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Tackling Transport-Induced Pollution in Cities: A Case Study in Paris*

Marion Leroutier†, Philippe Quirion‡

Abstract

Urban road transport is an important source of local pollution and CO_2 emissions. To tackle these externalities, it is crucial to understand who contributes to emissions today and what are the alternatives to high-emission trips. We estimate individual contributions to transport-induced emissions, by bringing together data from a travel demand survey in the Paris area and emission factor data for local pollutants and CO_2. We document high inequalities in emissions, with the top 20% of emitters contributing 75-85% of emissions on a representative weekday, depending on the pollutant. Top emissions result from a combination of high distances travelled, a high reliance on car and, mainly for local pollutants, a higher emission intensity of cars. We estimate with counterfactual travel times that 53% of current car drives could be shifted to electric bikes or public transport with a limited time increase. This would reduce the emissions from daily mobility by 19-21%, with corresponding annual health and climate benefits of around €245m.

Keywords: externalities, environmental inequalities, lmdi

JEL Codes: R40, Q52, Q53

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1 Introduction

Road transport is responsible for several well-documented environmental externalities (Parry et al., 2007). First, it contributes to outdoor air pollution, which has been identified by the WHO as the world's "largest single environmental health risk" (WHO, 2014), accounting for an estimated 4.2 million deaths per year. Beside its impact on physical health, air pollution negatively impacts mental health (Bishop et al., 2018; Braithwaite et al., 2019), the formation of human capital (Currie et al., 2014) and productivity (Chang et al., 2019). Road transport also contributes to greenhouse gas emissions, mostly carbon dioxide (CO_2), with an increasing contribution relative to other economic sectors in most developed countries (IEA 2019). This trend needs to be reverted to achieve emission reductions consistent with the Paris agreement.

This paper focuses on local pollutant and CO_2 emissions from transport in urban areas, where emissions are both more detrimental to health and possibly easier to tackle than in rural areas. On the first point, many urban areas suffer from high levels of pollution, including in developed countries subject to relatively strict environmental regulations: in Europe, France, Germany and the UK were condemned in 2018 for failing to meet air quality standards in several cities (European Commission, 2018). On the second point, urban areas present more alternatives to cars: the higher density makes active modes more attractive, and public transport is more widespread (Creutzig et al., 2020). Yet, policy proposals aiming at restricting driving for polluting cars, whether motivated by air quality or climate mitigation concerns, are controversial (Viegas, 2001; Le Parisien, 2019; Delhaes and Kersting, 2019; Isaksen and Johansen, 2020). It is then crucial to understand who the high emitters are, and whether they could easily switch to a low-emission alternative.

In this paper, we estimate how much individuals contribute to transport-related pollution via their daily travels. To do so, we combine individual travel information from a large representative survey conducted in the Paris area with mode-specific and vehicle-specific emission factors. We focus on two local pollutants having detrimental effects on health, nitrogen oxide (NOx) and fine particulate matter ($PM_{2.5}$), and the main greenhouse gas, carbon dioxide (CO_2). We find strong inequalities in emissions among individuals, with the top 20% of emitters contributing 75-85% of emissions on a representative weekday, depending on the pollutant.

We then investigate the characteristics associated with high emissions using two complementary methods: in a first step, we note that total emissions are the exact product of three channels: distance, modal choice, and emission intensity (per kilometer.passenger and within modes). We apply an exact factor decomposition analysis (LMDI) on emissions to understand how the respective contributions of these three channels to top emissions. For local pollution, higher distances travelled, a higher reliance on car, and higher emission intensities within modes contribute about the same to top emissions. In contrast, for CO_2 top emissions are mostly explained by high distances and a high reliance of cars, and less by differences in emission intensities.

In a second step, we investigate the individual characteristics associated with each of the three channels, focusing on car - the most emitting mode - for modal choice and emission intensity. Beyond the characteristics already documented in the literature, distance to the centre or employment status, we highlight the important association of some employment characteristics with the reliance on car, such as being a manual or trades worker, a self-employed white-collar, working in a factory or with atypical working hours. We also show the ambivalent role of income, which is associated with higher distances, a higher probability to use a car and a higher CO_2 emission intensity of cars, but not with a higher NOx and PM2.5 emission intensity.

Finally, we investigate the potential to reduce emissions. We use counterfactual transport time data from a transport Application Programming Interface (API) to estimate the modal shift potential. We find that 53% of current car drives could be shifted to regular, electric cycling or public transport against an increase in travel time of at most 10 min per trip and limited daily increase in travel time. Such modal shift would save 21% of the total NOx emissions induced by passenger daily mobility, 19% of the total $PM_{2.5}$ emissions and 19% of the total CO_2 emissions. We document, with less precision, the potential for teleworking (distance lever) and shifting to electric vehicles (emission intensity lever).

Our paper contributes to several strands of the literature: first, we contribute to the literature on environmental inequalities by investigating individual contribution to transport-related pollutants and CO_2 emissions. There is a vast literature examining cross-country inequalities in local pollution emissions - in relation to the Environmental Kuznets Curve hypothesis (Dinda, 2004) -, and a more limited literature examining inequalities at the individual or household level (Levinson and O'Brien, 2018). On CO_2 emissions, there is also flourishing literature looking at inequalities in individual carbon footprint at the country or regional scale (Sager, 2019; Ivanova and Wood, 2020). Most of the studies estimating individual emissions rely on input-output methodologies combined with micro-level consumer expenditure surveys, which provide very limited information on travel behavior (mostly the purchase of fuel and public transport tickets and subscription), and lack precise spatial information. As far as we know, the subset of papers specifically examining the incidence of carbon tax in relation to transport emissions also relies on consumer expenditure surveys as far as we know (Douenne, 2020; Cronin et al., 2018). Our paper is closer in spirit to studies from the transport and urban planning literature estimating (inequalities in) individual emissions from transport using detailed travel diaries from a sample of individuals (Brand and Preston, 2010; Yang et al., 2018; Brand et al., 2021). An important limitation of these studies, however, is to rely on low sample sizes, and, often, on non-representative surveys where highly educated individuals are over-represented. In contrast, we use a large representative survey (N=23,690). Finally, although we do not examine a policy in particular, our paper is connected to previous work having estimated the distributional impacts of different transport policies affecting car use in the Paris area, such as Bureau and Glachant (2008) or Bureau and Glachant (2011) analysing the distributional impact of road pricing for the first one, and of policies reducing the cost of public transit for the second one.

Second, we contribute to the literature examining the potential for emission reductions from transport, in particular the potential for modal shift (Javaid et al., 2020; Yang et al., 2018). By using data on trip duration by mode retrieved from a transport API, we are able to estimate the share of trips that can be done with another mode than car, based on observed individual travel data. Compared to previous work focusing on the potential for modal shift for short trips specifically (de Nazelle et al., 2010), or restricting the analysis to a modal shift to public transport or bike (Yang et al., 2018), we do not set a limit on trips' distances and we allow for substitution with an under-investigated transport mode, electric bike, which we show has a high potential.

Third, we contribute to the literature examining the trade-offs and complementarities in tackling both CO_2 and local pollution. Durrmeyer (2018) and Linn (2019) show that while effective in decreasing CO_2 emissions, CO_2-based vehicle taxes are likely to increase the emission of damaging air pollutants (NOx and $PM_{2.5}$), because they increase the share of diesel cars, less CO_2-intensive but more intensive in NOx and $PM_{2.5}$. The reverse trade-off may exist in the case of local transport policies driven by air pollution concerns, and low-emission zones indeed tend to be more restrictive for diesel cars than for gasoline cars. Our results suggest that a policy targeting cars' local pollutant emission intensity may also have different distributional impacts from a policy targeting the CO_2 emission intensity, since we find different associations between household income and the $PM_{2.5}$ vs. CO_2 emission intensity of car trips. At the same time, policies leading to a modal shift away from car would achieve both a reduction in local pollutant and CO_2 emissions.

The paper is organized as follows: Section 2 presents the local context of air pollution in the Paris area; Section 3 presents the data and methods used; Section 4 presents the results and section 5 discusses them.

2 Air pollution and transport emissions in Paris

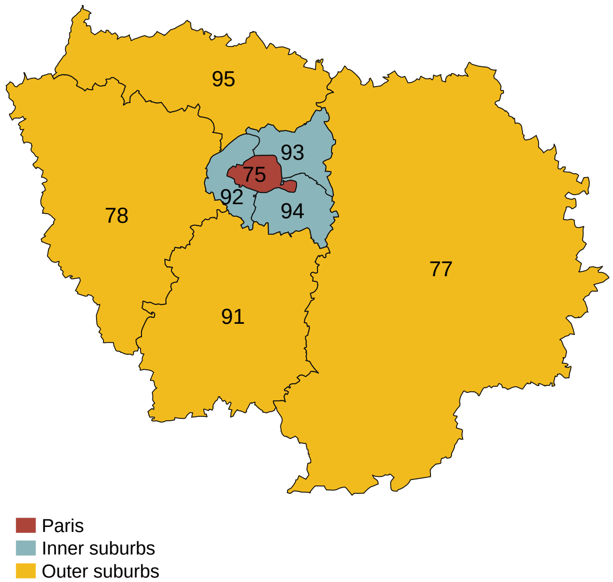
We consider the Paris metropolitan area, which we define here as the administrative *region* of Ile de France (IdF), represented on Figure 1a - the *region* is the first level of administrative subdivision in France.[1]. The IdF region has a population of 12.2 million inhabitants and is made of three layers: the city of Paris in the centre (red), a first layer around Paris called the "inner suburbs", made of three small *départements* (blue) - the second level of administrative subdivision in France, and a second layer called the "outer suburbs", made of four larger but less dense *départements* (yellow).

The Paris area is a typical monocentric city where most public transport lines converge to the centre. Air pollution levels regularly exceed recommended and legal thresholds. While concentrations of the main regulated pollutants[2] have been decreasing throughout the area over the past ten years, they remain high, especially in the city centre. Figure 1b shows NO_2 concentrations in 2015 and shows that the legal threshold of 40µg/m^3 is exceeded in Paris and the majority of the inner suburbs. Furthermore, despite the improvement in air quality, air pollution is the number one environmental concern in IdF according to a 2018 survey, and 61% of the respondents think that air pollution has increased in the past ten years.

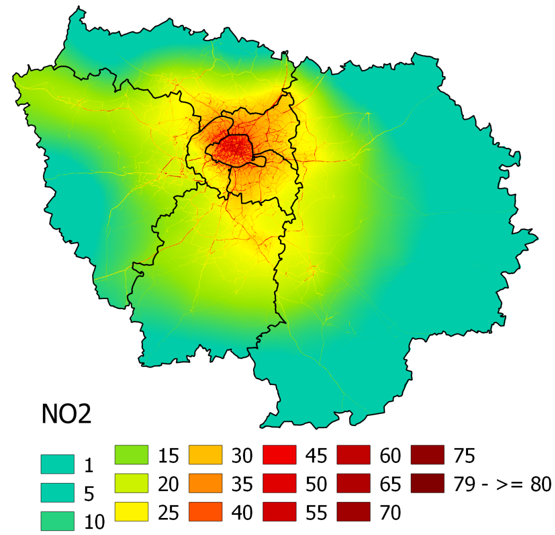
In this paper, we focus on emissions of two local air pollutants: NOx, a generic category of pollutants including NO_2, and $PM_{2.5}$. We choose these pollutants for two reasons: first, road traffic is a major contributor for these two pollutants: it is responsible for 56% of nitrogen oxides (NOx) and 35% of the $PM_{2.5}$ emissions of the region (Source: Airparif). Second, these two pollutants have detrimental effects on health: long-term exposure to NO_2 is associated with increases of bronchitis in asthmatic children and reduced lung function growth (World Health Organization, 2018). Exposure to $PM_{2.5}$ has detrimental effects on health and increases mortality risk in the short- (Deryugina et al., 2019) and long-term

[1]The Paris metropolitan area as defined by the French statistical institute does not include all the IdF region; it excludes a small part of the outer suburbs. We consider the whole region because our transport data are representative of the population from the entire region

[2]nitrogen dioxide NO_2, ozone O_3, and particulate matter PM_{10}



(a) The Paris Metropolitan Area



(b) NO_2 in 2015, µg/m^3

(Lepeule et al., 2012), without evidence of a threshold below which exposure would be harmless (World Health Organization, 2018). We also study the emissions of CO_2 emissions, road traffic being responsible for 32% of the region's total emissions (Source: Airparif).

To dampen local pollution from cars, several regional and local policies have been implemented. Short-term driving restrictions based on license plate numbers have been systematically imposed since 2014 during pollution peaks. Long-term measures advertised by the regional authority include developing the public transport network, building more cycling lanes, reserving lanes for buses, clean vehicles and car-pooling, as well as speed reduction on the ring road (Région Ile de France, 2016). By far, the most ambitious policy specifically targeting air pollution is the Low Emission Zone (LEZ) projected to be rolled-out in Paris and the surrounding municipalities between 2017 and 2024, which should progressively ban all polluting vehicles - defined by their age and fuel type - from the city centre. Yet this policy has met political opposition from some municipal authorities (Le Parisien, 2019). To reduce both local air pollution and CO_2 emissions from cars, the Paris metropolitan area also announced the complete ban of diesel cars by 2024 and of gasoline cars by 2030 (Le Monde, 2018).

3 Data and methodology

3.1 The Data

We combine four types of data from different sources.

Individual transport: 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 IdF region. The 2010 wave was conducted between October 2009 and May 2010, and between October 2010 and May 2011. The survey contains detailed information on the transport choices of 35,175 individuals from 14,885 households[3] on a given weekday[4]. The sample is representative of the IdF population (as characterized in the 2008 census) in terms of household size, type of housing and individual socio-economic and demographic profiles[5]. The EGT is also broadly representative of the 2011 IdF population (see Table A.3, comparing selected household characteristics for the entire EGT sample and from 2011 administrative data). The EGT also has detailed socio-demographic characteristics (see Table A.2 for descriptive statistics of the whole sample at the household level). For the present analysis, we use the subsample of adults having done at least one trip during the weekday (N=23,690). This represents 93.07% of the surveyed adults. Table 1 shows descriptive statistics for this subsample. In table A.4 we present a balancing test comparing mean observed characteristics for the full sample and the sample of adults with at least one trip recorded. The two samples are broadly balanced. There are small significant differences in the activity status, with a higher share of full-time employed individuals and lower shares of inactive individuals in the sample of mobile individuals. Mobile individuals are also more educated and have a higher income compared to the whole sample. We consider that this small selection bias is not an

[3]The sampling rate at the household level is 1/330. In 2010, the IdF region had a population of 11.79 millions inhabitants

[4]The respondents are asked about all their trips from the day preceding the interview, which can correspond to a day between Monday and Friday. We include survey day-of-week fixed effects in all our regression analyses.

[5]based on 30 categories combining gender, age, socio-professional category and main occupation

issue given the descriptive purpose of our analysis.

The survey records and geolocates all the places visited by each individual during the day with a grid size of 100 meters*100 meters. Within each trip defined by an origin and destination location, the data describes each journey stage, a journey stage being defined as a single travelling mode[6]. Only the trips starting or finishing within the IdF boundaries are recorded and geolocated. For all the trips starting (finishing) in the IdF region but finishing (starting) in another region, we do not know the departure (arrival) point's location, nor the trip distance. We use three variables in the analysis which are not readily available in the EGT data:

- **Actual distances travelled:** The EGT data only contains as-the-crow-flies distances for each trip and journey stage. We obtained data on actual distances from the regional transport authority, estimated with a shortest-path algorithm.

- **Continuous income variable:** in the EGT data, household income is self-declared and interval-coded in nine income brackets, with a non-response rate of 6%. In order to estimate the relationship between income deciles and contribution to emissions, we estimate the full distribution of income using an interval regression imputation method. Since the method assumes an underlying normal model for the partially observed imputed variable (given other predictors) and the distribution of income is usually log-normal, we apply a log transformation to the income brackets declared in the EGT. We then estimate the continuous income variable by including several socio-economic factors known to be correlated with income in the interval-coded regression.[7]

  For households with a missing income bracket, we use a predictive mean matching

[6]For example, a work commuting trip by subway including one change will include four journey stages: the first stage is the journey by foot from home to the subway station; the second stage is the subway journey with the first metro line, finishing at the subway station where the commuter changes lines; the third stage is the subway journey with the second metro line, finishing at the subway station near the workplace; the fourth stage is the journey by foot from the subway station to the workplace.

[7]List of predictors: age, age squared, gender, education level and socio-economic class of the household head; socio-economic category of her partner; number of household members working full-time and number working part-time; housing status of the household; dummy for whether the household is eligible to family allowances based on the number and age of children, to proxy for social transfers.

imputation method, using the same predictors and similarly predict their continuous income. Finally, we transform the obtained continuous variable of household monthly income into a variable of annual income per consumption unit (using the OECD equivalence scale). Table A.3 shows that the average income per consumption unit obtained with this imputation is close to the average income per consumption unit in IdF in 2011 obtained from administrative data.

- **Public transport stops within a one kilometre radius:** We create an indicator variable indicating whether a household lives less than one kilometer away from a public transport stop. To do so, we combine geocoded information on the location of each public transport stop in 2010 contained in a separate EGT file (including subway, regional train and streetcar), with information on households' place of residence.

Emission factors We use emission factor data by transport mode (and by type of vehicle for cars and two-wheelers) coming from a variety of sources, described in detail in the next section and in Appendix A.1.

Counterfactual travel time data To estimate modal shift options for car drivers, we estimated travel time for different transport modes for all the non-walking trips reported in the EGT data. This represents 68,110 trips made by 20,725 individuals, including 33,010 car drives made by 10,875 individuals. For each trip, we identified the departure and arrival points with the latitude and longitude of the centroid of the origin and destination squares. We then used the Google Console Directions API to predict each trip's duration for three different transport modes: driving, cycling and public transit. Our trip requests gave results for more than 99.9% of the cases for car and cycling trips and for 85% of the cases for public transit trips (34% of which suggested walking as the fastest way to arrive at destination). For the remaining 15% of trips, no public transit route exists between the departure and arrival point. Appendix A.2 provide more details on the exact data request and compares

Table 1: Summary statistics - Individuals ≥18 years old

	Mean	Sd
Residence: Paris	0.21	0.41
inner suburbs	0.37	0.48
outer suburbs	0.42	0.49
Age	45.72	16.62
Education: Primary school	0.06	0.23
Secondary education	0.39	0.49
Higher education < 3 years	0.14	0.35
Higher education ≥ 3 years	0.35	0.48
Still in education	0.07	0.25
SES: Farmers	0.00	0.03
Manual workers	0.11	0.31
Office workers	0.19	0.39
Intermediate professions	0.19	0.40
Traders and craftspeople	0.03	0.17
Managers and executives	0.20	0.40
Pensioner	0.20	0.40
Other	0.07	0.26
Estimated Net household income	40,786.73	25,901.23
Estimated Net household income per consumption unit	24,166.10	14,626.03
Distance to workplace (km)	10.57	10.69
Nb of trips prev. day	4.32	2.40
Modal share for trips: car	0.39	0.44
collective transportation	0.27	0.38
bicycle	0.02	0.11
two-wheeler	0.02	0.11
walking	0.31	0.37
other mode	0.00	0.05
Observations	23,690	

Note: Source: EGT data. Data 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.

travel times declared in the survey to those given by the API. The predicted times of the API are 20-39% lower than those declared by individuals, depending on the mode. Since we base our calculations on the API times only, it should not bias our estimation of modal shift potential too much. We use the API times for cycling trips to estimate the duration of the same trips had they been done with electric bikes instead of regular bikes. We assume an average cycling speed of 15km per hour and an average electric cycling speed of 19km per hour, following the figures from a 2015 survey [8], and apply this constant speed factor to the estimated travel times of cycling trips.

Charging stations for Electric Vehicles We use a GIS software to identify all the households having at least one electric vehicle (EV) charging station less than 500 meters away from home. We did not find an exhaustive dataset of all charging stations located in the IdF region. We instead combine geocoded data from four different sources: OpenStreetmap[9] (where many stations located in Paris centre are missing), the national open data service[10] (where many stations located in Paris centre are also missing), and subregional open data services providing data on two cities (Paris and Rueil-Malmaison).

3.2 Methodology

Building individual measures of contribution to pollution. We estimate individual- and trip-level contributions to local and global pollution based on the detailed information contained in the EGT. For local pollutants, we use NOx and $PM_{2.5}$. For global pollution, we use CO_2 emissions. The total emissions of pollutant P for individual i during the day are the sum of her emissions at the trip level, with T the total number of trips made during he day:

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

[9] `https://geodatamine.fr/dump/charging_station_geojson.zip`

[10] `https://www.data.gouv.fr/fr/datasets/fichier-consolide-des-bornes-de-recharge-pour-vehicules-elect`

$$E_{P,i} = \sum_{t \in T} E_{P,i,t} \quad (1)$$

We calculate emissions at the trip level $E_{P,i,t}$ using information on each journey stage j that t is made of. For each journey stage j, we know the (estimated) journey distance in kilometers, the travel mode used, the emission factor associated with the mode, and the number of passengers if the mode used is a private vehicle (car or two-wheeler).

i's emissions of Pollutant P on trip t made of J journey stages are defined as:

$$E_{P,i,t} = \sum_{j \in J}^{J} d_{j,i} e_{P,j,i} r_{j,i} \quad (2)$$

Where $d_{j,i}$ is the distance travelled by i on journey stage j, $e_{P,j,i}$ is the pollutant P's emission factor associated with travel mode m used in journey stage j in grams per kilometre driven; $r_{j,i}$ is the inverse of the occupancy rate[11] of mode m for individual i for journey stage j. For all the journey stages done with a collective transport mode, the occupancy rate is set to one, as an average occupancy rate is included in the estimation of their emission factor.

The assumptions made to estimate emission factors for each mode are explained below and more extensively in Appendix A.1. Active modes (walking, cycling, skate-boarding, etc,) have a zero emission factor for all three pollutants. The train and subway have a zero emission factor for NOx and CO_2[12], but not $PM_{2.5}$, due to the emissions from train brakes. For transportation modes with positive emission factors - buses, two-wheelers and cars for NOx and CO_2, plus electric public transport for $PM_{2.5}$, we use a combination of sources described in Appendix A.1.

Emission factors can exist in two versions for cars: the "true", on-road emission factor, which varies with the vehicle speed, quality of the road and driving conditions; and the type-approval values, given by car manufacturers and subject to emission standards under

[11] The occupancy rate is defined as the number of passengers in the vehicle.

[12] 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 satisfying to focus on exhaust emissions only.

EU rules. We use on-road emission factors for NOx and $PM_{2.5}$, but type-approval values for CO_2, for several reasons: first, the discrepancy between type-approval and real-world emissions is much stronger for NOx than for CO_2 emissions[13], so it matters more to correct the NOx emission factor than the CO_2 emission factor. Second, for cars' emission factors, there exists a rich vehicle-specific data source for type-approval CO_2 emission factors but not for NOx and PM2.5. Using it allows us to estimate CO_2 emission factors based on all the car characteristics declared by the household, in particular horsepower, a variable likely to be correlated with households' socioeconomic status. Since we seek to identify the socio-economic and spatial factors associated with emissions, this information is key. Third, for $PM_{2.5}$ specifically, using on-road emission factors allows us to take into account not only exhaust emissions, but also emissions from tyres and brakes, which represent a substantial share of emissions (OECD, 2020). The on-road emission factors for NOx and $PM_{2.5}$ come from two sources, which both rely on the EU vehicle emissions calculator Copert (see EMEP/EEA (2018) for more details). The type-approval CO_2 emission factors come from the national environmental agency Ademe for cars, and from the French Ministry of the Ecology for other transport modes.

The NOx, $PM_{2.5}$ and CO_2 emission factors by transport mode are summarized in table 2. 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). In reality, there is a large variation in the emission intensity of journey stages made with individual car in the survey (see Figures A.1, A.2 and A.3 showing the different values obtained for the emission

[13]Baldino et al. (2017) compare on-road and type-approval emission factors for recent diesel vehicles brought under the spotlight by the 2015 Volkswagen scandal. They find that average on-road CO_2 emissions are on average 30% higher than laboratory emission standards and type-approval values for a sample of Euro 5 and Euro 6 cars (registered after 2011), and report that the gap has been increasing over the 2001-2015 period. For NOx emissions, they find a much higher discrepancy with an average factor of 4 between the type-approval and real-world values.

Table 2: Assumed contribution to pollution emissions in different transport modes

Transport mode	**Unit**	**NOx (mg/km)**	**$PM_{2.5}$ (mg/km)**	**CO_2 (g/km)**
Walking and related modes	per passenger	0	0	0
Cycling	per passenger	0	0	0
Street-car	per passenger	0	7	0
Metro	per passenger	0	7	0
Train	per passenger	0	7	0
Bus	per passenger	242	5	117
Taxi	per passenger	1,178	127	332
Car not owned by the household	per vehicle	589	63	166
Two-wheeler not owned by the household	per vehicle	86	21	65

Note: NOx and PM2.5 emission factors reflect on-road emissions and CO_2 emission factors reflect type-approval values. All the assumptions are explained in Appendix A.1

intensities per passenger ($e_{P,j,i}r_{j,i}$), by transport mode and pollutant). The heterogenity in NOx emission factors for cars is the highest, with few extremely high values corresponding to old light-commercial vehicles.

We use these emission factors to calculate $E_{P,i}$ for NOx, $PM_{2.5}$ and CO_2. Given the scope of the EGT survey, these estimated individual emissions only include emissions from trips made within the metropolitan area for a representative weekday.

Exact factor decomposition analysis Starting from equation (2), we re-write individual emissions in the form of an extended Kaya identity (see Wang et al. (2005); Mahony (2013); Bigo (2019) for other examples), as the product of distance, modal share and emission intensity by mode. Note D_i the total distance travelled by individual i, $S_{m,i}$ the modal share of mode m, and $I_{P,m,i}$ the average emission intensity of mode m used by individual i for pollutant P (using the notations from equation 2, $I_{P,m,i} = e_{P,m,i}r_{m,i}$). If we call $d_{m,i}$ the total distance travelled by individual i with mode m and $E_{P,m,i}$ the total emissions of pollutant P from using mode m, we have:

$$E_{P,i} = \sum_{m \in M} D_i \frac{d_{m,i}}{D_i} \frac{E_{P,m,i}}{d_{m,i}} = \sum_{m \in M} D_i S_{mi} I_{P,m,i} \tag{3}$$

Given this multiplicative structure, we can use the Log Mean Divisia Index (LMDI) developed by Ang (2004, 2005) to decompose differences in individual-level emissions into differences in distance, modal choice, and the emission intensity by mode. We then calculate the contribution of each component in explaining the difference in emissions between an average individual from the middle quintile (the middle 20% of the distribution in emissions), and reference individuals from quintiles 1,2, 4 and 5 of emissions. The LMDI decomposition has been originally developed to explain changes in emissions over time and this is how it has been applied mostly in the literature. Ang et al. (2015) suggest that the LMDI is also an appropriate method to compare emissions between countries at a given point in time, since it combines ease of use with desirable properties of perfect decomposition and symmetry of decomposition. Some applications have used the LMDI for this purpose, using aggregate country-level data (Liu et al., 2017). Although the method has, to our knowledge, not been applied to individual-level data as we do here, our decomposition is mathematically equivalent to the cross-country case.

We proceed as follows: for each pollutant P, we define 5 quintiles of emissions, Q1 to Q5. We generate a reference individual for each quintile, that is, an individual having the average distance D_{Qk}, modal share $S_{m,Qk}$, and emission intensity $I_{m,Qk}$ of her quintile Qk, $k = 1..5$[14]. For the reference individual of quintile Qk, the extended Kaya equation reads:

$$E_{P,Qk} = \sum_{m \in M} D_{Qk} S_{m,Qk} I_{P,m,Qk} \tag{4}$$

As recommended in Ang et al. (2015), we define a benchmark individual, here the reference individual from quintile 3, to which we compare the reference individuals from each quintile. We then apply the LMDI decomposition. The difference in emissions between Qk, $k = 1, 2, 4, 5$ and Q3 can be decomposed into the difference in the distance (D), modal share (S) and intensity (I) components:

[14]this average individual has emissions $E_{P,i}$ that differ from the average emissions of her quintile, given the multiplicative form of the decomposition formula: the product of averages is not the average of the product

$$E_{P,Qk} - E_{P,Q3} = \Delta E_{P,Qk-Q3,tot} = \Delta E_{P,Qk-Q3,D} + \Delta E_{P,Qk-Q3,S} + \Delta E_{P,Qk-Q3,I} \tag{5}$$

Following Ang (2005), this can be rewritten:

$$E_{P,Qk} - E_{P,Q3} = \sum_{m \in M} w_m ln(\frac{D_{Qk}}{D_3}) + \sum_{m \in M} w_m ln(\frac{S_{m,Qk}}{S_{m,3}}) + \sum_{m \in M} w_m ln(\frac{I_{m,Qk}}{I_{m,3}}) \tag{6}$$

Where w_m is defined as:

$$w_m = \frac{E_{P,Qk} - E_{P,Q3}}{ln(E_{P,Qk,m}) - ln(E_{P,Q3,m})} \tag{7}$$

And $E_{P,Qk,m}$ are the emissions of pollutant P associated with mode m for quintile Qk.[15].

Individual characteristics associated with high emissions The LMDI decomposition is possible because individual emissions are defined as the exact product between total distance travelled, modal shares, and the emission intensity of different modes. These three components are not independent from each other and result from a complex chain of decisions taken at the individual or household level, including the choice of residence, workplace, vehicle bundle, and modal choice. Modelling all these decisions goes beyond the scope of this paper. We instead investigate in three separate regression analyses which individual characteristics are associated with distance, modal choice and emission intensity (focusing on car for modal choice and emission intensity).

To investigate the characteristics associated with distance travelled, we estimate a log-linear model. Defining $ln(y)$ the natural logarithm of total distance travelled during the day, x the set of covariates, and ϵ an error term, we set:

[15] The modal share of bus, two-wheeler and car is 0 for the bottom quintile of NOx emissions. To be able to apply the log formula, we apply the "Small Value" strategy suggested in Ang and Liu (2007), that is, we replace the zero values by $\delta = 10^{-100}$

$$ln(y) = x\beta + \epsilon \tag{8}$$

We then examine the characteristics associated with using a car at least once during the day with a logit model. Defining S_{car} the modal share of car, the model writes:

$$Pr(S_{car} > 0|x) = \Lambda(x\beta_2) = \frac{exp(x\beta_2)}{1 + exp(x\beta_2)} \tag{9}$$

We finally examine the characteristics associated with the average emission intensity of car trips. We calculate the average emission intensity of car trips for each individual with a positive car modal share. We estimate a simple linear model, and our results should be interpreted conditionally on driving a car on that day. Defining $I_{P,car}$ the average emission intensity of the car trips for pollutant P, and μ an error term, we estimate the following model for the three pollutants NOx, $PM_{2.5}$ and CO_2:

$$I_{P,car} = x\beta_3 + \mu \tag{10}$$

We run the models on two samples: the full sample of individuals, and the sample of individuals in employment, for whom we have rich information on employment characteristics. In all regressions, we control for survey day-specific effects: survey day-of-the-week (we do not have information on the exact survey date); whether the individual encountered a problem with taking transport that day (such as a car's breakdown, a public transport's strike, or bad weather conditions); whether the individual was on holidays or on sickness leave that day.

4 Results

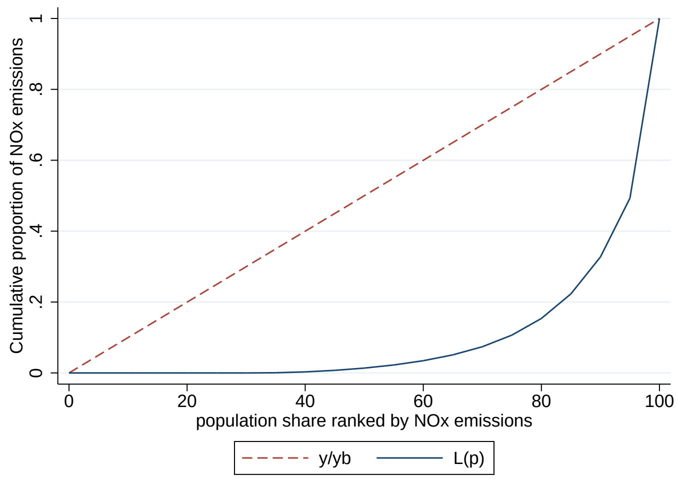
4.1 How unequal are contributions to emissions?

Figure 2 illustrates the high inequalities in daily emissions at the individual level using Lorenz curves: on a representative weekday, the top 20% of NOx emitters contribute 85% of NOx emissions, the middle 48% contribute 15%, and the bottom 32% have a zero contribution[16] (figure 2a). The top 20% of PM2.5 emitters contribute 78% of PM2.5 emissions, the middle 62% contribute 22%, and the bottom 18% have a zero contribution (figure 2b). The top 20% of CO_2 emitters contribute 75% of emissions, the middle 48% contribute 25%, while 32% have a zero contribution (figure 2c).

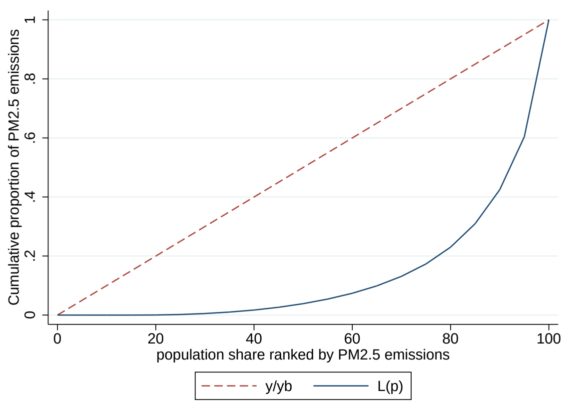
Top emitters are not exactly the same across pollutants but the correlation is high[17]: the top 20% of NOx emitters contribute 70% of CO_2 emissions. Inequalities of contribution to emissions at the trip level (as defined by equation 2) are higher than at the individual level, reflecting the high dispersion of trip distances (see Figure A.4).

[16]Only individuals with at least one trip are in the sample, so those with zero emissions are the ones travelling only with active modes, electric collective transportation or electric car

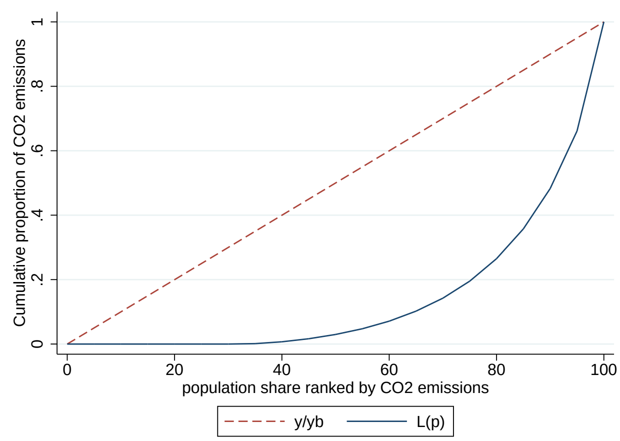
[17]the correlation coefficient between individual-level NOx and CO_2 emissions is 0.82



(a) NOx emissions



(b) $PM_{2.5}$ emissions



(c) CO_2 emissions

Figure 2: Lorenz curves for contributions to emissions at the individual level

Note: the x-axis shows the percentiles of individual-level emissions and the y-axis shows the share of total emissions generated by all the individuals below that percentile. The red curve shows how the distribution would look like if everyone contributed equally to emissions Source: EGT data. Sample: all adults with at least one trip on the day

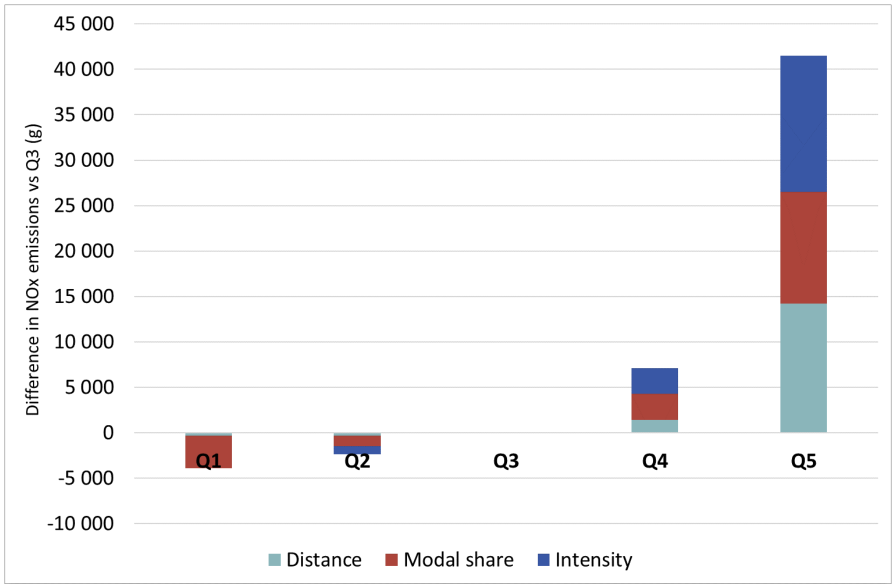
4.2 Are high emissions mostly due to high distances, high-emission modal shares or highly polluting cars?

Figure 3 show the results of the LMDI decomposition for NOx, PM2.5 and CO_2 emissions. Tables A.5, A.6, A.7 and A.8 show the components' values for each quintile and the LMDI Deltas. For NOx and CO2 emissions, the lower emissions of the bottom two quintiles are mostly explained by a different modal share, which is expected given the zero emission factor of public transport and active modes, the only modes taken by 32% of the individuals. For PM2.5, subway and train do not have a zero emission factor, such that distance plays a greater role in explaining the low emissions of the bottom two quintiles.

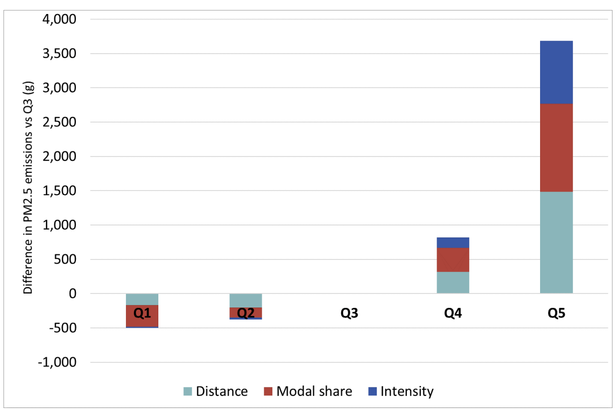
For NOx and PM2.5, emission intensity, distance and modal share contribute about the same way in explaining the difference between the Q5 and Q3. For example, for NOx, differences in emission intensity contribute 36%, differences in distance 34%, and differences in modal share 30%. For this pollutant, the values for each component are about 2.5 times greater for Q5 than for Q3, with daily distances travelled of 62km, a car modal share of 92%, and an emission intensity of car trips of 794 mg/km (see Table A.5).

For CO_2 emissions, the role of emission intensity is less important than that for local pollutants. Distance and modal share are more important, especially for the top two quintiles. Differences in distances explain 58% of the difference in emissions between Q5 and Q3 for CO_2 (a contribution 24 percentage points higher than for NOx). Differences in modal share explain 36% (6 percentage points higher than for NOx). Differences in emission intensity explain only 6% (30 percentage points lower than for NOx).

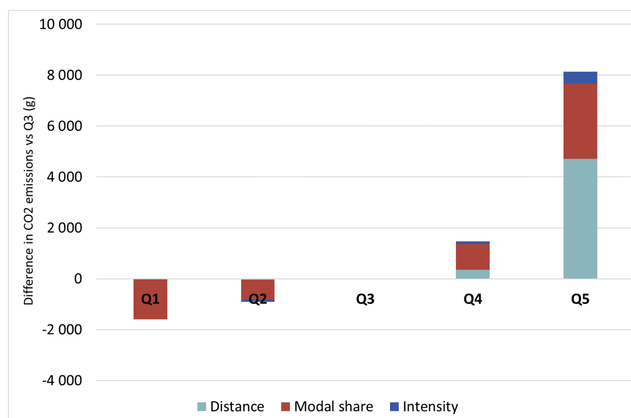
To summarize, the top 20% of NOx and PM2.5 emitters are individuals combining high distances travelled, by car, and with high-emitting cars. In contrast, the top 20% of CO_2 emitters are individuals combining high distances travelled and car trips, with cars only slightly more emission intensive than the average car.



(a) NOx



(b) $PM_{2.5}$



(c) CO_2

Figure 3: Contribution of distance, modal choice and emission intensity to the differences in emissions, by pollutant

Note: These graphs show, for each pollutant, the difference in emissions between the average individuals from quintiles 1, 2, 4 and 5 and the benchmark individual from quintile 3 (total length of the bars), decomposed into differences in total distance travelled, modal shares, and the emission intensity of a given mode. The LMDI formula used is the additive decomposition (Ang, 2004).

4.3 Who emits pollution?

We now turn to the individual and household characteristics associated with higher emissions. Column 1 of table 3 shows the estimated coefficients for the distance regression (equation 8). Columns 2 and 3 show the average marginal effects from the logit estimation on the propensity to use a car (equation 9), before and after controlling for having a motorized vehicle available on that day[18].

Spatial factors play an important role for distance and the propensity to use a car: living in central Paris is associated with distances shorter by 24%[19] and being 26 percentage point less likely to use a car compared to living in the inner suburbs (w/o controlling for car availability), while living in the outer suburbs is associated with distances longer by 48% and being 18 percentage point more likely to use a car. Living close to a transport stop is associated with distances shorter by 18%, probably partly capturing the fact that public transport stops are located in denser areas. Living close to a public transport stop is also associated with a decrease in the likelihood to use a car, an association that persists after controlling for the availability of a car[20].

The employment status is a second important characteristic. Being unemployed or inactive is associated with shorter distances, with decreases ranging from -49% (for the unemployed) to -67% (for pensioners) compared to being employed, and a much lower propensity to use a car. Income is a third important characteristic, in part via the positive correlation between income and car onership: being in the bottom decile is associated with a 22 percentage points lower probability to use a car compared to the six middle deciles when

[18] The omitted categories for the categorical variables present in the model are: for the place of residence, we omit living in the inner suburbs; for gender, we omit male; for income deciles, we take as reference the middle 40% and report coefficients for the two bottom deciles D1 and D2 and the two top deciles D9 and D10. For the activity status, we omit employed individuals; for education, we omit the "primary or secondary education" category; for the type of car owned by the household, we omit the "No car owned" category.

[19] for small values of estimated coefficients $\hat{\beta}$, a 1-unit change in X corresponds approximately to an expected increase in Y of $\hat{\beta}$%, but for larger values, the exact interpretation is that a 1-unit change in X corresponds to an expected value of Y multiplied by $e^{\hat{\beta}}$. Most of the obtained coefficients are relatively high in magnitude, so we use the exponential formula to interpret the results.

[20] the vehicle availability variable is defined at the individual level and concerns the reference day, it is different from the variables of car ownership defined at the household level

vehicle availability is not controlled for, but only a 6 percentage points lower probability after controlling for it. Symmetrically, being in the top two income deciles is not significantly associated with a higher probability to use a car once vehicle availability is accounted for. Even after including a rich set of socio-economic, spatial and demographic factors as well as controls relative to the survey day, the R-squared for the distance regression is quite low at 0.18, suggesting an important role for other, potentially unobserved factors driving mobility.

Table A.3 reports the estimated coefficients for the emission intensity regression (equation 10) for NOx, $PM_{2.5}$ and CO_2, before (columns 1, 3 and 5) and after (columns 2, 4 and 6) controlling for the type of vehicle owned by household. Some characteristics are associated with a higher emission intensity for all pollutants, such as living in Paris or owning a light-commercial vehicle. The other way around, being unemployed or inactive and, all else equal, having a higher education diploma, are associated with a lower emission intensity for all pollutants, all else equal.

Other characteristics have an ambiguous role, and are associated with an increase in the emission intensity for some pollutants and a decrease or no effect for others. In line with the well-documented differences in local pollution and CO_2 emission factors for diesel vs. gasoline cars, owning a diesel car is associated with a higher emission intensity for NOx and $PM_{2.5}$, but a lower emission intensity for CO_2, compared to owning a gasoline car. Being in the top income decile is strongly associated with a higher CO_2 emission intensity, even after controlling for the type of vehicle owned by the household. This positive correlation between top income and CO_2 emission intensity can be explained by the fact that rich households generally own heavier, larger and more powerful cars, attributes that correlate positively with the CO_2 emission factor. On the other hand, being in the bottom two deciles is associated with a significantly higher $PM_{2.5}$ and CO_2 intensity, and a higher NOx intensity (but the coefficient is not significant). This may be due to the fact that the cars owned by poorer households are older and more often light-commercial vehicles, two attributes that correlate positively with the emission intensity across all pollutants, and more often powered with

Table 3: Estimated coefficients for distance and propensity to use a car - all individuals

	(1) ln dist	(2) uses car	(3) uses car
Inner Paris	-0.277***	-0.262***	-0.154***
	(0.0273)	(0.0116)	(0.0116)
Outer suburbs	0.389***	0.180***	0.112***
	(0.0209)	(0.00764)	(0.00682)
Public transport stop	-0.204***	-0.166***	-0.121***
	(0.0218)	(0.00761)	(0.00670)
Motorized vehicle at hand			0.475***
			(0.00736)
Female	-0.297***	-0.0487***	0.00571
	(0.0159)	(0.00531)	(0.00479)
Household size	0.00405	0.0167***	0.00464*
	(0.00680)	(0.00256)	(0.00221)
D1	-0.222***	-0.217***	-0.0640***
	(0.0399)	(0.0146)	(0.0145)
D2	-0.179***	-0.124***	-0.0275*
	(0.0379)	(0.0128)	(0.0111)
D9	0.181***	0.0587***	0.0132
	(0.0299)	(0.0102)	(0.00952)
D10	0.196***	0.0641***	0.00180
	(0.0294)	(0.0103)	(0.00950)
Pupil/Student	0.250***	-0.192***	-0.0445***
	(0.0329)	(0.0138)	(0.0134)
Unemployed	-0.666***	-0.0854***	-0.0282*
	(0.0478)	(0.0141)	(0.0126)
Other inactive	-0.930***	-0.0413***	-0.0415***
	(0.0260)	(0.00806)	(0.00733)
Pensioner	-1.092***	-0.182***	-0.116***
	(0.109)	(0.0301)	(0.0316)
Higher education <3 years	0.271***	0.0569***	0.0121
	(0.0261)	(0.00884)	(0.00802)
Higher education ≥3 years	0.217***	0.0161*	-0.0216**
	(0.0225)	(0.00757)	(0.00685)
Constant	2.842***		
	(0.0372)		
N	23596	23600	23524
R-squared	0.1810		

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Standard errors clustered at the household level in parentheses. Columns (2) and (3) report the average marginal effects for each coefficient. All specifications also include survey-day fixed effects and indicator variables for problems with taking transport, being on leave or on sickness leave on the survey day. D1,...,D10: indicator for household income deciles diesel, which is positively correlated with $PM_{2.5}$ and NOx intensity. Like for the distance regression, the explanatory power of the socio-economic, spatial and demographic factors included in the regression is low, at 0.15-0.16 when the type of car owned by the household is accounted for.

Table A.11 show the results of fitting similar models on the subsample of individuals in employment, after adding controls for the distance to work, type of commute, type of workplace and type of job[21]. As expected, the type of commute influences the distances travelled and propensity to use a car: an increase by 1% of the as-the-crow-flies commuting distance is associated with total distances travelled higher by 0.5%, controlling for the type of commute flow (defined by the combination of residence location (Paris/inner suburbs/outer suburbs) and workplace location (Paris/inner suburbs/outer suburbs)). Commuting *type* matters more than commuting *distance* for the propensity to use a car: having to commute from suburbs to suburbs (reference category) is associated with an increase in the likelihood to use a car by 24 to 35 percentage points compared to commuting from Paris to the suburbs or Paris to Paris, probably reflecting the low density of the (radial) Parisian public transport network in the suburbs. The type of job does not affect distances travelled much once other spatial and socio-economic characteristics are taken into account. The R-squared of the distance regression is much higher than for the analysis of the whole sample, suggesting a high explanatory power of job location and employment characteristics.

While the type of occupation does not affect distances travelled much, there are strong associations between the type of occupation and the propensity to use a car: working in a factory is associated with an increase in the likelihood to use a car by 9.6 percentage points, as is having atypical working hours[22]. Having a self-employed white-collar profession or being a trades worker are associated with an increase in the likelihood by 12-14 percentage

[21]The omitted reference categories are: for the place of residence combined with the place of work: individuals living in the suburbs and working in the suburbs (inner or outer); for the employment status: working full-time; for the workplace type: working in any other place than a factory; for socio-professional category: intermediate professions.

[22]Atypical working hours are defined as going to work or coming back from work before 5am, or going to work after 4pm.

Table 4: Regression coefficients for the emission intensity of trips made by car - all individuals

	(1)	(2)	(3)	(4)	(5)	(6)
	NOx/km, all	NOx/km, all	PM25/km, all	$PM25_2$/km, all	CO_2/km, all	CO_2/km, all
Inner Paris	75.30*	68.62*	8.785***	8.096***	19.10***	19.18***
	(32.76)	(29.28)	(1.533)	(1.490)	(2.764)	(2.766)
Outer suburbs	-0.249	23.11	1.404*	2.876***	-3.564***	-3.365***
	(14.61)	(12.69)	(0.666)	(0.607)	(0.802)	(0.769)
Public transport stop	-6.142	-19.78	-0.720	-2.282***	1.516*	1.856**
	(13.66)	(12.64)	(0.632)	(0.590)	(0.732)	(0.706)
Female	-101.3***	-77.10***	-4.919***	-3.532***	-0.955	-0.724
	(11.35)	(10.64)	(0.510)	(0.480)	(0.718)	(0.708)
Household size	8.844	14.15*	0.699**	1.603***	-1.367***	-1.686***
	(6.351)	(5.760)	(0.263)	(0.242)	(0.296)	(0.287)
D1	69.77	12.12	5.815**	2.293	4.915*	4.247*
	(43.91)	(41.96)	(1.882)	(1.725)	(1.933)	(1.934)
D2	22.72	-12.96	7.292***	3.735**	3.073*	3.664*
	(26.15)	(26.35)	(1.542)	(1.441)	(1.541)	(1.529)
D9	-8.191	-7.537	-0.790	0.0830	3.058*	2.423*
	(21.14)	(19.83)	(0.894)	(0.841)	(1.241)	(1.198)
D10	-13.76	8.543	-1.475	0.990	7.681***	7.046***
	(22.07)	(20.22)	(0.871)	(0.822)	(1.281)	(1.254)
Pupil/Student	-113.7***	-79.07**	-5.967***	-2.465	2.654	1.976
	(22.55)	(24.96)	(1.434)	(1.401)	(1.884)	(1.915)
Unemployed	-80.51***	-63.81***	-4.410**	-3.763**	-6.428***	-6.039***
	(19.48)	(18.53)	(1.520)	(1.381)	(1.825)	(1.804)
Other inactive	-150.3***	-121.5***	-9.218***	-7.594***	-9.488***	-9.099***
	(13.82)	(12.66)	(0.726)	(0.671)	(0.985)	(0.965)
Pensioner	-55.32	-37.62	-0.838	-0.0630	-5.845	-5.437
	(35.30)	(43.42)	(3.978)	(3.921)	(5.265)	(5.094)
Higher education <3 years	-95.10***	-77.79***	-4.916***	-3.882***	-7.110***	-6.939***
	(18.03)	(16.23)	(0.801)	(0.744)	(0.999)	(0.965)
Higher education $\geq$ 3 years	-143.4***	-113.2***	-6.742***	-5.561***	-6.935***	-6.117***
	(17.09)	(15.02)	(0.708)	(0.653)	(0.896)	(0.863)
HH owns Diesel Car		129.0***		22.25***		-8.854***
		(7.261)		(0.623)		(0.857)
HH owns Gasoline LCV		1108.0***		29.02***		34.26***
		(129.6)		(2.867)		(3.134)
HH owns Diesel LCV		2171.3***		67.93***		68.58***
		(327.8)		(5.108)		(6.966)
Constant	696.4***	560.5***	58.96***	47.20***	160.5***	161.6***
	(29.49)	(25.73)	(1.284)	(1.196)	(1.504)	(1.498)
N	13097	13094	13097	13094	13097	13094
R-squared	0.0235	0.1514	0.0415	0.1642	0.0330	0.0803
Pseudo R-squared						

Standard errors clustered at the household level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: All specifications also include survey-day fixed effects and indicator variables for problems with taking transport, being on leave or on sickness leave on the survey day. D1,...,D10: indicators for household income deciles points. Having a low-skilled profession such as personal domestic services, office clerk in the public sector or unqualified manual worker is associated with a lower propensity to use a car, an association seemingly mediated by the lack of car availability. Finally, being a qualified manual worker, craft worker or trades worker is associated with a higher emission intensity for all pollutants, which may be due to the more widespread use of light-commercial vehicles for these professions.

4.4 What are the options to reduce emissions?

We investigate options to reduce emissions from car trips specifically, which are responsible for more than 90% of travel-related emissions in our data[23]. Options to reduce emissions may depend on the trip purpose. Figure 4 shows the distribution of trip purposes by number of car trips, distances travelled and emissions.[24] Work-related trips (commuting or business trips) contribute to around 55-60% of emissions, and other purposes (shopping/leisure/escort) to 40-45%.

We consider different options to reduce emissions. 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, which in terms

[23]96% of the NOx emissions, 90% of the $PM_{2.5}$ emissions, and 91% of the CO_2 emissions. In contrast, trips by metro or train are responsible for 0% of NOx, 7% of $PM_{2.5}$ and 0% of CO_2 emissions, trips by bus are responsible for 4% of NOx, 1% of $PM_{2.5}$ and 7% of CO_2 emissions, and trips by two-wheelers are responsible for 1% of NOx, 2% of $PM_{2.5}$ and 2% of CO_2 emissions

[24]We use information from the survey on the origin and destination motive (home/ workplace/ study place/ shopping. . .) to classify trips in 6 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 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 the 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.

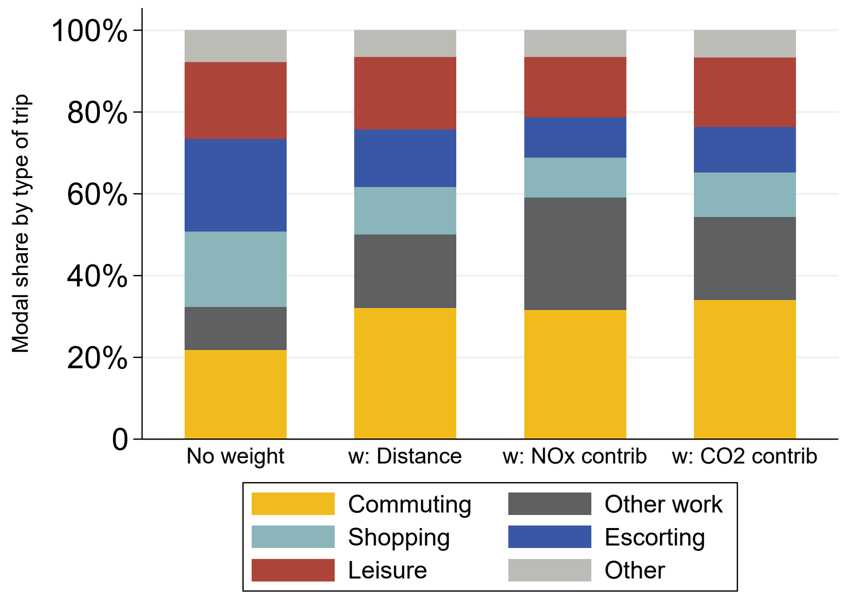


Figure 4: Share of trip purposes in the number of trips, distances travelled and emissions

Note: the first bar chart shows the proportion of trip purpose 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 and the fourth as a share of CO_2 emissions. Source: EGT data. Sample: all trips made by car or taxi by individuals aged above 18

of the extended Kaya equation will tackle the distance component; 2)shifting travel to the lowest carbon mode, which will tackle the modal share component; and 3)improving vehicles to be more energy-efficient and fuels less carbon intensive, which will tackle the emission intensity component. The framework is also suited to examine options to abate emissions of local pollutants. We investigate in depth the second option of modal shift, and estimate the share of car trips that could be shifted to low-emission modes. 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 possibly generate a rebound effect. We also investigate the extent to which teleworking could reduce the need to travel (option 1), assuming that place of residence and workplace do not change. Finally, we examine the potential for a shift to less emission-intensive cars by estimating the share of residents who could access a public charging station for EVs or install one at home.

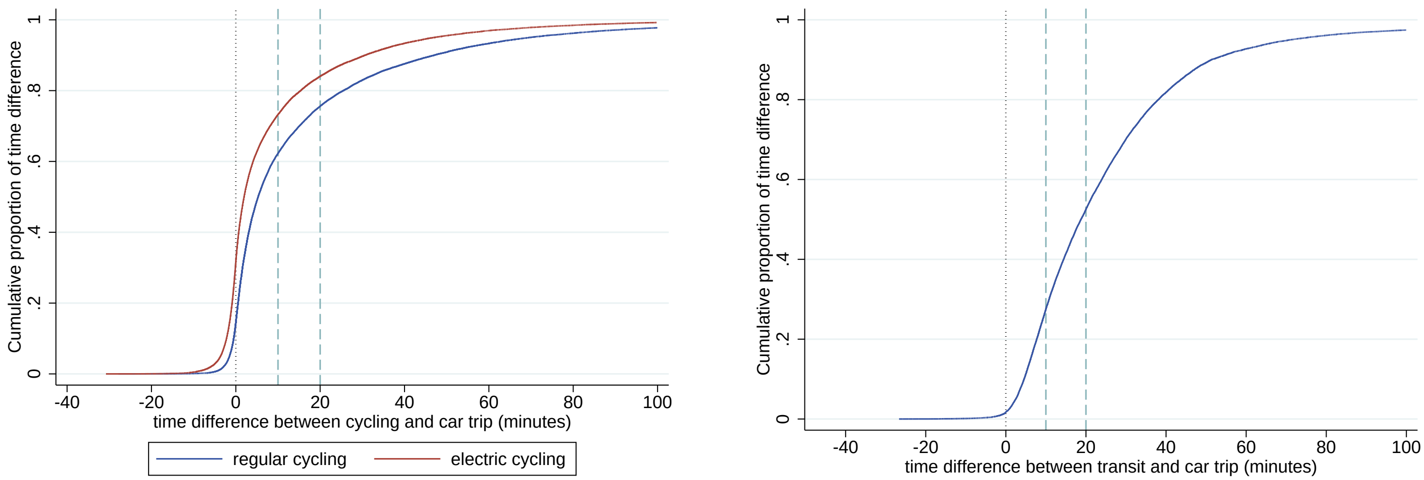
Shift to low-emission modes: We examine the share of car trips[25] that could easily be substituted with regular bicycle, electric bicycle, or public transit. Modal choice depends on several cost and preference parameters, and a model of modal choice goes beyond the scope of this paper. We focus here on two dimensions to examine feasibility of a modal shift: the travel time expressed in minutes, and the trip purpose. Based on these two dimensions, we formulate three scenarios of modal shift potential, with an increasing number of constraints. We compare the travel times with different modes for an existing trip using the counterfactual travel times from Google API. For each scenario, we calculate the proportion of possible modal shifts and the associated NOx, $PM_{2.5}$ and CO_2 emission savings.

Some constraints are common to the three scenarios. First, we impose that switching away from car is only possible if the travel time with the alternative mode is not longer by more than 10 min. Figure 5 shows the cumulative distribution function of the time difference between driving and cycling, driving and electric cycling, and driving and public transit for all the car trips in the sample. 62% of the trips would be at most 10 min longer by regular bike than by car (graph a, blue line), 73% by electric bike (graph a, red line), but only around 30% by public transit (graph b). Second, we impose an age constraint for cycling: we restrict modal shift to regular bikes to individuals below 60 and modal shift to electric bikes (requiring less effort) to individuals below 70[26]. Third, we impose that modal shift is not possible when the purpose of the trip is likely to entail carrying heavy materials, which includes work-related driving round (for professions such as plumbers or electricians) or escorting someone to a transport stop.

Other constraints are specific to each scenario: In scenario 1, we only use the time, age and type of trip constraints. In scenario 2, which is our preferred scenario, we impose two additional constraints: first, shifting to cycling or e-cycling is only allowed if the resulting daily distance cycled is lower than 20km for regular bikes, and 40km for electric bikes; second,

[25] defined as trips using car as their main mode, although some of them may contain journey stages with other modes

[26] These thresholds seem realistic given that 90% of the few cyclists observed in the EGT data are below 65 (97% of them use a non-electric bike).



(a) Cycling

(b) Public transit

Figure 5: Cumulative Distribution Function of the difference in travel time between car and cycling

Note: Sample: all trips currently done by car. Source: Authors' calculations based on Google API outputs. For example, the intersection of the blue line and the left dashed blue line indicates that 62% of the trips currently made by car would last at most 10 minutes more if they were done with a regular bicycle (blue line)

we impose that the additional time spent in transport during the day should not exceed 20 min. In scenario 3, we start with scenario 2 and impose an additional constraint for the type of trip: modal shift is not allowed for shopping trips to a large retail store or mall, which are likely to be associated with heavy loads to carry.

Table 5 reports, for each scenario, the share of trips that could be shifted to each mode, the share that could be shifted to at least one mode, and the associated NOx, $PM_{2.5}$ and CO_2 savings (expressed as a share of the total travel-related emissions in the sample). Adding the distance and time constraints between scenarios 1 and 2 decreases the share of car trips that could be cycled from 47% to 24%. The electric bike constraint is less binding, and the share of trips that could be e-cycled remains quite high in scenario 2, at 47%. Finally, 21% of trips could be done with public transit. Overall, 53% of all car trips, representing 21% of NOx and 19% of $PM_{2.5}$ and CO_2 emissions, have at least one substitute under scenario 2. This share is relatively low compared to the share of trips having a substitute because substitutable trips are shorter on average.

Table 5: Possibility of Modal shift at the car trip level

	Scenario 1	Scenario 2	Scenario 3
Switching to cycling possible	0.47	0.24	0.22
Switching to electric bike possible	0.66	0.47	0.43
Switching to public transport possible	0.21	0.21	0.19
At least one modal switch possible	0.68	0.53	0.49
NOx saved as a % of total	0.33	0.21	0.20
$PM_{2.5}$ saved as a % of total	0.32	0.19	0.18
CO_2 saved as a % of total	0.31	0.19	0.18
N	45,245	45,245	45,245

We estimate the monetary benefits associated with scenario 2, in terms of improved air quality and climate change abatement. For the unit cost of NOx and $PM_{2.5}$ emissions, we use monetary values from the European Commission report on the external costs of transport EU Commission (2020)[27]. We adjust the values for France given for the year 2016 for inflation and we obtain a unit cost of €28.03 per kilogram of NOx and €134.98 per kilogram of $PM_{2.5}$ in 2020. The value for $PM_{2.5}$ is conservative: we take the estimate for urban areas, which is three times lower than that for metropolitan areas, while part of the emission savings from Scenario 2 would occur in the Paris metropolitan area. For the unit cost of CO_2 emissions,

[27] 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 in 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 share 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.

we use the official value for the social cost of carbon in France in 2020 France Stratégie (2019), given in euro 2018, and adjust it for inflation to obtain a euro estimate in real terms. We obtain a unit cost of €84.5 per ton of CO_2.

We first calculate the external environmental costs of passenger transport in IdF, absent any modal shift. For this, we apply the individual EGT survey weights to estimate the total emissions generated by individuals given current modal choices. We then combine this total emission value with unit values of NOx, $PM_{2.5}$ and CO_2. We find that the daily mobility of residents generates an environmental cost of around €5.1m per day, of which €3.4m for local pollution and €1.7m for CO_2 emissions. Assuming that the survey is representative of the 220 annual working days[28], the annual environmental cost of daily mobility in IdF is at least €1,120m.

We then estimate the monetary benefits that would be realised under scenario 2, after estimating the absolute quantity of emission savings with the survey weights. We obtain daily benefits of €1.1m, of which €0.75m from avoided local pollution and €0.36m from avoided CO_2 emissions. With 220 working days, the corresponding annual benefit is €245m. One caveat is that using emission factors from 2010 may overestimate the quantity of NOx and $PM_{2.5}$ emissions saved compared to what would be obtained in 2020: the vehicle fleet from 2010 was on average more polluting than the vehicle fleet from 2020 due to a rising stringency of European pollution standards. But having a conservative estimate for the unit cost of $PM_{2.5}$ probably mitigates the risk of overestimation. We also 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 potential costs associated with modal shift (e.g, time lost, nor other types of benefits such as the health benefits from active mobility[29].

At the individual level, under scenario 2 30% of the drivers could not shift any of their

[28]The travel intensity reported in the survey is representative of an average weekday between October and May, where some individuals are on holiday but likely not a large share. There are probably fewer trips in IdF in July and August, two months were most people take several weeks of holidays in France

[29]The health benefits of walking and cycling induced by the increase in physical activity have been shows to significantly outweigh the risks due to pollution inhalation and cyclists' accidents (Rojas-Rueda et al., 2011; Rabl and de Nazelle, 2012)

car trips, and 28% could shift modes for part of their car trips only. These drivers are more likely to live in the outer suburbs (72%, versus 63% in the entire sample of drivers), and drive longer trips on average (47km per day, vs. 32 km per day in the entire sample of drivers). For these individuals, other solutions are needed. Below, we investigate the potential for teleworking (the distance or "Avoid" component) and the potential for shifting to an electric vehicle (the emission intensity or "Improve" component).

Avoid travelling by teleworking: Teleworking could be all the more relevant since 42% of the employed individuals unable to shift modes use car for commuting. Work-related car trips (either commuting or business trips) also have a lower-than-average potential for modal shift: in scenario 2, only 50% of commuting trips and 38% of business trips have a modal shift option (vs. 53% on average).

The potential for teleworking has recently gained prominence in the public debate and in the literature in the context of the Covid-19 pandemic and associated social distancing measures (Dingel and Neiman, 2020; Alipour et al., 2020; Lennox, 2020). We combine information on the socio-professional category and the workplace to define a variable of potential to telework[30]. 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[31]. According to these criteria, 39% of all the car commuters have a job type which could be done from home. If all the car commuters who cannot shift modes entirely worked from home, 16% of NOx and 15% of $PM_{2.5}$ and CO_2 emissions would be saved from the avoided commuting and business trips. Assuming that these individuals could telework two days a week (two fifths of their time), this would save an additional 6% of NOx, $PM_{2.5}$ and CO_2 emissions compared to the emission savings achieved via modal shift only.

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

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

Improve: shift to an Electric Vehicle: Another alternative to modal shift is a shift to an electric vehicle (EV). There are well-documented monetary and non-monetary barriers to the uptake of EVs: cost of purchase, availability of a charging station, cultural habits (Oxford Institute for Energy Studies, 2019). To identify who may be likely to shift to an EV under some assumptions, we would need a model of car purchasing decisions which is beyond the scope of this paper. We simply note two points suggesting that the barriers associated with the purchasing cost and charging point availability may be overcome with adequate policies. First, among the 58% of current drivers unable to shift modes for all their car trips, only 9% are from the two bottom deciles of income, such that their budget constraint is less binding than for the whole population. Second, at least 17%[32] of them have a publicly available EV charging station at less than 500m from their place of residence in 2020, and 77% of them have a private parking space at their place of residence, where a charging station could be installed. Finally, less than 1% of them drive more than 200km per day (with the limitation that trips outside the IdF region are not recorded), such that the autonomy of the EV should not be an issue for this daily mobility. Alternative vehicles such as two-seat microcars or delivery tricycles (known in the broad category of "Little Vehicles" (Schneider, 2018)) may also provide travel services currently provided by traditional cars at a lower cost than electric vehicles.

Table 6 summarizes teleworking and EV shift options at the individual level, for the entire sample of drivers (first column) and for the 58% of drivers who cannot shift all their car trips to low-emission modes (second column). Available options are very close across the two samples.

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

Table 6: Teleworking and EV shift options for current drivers

	Share of drivers	Share of drivers who cannot fully shift to low-emission modes
Teleworking possible	0.28	0.29
Teleworking possible and current commute by car	0.13	0.13
Has a private parking spot	0.76	0.77
Has a public EV charging station within 500m	0.18	0.17
N	13,140	7,562

5 Discussion

5.1 A 80-20 rule?

We find a strong concentration of local pollutant and CO_2 emissions as far as daily mobility is concerned. This result had, to our knowledge, not been reported before for a large city based on representative data of the residents. Brand and Preston (2010) report that the top 20% UK emitters contribute to 60% of CO_2 emissions from transport and mention a "60-20 rule", but their analysis is based on a small sample of residents from one UK region and includes both daily mobility and long-distance trips. Based on a small non-representative sample from Beijing residents, Yang et al. (2018) report that 20% of the top emitters contribute 70% of emissions, on both weekdays and weekends. Our results for the Paris area, based only on weekday trips within the area, suggest a "80-20" rule on average across the pollutants considered. Only considering weekdays seems relevant to analyse the potential for air pollution mitigation in the Paris area, because ambient pollution tends to be higher on weekdays, where car traffic and economic activity are higher. For CO_2 emissions, examining long-distance trips and weekends seems necessary to get the full picture of carbon footprint inequalities: indeed, residents from the city centre (who in our analysis contribute substantially less to emissions than suburban residents) tend to take the plane more often and emit more during their long-distance trips (Pottier et al., 2020).

5.2 Traditional and less traditional factors associated with emissions

Four factors associated with daily distances travelled and modal choice have previously been highlighted in the literature: employment status, household income, household residence location vis a vis the city centre, and agglomeration size (Nicolas and David, 2009; Blaudin De Thé et al., 2020; Pottier et al., 2020). Our results are consistent with this literature. We also highlight the role of the commute type in explaining the propensity to use a car, with suburbs-to-suburbs commutes being more reliant on cars.

A newer aspect of our work is to document the association between employment characteristics and the propensity to use a car, with individuals working at factories and manual, trades and crafts workers having a higher propensity to use a car. The high reliance on car of these professional categories could play a role in the political economy of opposition to policies regulating car use.

Another contribution is to highlight the different relationship between income and local pollutants' emission intensity on the one hand, and income and CO_2 emission intensity on the other hand. Two factors can drive up the emission intensity of individuals from the bottom decile: first, the NOx emission intensity of light-commercial-vehicles is much higher than the emission intensity of regular cars of the same age, and individuals with manual occupations from the middle and bottom deciles are more likely to have such cars; second, lower-income individuals have older cars on average, and the NOx and $PM_{2.5}$ emission factors are determined by the age and fuel type of the vehicle. In contrast, in our data the CO_2 emission factor depends on the age, fiscal horsepower and energy of the car. Higher-income people tend to have a higher fiscal horsepower and newer cars, and CO_2 emissions increase with fiscal horsepower but they do not vary much with the age of the car. This distribution of vehicle characteristics across income groups suggest that policies based on the NOx emission intensity of vehicles, such as Low-emission zones, whose exclusion criteria depend on the age of vehicles, could be more regressive than policies regulating the CO_2 emission intensity of vehicles, such as feebates.

5.3 From modal shift potential to actual modal shift

The LMDI decomposition suggests that the emission intensity of vehicles is only one driver of emissions, and a minor one for CO_2 emissions. Policies tackling modal shift and demand for distance are also needed. Regarding modal shift, we document a relatively large potential based on travel time criteria. Adequate policies are required to fulfil this potential: despite the potential of modal shift to cycling and electric cycling, its modal share is only 1.9% of total trips in 2018 in the Paris area (Omnil-Ile de France Mobilites, 2019).

The roles of the built environment on the one hand, and of cognitive factors such as statu-quo bias, overconfidence or framing effects on the other hand, have been underlined to explain modal choices and their stickiness (Javaid et al., 2020; Mattauch et al., 2016). For active modes, weather conditions may also play a role, with warm and dry weather conditions having a positive influence and rain, snow, wind, overly cold or hot weather having the opposite effect (Böcker et al., 2013). For electric bikes specifically, which we find enable a large part of the modal shifts, their relatively high cost and the risk of bike theft are other important factors hindering a wider adoption in the Paris area (Cazi, 2020), although sales have been increasing significantly since 2017 (Le Monde, 2021) (figures are at the national level). 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.

The forced experiment of the Covid-19 crisis could be an opportunity for a permanent shift in habits against the statu-quo, as observed in the case of other disruptions in usual travel habits such as public transport strikes (Larcom et al., 2017). Given the behavioral factors influencing modal choice, rolling out cycling infrastructure in a disrupted time could also have a multiplier effect. Recent evidence suggests that pop-up bike lanes rolled out to facilitate social distancing during Covid-19 have increased cycling between 11 and 48% in the following months, depending on the city considered (Kraus and Koch, 2021). One key question for future research is whether these relatively large effects will persist over time.

For drivers without a modal shift option, reducing distance and emission intensity is needed. Only 13% of drivers combine commuting by car and being able to work from home. But the emission savings associated with them teleworking are relatively high given their high commuting distance. In the long-term, urban planning could play a role in reducing demand for car trips, for example by improving the diversity and design of the suburbs (see Blaudin De Thé et al. (2020) for a discussion of these dimensions) and making cities more polycentric. Regarding policies tackling the emission intensity of cars, such as subsidies to buy EVs or low-emission cars, they are all the more needed in the outer suburbs, where individuals are less likely to be able to shift modes. However, to date the means-tested subsidies for new car purchases introduced with the Parisian Low Emission Zone are only available for household living within the planned LEZ boundaries (Paris and part of the inner suburbs), excluding households from the outer suburbs. One recommendation would be to open the subsidies to individuals living outside the Greater Paris area but working in the LEZ. Note that the per kilometer reduction in air pollution and CO_2 emissions allowed by electric vehicles is smaller than that allowed 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 damaging for health (Daellenbach et al., 2020).

5.4 Limits

The main limitation of our analysis is that we do not take into account the potential rebound effect of the different options to reduce emissions. In the case of modal shift, we imagine two possible types of rebound: first, rebound from individuals renouncing to have a car, who may spend the savings from not owning a car on carbon-intensive goods and services, as evidence 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 partially mitigated by a reduction of the space left to cars in the public space, proportional to the reduction of car use. In the case of teleworking, rebound may occur if people used the time freed up by the absence of commute for leisure travels. To our knowledge, the only empirical study estimating the impact of teleworking finds a net reduction in traffic and city-level pollution at the monthly level (Giovanis, 2018), but it does not measure the effects on long-distance trips.

Although we use data from 2010, we think that our results are still relevant to explain today's distribution of emissions in Paris. Preliminary results from the new wave of the EGT suvey (planned to be carried out between 2018 and 2022, but currently stalled due to the Covid-19 crisis) suggest that the average number of trips, time and distances spent travelling have not changed since 2010 (Omnil-Ile de France Mobilites, 2019). The average modal share changed only slightly, with a small decrease in car use (from 37.8% of the trips in 2010 to 34.4% in 2018), compensated by an increase in active transportation modes and collective transportation. Using data from 2010 may be more problematic to estimate the emission savings associated with our scenarios in absolute terms and the associated monetized benefits. But using conservative estimates for the unit cost of emissions likely counterbalances this risk.

6 Conclusion

We show that inequalities in contribution to transport-related emissions are large in the Paris area, with top emitters combining large distances travelled and a reliance on high-emitting cars. We document an important association between some employment characteristics and emissions. In a monocentric city like Paris, distance from the center and other spatial characteristics are also strongly associated with higher emissions. Although we report a high potential for modal shift in terms of the share of car trips where a low-emission substitute exists, the associated emission savings is only 20% because many long trips/trip with high-emission cars cannot be substituted. Policies encouraging a decrease in demand for travel and the adoption of low-emission cars are needed for the individuals unable to shift modes.

Regarding the external validity of our results, we expect that city size and density influence both the external cost of transport, as underlined Carozzi and Roth (2019); Gaigné et al. (2012) and the potential for modal shift, as underlined Nicolas and David (2009); Brand et al. (2021). For the relationship between density and the environmental externalities from transport, the urban economics literature points to a potential trade-off between CO_2 emissions and local pollution, because one is a global externality and the other affects local residents only: compact (more dense) cities are associated with shorter distances and more public transport so they may reduce the quantity of polluting emissions (Gaigné et al., 2012). So compact cities may be good for CO_2 emissions. At the same time, the cost of local air pollutants depends on how emissions translate into ambient concentrations and how many people are exposed to this pollution. Then, a higher density may lead to higher population-weighted pollution concentration, as evidenced by Carozzi and Roth (2019) in the US case, and also higher benefits from reducing local pollutant emissions. In contrast, the benefits from CO_2 emission reductions would be the same in all cities given the global nature of the climate change externality. Regarding the potential for modal shift, shifting to active modes may be easier in smaller cities with shorter distances travelled, but shifting to public transport may be harder, as the public transport network is usually less good in small cities.

We think that our results likely apply to other dense European cities with an important public transit network, such as London, Madrid or Rome, as well as other large French urban areas. In any case, it should be easy to replicate our analysis in other cities of the developed world, given the availability of transport survey data such as the one used in this paper in other cities (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

For “polluting” modes (buses, cars, two-wheelers), the emission factor $e_{P,m}$ comes from different sources.

Buses For buses, the NOx and $PM_{2.5}$ emission factors per passenger are derived from the local air quality agency's emission calculator[33]. 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 IdF 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 Ile de France, so we multiply the initial factor by 11/14.

[33]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 $PM_{2.5}$

Cars and two-wheelers owned by the household For two-wheelers and cars, 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 cars, we use the information on the type of car (passenger car/LCV), the year of first registration and the fuel type. For the CO_2 emission factors of cars, we also use the information on the car's horsepower; 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).

For cars, we use the NOx and $PM_{2.5}$ emission factors from the local air quality agency's emission calculator by type of fuel and date of registration of the car. The average speed, cold starts and horsepower of vehicles circulating in IdF are included as common parameters entering the calculation of emission factors for all fuel types and dates of registration. Regarding fuel type, the calculator distinguishes between diesel, gasoline, and electric cars. We assign LPG cars from the survey the same emission factor as a gasoline car from the same year. We assign hybrid cars from the survey the same emission factor as an electric car from the same year (this may underestimate emissions from hybrid cars, but they represent only 0.3% of the cars owned by households). The calculator does not have specific values for light-commercial vehicles. For these car types declared by the household, we proceed as follows: we take the emission factors for LCVs and cars from a different source, the Ominea database edited by a environmental agency called Citepa and giving reference values for emission factors for different economic sectors[34]. We calculate the ratio of LCVs to car emission factors according to that source for each type of car and LCV defined by their fuel type and registration year (and taking the value fo the "urban driving conditions" rather than "highway" or "rural"). We then multiply the NOx and $PM_{2.5}$ emission factors given for cars in the Airparif calculator by the OMINEA ratio, and obtain NOx and $PM_{2.5}$

[34] https://www.citepa.org/fr/ominea/

emission factors respecting the relative difference of LCVs vs cars given in the OMINEA database. Particulate matter emissions from tyres and brakes are not taken into account in the OMINEA data, so we are assuming that the ratio of $PM_{2.5}$ emission factors for LDVs over cars is the same for exhaust emissions and emissions from brakes and tyres.

For CO_2, we use data from the French Energy Agency (Ademe), which provides emission factors for all car models from 2001 to 2015. We build categories of car models defined by the same information as the one we have on the cars owned by households in the EGT data: year, fuel type (gasoline/petroleum/hybrid/electric/LPG), and administrative horsepower. Then, we calculate for each category the average CO_2 emission factor from the Ademe dataset, weighted by national-level market shares by brand[35]. We allocate to each car type from the EGT data the CO_2 emission factor from Ademe for the same car category. When the car owned by the household is older than 2001, we rely on data provided by Ademe[36] giving average emission factors of cars sold in France by fuel type, for the years 1995-2018. We estimate emission factors for the period before 1995 by applying the same annual trend for emissions as for the 1995-2000 period. For electric cars, we assign a zero emission factor. The Ademe data reports emission factors for commercial vehicles only. For light-commercial vehicles owned by the household, we use the estimations given in CGDD (2011).

For two-wheelers, 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

[35]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.

[36]http://carlabelling.ademe.fr/chiffrescles/r/evolutionTauxCo2

Table A.1: Emission factors for private vehicles not owned by the household

Transport mode	Unit	NOx (mg/km)	$PM_{2.5}$ (mg/km)	CO_2 (g/km)
Taxi	per passenger	1,178	127	332
Car not owned by the household	per vehicle	589	63	166
Two-wheeler not owned by the household	per vehicle	86	21	65

Note: Authors' calculations from Airparif, OMINEA,Ministère de la Transition écologique et solidaire (2018), Copert, Ademe

much an issue given the low modal share of two-wheelers ($< 1\%$).

Taxis and 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 $PM_{2.5}$ emission factors of a 2008 diesel car (in 2010 most taxis were diesel vehicles[37]). We impute the CO_2 emission factor of a 2008 diesel car of 7 hp. We take values for recent vehicles 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 scooter. Table A.1 shows the unique emission factor obtained for buses, taxis, cars and two-wheelers not owned by the household (here assuming one passenger per vehicle).

A.2 Method to retrieve counterfactual transport time with Google API

We pool together the trips likely to have exactly same duration based on Google's prediction algorithm: for transit trips during the day (from 6 am to 9h59 pm) and cycling trips, changing

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

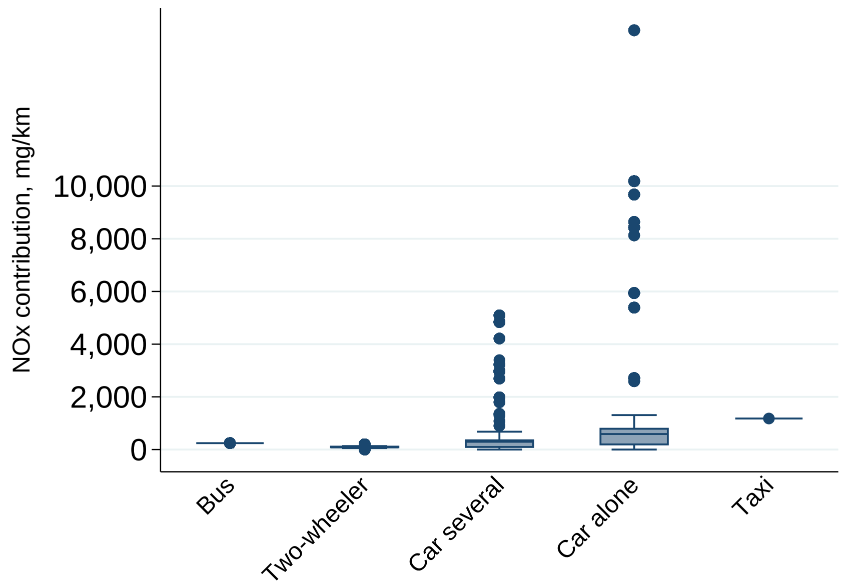


Figure A.1: Distribution of NOx emissions per passenger, by transportation mode

Note: For each transportation mode, the box plot shows the distribution of NOx emissions across journey stages using this transportation 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.

the direction of the trip or its hour did not change the resulting duration based on a trial on a few trips. So we grouped together all the trips with the same or the opposite point of departure and point of arrival, irrespective of the hour of departure. We are left with 49,242 trips with unique pair of {departure;origin}. We simulate day transit and all cycling trips so that they occur on a Tuesday morning. For driving trips, average traffic conditions are integrated in the algorithm, such that the hour of the trip and the direction of the flow can influence the trip duration. We group together trips with the same hour of departure, point of departure and point of arrival. We are left with 73,264 trips with unique point of departure X point of arrival X hour of departure. We simulate transit trips so that they occur on a Tuesday. Finally, we account for the fact that public transport is less frequent at night by estimating specific trip duration for public transport at night. For transit trips during the night (from 10 pm to 05h59 am), we group together trips the same way as for car

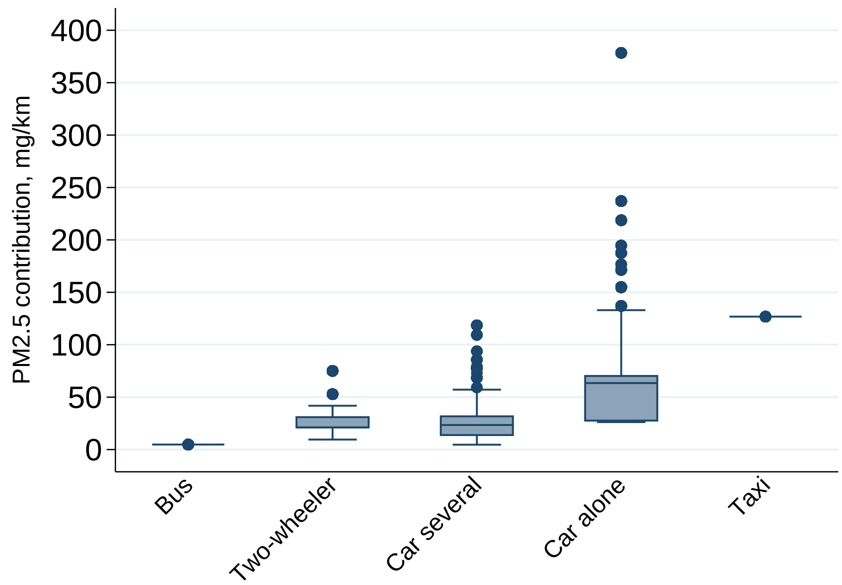


Figure A.2: Distribution of $PM_{2.5}$ emissions per passenger, by transportation mode

Note: For each transportation mode, the box plot shows the distribution of $PM_{2.5}$ emissions across journey stages using this transportation 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.

trips. We are left with 2,844 trips. We simulate night transit trips so that they occur on a Monday evening.

A comparison of Google Maps' trip duration output and the trip durations self-reported by individuals in the EGT data reveal that Google Map's durations are lower for all the three modes: cycling trips are on average 39% shorter according to Google Maps (but this is based on a very small sample of cycling trips in the EGT), driving trips 32% shorter, and transit trips 20% shorter (the comparison is made for trips actually using that mode in our data). Given the potential error in self-reported durations, the uncertainty margin of the API's estimations and the ten-year gap between the API request (2020) and the EGT data (2010), it is difficult to know which one is the true value, if any. What matters for us is that the relative time difference derived from the API's predictions for car, cycling and public transit trips reflects well the true relative difference in time. Given the higher discrepancy

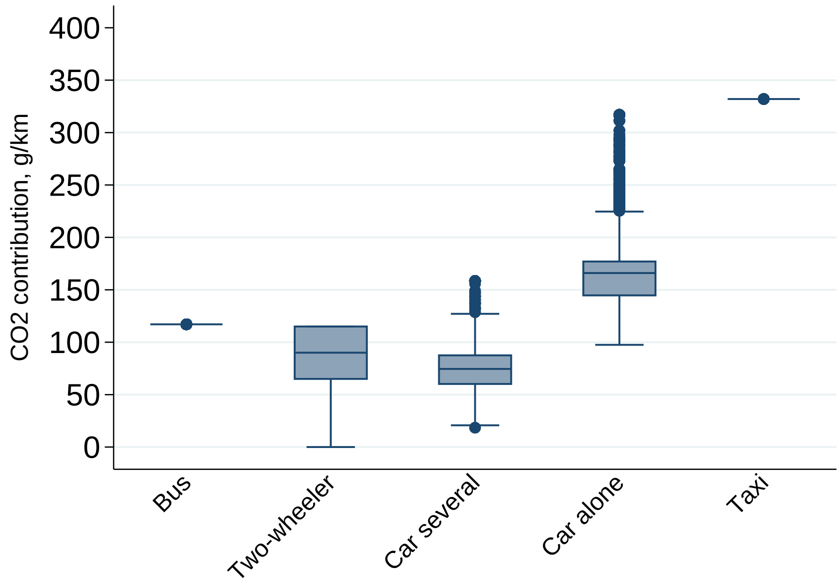


Figure A.3: Distribution of CO_2 emissions per passenger, by transportation mode

Note: For each transportation mode, the box plot shows the distribution of CO_2 emissions across journeys using this transportation 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.

for cycling compared to driving and the lower one for transit compared to driving, we may underestimate the ability with which individuals switch from car to public transport and slightly overestimate the ability with which individuals switch from car to cycling.

A.3 Additional Tables and figures

Table A.2: EGT-Descriptive statistics at the household level

	Mean	Sd
Nb. household members	2.33	1.38
Residence: Paris	0.23	0.42
inner suburbs	0.37	0.48
outer suburbs	0.40	0.49
Housing: Social housing	0.23	0.42
Private tenants	0.23	0.42
Home-owners	0.51	0.50
Other housing status	0.03	0.17
Age, person of reference	49.58	15.98
Estimated Net income	37,571.06	24,535.46
Estimated Net income per consumption unit	24,655.83	14,640.12
Observations	14,882	

Note: Source: EGT data. Data weighted with EGT household-level sampling weights

Table A.3: Balance between EGT survey data and administrative data on selected household characteristics

	EGT	Administrative data
Nb. household members	2.33	2.48
	(1.38)	(1.68)
Residence: Share living in Paris	0.23	0.22
	(0.42)	(0.42)
Share living in the inner suburbs	0.37	0.37
	(0.48)	(0.48)
Share living in the outer suburbs (%)	0.40	0.41
	(0.49)	(0.49)
Share living in Social housing (%)	0.23	0.22
	(0.42)	(0.41)
Housing: Share of private tenants	0.23	0.26
	(0.42)	(0.44)
Share of home-owners	0.51	0.49
	(0.50)	(0.50)
Share of other housing status	0.03	0.03
	(0.17)	(0.18)
Age, person of reference	49.58	52.04
	(15.98)	(17.10)
Net income per consumption unit	24,655.83*	25,969.40**
	(14,640.12)	(85,486.92)
Observations	14,882	4,830,037

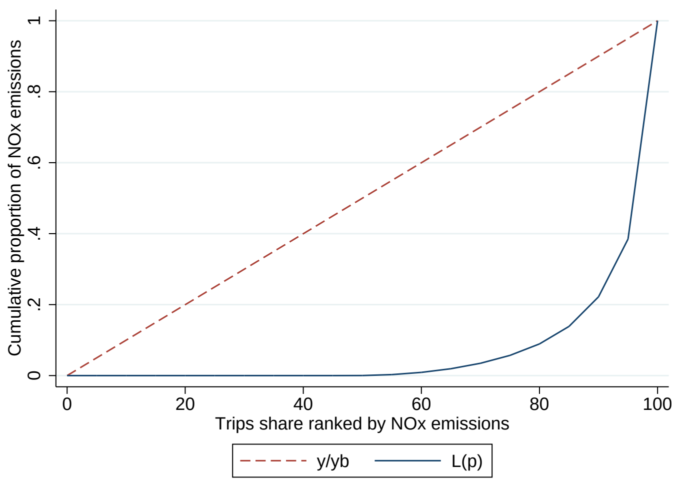
Note: EGT observations weighted with household-level sampling weights. Source for the administrative data: Filocom data for 2011, an exhaustive census of housing units by January 1st 2011. *The income variable from EGT has been imputed using an interval regression imputation method. **The income variable from Filocom comes from fiscal sources and does not include non-taxable income sources such as housing or family benefits.

Table A.4: Balancing test comparing the subsample of individuals with one trip recorder and the full sample

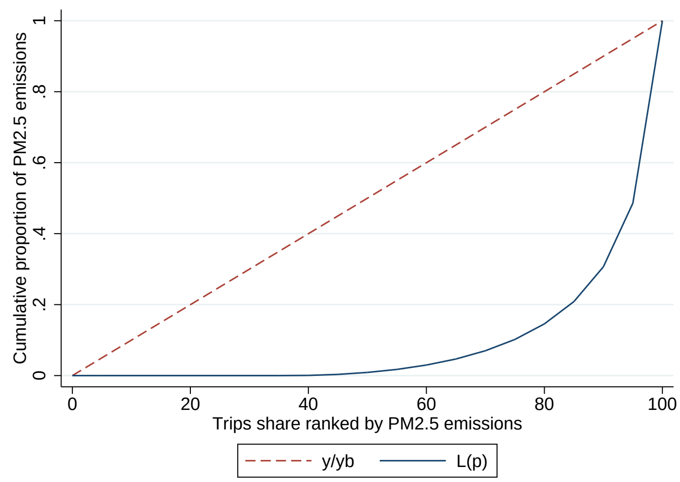
	1 Individuals travelling	2 Full sample	3 (1)-(2)
Residence: Share living in Paris	0.143	0.140	0.00340
	(0.350)	(0.347)	
Share living in the inner suburbs	0.366	0.365	0.00107
	(0.482)	(0.482)	
Share living in the outer suburbs	0.490	0.495	-0.00447
	(0.500)	(0.500)	
Age, person of reference	45.20	45.69	-0.496***
	(16.21)	(16.64)	
Education: Primary school	0.0514	0.0588	-0.00735***
	(0.221)	(0.235)	
Secondary education	0.393	0.400	-0.00725
	(0.488)	(0.490)	
Higher education $\leq$ 3 years	0.152	0.149	0.00248
	(0.359)	(0.356)	
Higher education $>$ 3 years	0.337	0.326	0.0104*
	(0.473)	(0.469)	
Still in education	0.0671	0.0654	0.00177
	(0.250)	(0.247)	
Socioprofessional category: Farmers	0.000756	0.000711	0.0000449
	(0.0275)	(0.0267)	
Manual workers	0.105	0.104	0.00102
	(0.307)	(0.306)	
Office workers	0.191	0.192	-0.000486
	(0.393)	(0.394)	
Intermediate professions	0.220	0.214	0.00628
	(0.414)	(0.410)	
Traders and craftspeople	0.0200	0.0198	0.000140
	(0.140)	(0.139)	
Managers and executives	0.197	0.190	0.00723*
	(0.398)	(0.392)	
Pensioner	0.198	0.213	-0.0155***
	(0.398)	(0.410)	
Other	0.0681	0.0669	0.00124
	(0.252)	(0.250)	
Activity status: Pupil/Student	0.0652	0.0633	0.00192
	(0.247)	(0.244)	
Part-time or full-time employed	0.648	0.624	0.0241***
	(0.478)	(0.484)	
Unemployed	0.0532	0.0578	-0.00454*
	(0.224)	(0.233)	
Other inactive	0.224	0.242	-0.0185***
	(0.417)	(0.429)	
Pensioner	0.00985	0.0128	-0.00298**
	(0.0988)	(0.113)	
Estimated Net income	40613.6	40036.8	576.8*
	(25157.6)	(24938.5)	
Estimated Net income per consumption unit	24051.2	23725.4	325.8*
	(14327.1)	(14262.1)	
Distance to workplace (km)	11.78	11.79	-0.0172
	(11.99)	(12.02)	
Observations	23690	25453	

mean coefficients; sd in parentheses

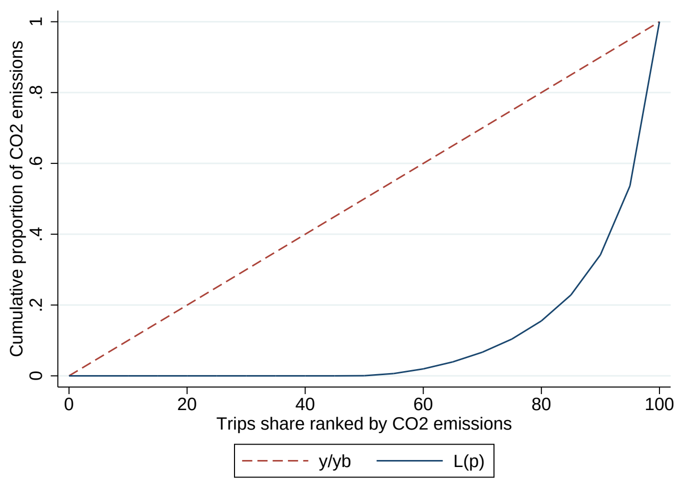
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$



(a) NOx emissions



(b) $PM_{2.5}$ emissions



(c) CO_2 emissions

Figure A.4: Lorenz curve, trip level

Note: the x-axis shows the percentiles of trip-level emissions and the y-axis shows the share of total emissions generated by all the trips below that percentile. The red curve shows how the distribution would look like if everyone contributed equally to emissions Source: EGT data. Sample: all trips made by adults.

Table A.5: Extended Kaya components by quintile of NOx emissions

	NOx (mg)	**Dist. (km)**	**Modal share (%)**			**Emission Intensity (mg/km)**		
			Bus	Two-Wheeler	*Car*	*Bus*	Two-Wheeler	*Car*
	$E_{NOx,Qk}$	D_{Qk}	$S_{bus,Qk}$	$S_{tw,Qk}$	$S_{car,Qk}$	$I_{NOx,bus,Qk}$	$I_{NOx,tw,Qk}$	$I_{NOx,car,Qk}$
Q1	27	16.0	0.000	0.000	0.005	242	NA*	NA*
Q2	1,740	22.6	0.082	0.018	0.289	242	93.3	191.2
Q3	4,118	25.6	0.187	0.035	0.373	242	103.7	300.0
Q4	11,251	31.5	0.106	0.033	0.674	242	122.6	486.0
Q5	45,593	62.2	0.018	0.005	0.918	242	127.9	793.5

*The modal share of these two modes is zero. In practice in the calculation of the LMDI, the same emission intensity of cars and two-wheelers as for Q3 has been imputed to Q1, such that these sub-components of modal share receive a 0 contribution to the difference compared to Q3

Table A.6: LMDI decomposition on NOx emissions at the individual level

	NOx (mg)	**Diff vs Q3 (mg)**	**Distance component(mg)**	**Modal share component(mg)**	**Emission intensity component(mg)**
	$E_{NOx,Qk}$	$\Delta E_{NOx,Q3,Qk,tot}$	$\Delta E_{NOx,Q3,Qk,D}$	$\Delta E_{NOx,Q3,Qk,S}$	$\Delta E_{NOx,Q3,Qk,I}$
Q1	27	-4,091	-303	-3,615	0.0
			(8%)	(92%)	(0%)
Q2	1,740	-2,377	-342	-1,150	-885
			(14%)	(48%)	(37%)
Q3	4,118	0	-	-	-
			-	-	-
Q4	11,251	7,134	1,422	2,886	2,826
			(20%)	(40%)	(40%)
Q5	45,593	41,475	14,215	12,295	14,965
			(34%)	(30%)	(36%)

Table A.7: Extended Kaya components by quintile of CO_2 emissions

	CO_2 (g)	**Dist. (km)**	**Modal share (%)**			**Emission Intensity (g/km)**		
			Bus	Two-Wheeler	*Car*	*Bus*	Two-Wheeler	*Car*
	$E_{CO_2,Qk}$	D_{Qk}	$S_{bus,Qk}$	$S_{tw,Qk}$	$S_{car,Qk}$	$I_{CO_2,bus,Qk}$	$I_{CO_2,tw,Qk}$	$I_{CO_2,car,Qk}$
Q1	0	15.9	0.000	0.000	0.000	NA*	NA*	NA*
Q2	646.0	23.4	0.107	0.009	0.206	117	74.6	130.8
Q3	1,348	24.0	0.180	0.021	0.382	117	82.2	142.7
Q4	3,005	27.6	0.096	0.0033	0.708	117	94.0	149.1
Q5	9,810	67.2	0.023	0.019	0.908	117	104.9	158.6

*The modal share of these two modes is zero. In practice in the calculation of the LMDI, the same emission intensity of cars and two-wheelers as for Q3 has been imputed to Q1, such that these sub-components of modal share receive a 0 contribution to the difference compared to Q3

Table A.8: LMDI decomposition CO_2 emissions at the individual level

	CO_2 (g)	**Diff vs Q3 (g)**	**Distance component(g)**	**Modal share component(g)**	**Emission intensity component(g)**
	$E_{CO_2,Qk}$	$\Delta E_{CO_2,Qk-Q3,tot}$	$\Delta E_{CO_2,Qk-Q3,D}$	$\Delta E_{CO_2,Qk-Q3,S}$	$\Delta E_{CO_2,Qk-Q3,I}$
Q1	0	-1,596	-14	-1,582	-
			(1%)	(99%)	(0%)
Q2	646.0	-914	-33	-798	-84
			(4%)	(87%)	(9%)
Q3	1,348	0	-	-	-
			-	-	-
Q4	3,005	1,463	351	1,016	96
			(24%)	(69%)	(6%)
Q5	9,810	8,134	4,711	2,963	460
			(58%)	(36%)	(6%)

Table A.9: Extended Kaya components by quintile of $PM_{2.5}$ emissions

	$PM_{2.5}$(mg)	**Dist. (km)**	**Modal share (%)**				**Emission Intensity (mg/km)**			
			Metro	*Bus*	Two-Wheeler	*Car*	*Metro*	*Bus*	Two-Wheeler	*Car*
	$E_{PM_{2.5},Qk}$	D_{Qk}	$S_{met,Qk}$	$S_{bus,Qk}$	$S_{tw,Qk}$	$S_{car,Qk}$	$I_{met,Qk}$	$I_{bus,Qk}$	$I_{tw,Qk}$	$I_{car,Qk}$
Q1	1.3	3.0	0.007	0.044	0.000	0.006	7.1	4.8	21.1	28.8
Q2	125	12.7	0.375	0.240	0.006	0.174	7.1	4.8	23.9	33.6
Q3	501	27.3	0.451	0.066	0.018	0.372	7.1	4.8	24.9	34.8
Q4	1,321	39.9	0.256	0.027	0.033	0.633	7.1	4.8	31.8	47.6
Q5	4,185	66.6	0.056	0.006	0.019	0.899	7.1	4.8	43.3	68.6

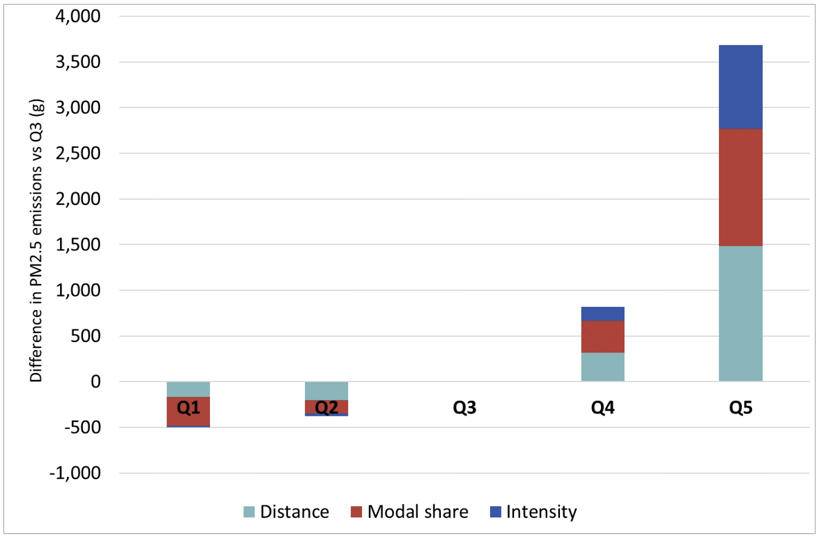


Figure A.5: Contribution of distance, modal choice and emission intensity to the differences in $PM_{2.5}$ emissions

Note: This graph shows the difference between $PM_{2.5}$ emissions from average individuals in quintiles 1, 2, 4 and 5 compared to the benchmark average individual in quintile 3, (total length of the bars), decomposed into differences in total distance travelled, modal shares, and the emission intensity of a given mode using the LMDI additive decomposition

Table A.10: LMDI decomposition on $PM_{2.5}$ emissions at the individual level

	$PM_{2.5}$ (mg)	**Diff vs Q3 (mg)**	**Distance component(mg)**	**Modal share component(mg)**	**Emission intensity component(mg)**
	$E_{PM_{2.5},Qk}$	$\Delta E_{PM_{2.5},Q3,Qk,tot}$	$\Delta E_{PM_{2.5},Q3,Qk,D}$	$\Delta E_{PM_{2.5},Q3,Qk,S}$	$\Delta E_{PM_{2.5},Q3,Qk,I}$
Q1	1.3	-499	-169	-312	-18
			(34%)	(63%)	(4%)
Q2	125	-376	-202	-146	-28
			(54%)	(39%)	(7%)
Q3	501	0	-	-	-
			-	-	-
Q4	1,321	820	316	350	154
			(39%)	(43%)	(19%)
Q5	4,185	3,684	1,483	1,284	917
			(40%)	(35%)	(25%)

Table A.11: Regression coefficients for distance, propensity to use a car and emission intensity - workers

	(1)	(2)	(3)	(4)	(5)	(6)
	ln dist, all	uses car, all	uses car, all	NOx/km	PM25/km	CO_2/km
Outer suburbs	0.190***	0.138***	0.0773***	-16.44	0.467	-4.792***
	(0.0201)	(0.00972)	(0.00850)	(19.71)	(0.839)	(1.018)
Public transport stop	-0.115***	-0.156***	-0.119***	4.205	-0.261	0.707
	(0.0198)	(0.00955)	(0.00834)	(16.77)	(0.784)	(0.916)
Motorized vehicle at hand			0.476***			
			(0.0105)			
ln Commuting distance	0.528***	0.0310***	0.0228***	11.71	2.303***	1.191**
	(0.0111)	(0.00352)	(0.00317)	(8.283)	(0.347)	(0.414)
Res: Paris, Work: Paris	-0.159***	-0.354***	-0.239***	169.0	14.46***	34.57***
	(0.0342)	(0.0172)	(0.0201)	(92.02)	(3.141)	(6.128)
Res: Paris, Work: Surburbs	-0.0493	-0.256***	-0.133***	-52.27	0.679	4.046
	(0.0331)	(0.0185)	(0.0192)	(27.95)	(2.077)	(3.245)
Res: Suburbs, Work: Paris	-0.0393	-0.236***	-0.196***	-31.58	-4.534***	0.905
	(0.0216)	(0.0108)	(0.0105)	(21.29)	(1.081)	(1.466)
D1	-0.0192	-0.146***	-0.0291	74.24	3.444	1.639
	(0.0483)	(0.0228)	(0.0209)	(65.49)	(2.555)	(2.727)
D2	0.00162	-0.106***	-0.0264	0.386	7.057***	2.759
	(0.0363)	(0.0173)	(0.0149)	(29.94)	(1.939)	(1.845)
D9	0.00679	0.0352**	0.00665	16.64	-0.797	0.959
	(0.0259)	(0.0121)	(0.0117)	(29.42)	(1.135)	(1.583)
D10	-0.0122	0.0416**	-0.00242	-10.55	-1.654	4.899**
	(0.0272)	(0.0131)	(0.0123)	(29.03)	(1.144)	(1.710)
Work in Factory	-0.0173	0.0957***	0.0723***	48.39	2.301	1.502
	(0.0358)	(0.0165)	(0.0135)	(40.11)	(1.587)	(1.754)
Work at individuals' home	0.169*	-0.0610	-0.00591	472.1*	9.850*	7.225
	(0.0797)	(0.0338)	(0.0302)	(196.8)	(4.477)	(5.058)
Work from home	1.208***	0.102**	0.0838*	-29.43	7.823	3.813
	(0.138)	(0.0385)	(0.0328)	(69.03)	(4.469)	(5.306)
Work Other	0.0970**	0.0338**	0.0340**	22.14	3.554**	2.398
	(0.0297)	(0.0130)	(0.0113)	(23.26)	(1.269)	(1.455)
Atypical working hours	0.0924*	0.0957***	0.0982***	-17.59	0.668	5.984**
	(0.0390)	(0.0235)	(0.0195)	(42.69)	(2.141)	(2.138)
Works part time	0.0370	-0.0225	-0.00736	-17.68	-0.0611	0.0324
	(0.0333)	(0.0138)	(0.0129)	(24.30)	(1.349)	(1.731)
Farmers	1.019	0.186	0.182	108.4	36.54	13.00
	(0.530)	(0.150)	(0.199)	(133.4)	(19.32)	(13.08)
Qualified Manual workers	-0.0354	-0.000418	0.0317*	112.7**	8.538***	6.921***
	(0.0379)	(0.0186)	(0.0153)	(37.12)	(1.771)	(2.029)
Unqualified Manual Workers	-0.105	-0.133***	-0.0145	54.19	4.458	6.390*
	(0.0557)	(0.0243)	(0.0211)	(52.71)	(2.451)	(2.651)
Office clerks public sector	-0.141***	-0.0603***	-0.00855	50.27	2.605	0.0435
	(0.0320)	(0.0143)	(0.0129)	(26.06)	(1.359)	(1.579)
Office clerks private sector	-0.0566*	-0.0188	0.0109	14.93	0.186	1.946
	(0.0284)	(0.0135)	(0.0127)	(25.85)	(1.253)	(1.513)
Personal Domestic Services	-0.159**	-0.153***	-0.0553*	-37.63	-0.166	3.822
	(0.0604)	(0.0271)	(0.0258)	(53.25)	(2.525)	(3.165)
Technicians	0.0385	-0.0138	-0.0122	30.88	1.557	1.687
	(0.0336)	(0.0180)	(0.0156)	(28.84)	(1.523)	(1.856)
Craftsworkers	0.0292	0.0509	0.0189	912.0*	26.45**	19.17*
	(0.185)	(0.0517)	(0.0461)	(445.1)	(9.279)	(9.117)
Trades workers	0.320*	0.140**	0.108**	582.5*	16.01***	15.11**
	(0.125)	(0.0444)	(0.0341)	(243.7)	(4.748)	(5.846)
CEOs	0.399**	0.145*	0.0837	79.62	-1.938	19.49**
	(0.140)	(0.0622)	(0.0473)	(128.6)	(4.226)	(6.828)
Self-employed white-collar	0.203*	0.126***	0.0945**	-100.9*	-5.962	2.624
	(0.0952)	(0.0330)	(0.0315)	(42.72)	(3.103)	(5.615)
Managers	0.00708	-0.0195	-0.0195	-30.36	-0.810	0.600
	(0.0228)	(0.0114)	(0.0105)	(16.70)	(0.964)	(1.353)
Female	-0.133***	-0.00118	0.0301***	-37.64**	-2.789***	-1.153
	(0.0176)	(0.00815)	(0.00720)	(14.42)	(0.762)	(1.018)
Household size	-0.0139*	0.0206***	0.00570*	12.92	0.578	-0.934*
	(0.00692)	(0.00325)	(0.00290)	(9.219)	(0.328)	(0.382)
Constant	2.386***			526.5***	52.37***	156.7***
	(0.140)			(111.3)	(5.366)	(6.318)
N	12793	12793	12753	7687	7687	7687
R-squared	0.4519			0.0401	0.0509	0.0571

Standard errors clustered at the household level in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: Columns (2) and (3) report the average marginal effects for each coefficient. All specifications also include survey-day fixed effects, variables for age and age squared, and indicator variables for problems with taking transport, being on leave or on sickness leave on the survey day. D1,...,D10: indicator for belonging to the first,..,tenth decile of household income.