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. According to our scenario analysis based on counterfactual travel time data for 45,000 observed car trips, 40% of car users could realistically shift to e-bike – mostly – or public transit – in a few cases – with an increase in travel time of one minute per day on average. Such modal shift would reduce CO_2 and local pollutant emissions from daily mobility by around 15%, generating climate and health benefits worth around €140 million per year. Inability to undertake a modal shift is associated with living in the outer suburbs, being retired, being a man and having a high income. Another 5% of total emissions could be avoided if all the “car-dependent” individuals able to work from home did so for two days a week. Holding demand for mobility and public transport infrastructure fixed, achieving greater emission reductions would require improving car use via a transition to electric vehicles.

Keywords: external cost of car use, modal shift, scenario analysis

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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, 2019; 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 current users of traditional cars have to reduce car use, how much these alternatives would reduce emissions, and who the car-dependent individuals are. We embed our analysis in the ”Avoid-Shift-Improve” (ASI) framework (Creutzig et al., 2018, 2022), which 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. We broaden the initial focus on greenhouse gas emissions to also include local pollutant emissions, which cause significant health damage in urban contexts.

We use a large representative transport survey of weekday mobility conducted in the Paris area in 2010, including 12,000 car users completing 45,000 car trips. 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. Accounting for the improvement in the emission intensity of cars in the past ten years, we estimate a total cost of around €939 million per year today, 90% of which is due to car use. We investigate the extent to which current car users are able to shift to low-emission modes, avoid traveling by teleworking, or improve by switching to electric vehicles.

We are able to investigate the "shift" component in greater depth thanks to rich counterfactual travel time data. 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% CO_2 emission reduction by 2030, and the threat of new financial sanctions for France if air pollution thresholds continue to be exceeded[1].

We build scenarios of modal shift potential based on counterfactual transport time data from a transport Application Programming Interface (API), the characteristics of the trip as observed in the survey, and the characteristics of the car user. From the API data we infer the travel time difference between driving and electrically-assisted bicycle – e-bike, and between driving and public transport, for all the car trips in the survey. In our preferred scenario, we consider that a chain of trips – defined as all the trips included between leaving

[1]in August 2021, France was fined €10 million for failing to meet air quality objectives in the first semester of 2021, see Conseil d'État (2021)

home and going back home – can only be shifted away from cars if i)travel time for that chain of trips increases by less than twenty minutes ii)the chain of trips does not include driving from customer to customer or driving to a large supermarket, iii)for a shift to e-bike only, the car user is below 70 years old. Under this scenario, we find that 35% of current car trips could be shifted to e-bike or public transport, with the former accounting for the majority of the shift. Such modal shift would save 15% of daily mobility emissions, with associated climate and health benefits worth around €140m per year. For most individuals, the twenty minutes threshold is not binding: among those who we deem able to shift, the increase in *daily* travel time would be only one minute on average, and 40% of individuals would actually experience a *decrease* in travel time.

We characterize a "car-dependent" group by investigating individual and household characteristics associated with being unable to entirely shift away from car use. Living in the outer suburbs is the most important factor, but other factors such as being in the top 20% of the income distribution or being a man are also associated with a higher propensity to be car-dependent. However, there remains sizeable unobserved heterogeneity in modal shift potential even after controlling for many characteristics.

We finally examine the extent to which "avoiding" travel via teleworking would be an option for these car-dependent individuals. Only 13% of them combine commuting by car and having an occupation which is likely to be feasible from home. We conclude that in the absence of long-term changes in the distribution of residents, jobs and leisure activities across the urban area, "improving" vehicles via a shift to electric vehicles seems necessary to achieve greater emission reductions.

Our paper contributes 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 bottom-up models. Our case study relies on a bottom-up approach, starting with micro-level data and quantifying emissions reduction options at the individual level. 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.

While the aforementioned literature focuses exclusively on the climate benefits associated with a decrease in car use, our analysis also includes health benefits from reduced local air pollution. In contrast to de Nazelle et al. (2010), who evaluate the potential for local pollution emission reduction from short trips in the US, we are able to include trips of any distance in our analysis thanks to the counterfactual travel time data. We also add to that paper by considering other emissions reduction options and by quantifying monetary benefits.

Second, although we do not estimate the distributional effects of one environmental policy in particular, our paper is related to the literature examining inequalities in the incidence of environmental policy costs. Several 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). The factors underlying such heterogeneity are not well understood (Drupp et al., 2021). In the case of transport, differences in the availability of low-emission substitutes partly explain why some households face higher policy costs; public transport availability has been suggested as an explanation for differences in fuel price elasticities between the US and Europe (Gillingham and Munk-Nielsen, 2019), and computable general equilibrium models examining the incidence of environmental transport policies typically assume a larger elasticity of substitution in urban compared to rural areas (Beck et al., 2016; Dugan et al., 2022). By analysing modal shift potential among residents *within* a given urban area, our analysis shows that there are sizeable differences in the ability to shift away from cars even at the very local level.

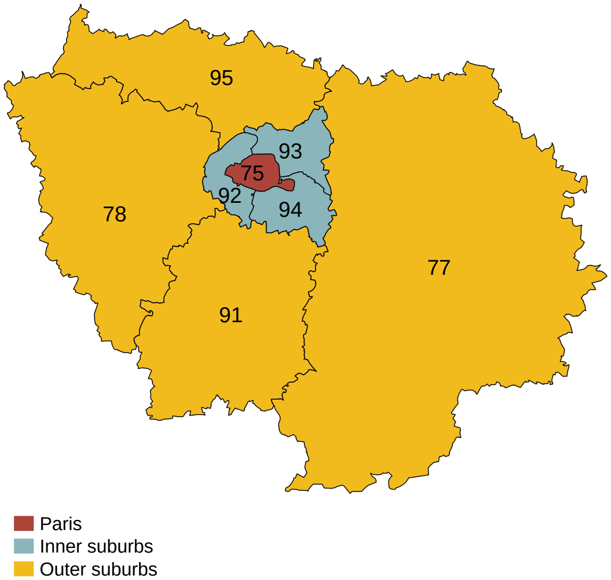
Finally, our paper adds to the literature examining the potential for teleworking and its environmental impact. Teleworking has recently gained prominence in the public debate and in the literature in the context of the Covid-19 pandemic (Dingel and Neiman, 2020; Alipour et al., 2020; Lennox, 2020). While recent papers have assessed the environmental benefits of teleworking in terms of CO_2 emission reductions (Bachelet et al. (2021) for Germany, Crowley et al. (2021) for Ireland), we also quantify benefits in terms of avoided local air pollutant emissions.

Section 2 presents the local context; section 3 presents the data and methods used; section 4 presents the environmental cost of daily mobility under the status quo; section 5 presents the results; Section 6 discusses the results and concludes.

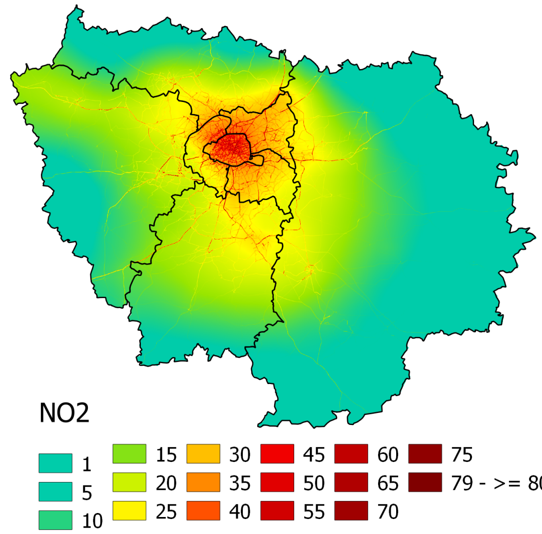
2 Background: the Paris area

The Paris area is defined here as the administrative *region* 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 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.



(a) The Paris Metropolitan Area



(b) NO_2 in 2015, µg/m^3

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, 2021). Road traffic is responsible for 53% of NOx emissions. It is also responsible for 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 inner suburbs from 2024 on, and gasoline cars from 2030 on (Le Monde, 2018).

3 Data and Methods

3.1 Data sources

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, since the 2020 survey was stalled because of the Covid-19 epidemics. 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 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 - where a trip is characterized by an origin and a destination goal and may involve several transport modes[2]. Table A.1 shows descriptive statistics for this subsample. In the scenario analysis, we further restrict the analysis to the 12,595 individuals who used a car at least once, either as a driver or passenger. They complete 45,897 car trips taking place within the Paris area in total[3]. 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).

[2]For example, going from home to work using a combination of walking, subway and bus is one single trip made of several journey stages, one journey stage per unique transport mode.

[3]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

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).

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.

Charging stations for Electric Vehicles We used GIS software to identify all the households having at least one charging station within 500 meters of their place of residence. 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[4] (where many stations located in Paris centre are missing), the national open data service[5] (where many stations located in Paris centre are also missing), and subregional open data services providing data on two municipalities (Paris and Rueil-Malmaison).

3.2 Data processing

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. First, we identified each trip's departure and arrival points with the latitude and longitude of the centroid of the origin and destination grid cells (the grid cells used for geolocation in the survey are 100m x 100m). We then pooled together the trips likely to have the same travel time with a given mode, based on how Google's prediction algorithm works:

[4] https://geodatamine.fr/dump/charging_station_geojson.zip
[5] https://www.data.gouv.fr/fr/datasets/fichier-consolide-des-bornes-de-recharge-pour-vehicules-elect

- 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 actual time when they took place.

- 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.

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[6]. We applied this constant speed factor of 15/19 to the API's cycling times.

[6]The survey was conducted in four European countries including France: https://6-t.co/etudes/donnees-inedites-vae-en-europe-panel/

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.

Estimating emission savings under different scenarios: We estimate status-quo 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. 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 when the vehicle used belongs to the household. In the few cases where the vehicle used does not belong to the household, a constant vehicle-specific emission factor is imputed.[7]

In contrast to Leroutier and Quirion (2022), we apply different NOx and $PM_{2.5}$ emission factors for the first few minutes of each trip, to reflect cold starts. Indeed, 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.

[7] As explained in Leroutier and Quirion (2022), there are two versions of emission factors: the on-road emission factor, which varies with the vehicle speed, quality of the road and driving conditions, and the type-approval values reported by car manufacturers, subject to maximum values under EU regulation. For NOx and $PM_{2.5}$, we use on-road emission factors because the discrepancy between type-approval and real-world emissions is large - Baldino et al. (2017) report an average factor of 4 between the type-approval and real-world NOx emission factors for a sample of diesel cars registered after 2011. For $PM_{2.5}$ specifically, using on-road emission factors also allows us to take into account emissions from tyres and brakes - rather than only those from exhausts - which represent a substantial proportion of emissions (OECD, 2020). For CO_2, type-approval values seem more relevant for two reasons. First, car model-specific CO_2 emission factor data exist, which we can link to the information on the vehicles owned by households to estimate precise emission factors varying by fuel type, age and horsepower. Second, while for local pollutants, type-approval values drastically underestimate real-world emissions, for CO_2 the difference between type-approval and real-world emissions is relatively small: for the same sample of diesel cars, Baldino et al. (2017) find that on-road CO_2 emissions are on average only 30% higher than type-approval values.

Table 1: Emission factors by mode (reproduced from Leroutier and Quirion (2022))

	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	0
Metro	per passenger-km	0	7	0
Train	per passenger-km	0	7	0
Bus	per passenger-km	242	5	117
Taxi	per passenger-km	1,178	127	332
Car not owned by the household	per vehicle-km	589	63	166
Two-wheeler not owned by the household	per vehicle-km	86	21	65

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).

Table 1 summarizes emission factors per transport mode. Active modes have a zero emission factor for all three pollutants. The train and subway have a zero emission factor for NOx and CO_2[8], but not $PM_{2.5}$, due to the emissions from train brakes. Car emission factors vary according to vehicle characteristics. On the table we only show 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.

[8]These modes embody some NOx and CO_2 emissions, but given our focus on air pollution mitigation *in the Paris area*, we think it is satisfactory to focus on exhaust emissions only.

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[9]. 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 90% of transport emissions on a typical weekday (89% of the CO_2 emissions, 93% of the NOx emissions and 86% of the $PM_{2.5}$ emissions). The disproportionate impact of car trips on emissions justifies our decision to focus our scenarios on car trips.

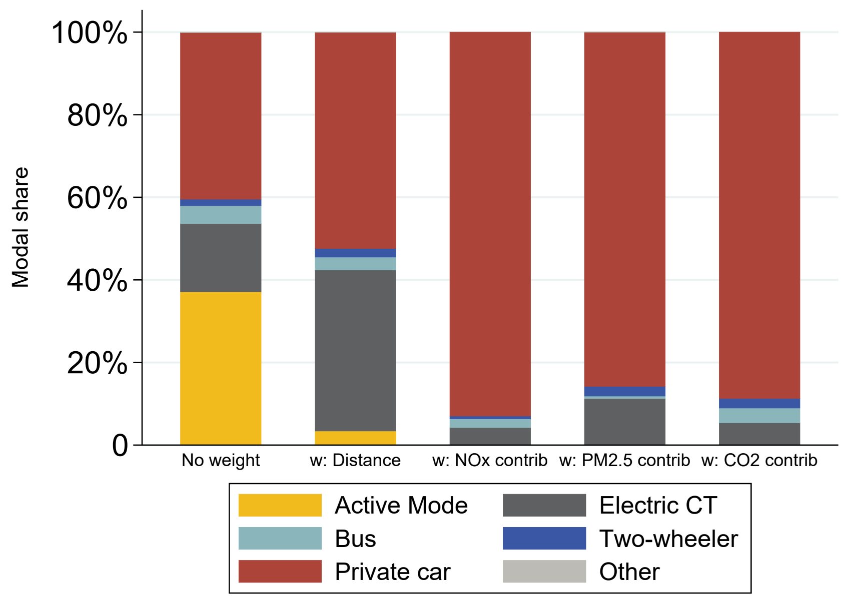


Figure 2: Modal shares in the number of trips, distances travelled and emissions

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: Authors' calculation based on EGT data. Sample: all trips made by individuals aged 18 and over. Individual sample weights included.

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[10] for car trips (on the left) in

[9] Many trips are composed of journey stages with different transport modes. We use the variable "main transport mode taken" at the trip level to allocate trips, distances and emissions by mode.

[10] We use information from the survey on the origin and destination motive (home/ workplace/ study place/ shopping…) to classify trips into six purposes: 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" (typically, this would be the location of

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.

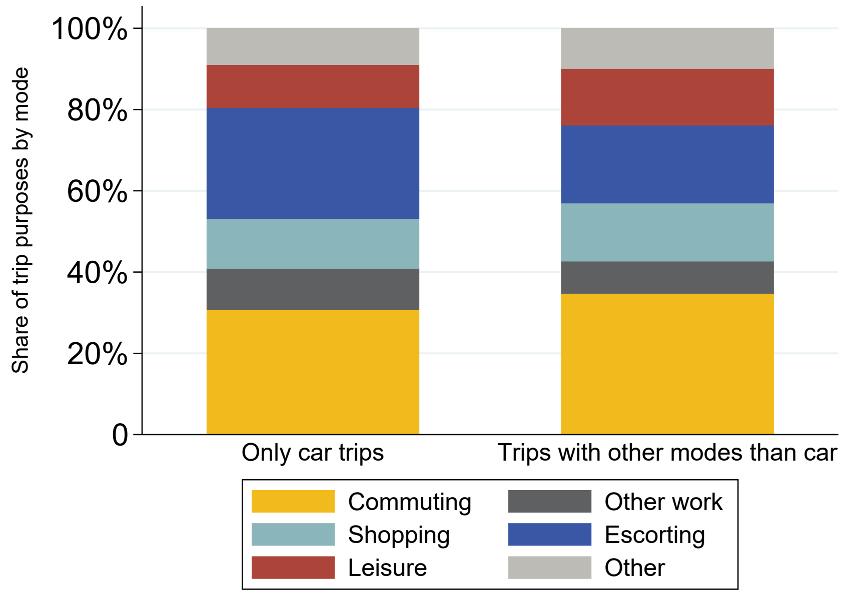


Figure 3: Proportion of trip purposes for car and non-car trips

Note: Source: Authors' calculation based on EGT data. Sample: all trips made by individuals aged 18 and above.

We focus the scenario analysis on the 12,595 individuals who use a car for a trip within the Paris area at least once during the day, either as passenger or driver. Figure 4 shows that the proportion of car users is higher in the outer suburbs than in central Paris or the inner suburbs.

a client meeting or a restaurant where the employee is having a lunch break), 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. We do not have information on the person being escorted, but typically this includes escorting children to school or after-school activities. A number of trips belong to chains: for example, the first trip starts at home and finishes at the children's school, and the second trip starts at the children's school and finishes at work. Given our classification, the first trip will be recorded as an escort trip and the second one as commuting. "Other trips" are all trips not covered by the previous purposes.

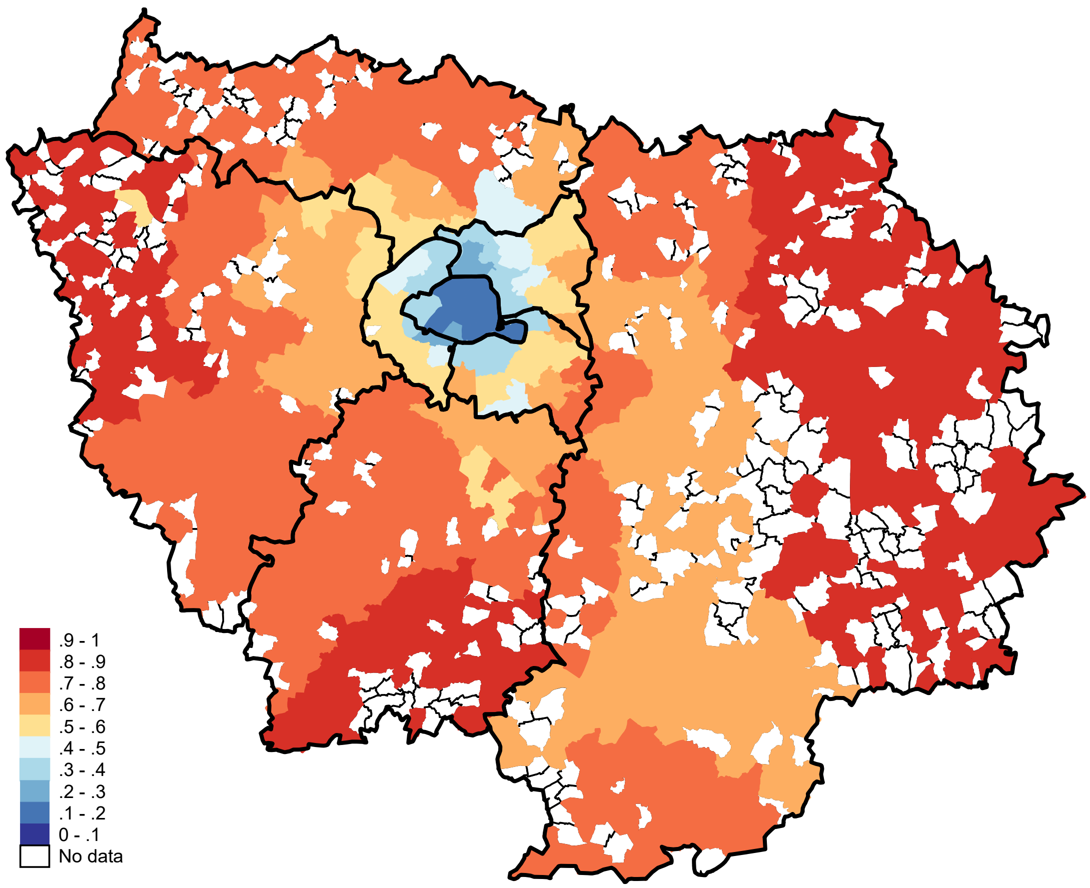


Figure 4: Share of car users by sampling zone (weighted average using individual sample weights)

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

3.4 Methods: The ASI framework and modal shift scenarios

The ASI framework: According to the "Avoid-Shift-Improve" framework (Creutzig et al., 2018), 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, 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 (option 1, avoid travelling), and the potential for a shift to electric vehicles (option 3, improving vehicles).

Modal shift scenarios: We examine the proportion of car trips that could be substituted with e-bike or public transit based on constraints put on i)the travel time difference between car and the substitute mode, ii)the type of trip, and iii)only for e-biking, the individual's age. Travel time is a proxy for time cost, which is an important component of total travel cost. The constraints on age and the type of trips capture non-cost preferences associated with driving, such as comfort or how practical a car is to transport several people or heavy loads.

We conduct this analysis at the trip chain level, where a trip chain is defined as the set of trips included between leaving home and coming back home. We do so because it does not seem realistic for a person to shift from car to another transport mode only for part of a trip chain. In the EGT data, 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. 66% of the car drivers' trip chains include at most two car trips: the individual drives from home to a certain location, and ultimately drives back home, without any other car trip in between[11]. The remaining 33% of trip chains include at least three car trips[12].

We formulate three scenarios of modal shift potential at the trip chain level, with increasingly strict constraints. The constraints are summarized in table 2. Regarding travel time differences, figure 5 shows the cumulative distribution function of travel time difference

[11]For example, she drives to work, goes from work to a client meeting by public transport, and drives back home at the end of the day.

[12]For example, the individual drives to work, then from work to the children's school, and finally from the children's school to home

between driving and e-biking (red line), and driving and public transit (blue line), for all the trip chains involving cars in the EGT[13]. More than 50% of the trip chains would be at most 20 minutes longer with e-bike, but only around 15% with public transit. We set a maximum travel time difference of 30 minutes for scenario 1, 20 minutes for scenario 2 and 10 minutes for scenario 3.

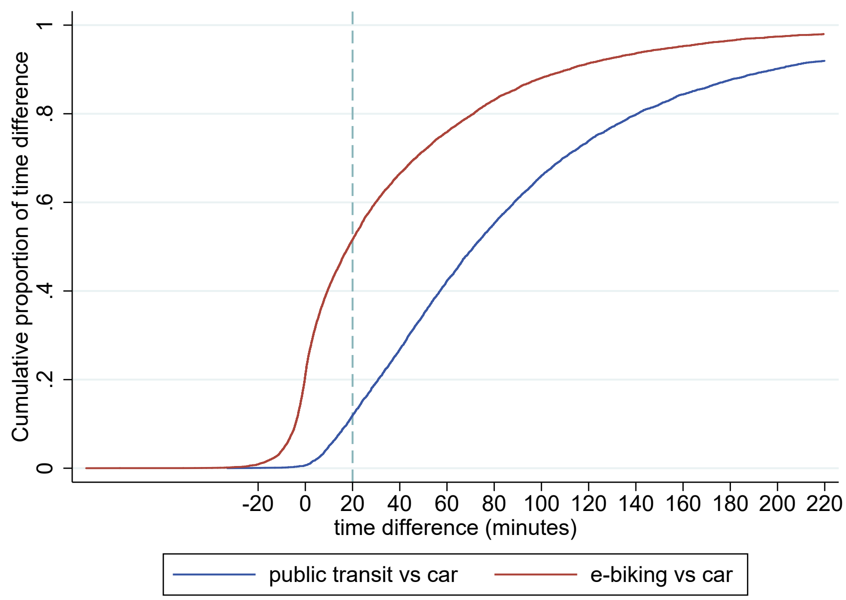


Figure 5: Cumulative Distribution Function of the difference in travel time between car, e-biking and public transit at the trip chain level

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.

Regarding the type of trip, in scenario 1 we impose no constraint. In scenario 2, we impose the constraint that the trip chain should not include any car trip whose 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 scenario 3, we add as an additional constraint that the trip chain should not include any car trip with more than one person

[13]Travel time differences at the trip chain level are based on trip-level travel time differences from the API's outputs, aggregated at the trip chain level

Table 2: The three scenarios considered

	Scenario 1	Scenario 2	Scenario 3
Travel time difference between trip chain with alternative mode and observed trip chain	$\leq$ 30min	$\leq$ 20min	$\leq$ 10min
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

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.

Regarding individuals' age for a shift to an e-bike, we impose the same constraint in all scenarios: that a shift to an e-bike is only feasible for individuals below 70. This age seems realistic 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).

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

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, and combine this quantity of emissions with the unit costs of CO_2 emissions, NOx and $PM_{2.5}$ from the literature. From the EGT, we obtain the fact that on a typical weekday, daily mobility generates around 20,696 tons of CO_2, 75 tons of NOx and 6.6 tons of $PM_{2.5}$. These results are based on the travel patterns and emission intensity of the vehicle fleet in 2010, the year of the survey. They may not accurately reflect today's environmental cost if the three components entering the emission calculations – the distances travelled, modal shares and mode-specific emission intensities – changed in the last ten years. Preliminary results from the 2020 wave of the EGT 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: 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[14]. Assuming that in 2020, households owned vehicles that were also eight years old on average, we can scale down our emission quantity by a factor corresponding to the difference in emission intensity between a car sold in 2002 and a car sold in 2012. In 2012, the average CO_2 emission intensity was 20% lower (124g/km, (Ademe, 2022)), the average NOx emission intensity was 31% lower (397mg/km), and the $PM_{2.5}$ emission intensity was 48% lower (28mg/km). After scaling down emissions, we find that today's daily mobility in Paris generates around 16,557 tons of CO_2, 51 tons of NOx and 3.4 tons of $PM_{2.5}$ per day (first part of table 3).

We give a monetary cost to these emissions based on individual pollutants' unit costs 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

[14]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

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)[15], dating back to 2016. 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 PM2.5 – 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 find that the daily mobility of residents generates an environmental cost of around 4.3 million euros (€4.3m) per day, of which €1.40m for CO_2 emissions and €2.9m for local pollution (€1.44m for NOx and €1.43m for $PM_{2.5}$). Assuming that the survey is representative of working days across the year[16], with 220 annual working days the annual environmental cost of daily weekday mobility in the Paris area amounts to €939m, of which €308m are climate-related costs and €631m are health costs. Emissions from car use represent 90% of the total cost.

[15] See Annex A and Annex C from EU Commission (2020), and pp59-67 of CE Delft (2018) for more details on the economic valuation of health and the assessment of air pollution costs. In short, the monetary values include the costs of air pollution in terms of individual health, crop losses, material and building damages, and biodiversity losses. The different cost factors are estimated in three steps, based on the methodology developed in the 2007 NEEDS project (NEEDS, 2007): first, emissions are translated into concentrations; second, concentrations are translated into health and environmental impacts using dose-response functions; third, health and environmental impacts are given a monetary value. Sources for the cost values include (NEEDS, 2007) and updates from more recent sources. For the health costs (which represent the largest proportion of costs), mortality and morbidity dose-response functions are based on a WHO study (WHO, 2013). Mortality impacts are monetized using an estimate of VOLY (Value of a Life Year) of €70,000 per life year for the EU28, derived from a literature review. The EU-level VOLY value is translated into country-specific values using unit value transfers adjusting for income differences across countries. Morbidity impacts are estimated using a conversion table expressing illness and disability as partial mortality in a QALY (quality-adjusted life year) framework, assuming that 1 QALY=1/1.087 VOLY.

[16] The travel intensity reported in the survey is representative of an average weekday between October and May outside school holidays, where some individuals are on holiday but probably not a large proportion. There are probably fewer trips in the Paris area in July and August, two months where most people take several weeks' holiday in France.

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

Cost category	Pollutant	Daily emissions (kg)	Unit cost (€/kg)	Cost (million €)
Climate-related	CO_2	16,556,766	0.0845	1.40
Health-related	NOx	51,438	28.03	1.44
Health-related	$PM_{2.5}$	3,407	419.38	1.43
Total cost, daily				4.3
Total cost, annual				939

5 Which Options have the Highest Potential to Reduce Emissions?

5.1 Shift to low-emission modes

For each of the three scenarios defined in section 3.4, we calculate the proportion of car trips that could be shifted to a low-emission mode and the associated net emission savings. For the shift to e-biking, net savings are simply the avoided emissions from cars: we neglect emissions from e-biking battery charging because of the extremely low energy consumption of this mode. For the shift to public transit, we calculate the difference in emissions between doing the trip with electric public transit and doing the same trip by car. We assume that people shift to electric public transport rather than bus because trips by electric public transit are much more common as a proportion of distances travelled: they make up 38% of total distances while bus only make up 3% (see second bar of figure 2). Table 4 reports the results. Across all scenarios, e-biking enables much more modal shift than public transport, whose contribution is marginal. Below we emphasise the results for the scenario with medium constraints, scenario 2. Under scenario 2, 35% of the car trips can be shifted to e-bike, and adding public transport shift only increases the proportion to 36%. The proportion of emissions saved, around 15% across pollutants, is relatively low compared to the proportion of trips having a substitute, because substitutable trips are shorter on average.

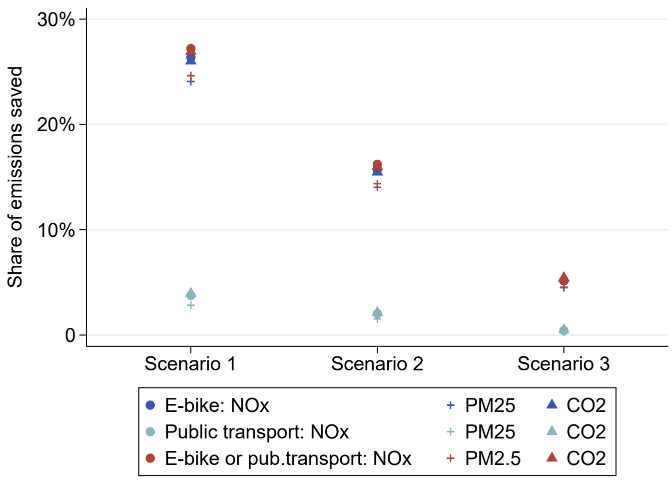
Figure 6a plots the emission savings by scenario and figure 6b shows the monetized value

Table 4: Proportion of car trips that could be avoided, modal shift potential assessed at the trip chain level

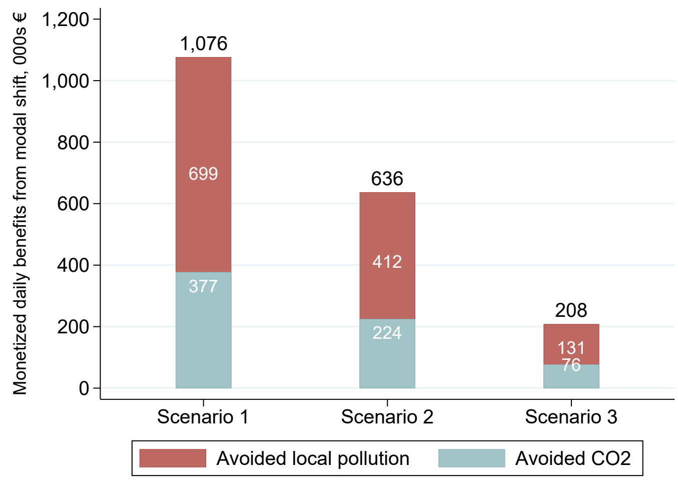
	Scenario 1	**Scenario 2**	Scenario 3
Switching to e-bike possible	56%	**35%**	10%
NOx saved as a % of total	26%	**16%**	5%
$PM_{2.5}$ saved as a % of total	28%	**14%**	5%
CO_2 saved as a % of total	26%	**15%**	5%
Switching to public transport possible	10%	**5%**	0.8%
NOx saved as a % of total	4%	**2%**	0.4%
$PM_{2.5}$ saved as a % of total	3%	**2%**	0.3%
CO_2 saved as a % of total	4%	**2%**	0.5%
Switching to e-bike or public transit possible	57%	**36%**	11%
NOx saved as a % of total	27%	**16%**	5%
$PM_{2.5}$ saved as a % of total	25%	**14%**	5%
CO_2 saved as a % of total	27%	**16%**	5%
N	45,897	45,897	45,897
N with survey weights	14,084,867	14,084,867	14,084,867

Note: Source: EGT data. Proportions are calculated using individual-level sampling weights. Results in bold indicate our preferred scenario.

of emission savings when shifting to e-bike or public transport is possible. Under scenario 2, modal shift is associated with environmental and health benefits of €0.64 million per day — this is after applying the same scale-down factor as above, to reflect the improvement in the emission intensity of the car fleet in 2020 compared to the time of the survey. Corresponding annual benefits amount to €141 million. Note that by focusing on the benefits of modal shift in terms of air pollution reduction and CO_2 mitigation, we do not include other types of benefits such as the health benefits from active mobility[17].



(a) Proportion of emissions saved depending on substitute used (some double counting)



(b) Monetized benefits associated with modal shift (no double counting)

Figure 6: Proportion of emissions saved and monetized benefits, modal shift scenario at the trip chain level

Notes: Source: EGT data with individual sampling weights. Sample: all trips made by adults with car as the main transport mode.

We calculate the increase in daily travel time to gauge whether it is realistic for individuals to incur the associated cost in terms of time lost, especially given that the total daily time spent commuting has been found to be remarkably stable over time (Marchetti, 1994). Figure 7 shows the cumulative distribution function of travel time change under scenario 2, for drivers who are able to at least partially shift away from car use. Actually, almost half of them would experience a net *decrease* in daily travel time if they used a low-emission

[17]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; Rabl and de Nazelle, 2012; Gössling et al., 2019)

mode. The other half would experience an increase in daily travel time of between 0 and 20 minutes. The average change in travel time is one minute. On average, the cost of modal shift in terms of time lost seems very limited under Scenario 2.

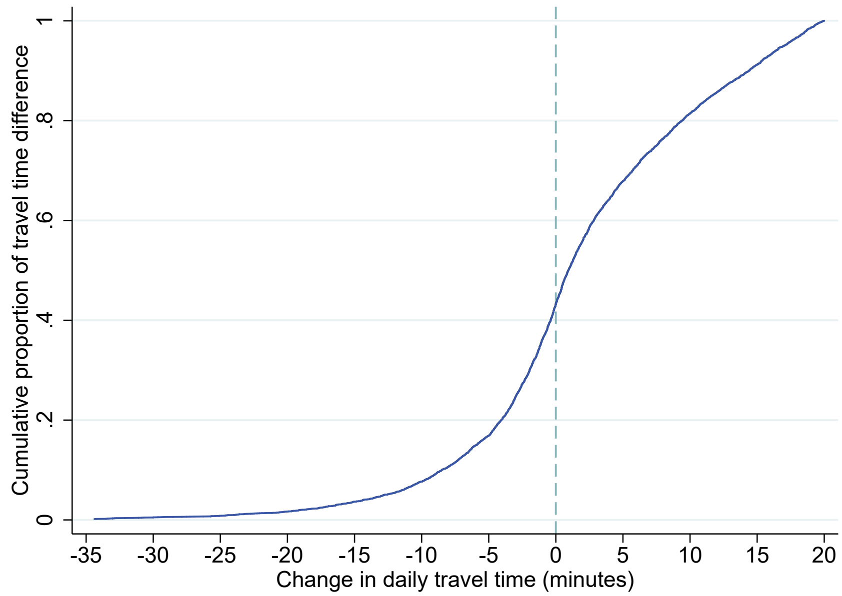


Figure 7: Cumulative Distribution Function of the difference in daily travel time between the car and the alternative, individuals able to shift at least part of their trips away from cars according to scenario 2.

Note: Sample: all individuals currently using the car at least once during the day and who are able to shift to e-biking or public transport for at least some of their car trips according to our scenario 2. Source: Authors' calculations based on Google API outputs.

Who are the car-dependent individuals? Under scenario 2, 40% of current drivers are able to shift away from car use entirely, a group which we call the "shifters". For the remaining 60%, at least one trip chain where they use a car would last more than 20 minutes more with another mode, or would involve car trips that we deem impossible to substitute (driving from customer to customer or bulky grocery shopping). We call this group the "car-dependent" individuals and investigate their characteristics. First, this group travels longer distances by car: their median distance is 35 kilometres, compared to 10 kilometres for the shifters. In terms of geography, the outer suburbs have a higher proportion of car-dependent individuals, as shown on figure 8. 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.

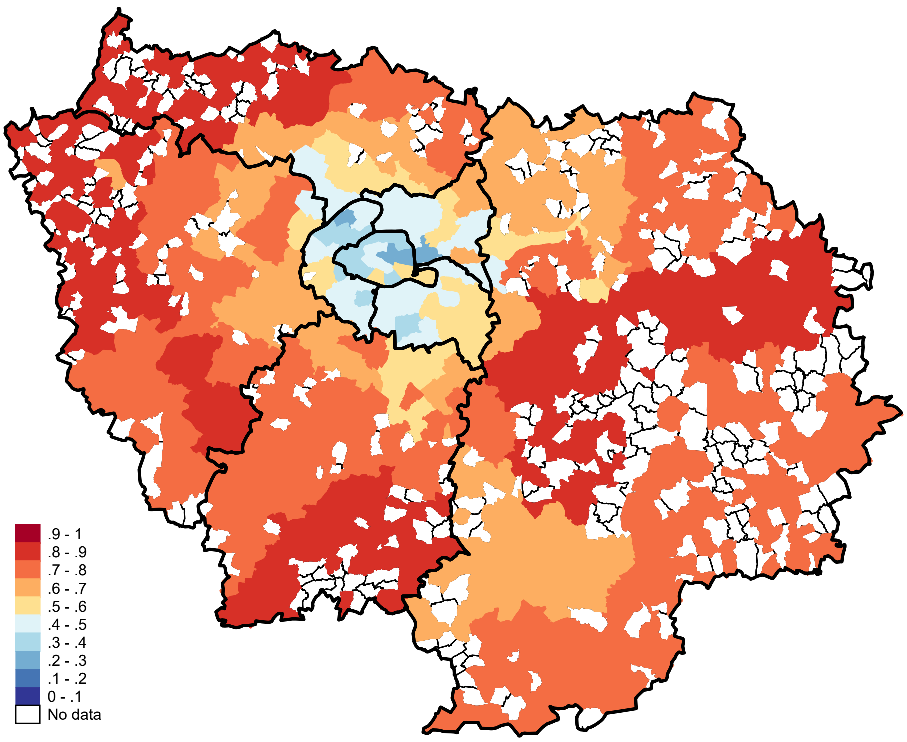


Figure 8: Proportion of individuals unable to shift away from cars ("car-dependent individuals"), averaged by sampling zone

Note: Source: EGT data with individual sampling weights. Sample: all individuals using a car at least once during the day.

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, being retired and having a high income — defined here as being in the top 20% of the distribution of household income per consumption unit — 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 and being a technician or shopkeeper are also associated with car-dependency. Retired individuals are less likely to be able to shift to e-bike given our age constraint of 70. Shopkeepers and technicians are more likely to be involved in driving from customer to customer. All the other characteristics (and also being a technician) are correlated with longer distances travelled (Leroutier and Quirion, 2022), which may explain why substituting away from the car is not realistic based on travel time. 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 0.04 for the analysis on the subsample of workers. This suggests that there is a lot of unobserved heterogeneity in the ability to shift away from car use.

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. We see that most coefficients keep the same sign and significance level. One exception is income: the association between having a high income and being unable to shift is still positive but not statistically significant any more when other characteristics are not controlled for. On the other hand, having a low income — defined here as being in the bottom 20% of the distribution of household income per consumption unit — becomes negatively associated with car dependency — in other words, it becomes positively associated with being able to shift.

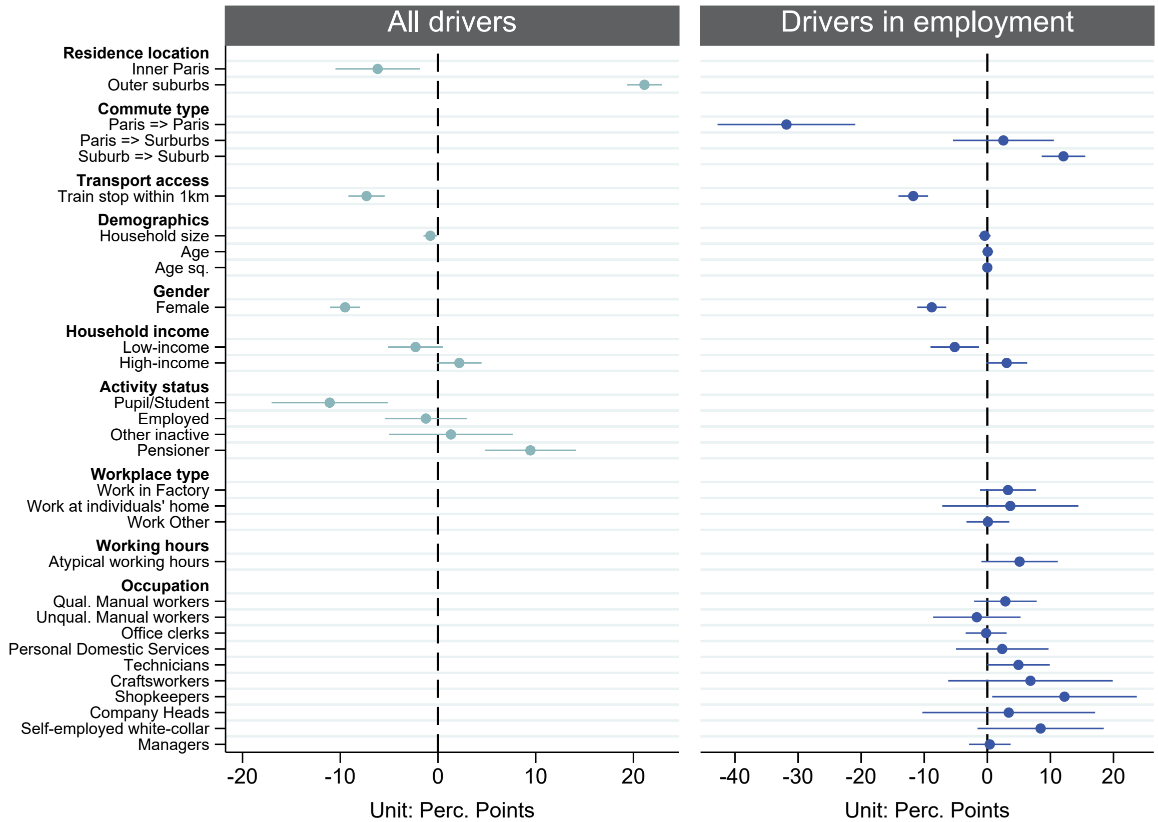


Figure 9: Characteristics associated with being unable to shift away from car use

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 Avoid travelling by teleworking

For the "car-dependent 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 two 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). In our sample, only 64% of the car-dependent individuals are employed, and among them, only 44% commute by car. Therefore, avoiding travel by teleworking could reduce emissions for at most 28% of them. We gauge whether these individuals' jobs could easily be done from home by combining information on their socio-professional category with information on their workplace[18]. 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[19].

According to these criteria, 13% of the car-dependent individuals could reduce emissions by working from home[20]. If they all worked from home two days a week[21], an additional 5% of total CO_2, NOx and $PM_{2.5}$ emissions could be avoided. The corresponding monetized benefits would be €0.22 million per day, that is, €48m annually.

Note that teleworking could also be an option for some of the individuals who we deem able to shift to low-emission modes – those we do not consider as car-dependent. If every car commuter whom we deem able to telework did so two days a week, it would cut total emissions by 7% for NOx and CO_2 and by 6% for $PM_{2.5}$.

5.3 Improve: shift to an Electric Vehicle

Another alternative to modal shift is to improve the emission intensity of vehicles by shifting to electric vehicles (EV). Note that the per kilometer reduction in air pollution and CO_2 emissions obtained thanks to electric vehicles is smaller than that obtained by shifts to active modes or electric public transport, due to higher lifecycle emissions of cars and the non-exhaust particulate emissions of electric cars (OECD, 2020), which are particularly

[18] We cannot use exactly the same definition of potential to telework as in the recent paper by Dingel and Neiman (2020) due to data limitations.

[19] as opposed to working in a factory, in other people's homes, in a hospital or school, in a public institution, or in a shop

[20] 40% of the employed car-dependent individuals who commute by car have a job type that can be done from home. So the proportion of car-dependent individuals for whom working from home would reduce emissions is $0.4 \times 0.44 \times 0.64 = 13\%$

[21] This is the frequency agreed upon in most of the company-wide agreements recently negotiated in the Paris area, see https://www.francebleu.fr/infos/economie-social/teletravail-en-ile-de-france-de-nombreux-accords-d-entreprise-autorisent-deux-jours-par-semaine-163042

damaging for health (Daellenbach et al., 2020).

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 simply list a few statistics from our dataset that suggest the non-monetary barriers may be overcome quite easily in the Paris area. First, 78% of the car-dependent individuals 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, 19% had access to a public charging station within 500 metres of their place of residence in 2020[22]. Third, fewer than 1% of them drive more than 200 kilometres per day (with the limitation that weekday trips outside the Paris area are not recorded), such that the autonomy of the EV should not be an issue for this daily mobility.

We are not able to say much about the monetary barriers. We simply note that while many of the car-dependent individuals live in the outer suburbs, the means-tested EV subsidies introduced with the Parisian Low Emission Zone are only available for households living within the planned LEZ boundaries, that is in Paris and part of the inner suburbs, which excludes households from the outer suburbs.

6 Discussion and 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. Among the Avoid and Shift options, shifting from cars to e-bikes has by far the highest potential: in our preferred scenario, 35% of the trips currently made by car could be shifted to e-biking, cutting emissions of CO_2 and

[22]This estimate is conservative because the data on EV charging stations appears not to be exhaustive.

local pollutants by 15% on average. In contrast, in the same scenario, only 5% of the trips currently made by car could be shifted to public transport given the current public transport infrastructure, cutting emissions by 2%. Combined, these two options could replace 36% of the trips currently made by car and save around 15% of emissions. Assuming that teleworking every day is not realistic, avoiding emissions from commuting by car through teleworking has a more limited potential: if every individual belonging to a socio-professional category for which teleworking is deemed possible worked from home two days a week, it would only cut emissions by 6-7%.

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.

Despite the potential of e-biking to shift away from cars, the modal share of all forms of cycling was only 1.9% of total trips in 2018 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 the potential barriers to an increase in cycling and measures that may overcome them. First, cycling infrastructure is associated with more cycling (Marqués et al., 2015; Buehler and Dill, 2016; Javaid et al., 2020). Although evidence for a causal relationship is lacking (Aldred, 2019), 41% of individuals who took part in a survey in 2017 reported the lack of cycling infrastructure as a reason for not cycling (FUB, 2017). Investments in cycling infrastructure seem all the more necessary given that many car users who would be able to shift to e-bike live in the suburbs, where the cycling network is less dense than in the center of Paris: Figure 10 shows that the proportion of car trips that could be shifted to e-biking according to scenario 2 exceeds 20% in most of the suburbs.

Second, the transport literature has shown the extent to which modal choice decisions are

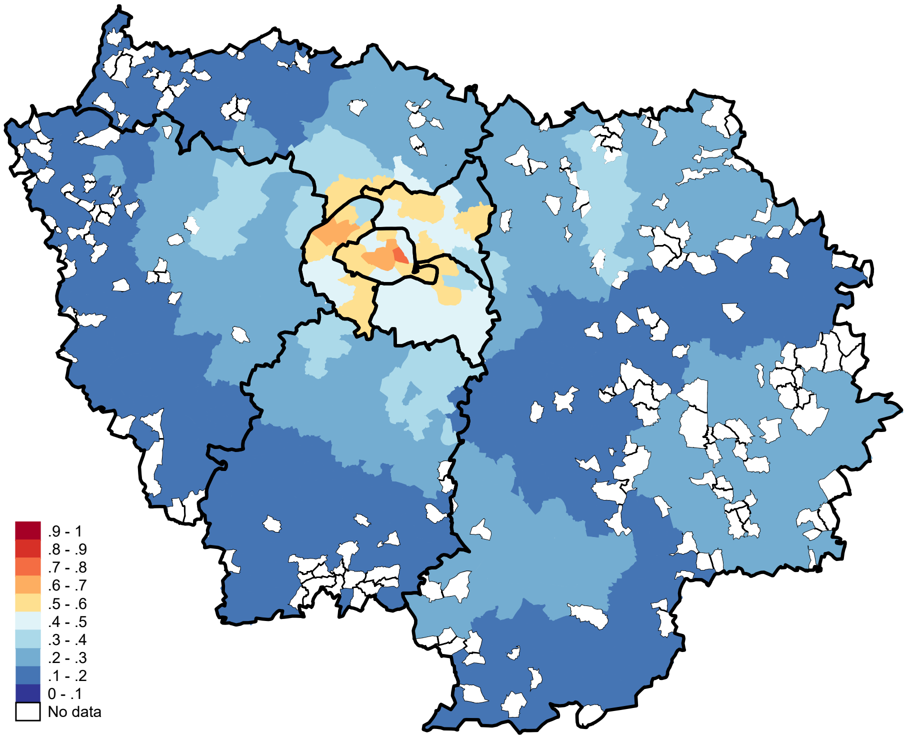


Figure 10: Proportion of car trips that could be made with e-biking (Scenario 2), by origin sampling zone

Note: Source: EGT data with individual sampling weights. Sample: all individuals using a car at least once during the day.

prone to status-quo bias (Mattauch et al., 2016). Shifting habits is especially difficult in the case of daily mobility. The forced experiment of the Covid-19 crisis 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). Given the behavioral factors influencing modal choice, rolling out cycling infrastructure during a period of disruption could also have a multiplier effect: The pop-up bike lanes rolled out to facilitate social distancing during Covid-19 increased cycling between 11% and 48% in the following months, depending on the city considered (Kraus and Koch, 2021). Finally, for e-bikes specifically, their relatively high cost and the risk of bike theft 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 the monetary costs of electric bikes and the risk of theft.

Even in the most optimistic of our scenarios, the Avoid and Shift options combined would not cut emissions by more than a third. 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. Our dataset provides limited, yet useful information to assess the potential of this option: the availability of EV charging stations is one of the main hurdles to the adoption of EVs; yet 78% of the car users who are unable to shift away from cars in our preferred scenario have a private parking space at their place of residence, where they could install a charging station. Furthermore, at least 17% had a publicly available charging station less than 500 metres from their place of residence in 2020, a proportion which will increase rapidly. Hence charging at home should not be a major obstacle to the deployment of electric cars.

Since gasoline and diesel cars remain largely dominant, 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, have a higher income, a lower access to a train station and are more often retired. 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. Targeting monetary transfers to these individuals in order to compensate a policy-induced increase in the cost of driving might be difficult.

One limitation of our analysis is that 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, rebound may occur if people used the time saved thanks to no longer commuting for leisure travel. 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 increases energy use (Hook et al., 2020).

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, 2019), 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 reproduces appendix A.1 in Leroutier and Quirion (2022), except for the "Cars owned by the household" paragraph.

Buses For buses, the NOx and $PM_{2.5}$ emission factors per passenger are derived from the local air quality agency's emission calculator[23]. 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.

[23]http://www.airparif.fr/calculateur-emissions/. Although the value given for particulate matter indicate a value in particulate matter of size below 10 microns (PM_{10}), most particles from engine combustion are actually smaller than 2.5µm: Karjalainen et al. (2014) mention that most exhaust particles from gasoline direct injection engines are around 0.1µmm;California Air Resources Board (2021) mention that more than 90% of diesel particulate matter is less than 1µm in diameter. The EMEP/EEA Copert methodology from which Airparif emission factors are calculated also assumes that all PM from exhaust are $PM_{2.5}$ (Ntziachristos and Zissis, 2020). A personal communication with the agency confirms that we can interpret the PM_{10} emission factors as $PM_{2.5}$

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 ($< 1\%$).

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:

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

$PM_{2.5}$ 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 $e_{NOx,j,i}$ divided by the number of passengers in the vehicle, $n_{j,i}$.

$$E_{P,i,t} = d_{j,i} e_{NOx,j,i} \frac{1}{n_{j,i}} \tag{3}$$

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 their average emission factors[24].

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

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

and

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

Noting $t_{j,i}$ the duration of the journey stage[25], 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 [26] available by fuel, vehicle type and euro norm category. For the fuel type, vehicle type and euro norm, we take the

[24]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.

[25]The duration of each journey stage is not readily available in the EGT, which only gives the self-declared duration of the trip. More than 99% of the journey stages by car are included in 3-stage trips, with a first journey stage by foot, a second journey stage by car and a last journey stage by foot. We retrieve the duration of the journey stage by car assuming a walking speed of 4km/h and taking the difference between the trip's duration and the walking duration.

[26]accessible here: https://www.eea.europa.eu/publications/emep-eea-guidebook-2019/part-b-sectoral-guidance-chapters/1-energy/1-a-combustion/road-transport-appendix-4-emission/at_download/file

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 × vehicle type × 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.[27]. 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).

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[28]), retrieved from

[27]Source: https://fr.climate-data.org/europe/france/ile-de-france-301/

[28]https://www.auto-moto.com/actualite/environnement/faut-il-interdire-les-taxis-diesels-la-question-qui-fache-49587.html

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, using as weights the national-level market shares by brand[29]. 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).

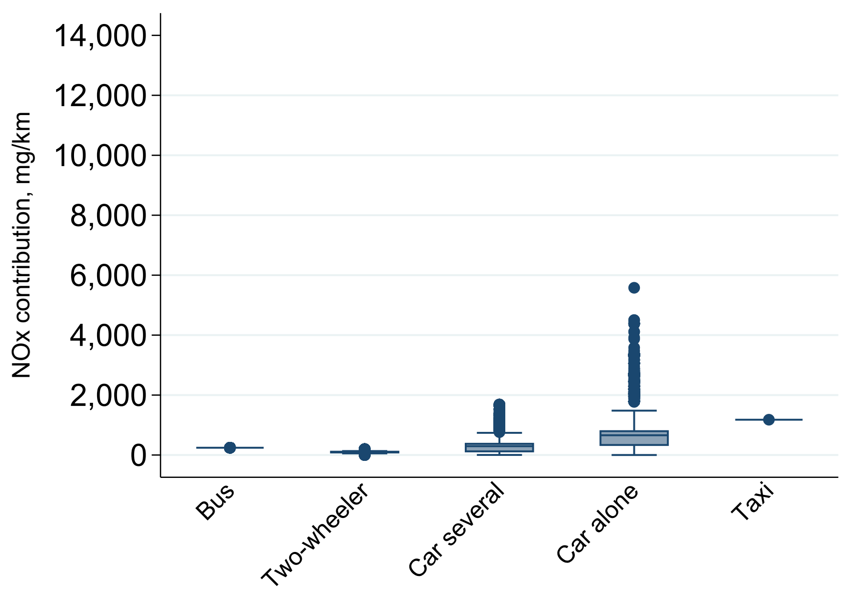


Figure A.1: Distribution of NOx emissions per passenger, by transportation mode

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.

[29]we take the average of the registration market shares over the years 2000, 2005 and 2010 obtained from the French car manufacturer's association CFCA.

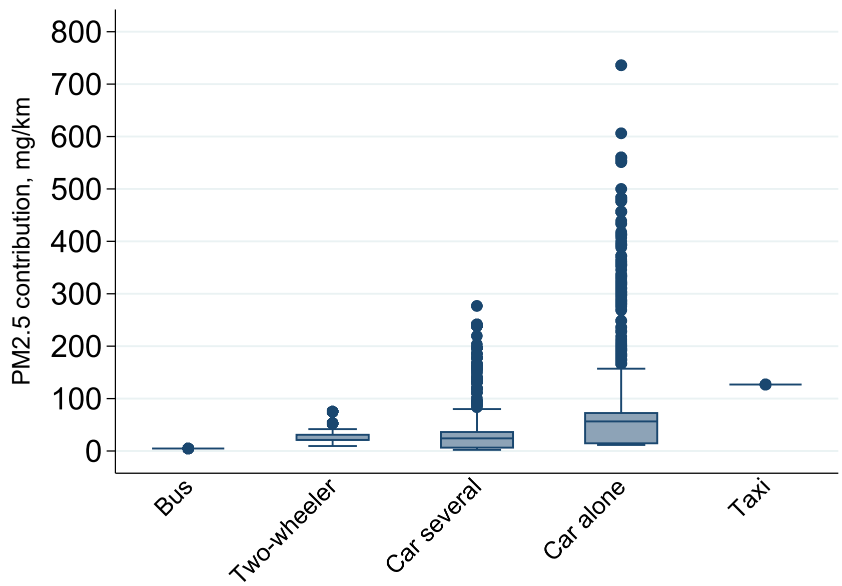


Figure A.2: Distribution of $PM_{2.5}$ emissions per passenger, by transportation mode

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.

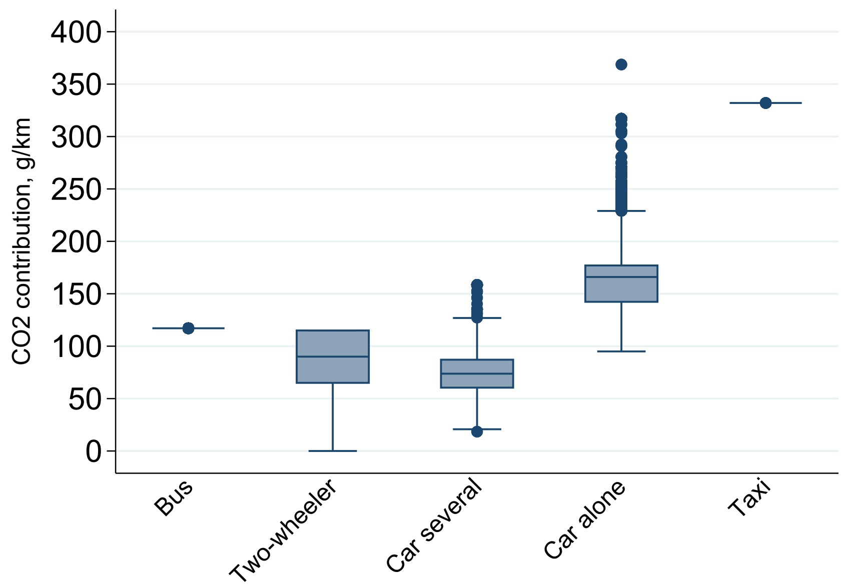


Figure A.3: Distribution of CO_2 emissions per passenger, by transportation mode

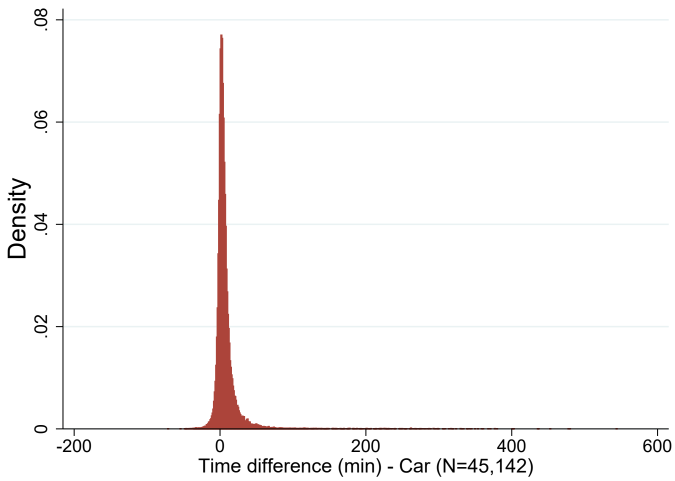
Note: The box plots show the distribution of CO_2 emissions across journey stages for each mode. Call Q1 the 25th percentile, Q3 the 75th percentile, and IQR the interquartile range. The bar in each box shows the median value, the lower and upper hinges of the box respectively show Q1 and Q3, and the 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

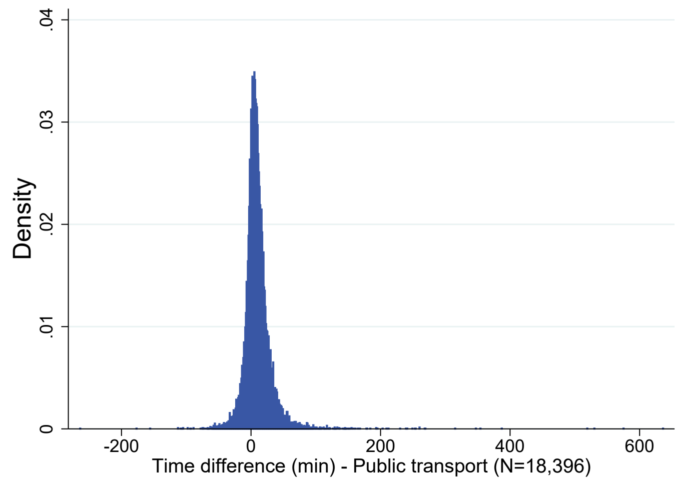
Table A.1: Summary statistics - Individuals ≥18 years old with at least one trip recorded - reproduced from Leroutier and Quirion (2022)

	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

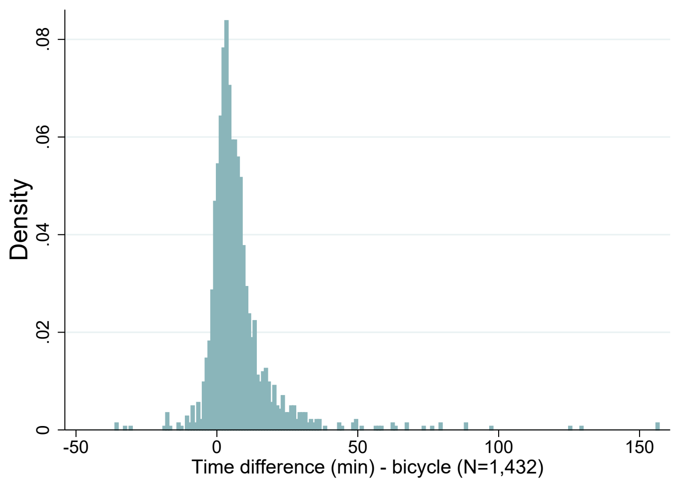
Note: Source: EGT data. Observations weighted with EGT individual-level sampling weights. SES stands for Socio-Economic Status. The eight categories follow the aggregate classification of the French Statistical Institute. Household income is estimated with a predictive mean matching imputation method. *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.

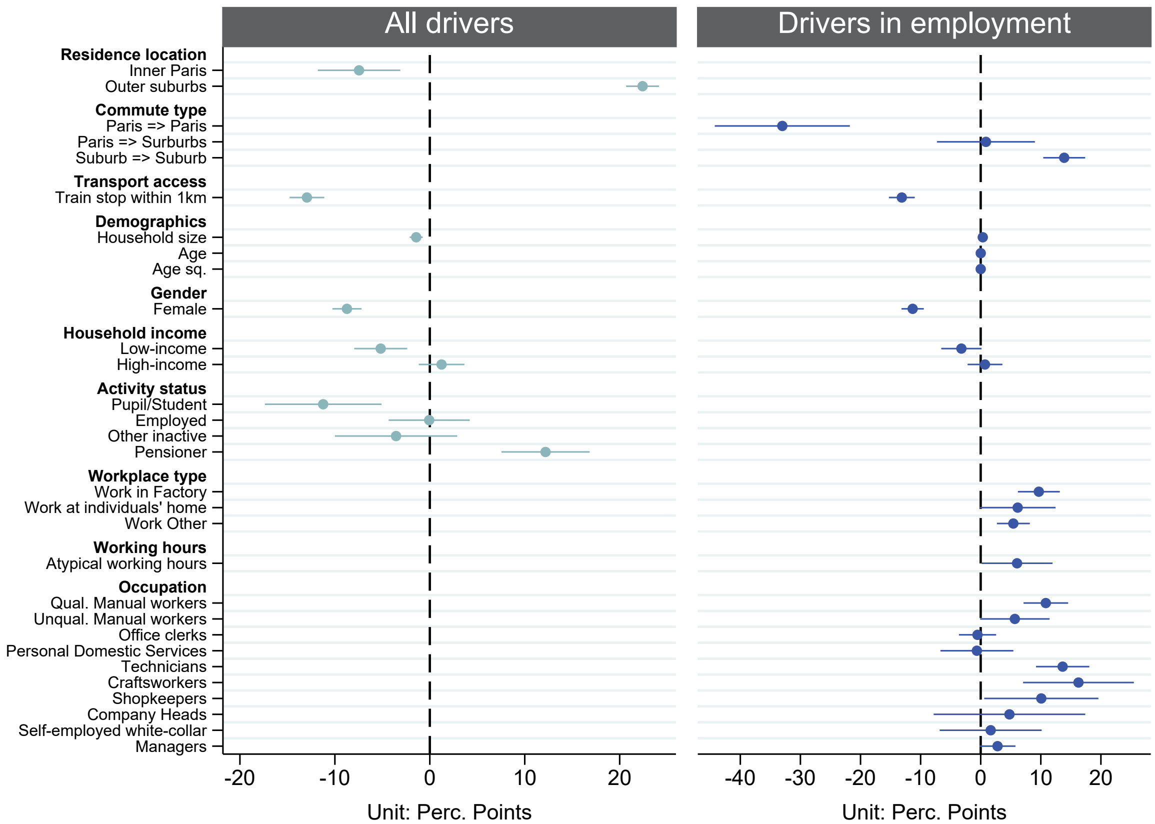


Figure A.5: Characteristics associated with being unable to shift away from car, bivariate regressions

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.