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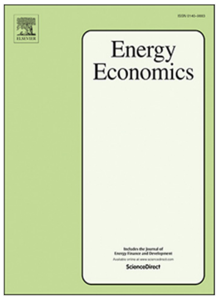

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Franziska Klein, Nicolas Taconet

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Unequal 'drivers': on the inequality of mobility emissions in Germany

Franziska Klein[1,2] and Nicolas Taconet*[3,4,5]

[1]Institut de Ciència i Tecnologia Ambientals, Universitat Autònoma de Barcelona
[2]Mercator Research Institute on Global Commons and Climate Change
[3]CIRED, Ecole Nationale des Ponts et Chaussées
[4]Technical University Berlin, Economics Faculty
[5]Potsdam Institute for Climate Impact Research

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Abstract

Transportation and mobility patterns contribute to greenhouse gas emissions. Understanding the drivers of these emissions, particularly for high emitters, is key to designing appropriate climate and mobility policies. In this article, we study the distribution of emissions from mobility in Germany and their drivers. We use a 2017 nation-wide mobility survey to calculate the carbon footprint of individuals associated with day-to-day and long-distance travels. We use quantile regression to investigate both socio-economic and attitudinal drivers of emissions across different categories of emitters, and for different mobility types. We discuss our results with respect to previous findings in the literature. Overall, we find that the top 10% of emitters are responsible for 51% of total emissions, and for 80% of emissions from long-distance travel. The statistical analysis reveals strong differences regarding the contribution of socio-economic drivers such as income or location at different levels of emissions. Attitudes towards different transportation modes also strongly correlate with differences in mobility behaviors.

*Email: nicolas.taconet@enpc.fr. Both authors contributed equally to this article.

1 Introduction

Personal mobility facilitates most of our social and economic activities. It enables us to reach distant places for purpose of work, social life or leisure, and – today more than ever – acts as a marker of social status (Ellaway et al., 2003; Mann and Abraham, 2006; Zhao and Zhao, 2020), thereby catering a multitude of needs. However, traveling often comes at great costs to society and the natural environment through externalities, such as accidents, traffic congestion, local pollution or greenhouse gas emissions (GHGs).

Transportation represents a significant share of global GHGs. Worldwide, the IEA estimates that the transportation sector amounted to 37% of CO2 emissions from end-use sectors in 2021.[1] According to Lamb et al. (2021) global transport emissions have increased by 2% yearly between 1990 and 2018. While overall emissions have decreased in Europe, transport emissions have increased by 0.4%, suggesting that reducing emissions in this sector proves particularly difficult. This stresses the importance of better understanding the drivers of these emissions to achieve long-term climate targets.

Emissions from mobility are very unequally distributed across individuals and highly concentrated at the top of the distribution. For instance, Brand and Boardman (2008) find that in the UK, the top 10% of GHG emitters are responsible for 43% of mobility emissions, while Ko et al. (2011) show that the top 10% in the Seoul metropolis area are responsible for 63% of carbon dioxide (CO2) emissions. Thus, policies aiming at reducing emissions in this sector should look into the determinants of the high emitters to understand the most effective ways to reduce these emissions and to unravel the potential distributive effects.

Previous literature emphasizes the role of socio-economic and demographic determinants on transport-related emissions (Büchs and Schnepf, 2013; Brand et al., 2013; Reichert et al., 2016). Such characteristics include income, age, gender or education and they explain part of the differences observed across individuals. For instance, in Germany, Aamaas et al. (2013) suggest that the contribution of the highest income group is 2.5 times greater than that of the lowest income group, while Brand and Preston (2010) estimate the ratio to be 3.5 in the UK. Geographic location is also an important driver, with households in densely urbanized areas typically emitting less for daily travels than those in less dense areas, while the contrary holds for long-distance trips (Czepkiewicz et al., 2018).

Besides, psycho-social variables are important determinants of mobility decisions (Pronello and Gaborieau, 2018). One can distinguish between different psychological factors, such as values, beliefs or attitudes. Values often relate to broader life goals and motivations (Schwartz and Bilsky, 1990), whereas beliefs are related to information about an object (Hoffmann et al., 2020), like the perceived necessity or ability to engage in a behaviour. This study integrates the impact of attitudes, which we define following Eagly and Chaiken as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor." (Eagly and Chaiken (1998), p. 583). While gaps between intentions and observed behaviours

[1]Source: https://www.iea.org/topics/transport

are common, Hunecke et al. (2010) find that attitudes are a better predictor of travel mode choice than values.

The contribution of this article is threefold. First, we are adding an analysis of drivers of long-and short-distance mobility for Germany, the most populous European country with the highest emissions for domestic transport, as well as international aviation.[2] Compared to Reichert et al. (2016), who analyse German GHG emissions from daily and long-distance travel as well, we use more recent data and focus on different emitter categories. Furthermore, this study adds a focus on psychological factors, in addition to spatial attributes and other socio-economic characteristics.

Second, we add attitudinal drivers in a large-scale (national) context. There is a vast literature that integrates attitudes with mobility. However, most of these studies are either performed with small samples or focus on very specific contexts, such as bicycle commuters (Li et al., 2013; Heinen et al., 2011), old age groups (Haustein, 2012), day trippers (Anable, 2005) or certain urban areas (Pronello and Camusso, 2011; Wang et al., 2023). In addition, only few studies have effectively linked travel emissions or environmental impact with attitudinal factors (Nilsson and Küller, 2000; Hunecke et al., 2007; Ao et al., 2019; Mattioli et al., 2023). Prillwitz and Barr (2011a) highlight another issue, namely that most of these studies focus on daily travel behaviour. In this article, we integrate attitudinal variables with both daily and occasional travel using a large nation-wide sample of the German population. We are only aware of one other study that includes psychological variables for mobility emissions on a national scale. Mattioli et al. (2023) study emitter types in the UK focusing in particular on people with 'dissonant' travel behaviours.

Third, we go beyond the average effect of socio-economic, demographic and attitudinal determinants of mobility emissions by analysing the role of drivers at different levels of the emitter distribution on the national level using quantile regression. While some studies have focused on different types of emitters, they apply the concept to smaller geographical areas Ko et al. (2011); Bel and Rosell (2017); Leroutier and Quirion (2022) or focus only on land-based passenger transport Brand et al. (2013). Focusing on average effects of any determinants of emissions hinders insights into how the same drivers can play different roles at distinct levels of the distribution, and in particular for high emitters. This is especially relevant in the case of transportation, because emissions are very unequally distributed. Further, oft-used OLS regressions are sensitive to outliers, which are typical as mobility data generally cover observations of mobility for a short period of time.

Here we address this issue by employing quantile regression, which allows us to determine the effect of the drivers along the distribution of the outcome variable (Koenker and Hallock, 2001). Quantile regression has been applied to a wide variety of ecological and economic data (Koenker, 2017; Cade and Noon, 2003), and is particularly suited to overcome heterogeneity of variance along the distribution, which we show holds in our mobility dataset. This allows us to identify which factors are most important among the high emitters.

In the context of households' emissions, we are aware of only two applications of quantile regression. Han et al. (2015) analyse households' total carbon footprint.

[2]Source: EEA

Closer to our work, Bel and Rosell (2017) apply the method to study the socio-economic drivers of emissions in the context of urban mobility. Our study differs from theirs in several respects. We extend the analysis to the national level, and to all mobility types. Bel and Rosell (2017), like most studies, focus on daily urban mobility, while we also investigate long-distance trips, which represent a significant share of individual emissions. In addition to socio-economic variables, we investigate the association of emissions with attitudinal variables, which we show explain a great share of the heterogeneity in emissions.

We rely on the 2017 German mobility survey Mobilität in Deutschland (MiD). The survey contains detailed data on household travels, which we use to quantify the greenhouse gas emissions associated with different types of transportation modes and purposes for each individual. We aggregate these emissions at the individual level and perform both OLS and quantile regressions to identify the drivers of total emissions, as well as those of emissions from long-distance travels.

Our study quantifies both the socio-economic and attitudinal drivers of emissions. Regarding the former, our results are broadly consistent with earlier studies, and confirm that income Büchs and Schnepf (2013); Brand and Preston (2010) and education Brand et al. (2013); Holz-Rau et al. (2014) are strongly correlated with mobility emissions. However, the analysis suggests some saturation effect of income, meaning that being in the highest income group or the one below it has a similar impact on emissions. We also unravel the different role these characteristics play for daily and long-distance mobility.

We shed light on the strong correlation between individuals' attitudes and their behaviors. In particular, we find that attitudes towards different transportation modes can explain some of the heterogeneity in mobility patterns. The evidence suggests that a positive attitudes towards driving and biking are each strongly correlated with higher overall emissions. For each of these associations, our method allows us to analyse the effect at different levels of the distribution, and in particular for the high-emitters.

The remainder of the paper is organised as follows. Section 2 discusses relevant results from the existing academic literature. Section 3 describes the data and method used to quantify emissions and investigate their drivers. Our results are presented in Section 4, and discussed in relation to the existing literature. Section 6 concludes.

2 Study context

The empirical literature on drivers of mobility-related carbon footprints is broad. It covers different geographical areas, methods, types of mobility behaviour and population groups. Still, several variables and hypotheses are commonly discussed. This section recaps some major insights and ongoing discussions to put our regression results into perspective.

Regarding socio-economic characteristics higher mobility emissions are typically associated with higher household income and education, as well as active labour force participation. Geographical location has been identified as an important determinant of mobility emissions. This is partly due to the built environment and infrastructure, partly due to self-selection. In particular, it is regularly found that living in dense urban areas is associated with lower day-to-day travel emissions, but higher long-distance travel emissions (Holden and Norland, 2005; Czepkiewicz et al., 2018; Reichert et al., 2016). While density effects lower the emission intensity of moving around an urban area, city-dwellers often have more dispersed social networks.

Other potential explanations for high emissions from long-distance trips include 'rebound effects' from spending money that is saved by not owning a car (Ottelin et al., 2014; Czepkiewicz et al., 2018), airport accessibility (Mattioli et al., 2021; Bruderer Enzler, 2017; Kim and Mokhtarian, 2021), but also urban lifestyles and potential self-selection: people may choose to live in city centers because they prefer to commute less, or because they want better access to transportation infrastructures such as airports to facilitate long-distance trips, rather than the other-way around (Boarnet and Crane, 2001). Finally, the so-called 'compensation hypothesis' emphasizes the need for people living in dense urban areas to compensate for limited access to green spaces (Holden and Norland, 2005).

With regard to demographic variables, household size can be expected to have some scale effects when income is controlled for. Travelling with several people may lower per capita mobility emissions. Brand and Preston (2010) find that age is only relevant above a certain threshold, because of the absence of everyday commuting for retired individuals, as well as a fewer long-distance trips, for instance for health reasons. Previous transport research shows that generally mobility emissions are higher for men than for women. This is also in line with time use studies, which show that men spend a larger share of their time commuting and more leisure time on out-of-home activities (Druckman et al., 2012) or that they spend more free time on mobility (Smetschka et al., 2019).

Various studies have also taken psycho-social variables into account. Hunecke et al. (2007) report that a positive attitude towards driving is associated with a significant increase in the share of trips with private motorised travel modes. They further find a positive, yet non-significant, relationship between pro-car attitudes and GHG emissions. Several hypotheses could explain such results. A first explanation relates to the modal choice: for a given trip, individuals who like to drive are more likely to favor the car over other transportation modes. Another reason lies in the fact that individuals who enjoy driving have a smaller disutility associated with long car commutes (or even a positive utility, because they enjoy the travel itself, as suggested by Ory and Mokhtarian (2005)), and thus are willing to accept longer commutes than others.

However, the association between a positive attitude to specific means of transport and mobility emissions with holiday travel seems to be weaker than with day-to-day mobility (Prillwitz and Barr, 2011a; Böhler et al., 2006). This stands in contrast to broader value systems, such as cosmopolitanism, which may be a more important cause for long-distance travel (see e.g. Czepkiewicz et al., 2020; Kim and Mokhtarian, 2021) and multi-modal travel behavior Groth et al. (2021). In general, it is likely that attitudes towards different modes of transportation reflect different lifestyles or even deeper value systems.

Several studies suggest that sustainable practices at home are associated with more emissions from long-distance trips. Again, several explanations lend themselves. First, such a result may be driven by groups with a specific mobility style that combines sustainable daily travel with frequent flying. Such groups have for example been termed ‘young travel-addicted urbanites’ (Magdolen et al., 2022), and their long-distance travel behaviour explained by cosmopolitan attitudes and globalised lifestyles (Czepkiewicz et al., 2019). Große et al. (2018) find that among Copenhagen residents ‘the car still accounts for a considerable share (60%) of weekend trips in Denmark among committed cyclists’. They also find that this group of ‘committed cyclists’ undertakes holiday/weekend trips most frequently. People who like to bike may take their bikes with them on long-distance trips and thus have to use a car. This would be in line with a study by Aall et al. (2011), who identify more outdoor recreation equipment as one of the reasons for more frequent use of cars on leisure trips in Norway.

Second, monetary savings from less private mobility on a day-to-day basis could lead to ’rebound’ effects in long-distance travel (see e.g. Czepkiewicz et al., 2018; Ottelin et al., 2014). Third, rebound effects can be fueled by mental accounting techniques as well. Kaklamanou et al. (2015) find evidence of beliefs that sustainable mobility practices at home can make up for unsustainable behaviors, such as flying abroad (’Compensatory Green Beliefs’).

Based on these previous results, we expect daily mobility emissions to be positively associated with income, education, being male and in employment, living in a rural area and having positive attitudes towards the car. We expect a negative correlation of daily emissions with old age and a positive attitude towards biking. The impact of attitudes on long-distance travel is more difficult to anticipate. If it is even relevant, the effect could go in either direction.

3 Methods

3.1 Survey and data set

Our study draws from the 2017 German Mobility Survey, MiD, which took place between May 2016 and October 2017. This survey is based on a two-stage interview process of a representative sample of German households. It contains detailed information about mobility behavior and access to transport modes, socio-economic status, spatial information, as well as some attitude-related questions. The earlier 2008 version of the survey is used for instance in Reichert et al. (2016).

In a first phase, information about the household, such as household size, or available transportation modes, is surveyed. In a second phase, all household members over the age of ten are interviewed individually about their mobility behaviour. Given that the random sampling is based on households, rather than individuals, larger households are over-represented. Therefore the survey provides weights which correct individuals’ observations to be representative of the general population. We use these weights in all analyses that follow.

To avoid an overly long questionnaire with potentially low response rates, only a share of the questions (’modules’) is asked to each respondent. In particular, we are interested in the following modules:

- Daily trips: reports all trips on the sample day (interviews within 14 day after the sample day).
- Journeys: reports all journeys (with overnight stays) over the past three months.
- Attitudes towards transport modes.

While each respondent in the base sample is asked about daily trips and longer journeys, detailed information related to attitudes is only available for a sub-sample. Dropping individuals who did not fill out the attitude module, and cleaning the data set (i.e. removing individuals who did not answer some of the questions), leaves us with detailed mobility information for 11,713 individuals (from approximately 24k initial observations). As the attitude module was not handed out at random, but influenced by local contracting authorities, deleting observations on the basis of this module runs the risk of biasing the sample. To address this concern, we perform a Kolmogorov-Smirnov test to show that the base sample's characteristics do not differ from our subsample (See Appendix D).

As with most mobility survey data, a concern is to define high- and low-emitters based on a short reporting period. For daily trips only one specific sample day is used, whereas the long-distance trips refer to a three-month period. While we assume that over- and underrepresentation of emissions should even out over the full sample size, there is a risk of confounding day-to-day variation of an individual with variation between respondents. We control for this to the extent possible by using day- and month-fixed effects.

3.2 Emissions calculation

Emission factors. We rely on emission factors from the Umweltbundesamt (UBA), the German Agency for the Environment[3] to convert mobility data into emissions. As the most recent available emission factor for air travel from the UBA is solely based on within-country flights, we use earlier estimates to compute emissions from air travel in a more detailed manner (Mottschall and Bergmann, 2013). These emission factors depend both on whether the flight is within or outside Germany, as well as the distance traveled. Note that these estimates include non-CO2 effects by weighing emissions for altitudes higher than 9000m by a specific factor. We acknowledge, however, that the inclusion of non-CO2 effects of air travel is subject to large uncertainty (Lee et al., 2010).

Since no estimates are available for motorcycles, trucks and on-demand bus, we use the 2015 estimates from the Handbook Emission Factors for Road Transport (HBEFA)[4] instead. All emission factors used are reported in Table 1.

[3]Accessible on their website: https://www.umweltbundesamt.de/themen/verkehr-laerm/emissionsdaten#verkehrsmittelvergleich_personenverkehr

[4]Accessible on their website: https://www.hbefa.net

Transportation mode	Emission factors	Unit	Source
Car	220	gCO2e/Vkm	UBA
Train (long-distance)	29	gCO2e/Pkm	UBA
Train (short-distance)	55	gCO2e/Pkm	UBA
Bus (long-distance)	29	gCO2e/Pkm	UBA
Bus (short-distance)	80	gCO2e/Pkm	UBA
Underground/tramway	55	gCO2e/Pkm	UBA
Motorcycles	109	gCO2e/Vkm	HBEFA
On-demand bus	228	gCO2e/Vkm	HBEFA
Truck	815	gCO2e/Vkm	HBEFA
Plane			
Within Germany (<500km)	246.7	gCO2e/Pkm	UBA
Within Germany (>500km)	233.6	gCO2e/Pkm	UBA
Outside Germany (<500km)	308.7	gCO2e/Pkm	UBA
Outside Germany (500-1000km)	302.3	gCO2e/Pkm	UBA
Outside Germany (1000-2000km)	241.3	gCO2e/Pkm	UBA
Outside Germany (2000-5000km)	201.6	gCO2e/Pkm	UBA
Outside Germany (5000-10000km)	229.0	gCO2e/Pkm	UBA
Outside Germany (>10000km)	243.0	gCO2e/Pkm	UBA

Table 1: Emission factors by transportation mode.
gCO2e: grams of CO2 equivalent. *Vkm*: vehicle kilometre. *Pkm*: person kilometre.

Relying on a single emission factor for road transportation has several limitations. First, we are not able to account for variation of emission intensity across private vehicles, which could be related to socio-economic characteristics of households. Second, it does not factor in that vehicle fuel consumption differs between road types, such as within-city streets and highways. While we acknowledge these limitations, relying on single emission factor is a common assumption, and can be considered acceptable as long as the heterogeneity between modes is greater than within modes.

Computing respondents' emissions. We restrict our analysis to adults, i.e. individuals above 18 years old. To convert the information about mobility into individual emissions we account for the number of travelers in the vehicle whenever private motorised travel modes are used.

For daily mobility, the interviewees are asked about the number of trips on the given day, but can only report details for a maximum of 8 to 12 trips. Similarly, for long-distance travels, only three journeys are reported comprehensively over the past three months, although the total number of journeys over that period may be higher. We account for these unreported trips by increasing emissions proportionately for each type of travel, assuming that the footprint of unreported travels would be the same as that of reported ones. One conceptual problem when distinguishing long- and short-distance travel with the MiD survey is that some trips without overnight stays can be longer than some of the journeys, which include overnight stays. We follow the conventional cut-off of 100km in the literature (Reichert et al., 2016) and exclude day trips that are further, and overnight stays that are less than 100km away. The former reduces the sample size of daily trips from 960 to 880 thousand observations. The latter lowers the observations of long-distance trips from 39 to 35 thousand.

Finally, of all the work-related travels, we choose to keep commuting in the individuals' emissions, but exclude any other form of mobility for work on both a daily basis or long-distance trips in the main regression models. We do so, because first, such trips can be seen as more constrained choices compared to mobility for commuting or leisure purposes, especially when driving is part of the job. Second, business travel may create spill-over effects into leisure travel behaviour (see e.g. Cohen et al., 2018), which would cause endogeneity bias. Third, it is debatable whether work-related travel emissions should be accounted to consumption- or production-based emissions. For comparison, we present the results of our analysis when business travel is included as a sensitivity analysis.

Hence, for $k \in$ (daily trips, long-distance journeys), we can compute the two sources of annual emissions:

$$E_k = p_k m_k \sum_{j \in trips} e_j l_j \tag{1}$$

Where e_j is the emission factor of the vehicle used for trip j, l_j is a load factor (the inverse of the number of participants for private mobility, 1 otherwise), m_k is a scale factor accounting for unreported travels (equal to the number of actual trips divided by the number of trips reporting details on distance, travel mode, etc.), and p_k is a scale factor to get the annual emissions, accounting for the period over which trips are reported (equal to 365 for daily mobility, and to four for long-distance journeys).

Hence, individuals' total annual emissions are

$$E_{total} = E_{daily} + E_{journeys} \tag{2}$$

3.3 Quantile regression

To understand how different individual characteristics contribute to explaining differences in mobility emissions, we regress E_{total} on a number of predictors. To highlight differences between daily and long-distance mobility, we also perform a regression analysis with annual emissions from daily E_{daily} and long-distance travel $E_{journeys}$ separately.

Given that outliers are common with mobility data and that the distribution of the target variable, mobility emissions, is likely different for low or high emitters, we chose a quantile regression (QR) strategy. QR is an extension of the linear regression model (OLS) whereby coefficients are allowed to vary along the distribution of the dependent variable (Koenker, 2017). While OLS minimizes the sum of squared residuals, QR minimizes a sum of absolute residuals Koenker and Hallock (2001). QR performs a local fitting of the data, segmenting the sample according to the outcome variable. The coefficients of the model are point estimates that can be interpreted as a one-unit change in y at quantile τ.

It is particularly interesting in the context of mobility emissions given their unequal distribution, as it relaxes the assumption of a linear relationship between the dependent variable and the predictors. Instead, it uncovers how this relationship varies along the distribution of the outcome variable.

This method differs from the one- (Büchs and Schnepf, 2013; Brand et al., 2013) or two-stage OLS regressions (Reichert et al., 2016) typically used in earlier studies. With quantile regression, we can analyse how individuals' characteristics play a different role for moderate or high emitters, as in Bel and Rosell (2017).

We apply both OLS and quantile regression to highlight the difference in results. Rather than testing a specific theory, the study explores a large range of potential drivers of mobility emissions and quantifies their correlations with mobility emissions. The independent variables we consider in our model are household income, household size, age, employment, gender, location, migration background, ownership of a car, having a second home, and a car-sharing membership. In addition, we include attitudes of individuals towards different transportation modes. All regressions include time fixed-effects for the sample days and month of the interview. To avoid inflating the number of covariates, we distinguish between weekdays (Monday through Friday), Saturdays and Sundays, and group the interview months according to three distinct travel seasons. We categorise months as low, medium or high travel season based on the actual emissions from long-distance travel observed.

Similar to Bel and Rosell (2017) we define the quantile function as:

$$Q_{Y_i}(\tau) = \beta(\tau)X_i + \theta_i \tag{3}$$

where X_i is the regression matrix containing the above-mentioned covariates (e.g. age, income group, gender, etc.). This function estimates the coefficients at any quantile point τ (in our case the median, the 75th and 90th percentile). In principle, any number of quantiles can be chosen for a QR model. As our data set contains a large number of zeros, however, the lowest quantile to return an interpretable result is the median. This holds particularly for long-distance emissions. All QR and OLS models are estimated in R (Version Version 1.3.959) using the *quantreg* packages, as well as in STATA (Version 14 using functions qreg and qreg2). The code can be found at this link on Github.

We compare all QR results with a standard linear OLS regression model. A Variance Inflation Factor (VIF) test is performed to test the OLS model of total emissions for potential multicollinearity. The resulting low values indicate no multicollinearity among the independent variables (See Appendix C for detailed results). Plotting the emission data reveals that residuals are non-normally distributed and heteroskedastic (see Appendix C). Hence we report heteroskedasticity-robust bootstrapped standard errors for all models (Koenker and Hallock, 2001). The patterns observed in Figure 4 for a selected number of variables also suggest that the variance of the dependent variable increases with the level of the outcome variable.

3.4 Descriptive statistics

Analyzing daily and long-distance travel data for our sample of more than 11k individuals, we find that overall, private vehicles contribute to the vast majority of total emissions, as they represent a large share of daily mobility. However, air travel dominates emissions from long-distance travels (see Figure 1).

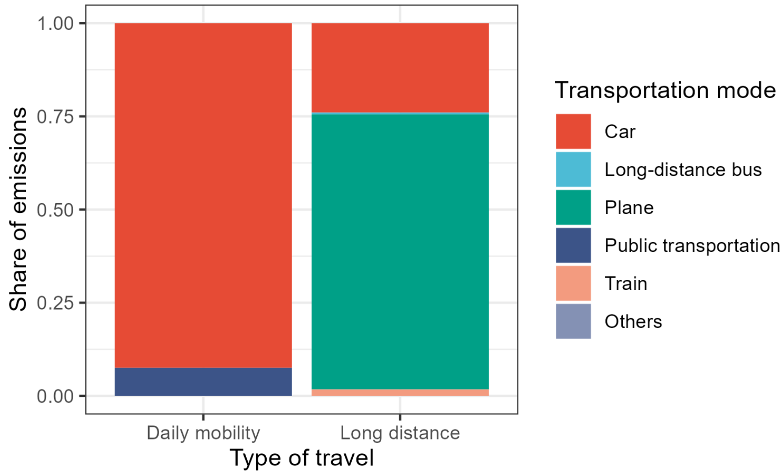


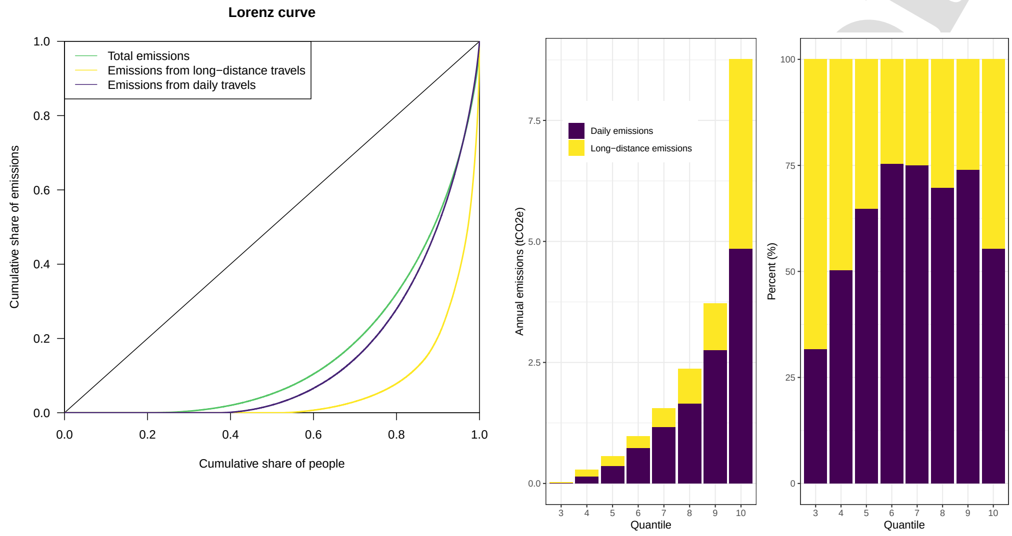
Figure 1: Emission contribution by transport mode and type of travels.

In line with previous studies, we find that emissions are unequally distributed among individuals. Computing the Lorenz curves for emissions from total, daily and long-distance mobility (see Figure 2a), we find the top 10% emitters contribute to 51% of total emissions, and as much as 80% of emissions from long-distance travel, respectively. The Gini coefficients are respectively 0.67 for total emissions, 0.71 for emissions from daily mobility and 0.88 for emissions from long-distance travels[5]. This indicates that individuals emitting through long-distance trips are not the same ones who emit most in their day-to-day mobility, so both types of mobility contribute to making individuals belong to the high emitters group. This further justifies the decision to look into drivers of long-distance versus daily mobility.

It should be highlighted that there is a very high number of zero mobility emissions. Given that information on daily trips is based on a single sample day, the regression sample contains two types of zeros: those who traveled only by foot or bike, and those who did not travel at all on the sample day. Based on this distribution of emissions, we focus on estimating the 50th, 75th and 90th percentiles. Their coefficients should be interpreted as the marginal effect at the respective quantile of emissions of the whole representative sample, rather than as quantiles of emissions from all travellers (as there are non-travellers in the sample).

Figure 2 presents the distribution of absolute emissions across quantiles on the left and the share of mobility emissions on the right, both by type of travel: daily versus long-distance trips. It shows that individuals belonging to the highest emission decile emit on average 11 tCO2e per year, which is about ten times more than those at the

[5]It should be noted that the single sample day for daily travel is less reliable than the three-month period considered for long-distance travel. If sampling inflates the share of zeros in daily travel, this will inflate the inequality measure compared to long-distance travel.



(a) Overall distribution

(b) Emissions by decile and source

Figure 2: Distribution of mobility emissions

median.

Appendix D presents the summary statistics of the main covariates used in our regression analysis.

4 Results

Given that we are interested in the impact of attitudes in particular, we first perform the regression model without any attitudinal variables and then add attitudes as additional control variables to investigate their effect on the other coefficients. An overview of the of the OLS and quantile regression results including attitudinal variables is shown in Figure 3. The detailed tables can be found in Appendix E (results of the same models without attitudes in Appendix F.3). We will first discuss the role of various socio-economic and demographic factors in Section 4.1. We then present the correlation of attitudes towards different transport modes (Section 4.4) with mobility emissions. All variable labels and reference categories are detailed in Appendix A.

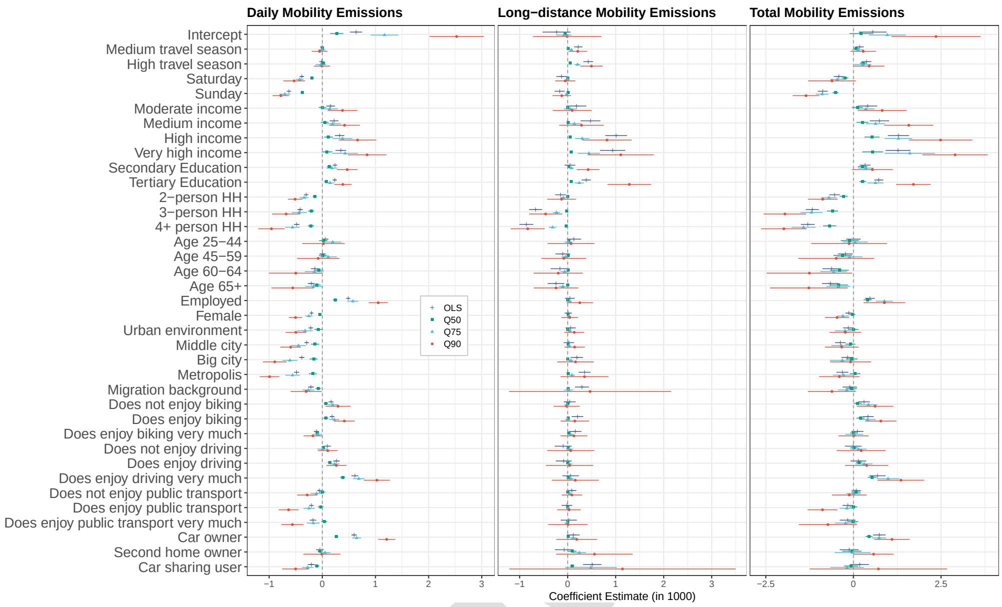


Figure 3: Regression coefficients for different types of mobility emissions

4.1 Socio-economic factors

Income. In line with previous research, we find that higher household income is strongly and positively associated with mobility emissions, both for total and long-distance trips. Being within the highest income group increases total annual mobility emissions by 1.6 tons of CO2e (tCO2e) at the 75th percentile, and by as much as 2.9 tCO2e at the 90th percentile of emitters. However the contribution of income to emissions seems to saturate, especially for long-distance emissions, as the coefficients for the highest income group is not much higher than the one for the second highest. This result stands in contrast to findings by Büchs and Schnepf (2013) that annual transport emissions increase strongest above a household income of approximately GBP 8000. One possible explanation for this difference could be the emissions calculation. Since Büchs and Schnepf (2013) rely on fuel expenditure their emissions capture distances travelled as well as emission-intensities of different vehicles. Combining this with our results would indicate that the highest income group does not necessarily travel longer distances, but that they are travelling more fuel intensively. When we look at day-to-day travel specifically, income only contributes to emissions at the 75th percentile of emitters. Emissions increase disproportionately strong with income at the upper end of the distribution, meaning that it is a more important contributor among high daily emitters.

When attitudes are not controlled for, some income coefficients are underestimated and less significant. This concerns the effect of being in the medium household income group (2000-4000e/m) on daily emissions and the impact of being in the moderate income group (900-2000e/m) on long-distance emissions. Being in these income groups appear to intersect with attitudes that correlate with lower mobility emissions.

Education. Similar to income, education - and especially tertiary education - is associated with significantly higher mobility emissions. Again, the effect is significant across all quantiles, with increasing effect size for high emitters. The coefficient for tertiary education is more than six times as high at Q90 as at Q50 in the case of total emissions. This pattern is driven by long-distance emissions, while daily emissions are not significantly different across education groups.

Employment. Consistent with Ko et al. (2011), we find that being in employment is a significant contributor to total mobility emissions, with low variation across quantiles. This result translates to daily emissions. While Brand and Preston (2010) find that the effect of employment is not significant for long-distance mobility emissions, we can only confirm this through the OLS model. The quantile regression results suggest that being employed increases long-distance emissions significantly. Note that this is despite the exclusion of business travel here.

Second home In the main regression model living in a second home part of the time significantly increases long-distance emissions for all emitter quantiles, while the OLS regression coefficient is insignificant at the pre-specified levels. When we include business travel (see sensitivity analysis and Appendix 16), the effect is larger and the OLS coefficient also becomes significant. It should be noted that access to a second home can have numerous different explanations. People may have a second home where they spend holidays or weekends, but also a partner or work place in a location relatively far from home. Such multi-locality, a lifestyle where a person lives in more than one place with regular or irregular presences and absences, can arise from mobility needs for the purpose of work or personal relationships and can impact mobility behaviour in a sustained way. There is a growing body of research on such multi-modal behaviours in Germany (Danielzyk et al., 2020; Greinke and Lange, 2022).

4.2 Demographic factors

Household size. Larger household size is associated with lower per capita mobility emissions, probably due to scale effects, such as ride sharing. Besides, different household sizes can reflect different lifestyles. Singles may spend more time out of their home and with friends, whereas couples, especially with children, might centre more around their home, having to transport furniture, or they travel together. Büchs and Schnepf (2013), for instance, find that in the UK transport emissions of two-adult households are three times higher than for single adult households on average. At the same time, it should be noted that dividing travel emissions by passenger numbers attributes part of the mobility emissions to children. Under the assumption that adults are making the travel choices, this can lead to an underestimation of per capita emissions from a responsibility perspective.

Age. Total mobility emissions decrease with age. Both daily and long-distance emissions drop significantly for the age groups above 60 years. This result is in line with Brand and Preston (2010), but can only partly be attributed to the absence of everyday commuting, because the commuting effect of many participants is already captured in the positive and significant coefficient of being employed. Yet, some people commute, of course, even though they are not formally employed (e.g. students). Probably older people also move around less for errands and leisure activities.

Total mobility emissions are also lower in the age group 40-45 years, driven by differences at the median emitters. The negative effect of age on long-distance emissions only holds for the OLS regression model. The quantile model finds no evidence that older people create fewer long-distance emissions. When we exclude attitudes from the regression model the coefficient for being in the age group 45-59 on daily mobility emissions turns significant.

Gender. Long-distance emissions differ by gender only at the lower end of the distribution. In this group, being female is associated with higher emissions. On the other hand, women produce significantly less daily (and overall) mobility emissions. This gender gap is particularly pronounced within the top 25% of emitters. The effect of being female on total emissions is overestimated in size and significance when attitudes are not controlled for.

Migration background. Having a migration background is negatively correlated with daily mobility emissions, but it has no significant effect on long-distance emissions. The resulting total mobility emissions do not show a significant difference for those with a migration background.

Car sharing. Unsurprisingly, car sharing is especially relevant for day-to-day emissions. It significantly reduces this type of mobility emissions across all estimated models. For long-distance emissions car sharing has a significant positive effect at the lower emitter percentiles, but not among the highest emitters. Car sharing remains a marginal phenomenon in Germany, with only 4.8% of respondents in our regression sample reporting a car sharing membership. It is also restricted mostly to young, male, urban dwellers Nobis and Kuhnimhof (2018). This mode is typically used for shopping or errands, often on the weekends and either for very short trips (<2km) or for trips between 15 and 30km. Since about half of the car sharing members do not own a car, and even those who own a car travel disproportionately much by bike and public transport, we suspect that any single trip done with a shared car adds a comparatively large amount of emissions to their carbon footprint.

However, the positive link with long-distance emissions may not arise directly from the use of car sharing, but rather reflect lifestyle characteristics that are not captured by the other variables in our model. Recent research on German cities could provide an explanation for the link between certain social milieus and sharing behaviours. Findings by Groth et al. (2023) suggest that the supply of new mobility services, such as car- or bike sharing, is concentrated on socio-spatially exclusive areas in Global Cities, providing disproportionate access for economic and cultural elites.

4.3 Spatial factors and modal access

Location. In line with the existing literature, the OLS results suggest that on average urbanites emit more for long-distance trips and less for daily and overall mobility.

However, the significance levels vary strongly between groups. For total emissions, only the OLS result is significant. When the outcome variable is daily emissions, any sort of agglomeration shows a significant negative effect on emissions, compared to the baseline (rural area). Long-distance emissions are higher for dwellers of all agglomerations, with the exception of middle-sized cities. An interesting result is that living in a smaller urban area increases long-distance emissions in the high-emitter group, whereas the effect of living in a metropolis is more relevant for the lower emitter quantiles.

Comparing location coefficients with and without controlling for attitudes reveals the correlation between where people live and their psychological characteristics. The negative effect of living in a big city on total emissions, for instance, is overestimated when attitudes are not controlled for. Similarly, part of the lower daily emissions of city- and metropolis-dwellers seems to be explained by attitudes, rather than the built environment alone. This possibly supports the self-selection hypothesis.

Car ownership. Finally, we find that car ownership has a strong and positive effect on all emission outcomes we model: total, daily and long-distance emissions. This appears to be in contrast to results by Ottelin et al. (2014), who find that reduced driving in dense urban areas rebounds as higher flight emissions. However, their study has a more narrow focus on middle-income households in the Helsinki metropolitan region, while we use data from a representative national sample, which includes various urban forms and income levels. Furthermore, there might be cultural and geographical differences at play. The car has a dominant role in German mobility behaviour, including in long-distance travel. Almost one quarter of all long-distance emissions in our sample is caused by car travel. However, the effect of car ownership in terms of coefficient size is larger for daily (and overall) mobility emissions. The latter is also more affected by attitudes towards different transport modes. Without accounting for attitudes, the model overestimates the effect size of car ownership on total and daily mobility emissions.

4.4 Attitudes towards transportation modes

Our results show that attitudes towards various transportation modes (enjoyment of biking, driving a car and taking public transport) can be relevant to understand the heterogeneity in personal mobility footprints.

Enjoying to drive. Individuals who enjoy driving a car tend to have higher levels of daily mobility emissions. This is in line with findings from Hunecke et al. (2007). Even moderately disliking to drive (compared to fully rejecting the statement that one enjoys to drive) is associated with significantly higher daily emissions. It is worth noting that the size of these effects is large: enjoying very much to drive a car is associated on average with an additional 0.68 tCO_2 of total mobility emissions on average (0.79 tCO_2 for daily emissions), which is greater than the median emissions, and almost on par with the effect of tertiary education.

While the effect of enjoying to drive is strong and significant for daily emissions, total mobility emissions are only significantly higher for respondents who fully enjoy driving. This effect holds across all quantiles. The association with long-distance emissions is less clear. This coincides with insights from other studies about a weaker association of attitudes towards specific transport means with holiday travel, compared to day-to-day mobility (Prillwitz and Barr, 2011b; Böhler et al., 2006). It stands in contrast to other types of attitudes or values, especially lifestyle-related attitudes, such as cosmopolitanism, which may be more closely related to long-distance travel (see e.g. Czepkiewicz et al., 2020; Kim and Mokhtarian, 2021).

Enjoying public transportation. As far as public transportation is concerned, the OLS regression suggests that agreeing with the statement "I enjoy public transportation" is associated with lower total and daily emissions, compared to participants who fully disagree with this statement. The QR results reveal that this effect is driven by the high-emitters alone. Strongly agreeing with this statement only has a significant effect on daily mobility emissions.

Enjoying to bike. Attitudes about biking also affect emissions. Moderate attitudes towards biking are associated with higher daily and total mobility emissions. Especially for the moderately positive attitude, this result is counter-intuitive. One would expect that people who enjoy biking are more likely to use this low-carbon means of transportation for daily mobility. However, it seems that if this should be the case, attitudes towards biking are associated with other unobserved characteristics, which foster mobility emissions. The results tend to be more relevant (effect size and significance) towards the upper end of the distribution.

Long distance emissions are higher for participants who enjoy biking. This effect is not straightforward. As mentioned above, opinions about biking potentially overlap with other characteristics, which are themselves linked to higher emissions. An interesting result is that for long-distance travels, strongly positive attitudes towards biking are associated with higher emissions for the bottom 75% of emitters. As already discussed in Section 2, there may be different explanations for this. First, enjoying to bike could correlate with enjoying to travel because both are indicators for an active life. The finding may at least in part represent a group of 'multimodal' young people, who tend to belong to a 'cosmopolitan' social milieu (Groth et al., 2021), a lifestyle typically connected with above average air travel (Czepkiewicz et al., 2020). A second explanation could be some form of compensation behaviour, for instance in the form of 'moral licensing', i.e. a justification of emission-intensive long-distance trips through pro-environmental behaviour (biking) at home. Indeed, the effect for a positive bike attitude vanishes when we control for the frequency of bike and public transportation use (see Appendix 9). Still, among the lower 50% of emitters, using a bike regularly is associated with higher long-distance emissions. Last but not least, assuming that people who like to bike often take their bikes with them on long-distance trips, they may may find it more convenient to use a car.

To summarise, the most important contributing characteristics (coefficients of more than 1 tCO2e) of high day-to-day emitters are enjoying to drive and a high household income (>6000€/month). Living in a three-person household (compared to a single person household) and being older in the age group 60-64 years show the largest significant negative coefficients showing that certain aspects of culture and lifestyle, as well as mobility needs, are just as relevant in determining mobility emissions as are economic factors. It should be noted, that the weekday, and Sunday in particular, has a large significant impact on short-distance trips as well.

Regarding long-distance emissions, the most important drivers among the top 10% emitters are by far second home access, high household income (>4000€/month) and tertiary education. Also significant, but with an effect size almost a magnitude smaller are car ownership, being employed and living in an urban environment. Interestingly, attitudes towards biking and driving are more relevant for long-distance emissions of the lower emitter groups. Again, the timing of the survey is highly relevant with significantly higher long-distance emissions during typical travel months.

Comparing the OLS model with the QR model, the direction of the effects observed are similar. However, the QR model allows for a better understanding which categories of emitters are driving the results. It also enables us to highlight the association of the independent variables with emissions for high emitters in particular.Figure 4 shows the OLS (red) and QR (black) estimates for selected variables. The dashed red lines represent the OLS confidence intervals, whereas the grey-shaded area is the equivalent for the QR. Except for the age groups 25-40 and 60-64, some of the quantile regression coefficients always fall outside of the OLS confidence intervals. This suggests that the effects of these covariates may not be constant across the conditional distribution of total mobility emissions.

For OLS models we compute R squared and for quantile regressions pseudo R squared. This shows that the OLS regressions explain approximately 10% of variation in total emissions, long-distance travels and daily mobility, but only 3% for emissions from flights. Relatively low squared R are common when studying transportation behaviors, because of the diversity of omitted variables potentially contributing to mobility patterns and thus emissions. Low values are also due to a high number of both zero-value and extreme observations owing to limited time coverage of mobility (Stewart, 2018). Finally, we report the Machado-Santos-Silva test for heteroscedasticity.

5 Sensitivity analysis and additional models

The choice of covariates and outcome variables in the main regression model is selective. This section tests whether and how other control variables and a different specification of the outcome variable affect the results. In particular, we test the sensitivity of our results with respect to satisfaction with and frequency of use of various transport modes as additional controls. We also test the model for emissions from air travel specifically to identify drivers of high air travel emitters compared to overall long-distance emitters. Lastly, we test how results change when mobility emissions include business travel. Regression results including other spatial variables can be found in the supplementary materials.

5.1 Additional control variables

Satisfaction with travel modes. Besides enjoyment of different transportation modes, the MiD survey asks participants about their satisfaction with different transportation modes. In particular, participants are asked to state how they rate the

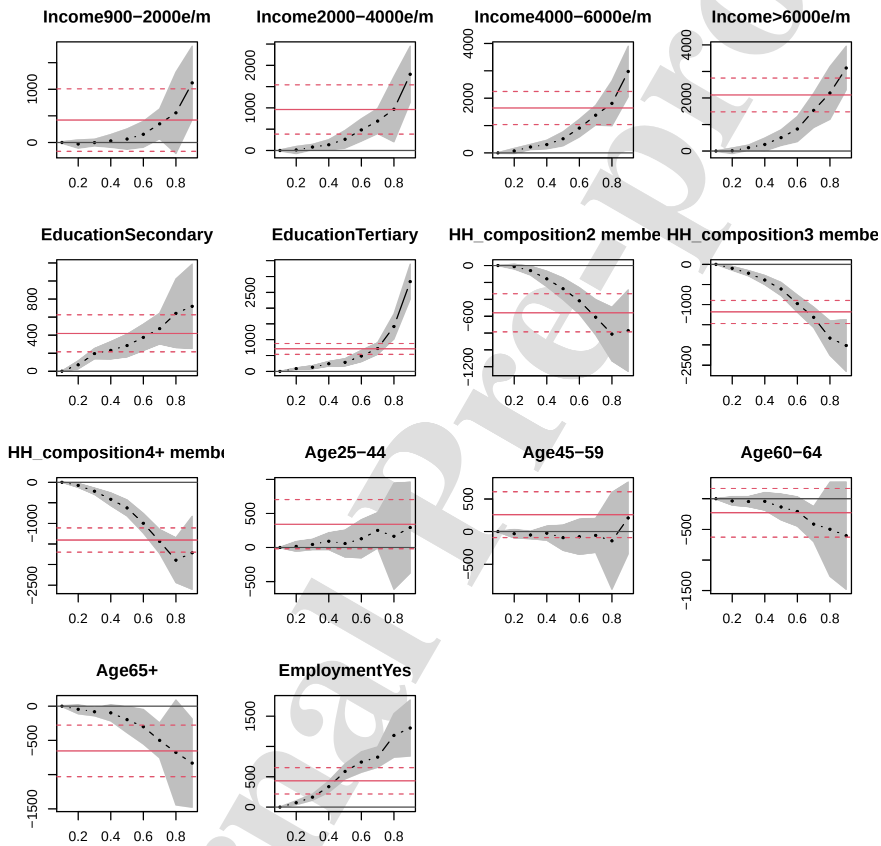


Figure 4: Quantile versus OLS regression

Note: Values of QR regression coefficients along the distribution of the dependent variable (dotted black line) and associated confidence interval for a selected number of independent variables. The red lines represent the point estimate and confidence interval for the OLS model.

general traffic situation in their area for the respective transportation means. Such satisfaction with different modes could be argued to be a precondition for enjoyment, so we expect some overlap in the effect of both variables. Indeed, when we add satisfaction to the model for total mobility emissions, most coefficients are not significant at the specified levels (see Appendix F.2, table 11 for detailed results).

The only coefficients that are significant are those from satisfaction with public transport. An increase in satisfaction with public transportation tends to be associated with an increase in emissions, this being driven mostly by the high emitter category. A potential explanation for this surprising result could be that using public transportation often is linked to lower emissions, but also to a more negative perception of this transportation mode.

Use of sustainable transport modes. As mentioned in the previous sections, one hypothesis is that more frequent use of sustainable transport modes in the day-to-day life of an individual may contribute to higher long-distance emissions due to various potential compensation mechanisms. To investigate this issue a little closer, we perform a regression including the frequency of bike and public transportation use (see Appendix F.1).

Those who cycle daily produce less daily mobility emissions over the whole distribution. When it comes to spillover effects to long-distance travel, daily cycling is associated with significantly higher long-distance emissions. The effect is also noticeable for at the lower quantile for people who bike less than 3 times a month. It should be highlighted, though, that the reduction in daily emissions outweighs the increase in long-distance emissions by a factor of 2.

Regarding the use of public transportation, only daily use of public transportation is associated with a reduction in daily emissions. Using public transportation occasionally, on the other hand, is associated with higher long-distance emissions compared to the reference category (people who never use it).

5.2 Emissions from air travel

Long-distance travel emissions are dominated by emissions from air travel and are partly driven by superflyers (Gössling and Humpe, 2020). Table 2 shows the regression results for emissions from air travel only. Since emissions from air travel are even more concentrated, i.e. there are no air travel emissions at all for the bottom half of emitters (see Appendix B), we choose different quantiles here than for the main regression model (namely 90th, 95th and 99th percentile).

Overall, the OLS regression shows that income, education, household composition, age, migration background an attitudes toward different transportations modes have a significant effect on emissions from flying. High income plays an even more important role for air travel than for overall long-distance travel emissions. A household size of three or more people has a significant negative effect on air travel emissions, indicating that "superflyers" tend to live in small households.

Perhaps the most interesting result is the influence of attitudes towards driving a car. While our results for total emissions showed that enjoying to drive increases total mobility emissions - especially in the lower emitter groups-, even a moderately positive attitude towards the car is associated with a 0.5 tCO2e reduction in air travel emissions, the effect being highly concentrated the top emitters. Conversely, a positive attitude towards biking is associated with an increase of emissions linked to air travel.

Dropping the control variables for attitudes in the regression model does not affect significantly the coefficients for air travel (see in Appendix table 15).

Table 2: Regression for emissions from air travel.

	OLS		*quantile regression*	
		90th	(95th	(99th)
Constant	442.6** (211.8)	372.0 (1, 191.2)	1, 875.6 (4, 812.0)	14, 105.2* (7, 302.3)
Month2_medium	196.8*** (54.9)	348.5** (164.7)	489.2 (300.5)	1, 897.1** (940.6)
Month3_high	93.2 (61.4)	330.2* (182.5)	195.5 (282.5)	132.4 (617.4)
Weekday2_Saturday	−164.5** (68.7)	−98.7 (185.5)	−416.6 (262.3)	−1, 279.6** (595.4)
Weekday3_Sunday	−183.3*** (64.1)	−248.9 (188.6)	−558.3* (310.4)	−769.6 (1, 076.2)
Income900-2000e/m	39.5 (150.0)	114.0 (886.2)	660.9 (1, 580.6)	608.5 (1, 142.5)
Income2000-4000e/m	200.8 (150.9)	454.4 (918.4)	1, 172.4 (1, 597.9)	2, 872.9** (1, 310.4)
Income4000-6000e/m	468.5*** (160.6)	996.0 (935.1)	1, 698.5 (1, 636.1)	4, 870.8*** (1, 655.0)
Income>6000e/m	390.2** (177.4)	1, 067.1 (948.2)	1, 751.4 (1, 676.8)	4, 161.2** (1, 724.4)
EducationSecondary	−108.2 (66.0)	−145.8 (209.8)	−145.6 (253.4)	−371.4 (730.6)
EducationTertiary	152.8*** (55.3)	−121.0 (206.5)	911.7 (620.6)	4, 565.2*** (1, 200.2)
HH_composition2 members	24.7 (69.8)	527.3** (241.2)	503.0 (531.8)	69.4 (1, 188.0)
HH_composition3 members	−338.5*** (84.9)	−419.7* (253.8)	−755.7 (558.8)	−2, 231.2** (1, 013.8)
HH_composition4+ members	−358.3*** (86.9)	−569.2** (277.4)	−973.7 (652.7)	−2, 131.6* (1, 249.7)
Age25-44	80.5 (93.7)	263.8 (310.9)	124.0 (655.2)	459.0 (1, 106.6)
Age45-59	−125.7 (97.1)	7.1 (345.9)	−189.7 (621.4)	90.8 (1, 009.0)
Age60-64	−238.6** (121.4)	−84.8 (453.4)	−572.7 (684.1)	−580.6 (1, 172.9)
Age65+	−251.2** (111.4)	−145.6 (354.5)	−615.8 (725.6)	−1, 474.6 (1, 169.8)
EmploymentYes	−72.2 (66.4)	221.2 (215.5)	−278.1 (399.7)	−1, 227.1 (947.2)
GenderWoman	68.6 (46.1)	56.2 (146.7)	−149.2 (271.4)	608.5 (748.7)
LocationUrban environment	8.4 (68.8)	166.0 (255.2)	59.0 (479.8)	3, 610.1** (1, 561.7)
LocationMiddle city	−126.9* (68.2)	49.9 (181.7)	60.0 (399.0)	270.4 (908.8)
LocationBig city	115.2 (80.6)	608.9** (310.3)	667.7 (761.3)	1, 672.6 (1, 769.5)
LocationMetropole	−42.8 (76.5)	225.6 (189.2)	161.5 (334.8)	93.4 (879.2)
Migration_backgroundYes	388.6*** (89.9)	1, 090.2*** (387.2)	1, 074.6 (910.6)	3, 088.0 (2, 477.1)
Enjoy_BikingDisagree	21.5 (82.3)	−24.1 (215.8)	349.1 (455.8)	1, 279.6 (879.2)
Enjoy_BikingAgree	153.9* (79.8)	127.2 (259.4)	865.9** (414.1)	2, 556.4*** (970.8)
Enjoy_BikingFully agree	34.3 (82.4)	−203.9 (195.5)	200.8 (386.8)	869.3 (924.9)
Enjoy_CarDisagree	−512.5*** (112.3)	−535.6 (763.2)	−1, 228.7 (4, 447.5)	−14, 246.3** (7, 109.8)
Enjoy_CarAgree	−459.0*** (108.1)	−510.5 (761.3)	−1, 120.3 (4, 463.6)	−13, 368.0* (7, 036.2)
Enjoy_CarFully agree	−364.4*** (112.6)	−311.3 (758.2)	−608.1 (4, 447.7)	−11, 458.1 (6, 997.0)
Enjoy_PublicTransportDisagree	−48.0 (58.9)	−5.7 (243.5)	−372.2 (444.2)	−699.8 (1, 067.8)
Enjoy_PublicTransportAgree	−81.1 (68.0)	−30.9 (233.3)	−583.6 (411.6)	−808.9 (995.5)
Enjoy_PublicTransportFully agree	−142.6 (100.3)	−203.2 (264.5)	−626.0 (540.7)	−190.3 (1, 193.5)
Car_ownershipYes	283.8*** (84.5)	252.3 (177.9)	184.3 (418.0)	844.3 (855.5)
Second_HomeYes	−69.5 (110.1)	213.8 (323.6)	−627.6 (504.6)	−1, 201.7 (1, 310.0)
Car_sharingYes	82.5 (104.7)	59.9 (253.2)	188.7 (1, 603.9)	72.9 (1, 338.2)
Observations	6,292	6,292	6,292	6,292
(pseudo) R^2	0.03	0.04	0.03	0.12
Machado-Santos-Silva test		41.1	61.5	35.9
Note:				*p<0.1; **p<0.05; ***p<0.01

5.3 Emissions from business travel

We excluded business travel from the main regression model, based on three arguments. First, the decision about trip frequency or means of transportation may be more constrained, as compared to private trips. Second, it is unclear whether such emissions should be attributed to the individual traveling, or added to the emissions for the production of the good or service for which the trip is made, and hence attributed to the consumer household. Third, business travel may create spill-over effects into leisure travel behaviour (see e.g. Cohen et al., 2018), which could cause endogeneity bias. Yet, checking whether the main contributing factors differ when we include business trips may be an interesting base for discussion. The detailed results across quantiles can be found in Appendices 18, 16 and 19.

Total emissions. Most associations are similar for overall mobility emissions, independent of whether business travel is included. The size effect of having a high income tends to be greater when including business travels. Older age and household composition tend to be similar, whether business travels are accounted for or not. However, there are two variables which stand out: employment status and gender. While the effect of being employed is about 50% higher when we include business trips, the negative coefficient for being a woman increases more than threefold.

Long-distance emissions. The pattern looks rather similar for long-distance emissions. Income tends to have a greater effect on emissions once we include business emissions, and we observe the same differences for gender and unemployment, gender playing a greater role in the regression with business emissions while unemployment becomes significant. Having a second home also becomes significant, and has a strong effect once we include business trips. The causality for the latter likely runs in the opposite direction, meaning that those who often travel to a specific place on business are more likely to maintain a second home there. Conversely, car ownership, becomes insignificant when we account for business emissions. We also observe some changes in the effect of attitude towards transportation modes.

Daily emissions. For daily mobility, most coefficients are fairly similar when including business travels.

6 Conclusions

This article studies the greenhouse gas emissions from individual mobility in Germany. Using a recent mobility survey, we document the unequal contribution of individuals to emissions. We show that the top 10% of emitters contribute respectively to 51% of total mobility-related emissions, and to 80% of long-distance travel emissions. This stresses the importance of better understanding the drivers of these high-emitters for effective emission mitigation policies in the transport sector.

We thus analyse the drivers of mobility emissions for different categories of emitters. Performing a quantile regression allows us to highlight how socio-economic, demographic and attitudinal drivers affect total mobility emissions as well as emissions from daily versus long-distance travels. Our results confirm findings from the literature that higher income and education both correlate positively with emissions from all types of mobility. However, the effect of income seems to saturate at some point, and the coefficients for the two highest income groups are similar in magnitude. In addition, the results also reveal that the relevance of various drivers differs across emitter groups and depends on the type of travel performed.

The most important drivers for day-to-day mobility emissions are a high household income, enjoying to drive and car ownership, as well as tertiary education. Each of these characteristics is associated with additional emissions of more than 1 tCO2e. Long-distance travel emissions are dominated by high incomes and tertiary education. Living in a city is found to lead to fewer emissions overall, an effect that is driven by the decrease in daily emissions, and outweighs the countervailing increase in long-distance trips.

Besides socio-economic and demographic variables, we also analyse the role of attitudes towards different transportation modes. In terms of coefficient size, a positive attitude regarding the car is particularly relevant for total emissions. This effect is mainly driven by the clear association between attitude towards the car and daily emissions, suggesting an important role of preferences on the modal choice and distance traveled for commuting and daily leisure. At the same time, we find that enjoying to drive a car is associated with lower air travel emissions among 'super-flyers' (top 1%), suggesting some substitution of even more polluting long-distance travel by car in our sample.

Attitudes towards more sustainable transportation modes are also significantly associated with differences in mobility emissions. A positive attitude towards public transport, for instance, is associated with lower daily emissions, particularly in higher emitter groups. Enjoying to bike is associated with higher daily emissions among high emitters and with higher long-distance emissions among lower emitter groups.

While we establish robust links between mobility emissions and different socio-economic and attitudinal characteristics of individuals, more research is needed to uncover the causal mechanisms behind these associations. An important limitation with respect to the data set is the short reporting period for daily emissions (one sample day). Regarding the role of psychological factors in mobility decisions, we are limited by data availability and thus solely focus on attitudes to different transport modes. Hence our study is by no means exhaustive on the psychological side. While attitudes have been shown to be important - and we found significant effects - one might argue that broader values or worldviews should be considered as well. A serious criticism of attitudes specifically has recently been raised by (van Wee et al., 2019) and (Moody and Zhao, 2020). They stress the importance of the built environment and travel behaviours on the formation of attitudes (Mattauch et al., 2016), which raises concerns regarding reverse causality (in our case from travel emissions to attitudes). This is a topic that needs further investigation before causal inferences can be drawn.

All in all, our results point to strong heterogeneity in the effect of socio-economic and attitudinal drivers on emissions, which need to be considered to design climate policies. For instance, knowing that enjoyment of distinct transport modes is relevant at different points of the emitter distribution can help better target information policies or infrastructure development. Focusing on high-emitters could significantly increase abatement potential, given the share of emissions they represent. Our findings can further be used to better understand the distributional effects of transportation policies. The importance of drivers beyond income suggest that these policies could have strong effects on horizontal equity.

Code availability

We performed the analysis and built figures using R and Stata. The code is available on Github at the following link: https://github.com/ntaconet/Mobility_Germany/. The German Household Mobility survey is not publicly accessible but can be obtained from the Bundesministeriums für Verkehr und digitale Infrastruktur (BMVI).

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- The study examines the distribution of emissions from mobility in Germany and identifies the drivers of these emissions, particularly among high emitters.
- The top 10% of emitters in Germany are found to be responsible for 51% of total emissions from mobility, highlighting the unequal distribution of emissions.
- Emissions from long-distance travel are particularly concentrated among high emitters, with the top 10% accounting for 80% of emissions in this category.
- Socio-economic factors, such as income and location, significantly influence emissions from mobility across different levels of emitters.
- Attitudes towards different transportation modes are shown to strongly correlate with variations in mobility behaviors and emissions, underscoring the importance of behavioral factors.