We adjust the values for inflation and obtain a unit cost of €28.03 per kilogram of NOx and €419.38 per kilogram of $PM_{2.5}$ in 2020.

For each pollutant we multiply the quantity of emissions by the relevant unit cost. We obtain pollutant-specific and total monetary costs associated with total daily mobility. To go from daily to annual costs we multiply the total by 220, the average number of working days. This is assuming that the survey is representative of working days across the year.

4.2 The ASI framework

According to the "Avoid-Shift-Improve" framework, policies to limit greenhouse gas emissions in the transport sector can be classified into measures aiming at 1)avoiding the need to travel by reducing distances; 2)shifting travel to a low-carbon mode; and 3)improving vehicles to be more energy-efficient and fuels to be less carbon intensive: in other words, reducing the emission intensity of trips for a given mode. The framework is also suited to examining options to abate emissions of local pollutants. We investigate the second option of modal shift in depth, and estimate the proportion of car trips that could be shifted to a low-emission mode. By doing so, we abstract from general equilibrium effects such as the impact of modal shift on road congestion and the demand for driving, or the impact of a reduction in commuting on housing prices, which could generate a rebound effect. We then characterize a group of "car-dependent" individuals, those unable to shift away from car for at least one car trip. Finally, we investigate, both for the subsample of car-dependent individuals and for the whole sample of car-users, the extent to which teleworking could reduce emissions (Avoid travelling), and the potential for replacing combustion-engine vehicles by electric vehicles (Improving vehicles).

4.2.1 Shift: modal shift scenarios

Our goal is to examine the proportion of car trips that could be substituted with e-bike or public transit. Among existing studies examining modal shift potential, two types of methods are used. The first method estimates elasticity parameters with a discrete choice model of modal choices, and uses them to estimate the effect of policies affecting the relative cost of car and low-emission modes. For example, the inter-modal cross elasticity measure reflects how much demand for a given mode decreases when the monetary or time cost of alternative modes decreases. As mentioned in introduction, this method is hard to use for transport modes rarely used in existing survey data such as e-bikes, which represent just 0.03% of all the trips in our survey.

The second method, which we use here, is scenario analysis, where a set of trips are deemed feasible with bike or public transport given some criteria. There, modal choice is not embedded in a micro-economic model of utility-maximizing agents. Rather, trade-offs and costs are implicitly considered based on the criteria used in the scenarios.

We formulate three scenarios in which car trips could be shifted away from car. We use three types of constraints: i)the travel time difference between car and the substitute mode, ii)only for e-biking, the individual's age, and iii)the type of trip. Scenarios only vary with respect to the third constraint.

Other studies having information at the trip level often examine bike shift potential by defining a maximum "cyclable" distance, and consider that all car trips shorter than that distance could be shifted (see for example de Nazelle et al. (2010); Mason et al. (2015); Philips et al. (2022)). We consider that individuals' travel time and the associated opportunity cost better reflects how costly it is for them to shift away from car. Instead of looking at the travel time change at the trip level, like Yang et al. (2018) or Bucher et al. (2019), we focus more specifically on the total daily time spent commuting, which has been found to be remarkably stable over time (Marchetti, 1994). In the Paris area, car users – individuals with at least one trip by car – have an average daily travel time of 113 minutes in our data from 2010, and it remains 113 minutes in the preliminary data from 2020. Given this, it seems unlikely that individuals would be willing to shift if it implies a strong increase in daily travel time.

A large share of modal shifts induce a change in daily travel time between -5 minutes and +10 minutes. Therefore, defining the ability to shift based on whether or not a certain travel time threshold is exceeded gives results that are quite sensitive to the choice of threshold. Results on the share of trips that can be shifted and the share of car users able to shift are presented in the form of cumulative distributive functions of the change in daily travel time. We nevertheless highlight results for two key travel time thresholds: one at 0 minute increase in daily travel time - such that shifting away from car not only generates climate and health benefits, but also private benefits in terms of time saved; and one at 10 minutes increase in daily travel time, which represents 8% of the average daily travel time.

In addition, we impose that a shift to an e-bike is only feasible for individuals below 70. This age threshold seems conservative in a world where cycling is becoming increasingly common. In the Netherlands, a country where cycling represents 27% of all trips, individuals over 60 cycle as often as individuals between 16 and 59 (Goel et al., 2021); the weekly time spent cycling even peaks between 65 and 69 (Fishman et al., 2015).

Many studies consider whether a shift is possible or not given some characteristics of the trip, considering all trips made during the day as independent from each other. However, often individuals decide on the transport mode based on the entire chain of trips they have to make (Scheiner, 2010), where a trip chain is defined as the set of trips done between the time the person leaves home and the time the person comes back home. Like Neves and Brand (2019), we consider unrealistic for a person to shift from car to another transport mode only for part of a trip chain. Trip chains more complex than a round-trip are frequent in the data: 33% of trip chains include at least three car trips. Further, 50% of the car drivers make more than one trip chain during the day: they come back home at some point during the day and leave again, sometimes multiple times. In our scenarios, we consider that car trips can only be shifted to a low-emission mode if all the car trips within that chain can be shifted.

The last constraint, which we allow to vary by scenario, imposes that some trip purposes can not easily be shifted away from car. In scenario 1 we impose no constraint. In scenario 2, we impose the constraint that the trip chain should not include any car trip which purpose is a work-related driving round (for professions such as plumbers or electricians) or going grocery shopping to a large supermarket. Those trips are likely to involve carrying heavy loads, for which shifting away from car may be difficult. In the EGT data, the purpose "grocery shopping at a large supermarket" represents 4.7% of the car trips, but less than 2% of observed bike and public transport trips. Professional rounds represent 0.7% of the car trips but only 0.3% of the bike trips and 0.1% of the public transport trips. In scenario 3, we add as an additional constraint that the trip chain should not include any car trip with more than one person in the car. This constraint reflects the practical benefit of the car for transporting several people, as well as the larger difference in monetary cost between the car and the alternative in that case: while the car fuel cost is spread out across the passengers, each would have to pay for their own e-bike or public transport ticket. The constraints we put on the type of trip are consistent with results from a survey conducted in Sweden, asking to what extent e-bike can replace the car for different travel purposes: commuting and leisure trips were found to be easier to replace, grocery shopping and trips for dropping off and picking up one's children less so (Söderberg f.k.a. Andersson et al., 2021). The scenarios are summarised in table 2. In some of the results presented, we focus on scenario 2, which we consider a median scenario. It acknowledges that car is hard to give up for some trips, in particular where heavy loads are carried; but compared to scenario 3 it allows a modal shift even when there are several passengers in the car. When all passengers are adults, a modal shift to e-bikes seems feasible. When some of the passengers are young children, e-cargo bikes may be used.

For each of the three scenarios, we classify car trip chains based on whether or not they could be shifted to public transport or e-bike according to the scenario's constraints. For each trip chain for which a modal shift away from car is deemed possible, we calculate the difference in travel time between using car and using the low-emission mode with the shortest travel time. Figure 5 shows the cumulative distribution function of travel time difference between driving and e-biking (red line), and driving and public transit (blue line), for all the trip chains involving car in the EGT. More than 50% of the trip chains would be less than 20 minutes longer with e-bike, but only around 15% with public transit. We further aggregate the change in travel time at the individual level, which equates to the change in daily travel time.

Finally, we calculate the emissions that could be saved thanks to the shift by comparing current emissions (when the car is used) with the emissions if the counterfactual transport mode was used. For e-bike, we assume zero emissions. We neglect emissions from e-biking battery charging because of the extremely low energy consumption of this mode: using data on e-bike electricity consumption from Weiss et al. (2020) and official data on the carbon emission content of the French electricity mix, we obtain an average emission intensity of e-bike of around 0.3 gCO_2/km, ten times lower than for street-car, the lowest emitting public transport mode. For the shift to public transit, we assume that people shift to electric public transport rather than bus, because trips by electric public transport are much more common as a proportion of distances travelled: they make up 38% of total distances while bus only makes up 3% (see second bar of figure 2).

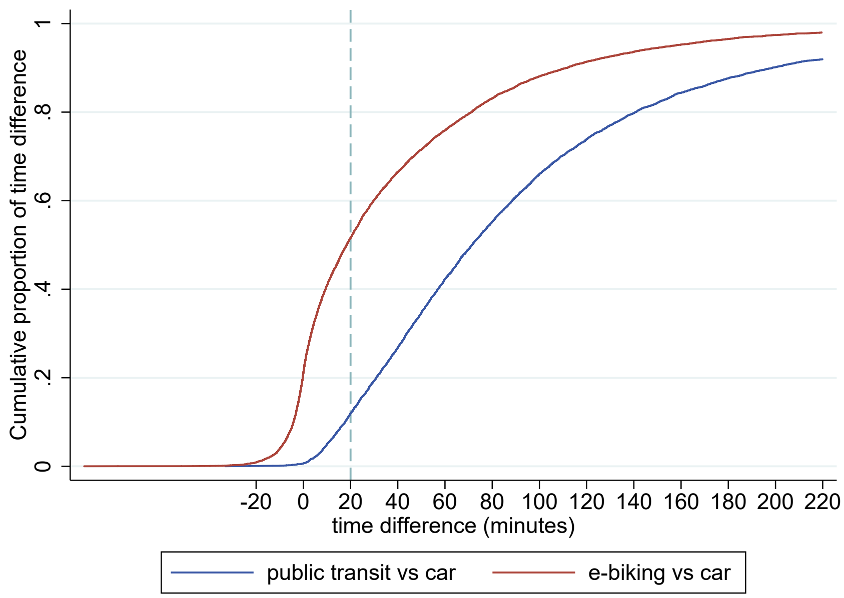


Figure 5: Cumulative Distribution Function of the difference in travel time between car, e-biking and public transit at the trip chain level

Note: Sample: all trip chains involving at least one car trip (N=6,065). Source: Authors' calculations based on Google API outputs. The dashed blue lines represent a 20-minute time difference. For example, the intersection of the red line and the dashed blue line indicates that more than 50% of the trip chains would be at most 20 min longer by e-bike than by car.

Table 2: The three scenarios considered

	Scenario 1	Scenario 2	Scenario 3
Trip chains for which modal shift is possible	All	All but those including work-related driving rounds & car trips for grocery shopping	All but those including work-related driving rounds & car trips for grocery shopping & trips with > 1 passengers
Age constraint for e-biking	≤ 70	≤ 70	≤ 70

4.2.2 Avoid: assessing the ability to telework

For individuals unable to shift modes, avoiding travel is another option for reducing emissions. Holding urban planning, places of work and places of residence fixed, one obvious measure to reduce demand for driving is teleworking, a practice that has gained prominence in the past three years in the context of the Covid-19 pandemic. However, the potential for reducing emissions via teleworking will depend on the employment status of car-users, their commute mode, and whether their job can be done from home (Hook et al., 2020).

We gauge whether employed individuals have a job that could easily be done from home by combining information on their socio-professional category with information on their workplace. We consider that teleworking is not possible for manual workers, farmers or traders, craftspeople, CEOs. For the other socio-professional categories, we consider that teleworking is possible for employees from the private and public sector as long as they work in an office, as opposed to working in a factory - many factory/manual jobs cannot be done from home -, in other people's homes, in user-facing public institutions (hospital, school), in public institutions more broadly, or in customer-facing jobs such as a shop.

The frequency of teleworking was very rare in France before Covid-19: less than 3% in 2017 (DARES, 2017). Based on the fact that most of the company-wide agreements negotiated in the Paris area after the Covid-19 pandemic include a frequency of teleworking of two days a week (Benjebria, 2021), we consider it to be a realistic frequency. We therefore quantify emission reductions based on a two days-a-week teleworking frequency, compared to an average frequency close to zero in the survey data.

When we estimate transport emissions saved from teleworking, we abstract from a possible rebound effect. Rebound may occur if people used the time saved thanks to no longer commuting for leisure travel. We also abstract form the potential increase in emissions from buildings due to the increase in residential energy use that could offset the energy use in a collective office. However, a systematic review of evidence indicates that out of 39 studies on the effect of teleworking on energy use, 26 found that teleworking reduced energy use — and presumably emissions — and only 8 found that teleworking has a neutral effect or increased energy use (Hook et al., 2020).

4.2.3 Improve: assessing the ability to replace combustion-engine cars with electric vehicles

Another alternative to modal shift is to improve the emission intensity of vehicles by shifting to electric vehicles (EV). There are well-documented monetary and non-monetary barriers to the uptake of EVs, including purchase cost, availability of charging stations and cultural habits (Oxford Institute for Energy Studies, 2019; Sovacool et al., 2019). Including all these factors in a car purchase decision model goes beyond the scope of this paper. We instead use information available in the survey on total distances driven and availability of parking space to gauge how challenging it would be to use and charge an EV for the car-dependent individuals.

Further, we use the geocoded information available in the survey to infer the share of households having at least one public EV charging station within 500 meters of their place of residence in 2020. We did not find an exhaustive dataset of all charging stations located in the Paris area. We instead combined geocoded data from four different sources: OpenStreetmap (GeoDataMine, 2021) , where many stations located in Paris centre are missing, the national open data service Data.gouv.fr (2021), where many stations located in Paris centre are also missing, and subregional open data services providing data on two municipalities (Paris and Rueil-Malmaison).

5 Results

5.1 The Environmental Cost of Daily Mobility in the Status-quo Situation

We find that on a typical weekday, daily mobility in the Paris area generates around 17,109 tons of CO_2, 52 tons of NOx and 4 tons of $PM_{2.5}$ (third column of table 3). The associated environmental cost totals 4.4 million euros (€4.4m) per day, of which €1.45m of climate-related costs due to CO_2 emissions and €3.0m of health-related costs due to local pollution (fifth column of table 3). The corresponding annual cost amounts to €977m, of which €318m are climate-related costs and €659m are health-related costs. Emissions from car use represent 86% of the total cost (€840m), justifying our focus on options to reduce car use in the remainder of the analysis.

Table 3: Environmental cost of daily (weekday) mobility in the status-quo situation

Cost category	Pollutant	Daily emissions (kg)	Unit cost (€/kg)	Daily Cost (million €)	Annual Cost (million €)
Climate-related	CO_2	17,109,104	0.0845	1.45	318
Health-related	NOx	51,604	28.03	1.45	318
Health-related	$PM_{2.5}$	3,692	419.38	1.55	341
Total				**4.44**	**977**

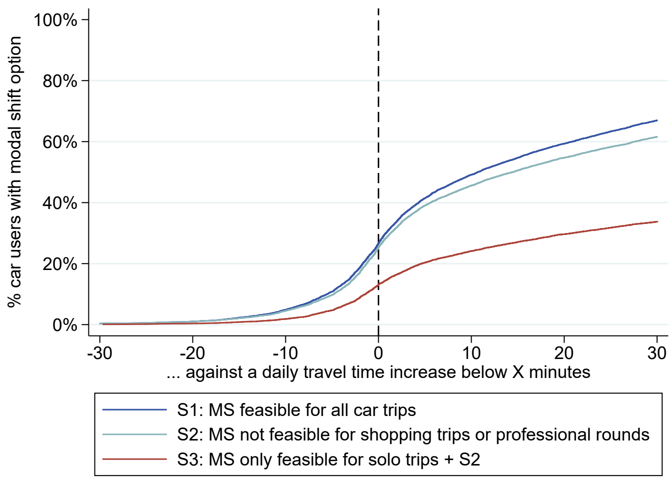
5.2 Potential to reduce emissions with the Shift, Avoid and Improve options

5.2.1 Shift to low-emission modes

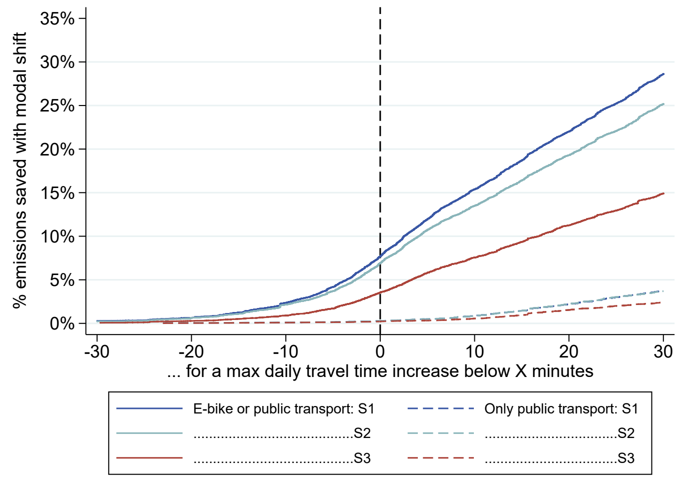
Figure 6a shows the cumulative distribution of car users deemed able to shift at least one of their trip chains according to each scenario against the travel time change implied by the shift. Consistent with the increasingly strict constraints from Scenario 1 to Scenario 3, the share of car users able to shift is always the greatest for Scenario 1 and the lowest for Scenario 3. Imposing that a modal shift is only feasible for solo trips in Scenario 3 significantly reduces the possibility of modal sift compared to Scenarios 1 and 2. A modal shift away from car would actually reduce daily travel time for a non-negligible share of car users, 27% in Scenario 1, 25% in Scenario 2 and 13% in Scenario 3. If individuals were willing to accept a 10 minutes increase in travel time, 49% of them could shift to a low-emission mode under Scenario 1, 46% under Scenario 2 and 24% under scenario 3.

Figure 6b shows the share of total emissions that could be saved under each scenario and maximum daily travel time increase, and highlights the higher contribution of e-bikes to the shift potential, compared to public transport. We calculate separately the shares of NOx, $PM_{2.5}$ and CO_2 emissions saved and take the average of the three shares for each value of travel time increase. The continuous line shows emission savings when both the shift to an e-bike and the shift to public transport are considered, while the dotted lines show the corresponding increases if only a shift to public transport is possible. Public transport alone only allows limited modal shift and limited emission savings, below 1% for an increase in daily travel time below 10 minutes. For the same maximum increase in daily travel time, allowing a shift to e-bike yields emission savings of between 8% and 15%, depending on the scenario. Based on the median Scenario 2 and a travel time increase below 10 minutes, 14% of emissions could be saved. The proportion is relatively low compared to the proportion of trips having a substitute, because substitutable trips are shorter on average.

Figure 7 shows the cumulative emission savings for each scenario when both e-bike and public transport are allowed. The annual monetary benefits associated with the emission savings are indicated for selected travel time thresholds. Even when no travel time increase is allowed, annual climate and health benefits can be substantial, between €33m and €71m depending on the Scenario. For a travel time increase below 10 minutes, the benefits reach €70m for the most restrictive Scenario 3, €125m for Scenario 2 and €142m for Scenario 1. Note that by focusing on the benefits of modal shift in terms of air pollution reduction and CO_2 mitigation, we do not include the individual health benefits from the increased physical activity in the case of e-bike. The health benefits of walking and cycling induced by the increase in physical activity have been shown to significantly outweigh the risks due to pollution inhalation and cyclists' accidents (Rojas-Rueda et al., 2011; Gössling et al., 2019).



(a) Share of car users that can shift and corresponding daily travel time increase



(b) Share of emissions saved and associated increase in daily travel time: low contribution of public transport

Figure 6: Share of car users able to shift and emissions saved by scenario

Source: EGT data with individual sampling weights. MS: modal shift; S1: Scenario 1; S2: Scenario 2; S3: Scenario 3.

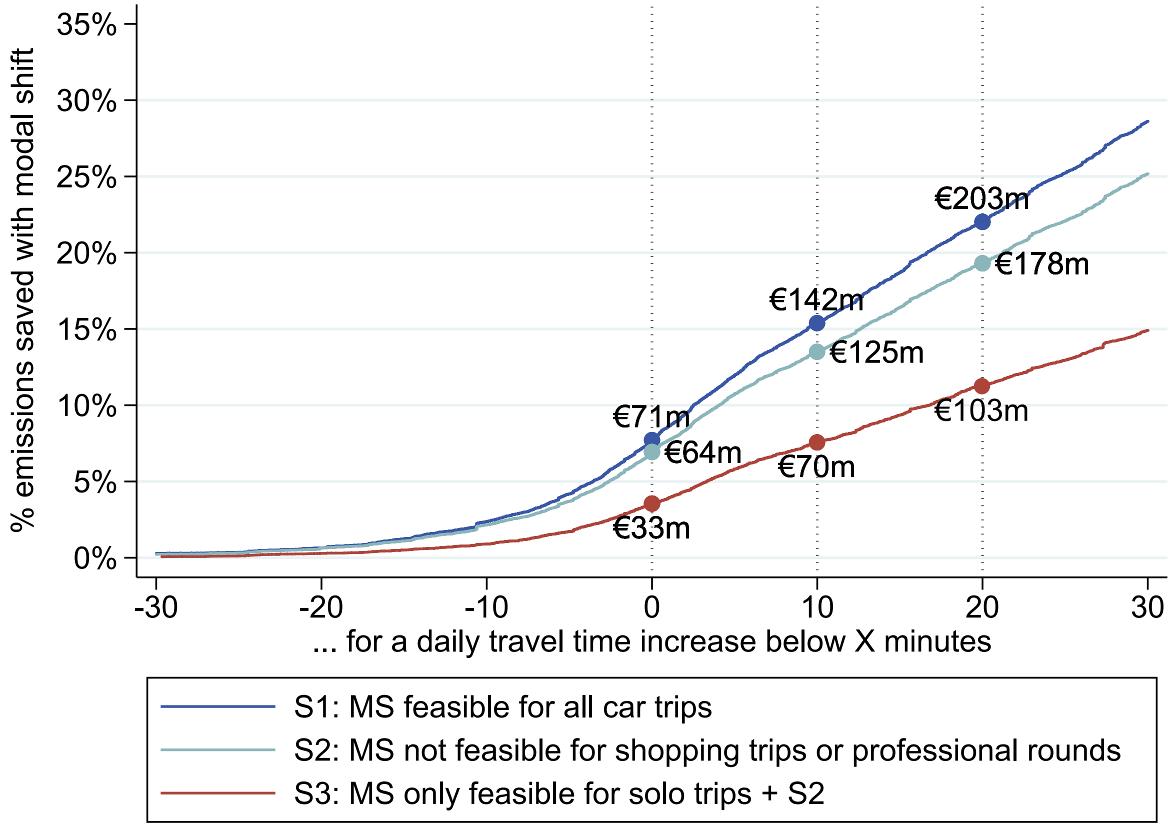


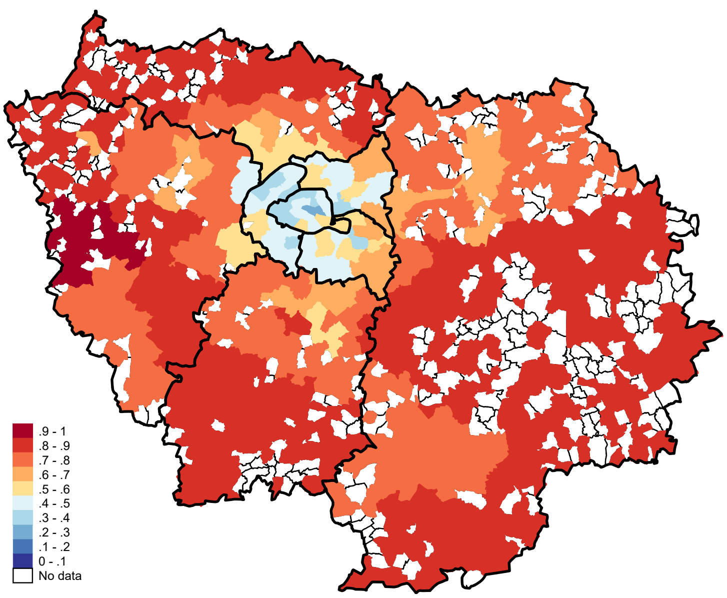
Figure 7: Share of emissions saved and associated monetary benefits

Source: EGT data with individual sampling weights. MS: modal shift; S1: Scenario 1; S2: Scenario 2; S3: Scenario 3. The labels indicate the environmental and health benefits associated with a given modal shift scenario and daily travel time increase.

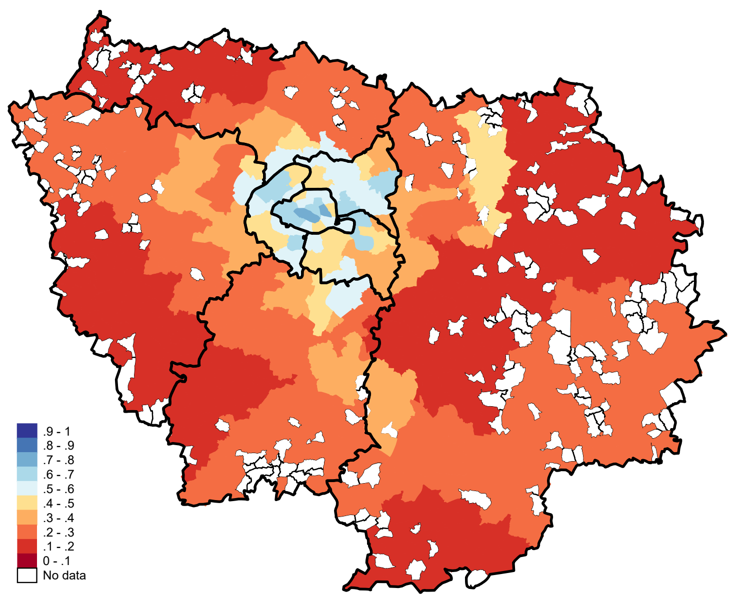
5.2.2 Who are the car-dependent individuals?

We define car-dependent individuals as those who are not able to shift entirely away from car for all their car trips under Scenario 2 and a maximum increase in daily travel time of 10 minutes. This is in contrast to figure 6b, which shows the cumulative share of car users who are able to shift **at least one** of their chain trips to a low-carbon mode. 59% of current car drivers fall into this category. For these individuals, options other than modal shift are needed to reduce emissions, or they risk bearing a high cost if policies increase the cost of driving a polluting car.

Individuals from this group travel significantly longer distances by car: their median daily distance is 35 kilometres compared to 9 kilometres for the "shifters" – those who are not car-dependent. They tend to live further away from the centre: the outer suburbs have a high proportion of car-dependent individuals, as illustrated in figure 8a. This is presumably correlated with the lower availability of public transit in these low-density areas. The e-bike option may also be less competitive in those areas given the longer distances travelled and the relatively higher car speed compared to the city centre. Figure 8b shows the share of trip chains that could be shifted away from car by sampling zone. Although the suburbs are traditionally associated with a car-centric way of life, even in those areas a relatively high fraction of the car trips could be shifted.



(a) Proportion of individuals unable to shift away from cars ("car-dependent individuals"), averaged by sampling zone



(b) Proportion of trips that could be shifted to a low-emission mode, by origin sampling zone

Figure 8: Car-dependent individuals vs. share of trips that can be shifted by sampling zone

Notes: Source: EGT data with individual sampling weights.

We investigate the geographical, socio-economic and demographic characteristics associated with being car-dependent in a multivariate logit model. We run two models, one for all car-users and one for the employed only, whose ability to shift away from car may be influenced by their job characteristics. Figure 9 shows the estimated marginal effects for each characteristic along with the 95% confidence intervals. All else being equal, being a man, living in the outer suburbs, living far from a public transport stop, and having a high income – as defined by being in the top quintile of household income – are associated with a higher probability of being unable to shift away from car use. For those in employment, having to commute from suburb to suburb, having atypical working hours and being a technician are also associated with car-dependency. All those characteristics are correlated with longer distances travelled (Leroutier and Quirion, 2022), which makes it challenging to substitute away from car without increasing daily travel time too much. Even after including a rich set of characteristics in the model, there is a still a lot of unobserved heterogeneity in the ability to shift away from car use: the explanatory power of the regression is quite low, with a pseudo R-squared at 0.07 for the analysis on the full sample and 0.05 for the analysis on the subsample of workers.

The marginal effects reported in figure 9 reflect partial correlations, controlling for the other characteristics included in the regression. Figure A.5 shows the coefficient estimates for the same characteristics, but based on regressions with only one individual characteristic of interest on the right-hand side. Most coefficients keep the same sign and significance level. For the sample of drivers in employment, the type of workplace is highly correlated with the occupation and its effect stands out more in this simple correlation analysis: compared to individuals working in offices, individuals working in factories and at other peoples' homes are more likely to be car-dependent. Individuals working at other people's home are likely to drive long trip chains, going from one place to another, while those working in factories typically travel longer distances, as found in Leroutier and Quirion (2022). In terms of occupation, when the simple correlation is considered, being a manual worker, technician, craftsworker or manager becomes significantly associated with being unable to shift away from car. All these professions correlate with being in the top 20% emitters (Leroutier and Quirion, 2022).

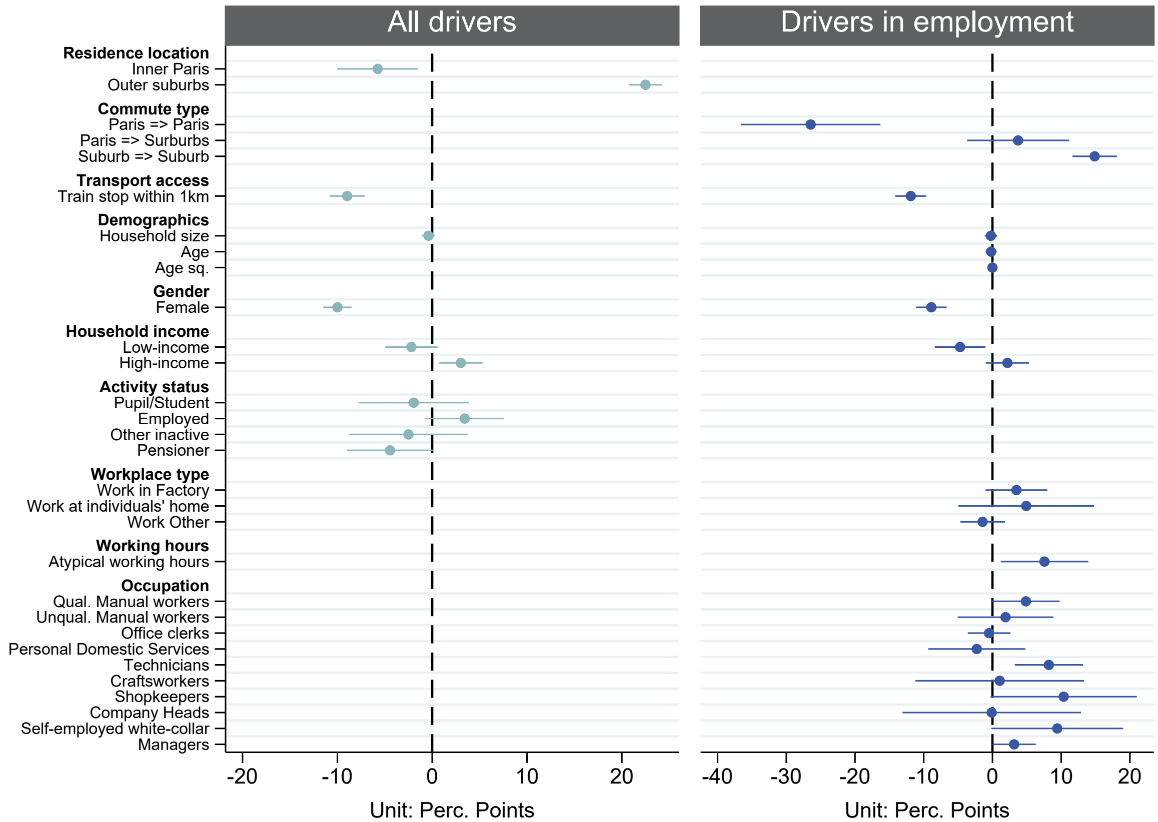


Figure 9: Characteristics associated with being unable to shift away from car use

Notes: from left to right: selected X covariates are listed on the left, by category. Omitted categories for the categorical variables: Location: inner suburbs; Gender: male; Employment status: unemployed; Commute type: Suburbs => Paris; Workplace type: Work in office; Occupation: Intermediate professions. Standard errors are clustered at the household level. The first panel shows the average marginal effect of each characteristic on the likelihood of not being able to shift away from cars for the sample of all car users, and the second panel shows the same for the subsample of individuals in employment, with several job characteristics used as additional covariates. Regressions are unweighted.

5.2.3 Avoid travelling by teleworking

This option could only reduce emissions for the 71% of car-dependent individuals who are employed, and only for the 45% of them who commute by car in the status quo. Thus, this option could reduce emissions for at most 32% of car-dependent individuals. According to the criteria defined in section 4.2, 39% of the employed car-dependent individuals who commute by car have a job type that can be done from home. Factoring in that they represent just 32% of the car-dependent individuals, we find that 12% of the car-dependent individuals could reduce emissions by working from home. If they all worked from home two days a week – or two more days for the few individuals already occasionally teleworking –, an additional 5.5% of total CO_2, NOx and $PM_{2.5}$ emissions could be avoided. The corresponding monetized benefits would be €54m annually. Teleworking could also be an option for some of the "shifters". If every car commuter whom we deem able to telework did so two (more) days a week, it would cut total emissions by 16% averaged over the three pollutants.

5.2.4 Improve: shift to an Electric Vehicle

Based on the information collected in the survey, the non-financial barriers associated with a transition to EVs do not look that high for the sample of car-dependent individuals.

First, 76% of them have a private parking space at their place of residence, where a charging station could be installed. Second, among those without a private parking space, 23% had access to a public charging station within 500 metres of their place of residence in 2020. This proportion is increasing rapidly: the Paris region has promised to triple the number of charging stations from 2020 to the end of 2023 (Région Ile de France, 2020). Third, fewer than 0.5% of them drive more than 200 kilometres per day based on the distances travelled for within-Paris area trips – and only 0.8% of all the trips recorded are partly outside the Paris area –, such that the autonomy of the EV should not be an issue for this daily mobility.

6 Discussion

Despite the potential of e-biking to shift away from cars, in 2018 the modal share of all forms of cycling was only 1.9% of total trips in the Paris area (Omnil-Ile de France Mobilites, 2019). Given the gap between the actual and potential modal share of (e)-cycling, it is worth highlighting two potential barriers to an increase in cycling and measures that may overcome them. First, in a 2017 survey, 41% of individuals reported the lack of cycling infrastructure as a reason for not cycling (FUB, 2017). Although evidence for a causal relationship is lacking

(Aldred, 2019), more cycling infrastructure is associated with more cycling (Marqués et al., 2015; Buehler and Dill, 2016; Javaid et al., 2020). Investments in cycling infrastructure seem all the more necessary given the significant share of car trip that we found could be shifted to e-bikes based on a travel time and type of trip constraints, but which take place in the suburbs, where the cycling network is less dense than in the centre of Paris (see Figure 8b).

Given the extent to which modal choice decisions are prone to status-quo bias (Mattauch et al., 2016), rolling out cycling infrastructure during a period of disruption such as the recent lockdowns associated with Covid-19 could also have a multiplier effect: it could be an opportunity for a permanent shift in habits against the status-quo, as observed in the case of other disruptions in normal travel habits such as public transport strikes (Larcom et al., 2017). In the short-term, the pop-up bike lanes rolled out to facilitate social distancing right after Covid-19 were found to increase cycling between 11% and 48% in the following months (depending on the city considered) (Kraus and Koch, 2021). A second barrier to a greater uptake of e-bikes is their relatively high cost and the risk of bike theft, which are important factors hindering wider adoption in the Paris area (Cazi, 2020). Electric bike-sharing options may be a good way to promote a higher take-up while addressing these issues.

There are three main limitations to our analysis. First, we do not take into account the potential rebound effect of the different emissions reduction options. In the case of modal shift, we imagine two possible types of rebound: first, rebound from individuals renouncing car ownership, who may spend the savings from not owning a car on carbon-intensive goods and services, as evidenced in a study on Finland (Ottelin et al., 2017). A second type of rebound effect could occur via a reduction in congestion which would increase the marginal utility of driving. More research is needed to estimate the magnitude of such an effect, but it could be partly mitigated by reducing the space made available to cars in public areas. In the case of teleworking, as mentioned in section 4.2 there is mixed evidence so far that it leads to a significant rebound effect.

Second, although we adjust emission factors to reflect current transport emissions, our analysis relies on transport patterns observed in the Paris area in 2010. Based on the more recent but incomplete survey wave from 2018-2019, transport patterns have not changed much between 2010 and 2019. Daily travel distances and modal shares are very similar, the main change being a decrease in the car modal share from 39% to 36%, compensated by an increase in walking from 31% to 33% and in cycling from 1.5% to 1.9%. The share of individuals owning an electric vehicle, while increasing between 2010 and 2020, also remains very low at 0.7%. While we cannot exclude more significant changes in the aftermath of Covid-19, these changes are not captured in any large-scale representative survey at the time where we are writing this article.

Third, we do not consider policies which could reduce travel demand by affecting individual choices of residence and workplace. Indeed, a large literature has shown that commuting distance tend to be larger than predicted by urban models, a difference termed "excess commuting" (Kanaroglou et al., 2015; Viguié, 2015). However these policies typically take many years to bring significant results. Furthermore, shortening commuting distances can stimulate car use at the expense of public transport, as shown for the Paris region by Korsu and Le Néchet (2017).

7 Conclusion

Using a representative transport survey from the Paris area, an emission factor database and counterfactual travel time data, we have analysed the potential of several of the "Avoid, Shift and Improve" options to reduce emissions from transportation in the Paris region: avoiding emissions through teleworking, shifting from cars to cycling or public transport, and improving cars, i.e. reducing their specific emissions. In our second scenario, 25% of car users may be able to shift away from cars for parts of their trips while experiencing a net *decrease* in travel time, and 46% may be able to shift away under an increase in daily travel time of at most 10 minutes. 14% of carbon and air pollution emissions could be saved, generating 125 million euros of annual climate and health benefits. This is for a scenario where the only car trips considered infeasible by e-bike or public transport are those included in a chain of trips with at least one large shopping trip or one professional round. If one further considers that trips involving several car passengers are unlikely to be shifted, the proportions decrease significantly: under that scenario, only 13% of the car users may be able to shift while saving time, only 24% while staying below a travel time increase of 10 minutes, and only 8% of emissions, worth €70m, could be saved.

Between e-bike and public transport, e-bikes have by far the highest potential for a shift if the public transport network is kept fixed. We have not been able to include the reliability of the various transportation modes in our analysis due to lack of data, but this factor would probably reinforce our conclusion about the large potential of e-biking. Indeed, as highlighted e.g. by Batabyal and Nijkamp (2013), public transport schedules are not always reliable — especially for buses — and the time required for car commuting at peak hours is also uncertain. By contrast, cycling speed is more reliable since cyclists are not blocked by traffic jams.

It is useful to identify the "car-dependent" individuals, i.e. those whom we deem unable to shift away from car use for at least some of their daily trips. These individuals live predominantly in the outer suburbs, travel much more than the average individual, and have a lower access to a public transport station. Despite the richness of our data, we are only able to explain a small proportion of the variation in the ability to shift away from car. Therefore, targeting monetary transfers to these individuals in order to compensate a policy-induced increase in the cost of driving might be difficult. We estimate that if every car-dependent individual belonging to a socio-professional category for which teleworking is deemed possible worked from home two (more) days per week, it may cut emissions by an additional 5.5%, assuming no rebound effect.

Even in the most optimistic of our scenarios, the Shift and Avoid options combined would not cut emissions by more than 20%. To reduce emissions further, it is therefore necessary to implement some Improve options by lowering the emission intensity of cars, especially switching to electric cars. We found that the availability of EV charging stations, one of the main hurdles to the adoption of EVs, should not be a major challenge in our setting: beside the 76% of car users having a private parking space at their place of residence, where they could install a charging station, 23% of the remaining car users had a public charging station within 10 minutes walk from their place of residence in 2020, a proportion which should increase rapidly. With the information available in the survey, we are not able to say much about the monetary barriers to EV uptake. We note that low-income individuals are not especially over-represented among the car-dependent individuals. Geography matters much more than income here, with many of the car-dependent individuals living in the outer suburbs. These individuals, however, face stronger financial constraints to buy an EV than individuals living in Paris and in the inner suburbs, because they are not eligible to the means-tested EV subsidies introduced with the Parisian Low Emission Zone – the subsidies are restricted to households living within the planned LEZ boundaries.

Regarding the external validity of our results, we expect that the external cost of transport in terms of air pollution is particularly high in a densely-populated zone such as the Paris area (Carozzi and Roth, 2023), while the potential for modal shift is also relatively high (Nicolas and David, 2009; Brand et al., 2021). We think that our results are likely to apply to other large European cities with a dense public transport network, such as London, Madrid and Rome, as well as to other large French urban areas. Our analysis should be easy to replicate in other cities in the developed world, which often have transport surveys similar to the one used in this paper (for example, the London Travel Demand Survey).

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A Appendix

A.1 Assumptions on NOx, $PM_{2.5}$ and CO_2 emissions by transport mode

This appendix partly reproduces appendix A.1 in Leroutier and Quirion (2022).

A.1.1 Buses

For buses, the NOx and $PM_{2.5}$ emission factors per passenger are derived from the local air quality agency's emission calculator (Airparif, 2021a).[2] They give an emission factor of 180mg/km for an average bus in 2017. The average bus in France is 7.7 years old (Source: Observatoire de la mobilité), so the value for 2017 is for buses registered in 2009 on average. Assuming that the age of the fleet was the same in 2010, the average bus taken by the surveyed individuals in 2010 had been registered in 2002. We adjust for the difference in the years of the data by multiplying the Airparif bus emission factor for 2017 by the ratio of NOx and $PM_{2.5}$ emission factors for cars registered in 2002 compared to 2010, assuming that the improvement in emission factors was similar for buses and for cars over the period.

The CO_2 emission factor per passenger is derived from national values given in Ministère de la Transition écologique et solidaire (2018) and scaled down to adjust for the higher average number of passengers in the Paris area compared to other regions. The initial value assumes 11 passengers by bus on average. Traffic data from the regional transport authority give an average of 14 passengers by bus in the Paris area, so we multiply the initial factor by 11/14.

[2] Although the value given for particulate matter indicate a value in particulate matter of size below 10 microns (PM_{10}), most particles from exhaust are actually less than 1µm in diameter (Karjalainen et al., 2014; California Air Resources Board, 2021). A personal communication with the agency confirms that we can interpret the PM_{10} emission factors as $PM_{2.5}$.

A.1.2 Two-wheelers owned by the household

For two-wheelers, the vehicle used is a vehicle owned by the household in 89% of the cases. We estimate the NOx, $PM_{2.5}$ and CO_2 emission factors of these vehicles based on their characteristics reported in the survey. For the NOx and $PM_{2.5}$ emission factors of two-wheelers, we use the year of first registration only, while for the CO_2 emission factor of two-wheelers, we also use the fuel type and type of two-wheeler (e.g, moped versus motorbike).

We use the NOx and $PM_{2.5}$ emission factors from the local air quality agency's emission calculator, scaled up to reflect 2010 values rather than 2019 ones. We apply the CO_2 emission factors from Barbusse (2005), which are differentiated by fuel type and by type of two-wheeler. The study dates back 2005 and the emissions are calculated for motorcycles first registered between 2003 and 2005. But this is a relatively good proxy for the median emission factor of the motorcycles owned by EGT households, which median first registration date is 2005. This single emission factor does not allow to reflect the heterogeneity in the registration year (from 1951 to 2011), but we do not think it is too much an issue given the low modal share of two-wheelers ($< 1\%$).

A.1.3 Cars owned by the household

For cars owned by the household, we account for cold starts. Under the EMEP/EEA method explained in Ntziachristos and Zissis (2020), for each journey stage by car j made by individual i, NOx emissions $E_{NOx,i,j}$ can be calculated as the sum of hot and cold exhaust emissions:

$$E_{NOx,i,j} = E^{hot}_{NOx,i,j} + E^{cold}_{NOx,i,j} \tag{1}$$

$PM_{2.5}$ emissions can be calculated as the sum of hot and cold exhaust emissions, plus emissions from tyre and brake wear, plus emissions from road surface wear.

$$E_{PM2.5,i,j} = E^{hot}_{PM2.5,i,j} + E^{cold}_{PM2.5,i,j} + E^{tyrebreak}_{PM2.5,i,j} + E^{roadsurf}_{PM2.5,i,j} \quad (2)$$

For both NOx and $PM_{2.5}$ or for a generic pollutant P, emissions associated with journey stage j are also the product of distance $d_{j,i}$, the vehicle-specific emission factor $e_{NOx,j,i}$, and the vehicle's occupancy rate $r_{j,i}$ (equal to one divided by the number of passengers in the vehicle).

$$E_{P,i,t} = d_{j,i} e_{NOx,j,i} r_{j,i} \quad (3)$$

The amount of hot and cold emissions depends on the fraction of the distance driven with a cold engine. According to the EMEP/EEA guidance, this fraction is a function of the vehicle fuel, euro norm, trip distance and exterior temperature. To simplify, we instead set that the first 8 minutes of the trip are made with a cold engine, which is the assumption made by Airparif to calculate average emission factors[3].

Assuming that β is the share of the trip made with a cold engine, drawing on equation 1 and 3 we have:

$$E_{NOx,i,j} = d_{j,i}((1-\beta)e^{hot}_{NOx,j,i} + \beta e^{cold}_{NOx,j,i}) r_{j,i} \quad (4)$$

and

$$E_{PM2.5,i,j} = d_{j,i}((1-\beta)e^{hot}_{PM2.5,j,i} + \beta e^{cold}_{PM2.5,j,i} + e^{tyrebrake}_{PM2.5,j,i} + e^{roadsurf}_{PM2.5,j,i}) r_{j,i} \quad (5)$$

Noting $t_{j,i}$ the duration of the journey stage, we set β to the maximum between 100% and $8/t_{j,i}$ to reflect that the first 8 minutes are made with a cold engine.

For $e^{hot}_{NOx,j,i}$ and $e^{hot}_{PM2.5,j,i}$, we use the EMEP-EEA values (European Environment Agency, 2019) available by fuel, vehicle type and euro norm category. For the fuel type, vehicle type

[3]This assumption is consistent with what is obtained in Ntziachristos and Zissis (2020) for a 10 kilometre trip with a diesel or old petrol car at an average speed of 25km/hour.

and euro norm, we take the characteristics of the vehicle taken for the trip (since we restrict the analysis to vehicles owned by the household, we have the vehicle characteristics). For each fuel $\times$ vehicle type $\times$ euro norm category, the emission factor depends on the average trip speed. We take a single value of 30km/h, corresponding to the average car trip speed in the EGT survey, derived from the travel time and distance results given by the Google console.

For $e^{tyrebrake}_{PM2.5,j,i}$ and $e^{roadsurf}_{PM2.5,j,i}$, we use the EMEP-EEA values from Ntziachristos and Boulter (2019), available by type of vehicle (passenger cars/light-duty trucks/heavy-duty trucks).

To obtain $e^{cold}_{PM2.5,j,i}$ and $e^{cold}_{NOx,j,i}$, we use the formula given in Ntziachristos and Zissis (2020) to calculate the ratios $e^{cold}_{PM2.5,j,i}/e^{hot}_{PM2.5,j,i}$ and $e^{cold}_{NOx,j,i}/e^{hot}_{NOx,j,i}$ (call the generic ratio e^{cold}/e^{hot}, and multiply this ratio by the hot emission factor. The ratio e^{cold}/e^{hot} depends on the pollutant, fuel type, vehicle type, euro norm, average outdoor temperature and average trip speed. For the fuel type, vehicle type and euro norm, we take the characteristics of the vehicle taken for the trip. We take 11.7°C as the average temperature, which is the average annual temperature for the Paris area (Climate Data, 2021). For the average speed, we do not estimate each journey stage's speed. Instead, we allocated to a journey stage the average speed of it origin-destination category, derived from the travel time and distance results given by the Google console. Trips starting and finishing in Paris have an average speed of 15km/h. Trips in Paris and the inner suburbs outside the Paris-Paris trips have an average speed of 22km/h. Trips starting and finishing in the outer suburbs have an average speed of 33km/h. Finally, trips starting or finishing in the outer suburbs and finishing or starting in Paris or the inner suburbs have an average speed of 40km/h. Note that $e^{cold}_{PM2.5,j,i}$ is available only for diesel cars and is assumed to be zero for petrol cars in Ntziachristos and Zissis (2020).

A.1.4 Taxis, cars and two-wheelers not owned by the household

When the vehicle used is a car not owned by the household or is a taxi, we impute the NOx and $PM_{2.5}$ per kilometer emission factor of a 2008 diesel car (in 2010 most taxis were diesel vehicles, retrieved from the local air quality agency's emission calculator. We impute the CO_2 emission factor of a 2008 diesel car of 7 hp, retrieved from the French Energy Agency (Ademe), which provides emission factors for all car models from 2001 to 2015. We average emission factors at the year x fuel type x administrative horsepower level. We use as weights the national-level market shares by brand based on the 2000, 2005 and 2010 registration market shares obtained from the French car manufacturer's association CFCA. We take emission factor values for 2008 cars because vehicles not owned by the household are likely to be company cars, which are often relatively new. For taxis, we multiply the emission factor by two to account for the fares driven without passengers, following the recommendations of Ministère de la Transition écologique et solidaire (2018). When the vehicle used is a two-wheeler not owned by the household, we impute the NOx and $PM_{2.5}$ emission factors of a Euro 3 two-wheeler from the Airparif calculator, and the CO_2 emission factor from a moped, retrieved from Barbusse (2005).

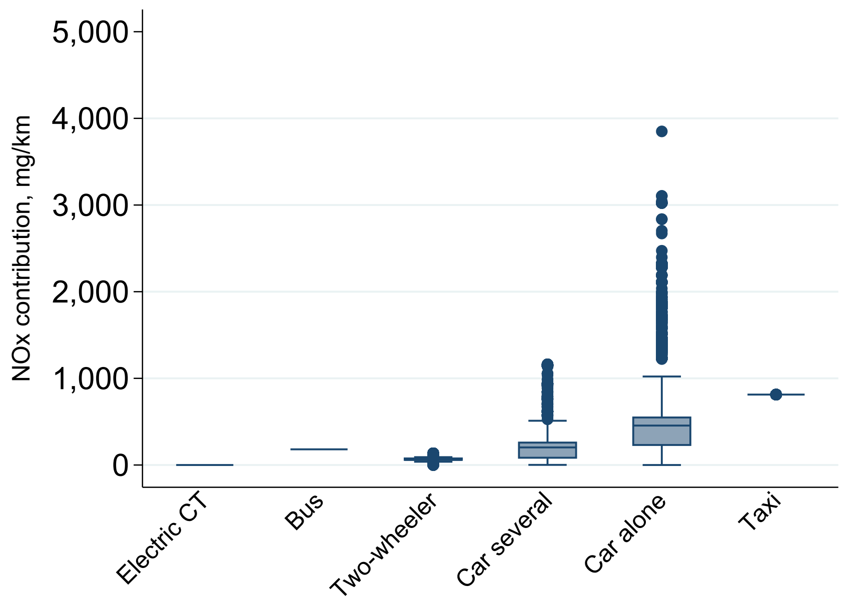


Figure A.1: Distribution of NOx emissions per passenger, by transportation mode

Note: The box plots show the distribution of NOx emissions across journey stages for each mode. Call Q1 the 25th percentile, Q3 the 75th percentile, and IQR the interquartile range. The bar in each box shows the median value, the lower and upper hinges of the box respectively show Q1 and Q3, and the lower and upper lines show the lower and upper adjacent values defined at $Q1 - 1.5 \times IQR$ for the lower adjacent value, and $Q3 + 1.5 \times IQR$ for the upper adjacent value.

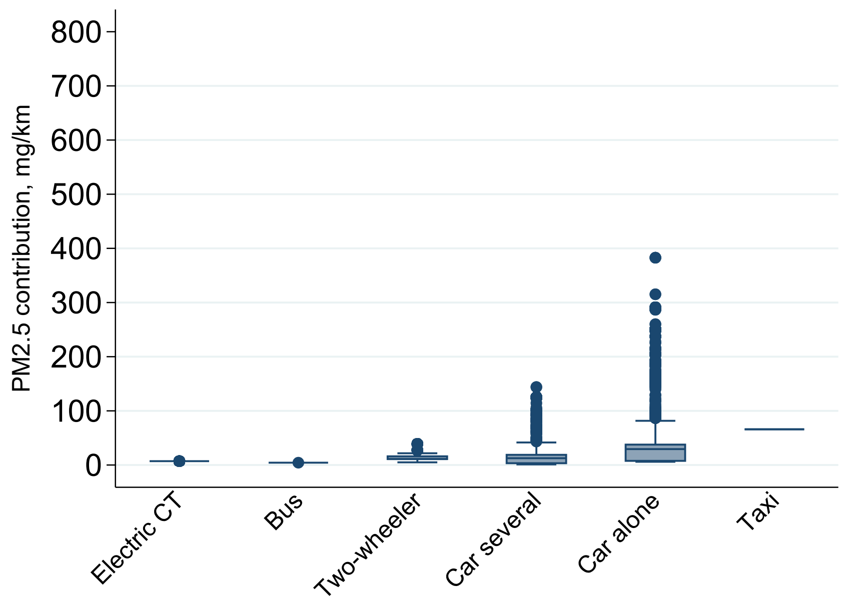


Figure A.2: Distribution of $PM_{2.5}$ emissions per passenger, by transportation mode

Note: The box plots show the distribution of $PM_{2.5}$ emissions across journey stages for each mode. Call Q1 the 25th percentile, Q3 the 75th percentile, and IQR the interquartile range. The bar in each box shows the median value, the lower and upper hinges of the box respectively show Q1 and Q3, and the lower and upper lines show the lower and upper adjacent values defined at $Q1 - 1.5 \times IQR$ for the lower adjacent value, and $Q3 + 1.5 \times IQR$ for the upper adjacent value.

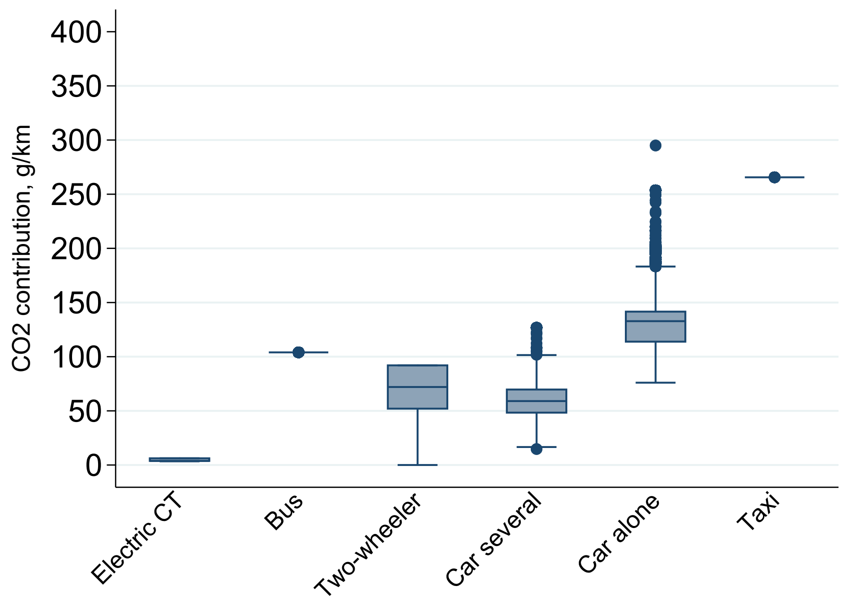


Figure A.3: Distribution of CO_2 emissions per passenger, by transportation mode

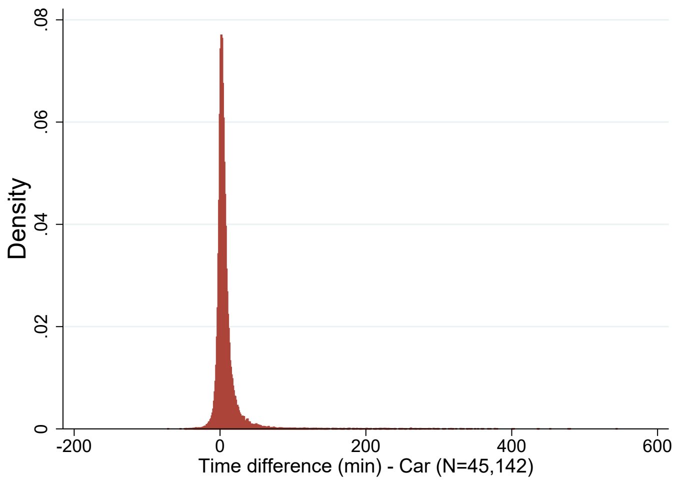
Note: The box plots show the distribution of CO_2 emissions across journey stages for each mode. Call Q1 the 25th percentile, Q3 the 75th percentile, and IQR the interquartile range. The bar in each box shows the median value, the lower and upper hinges of the box respectively show Q1 and Q3, and the lower and upper lines show the lower and upper adjacent values defined at $Q1 - 1.5 \times IQR$ for the lower adjacent value, and $Q3 + 1.5 \times IQR$ for the upper adjacent value.

A.2 Additional Tables and figures

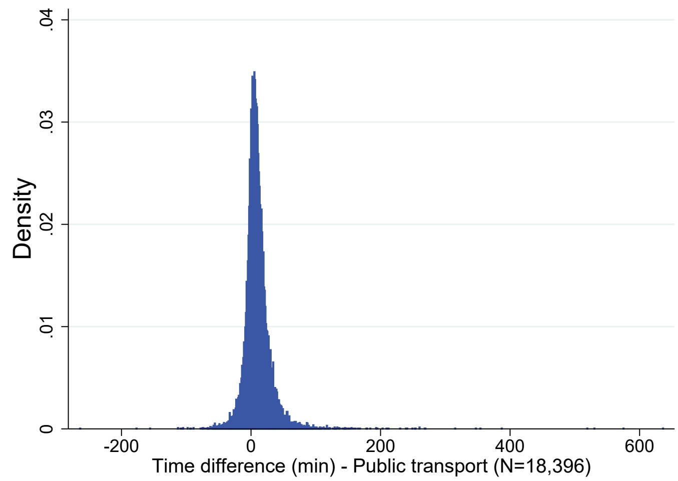
Table A.1: Summary statistics - Individuals ≥18 years old with at least one trip recorded - reproduced from Leroutier and Quirion (2022)

	Mean	Sd	N
Residence: Paris	21%		23,690
Inner suburbs	37%		
Outer suburbs	42%		
Education: Primary school	6%		23,636
Secondary education	39%		
Higher education < 3 years	14%		
Higher education ≥ 3 years	35%		
Still in education	7%		
SES: Farmers	0%		22,495
Manual workers	11%		
Office workers	19%		
Intermediate professions	19%		
Traders and craftspeople	3%		
Managers and executives	20%		
Pensioner	20%		
Other	7%		
Age	45.72	16.62	23,690
Net household income (€ 2010)	40,910.90	26,462.14	23,683
Net household income per consumption unit (€ 2010)	24,298.50	14,725.03	23,683
Actual distance to workplace (km)*	14.77	14.35	8,374*
Nb of trips prev. day	4.32	2.40	
Modal share for trips: Car	39%		23,690
Collective transportation	27%		
Bicycle	2%		
Two-wheeler	2%		
Walking	31%		
Other mode	< 1%		
Daily distance travelled (km)	28.88	31.60	23,690
Daily travel time (min)	107.19	76.06	23,690
Average trip distance (km)	8.26	10.53	23,444
Average trip duration (min)	29.30	24.26	23,458

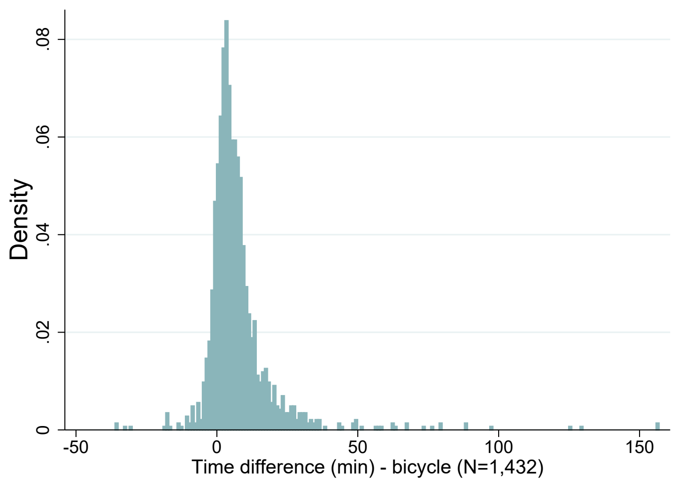
Note: Source: EGT data. Observations weighted with EGT individual-level sampling weights. SES stands for Socio-Economic Status. The eight categories follow the aggregate classification of the French Statistical Institute. Household income is estimated with a predictive mean matching imputation method. *Actual distance to workplace is only observed for workers making one commuting trip starting exactly at home and finishing exactly at work during the day, hence the lower sample size.



(a) Car



(b) Public transit



(c) Bike

Figure A.4: Difference between self-declared trip durations and trip duration according to Google

Note: Source: EGT data. Sample: all trips made by adults with car, public transport of bicycle as the main transport mode.

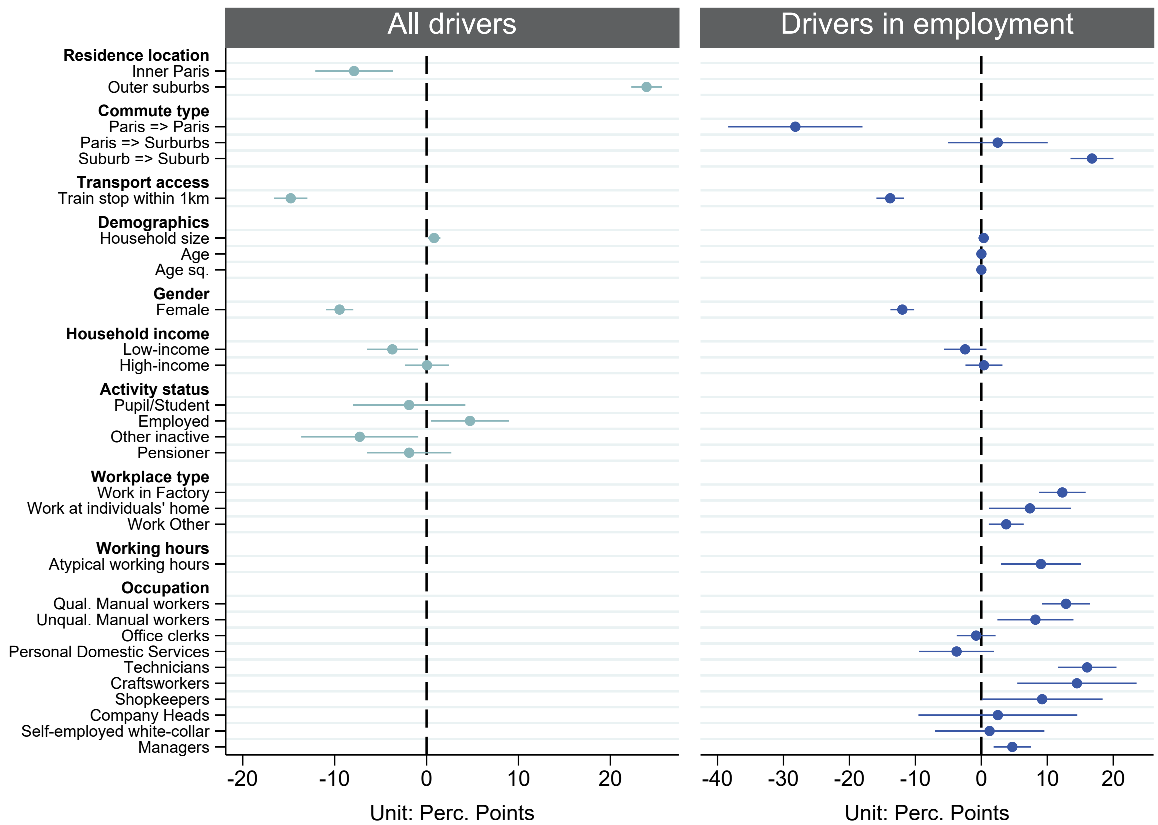


Figure A.5: Characteristics associated with being unable to shift away from car, bivariate regressions

Notes: Regressions with one single covariate of interest. from left to right: selected X covariates are listed on the left, by category. Omitted categories for the categorical variables: Location: inner suburbs; Gender: male; Employment status: unemployed; Commute type: Suburbs => Paris; Workplace type: Work in office; Occupation: Intermediate professions. Standard errors are clustered at the household level. The first panel shows the average marginal effect of each characteristic on the likelihood to not be able to shift away from cars for the sample of all car users, and the second panel shows the same for the subsample of individuals in employment, with several job characteristics used as additional covariates. Regressions are unweighted.