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Mobility Gini: distributional effects of climate policies through transportation choices

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Abstract

The energy transition implies significant changes for the transport sector. In particular, the mobility of households will be largely impacted by public policies aiming at mitigating climate change. However, such policies may have adverse distributional effects that enhance the mobility cost for low-income people or even prevent them from being mobile. Therefore, we build a geographical distribution index based on availability and costs of transportation - a Mobility Gini. This index encompasses household heterogeneity towards transportation choices, household value of travel time and comfort, and transportation offers in the different regions. In addition, we develop the Emissions Mobility Gini to account for lack of access to clean transport. To understand the decision making process of households, we develop a theoretical model of transport choice versus consumption of other goods. With this model, we test the effects of policies for the Just and Clean transition of the transport sector on household choices and their effects on our proposed inequality measures. Thanks to the methods proposed here, we quantify the potential inequality effects of climate policies for the transport transition.

Keywords: household heterogeneity, value of travel time, transportation cost, redistribution, household utility choice model

JEL Codes: R38; R41; D63; R22; Q52; Q56

1 Introduction

The energy transition, as it would be implemented in the European Union, encompasses significant changes in the transport sector. In particular, the mobility of households will be largely impacted by public policies aiming at mitigating climate change. For instance, the announcement of European countries to ban internal combustion engine vehicles (ICEVs)[1] and replace them with electric vehicles (EVs) will impact households directly as the cost of the latter is, in general terms, higher than the former. Such policies may have significant distributional effects. Therefore, we build a geographical distribution index based on availability and costs of transportation - a Mobility Gini - to provide a tool to measure the effects of climate policies on transport inequality.

Climate policies aiming at reducing greenhouse gases (GHG) emissions in the transport sector will impact households depending on their financial and time constraints. For the richest part of the population, for example, owning an electric car is an affordable option. However, if forced to transition, certain households with high shares of transportation spending will have to adjust their expenditures in other areas. Other households will not even be able to transition and will see their options, for instance in terms of choice of housing and work, limited by the places they can reach with public transport. Disparities in mobility presents a distinct form of inequality that should be distinguished from disparities in income distribution. However, it is important to recognize that both income inequality and transportation inequalities contribute to a vicious cycle of poverty and societal imbalance. Insufficient access to transportation reduces individuals' ability to reach employment opportunities, educational institutions, healthcare facilities, and social networks ITF (2017).

While trying to decarbonize the transport sector, the question of how Just and how redistributive will the transition be is yet to be answered. If it worsens inequalities, not only would the cost of the transition for the economy be increased, but the risk that climate policies are not accepted by the population in the first place, hence not implemented, is very high, which may jeopardize the energy transition (see Douenne & Fabre (2022)). It is for these reasons that understanding current transport disparities trends and how it would be affected by climate policies is key to designing instruments for the transition towards cleaner mobility.

Up until now, the most common indicator accounting for the real value of transportation time (VOTT) does not consider the heterogeneity of consumers (nor of the households), see for instance Wardman et al. (2016). The phrase "time is money" is used often but does not account for the fact that those at the highest income level enjoy a higher degree of comfort in transportation (e.g. they can spend less time on public transport or use solely a private car for their travel needs), while those at the lowest income level have to spend extra time traveling by public transportation.

[1] except if they use carbon-neutral fuels, following Germany pushing back against electric vehicles only in summer 2023 https://www.euronews.com/green/2023/03/22/eu-to-ban-petrol-and-diesel-cars-by-2035-heres-why-some-countries-are-pushing-back

Thus, the contribution of this paper is two-fold. First, in order to account for the effect of climate policies on the mobility behavior- change in the amount of transportation and/or in the transportation mode, we build a theoretical model of household choice of transport and consumption. In particular, in addition to VOTT, we account for the concept of *"travel discomfort"*, which refers to all components but the price and time that makes the individuals of the household willing to prefer one transportation over the other. It is mentioned for example in de Grange et al. (2015); Kamplimath et al. (2021); Sekulić et al. (2013); Masoumi (2019); Sivilevivius et al. (2012); Batley et al. (2019b), where it mainly refers to consumer physical and personal comfort, convenience, and enjoyment when traveling.

Second, we create an index capturing the disparities in transportation: a Mobility Gini that accounts for the heterogeneity in households' mobility behaviors, needs and constraints. In line with the existing "Electricity Gini" of Levinson & Silva (2019), the goal of this paper is to build a reproducible methodology to quantify the degree of heterogeneity in transport cost in different regions and for different households. The importance of such a precise index was already highlighted in the works of Levinson & Silva (2019) who argue that income does not fully explain the heterogeneity in (electricity) demand of a household. As a consequence, when building an index of mobility (i.e. transport) inequality we have to take into account not only income but also the needs, constraints and characteristics of the household or the heterogeneity of households (e.g there might be several working people in the household, as in Fanning Madden (1981)).

In addition, we compute Mobility Gini indices with different scopes, depending on whether only monetary and time costs are included or GHG-transport related emissions (with their costs) are included[2]. We have developed an emission Mobility Gini index that accounts for the additional costs in terms of greenhouse gas (GHG) emissions associated with various transport options. We have incorporated GHG emission intensities for distinct pollutants like CO_2, CO, CH_4, NO_x, and $PM10$, reported in emissions per kilometer for each specific transportation means. The resultant emission-based Mobility Gini index serves as a metric highlighting disparities in access to "clean" transportation within specific time frames and regions. Such Mobility Gini indices allow us first to compare income and mobility (i.e. transport) inequalities to appraise the extent to which focusing on the former only is misleading. In addition, we study changes over time in mobility inequalities (due to costs and access to clean transport) to identify recent trends and propose solutions.

The model is tested on the German Mobility Panel (MOP) Survey for the years 2004 to 2020. The model and the Mobility Gini indices are used to simulate shocks due to policies for the transport transition. For instance, we test how distances traveled by each method of transport available to a household and the consumption of other goods would change following a 20% increase in price of cars (due to the ban of combustion engines / introduction of EVs), a 20% decrease in price of cars, and a 15% decrease in the price of bikes (due to subsidies).

[2]The different Mobility Gini indices are further explained in the section 2.5

Our results help explain the behavior of heterogeneous households when faced with climate policies and quantify the degree of inequality before and after a given policy. Our results could serve policy-makers to make informed decisions to design instruments for the energy transition. In addition, our methodology can be easily replicated for all the EU and other countries with National Travel Surveys.

The next section is devoted to the theoretical framework. This section also presents the calibration of the model's parameters, including the values of travel discomfort for each of the transportation modes and defines the Mobility Gini indices. Section 3 presents the data used, while Section 4 provides values for the Mobility Gini indices in Germany. The results of the simulations on the policy shocks and their effects on inequalities are presented in Section 5. Our results allow us to draw policy directions regarding the limitations of income indices and the effect of climate policies on transport poverty before concluding with Section 6.

2 Theoretical framework

2.1 A household model of transportation choice

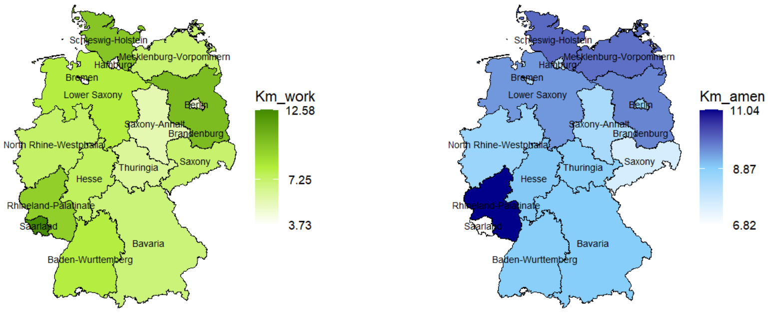
In the following section, we consider a rational household i whose work location and living place are exogenous (and heterogeneous across households).[3] Furthermore, the household has constrained net income, and a limited amount of time. As such, the household has to make trade-offs between different costs of transportation means and consumption. Figure 1 presents the average distances traveled by households for work and for amenities by region, the latter includes all non-work related activities such as shopping, running errands, leisure, dropping off or picking someone up. Figure 1 shows that this distance traveled by households daily for amenities is very heterogeneous among German regions. For each means of transportation j, distance traveled for amenities can be written as a fraction α_j of the total distance traveled d_j, hence distance traveled for amenities is simply $\sum_j \alpha_j d_j$ and provides a proxy for the utility of a leisure good.

The total traveled distance of each household can be explained as the sum of the distance traveled for amenities and for work using all transportation methods. We consider the existence of six different means of transportation j which are respectively: 1) Foot, 2) Bike, 3) Car, 4) Motorbike, 5) Public Transportation - inner city (i.e., City Bus, Tram/Metro and Urban train) 6) Trains (i.e. Long distance trains inter regions). For illustration, Figure 2 presents the heterogeneity in total distance traveled combining their use for both amenities and work in each region (for selected methods). See section 3 for details on the transportation use per transportation means and by purposes.

The utility also depends on the other goods the household can purchase, x (considered

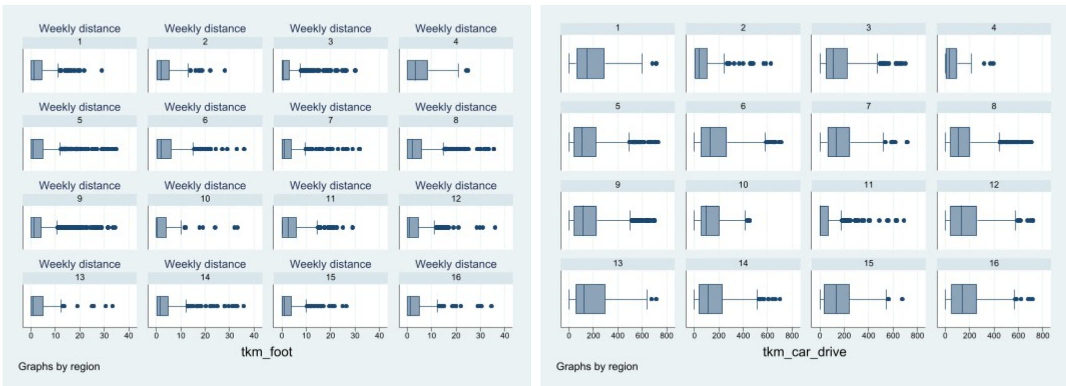
[3]This paper is not about the choice of the place of living or work location but once these decisions are made, on the arbitrage between transportation utility and costs, based on transportation options. We consider that once the choice of the household location is made it stays constant over the time period studied.

Figure 1: Daily distances for work and amenities



Notes: The daily distances shown are the average at household level per region. For comparison purpose, we present both the distances traveled for work (Km_work on the Left hand side) and for amenities (Km_amen on the right hand side). Amenities include going shopping, running errands, leisure, dropping of or picking someone up. It excludes going to work and work-related trips.

Figure 2: Heterogeneity in total distances traveled



Note: Boxplots illustrate the highly heterogeneous weekly distances traveled by foot and by car for the households in each region in our sample.

homogeneous among households), the amount of non-leisure time, that includes travel and working time, and the travel discomfort[4] (TD) the individuals of the household experienced by using different means of transportation that arises with the transportation means used for work and amenities. We also introduced a component accounting for leisure time, i.e. the time spent for the non-work and non-travel related activities, noted a for amusement. Therefore, the utility is :

$$U\left(\sum_j \alpha_j d_j, x, a, TD\right) \tag{1}$$

where the first derivatives with respect to the amenities related travels $\sum_j \alpha_j d_j$, the consumption good x and amusement time a are positive while it is negative for the travel discomfort TD.

[4]The travel discomfort is further explained in Section 2.2

Considering the place of work as household specific though exogenous,[5] the rational household maximizes its utility by choosing distances traveled with each transportation means $\sum d_j$ together with the amount of consumption x, taking into account the budget constraint (2) and the time constraint (3):

$$\bar{T} * w = x + c + w * a \tag{2}$$

$$\bar{T} = t + \sum_j \frac{d_j}{\bar{s_j}} + a \tag{3}$$

where $\bar{T}$ is the total number of hours, w is hourly wage and c the cost of transportation time. t is the working time, d_j is the distance traveled using transportation means j whose speed is s_j

Hence, $\sum_j \frac{d_j}{s_j}$ is the time spent in transportation.

The total financial transportation cost of each household c can be written as the sum of the distance traveled by each transport mode d_j times the ride cost of each transport mode r_j. It can be expressed as follows:

$$c = \sum_j d_j * r_j \tag{4}$$

The ride cost r_j can be further decomposed and depends on the levelized cost per kilometer $LCOKm$ (here after always noted as L_j[6]), the wage w, and the speed s_j of travel. It can be written as follows:

$$r_j = L_j + \frac{w}{s_j} \tag{5}$$

Hence the total financial cost encompasses both the user cost $(d_j * L_j)$ and the opportunity cost of time $(d_j * w/s_j)$ of each transportation means j. Do note that though convenient for modeling, the LCOKm bears the drawbacks of being endogenous with respect to the distance as a longer distance spread the acquisition over more kilometers. In what follows, we assume that the change in distance is small enough not to significantly affect the LCOKm.

2.2 Travel discomfort

This paper completes the literature by estimating the heterogeneous travel discomfort of consumers. In the literature, the travel discomfort term is mentioned for example in de Grange et al. (2015); Kamplimath et al. (2021); Sekulić et al. (2013); Masoumi (2019); Sivilevivius et al. (2012), where it mainly refers to consumer physical and personal comfort, convenience, and enjoyment when traveling. Travel discomfort usually refers to all components, but the price, that make the consumer willing to prefer one transportation

[5]This implies that the individual has no other choice for the work location.

[6]The detail of the formulas to calculate L_j, the levelized cost of traveling 1km by transport method j, can be found in Appendix A. For more details on L_j see Rangel Guevara (2024).

means over the other transportation options. For instance, it captures the value of reliability (VOR) of transportation that is shown to be significative in the literature (see Small (2012) or Borjesson et al. (2012)). However, it also encompasses time spent in the transportation means (see de Lapparent & Koning (2016); Kumagai et al. (2021); Kisgyorgy & Toth (2020); Schmid et al. (2021); Haywood & Koning (2015); Nalmpantis et al. (2019); Zhang et al. (2019); Fu & Farber (2017); de Moraes Ramos et al. (2020)). As a result, it is often called "value of time". This means that it mixes the two concepts of opportunity cost of time and the real (dis)comfort during the travel, and is therefore rather qualified as "value of *travel* time".

However we want to disentangle the two concepts. We already account for the opportunity cost of time through the financial transportation cost r_j. We consider separately the travel discomfort as the (dis)utility of the household with respect to the comfort of transportation means. Hence, in this paper travel discomfort refers to all components, but price *and time*, that make the consumer willing to prefer one transportation means over the other transportation options. This travel discomfort TD_j is dependent on the household's socio-economic characteristics but also on the means of transportation j, its speed s_j and the distance traveled d_j:

$$TD_j = \beta_j(d_j)\frac{d_j}{s_j} \tag{6}$$

where $\beta_j(d_j)$ is the discomfort for the household of 1h traveled with transportation means j (hence $\beta_j < 0$ if the household enjoys its traveled time). The discomfort coefficients measured (β_j is a function of d_j; in particular, it could be non-monotonous with respect to distance. For instance for small distances, the discomfort per hour could be decreasing with the distance while for large distances, it could be increasing with the distance. The betas represent observed discomfort, as estimated by our model using data from the survey. Beta is by km but used to construct TD which is for 1h. We aim at producing an heterogeneous travel discomfort value for each transportation means, accounting for various household socio-economic characteristics.

To the best of our knowledge, such a comprehensive indicator contributes to the literature by providing a micro-economical and more feasible way of decomposing the value of time vs. discomfort[7] In the existing literature, it is currently addressed through the deployment of large Stated Preference (SP) surveys combined with the use of Random Utility Models (RUM) to decompose the heterogeneity of consumers. The results allow to obtain willingness-to-pay (WTP) for travel time savings and/or elasticities with respect to income, distance, time and costs (Hess et al., 2017; Batley et al., 2019a). This type of work is cumbersome and may induce biases between the estimates recovered via SP vs. Revealed Preference (RP) studies.[8]. The estimates of discomfort proposed here are

[7] The discomfort value we are defining in this paper does not depend on the use of the transport type for work or non-work related purpose. We consider that the household endure the same discomfort regardless the purpose of the journey.

[8] In particular, *hypothetical bias* arises in SP experiments as the individuals may overstate their preferences since they are not facing trade-offs in real life (Loomis, 2011)

calculated from data on daily life choices of the households, via a National Travel Survey.[9] Due to the nature of our data and the methodology used, they can be considered a more accurate representation of the reality.

2.3 Solving for consumption and transportation

We assume a specification for the utility function, that is separable between (i) a CES combination of leisure and consumption goods, (ii) disutility of non-leisure time (*i.e.* time spent working or in transportation) and (iii) travel discomfort with respect to all transportation means used by the household:

$$U = \left[\gamma \ln(\sum_j \alpha_j d_j) + (1-\gamma)\ln(x)\right] - \frac{\delta}{2}\left(t + \sum_j \frac{d_j}{s_j}\right)^2 - \sum_j \beta_j(d_j)\frac{d_j}{s_j} \tag{7}$$

where the elasticity of substitution between the leisure good (which is here proxied by the total distances traveled for amenities purposes $\sum_j \alpha_j d_j$) and the consumption good x is equal to one.[10] Non leisure time is $\left(t + \sum_j \frac{d_j}{s_j}\right)$ and its disutility is specified using an analogy with the disutility of work (see Eichenbaum et al. (2020)). Recall that $\beta_j(d_j)$ is the discomfort for the household of 1h traveled, that is a function of d_j. As can be observed in equation (7), the last element in the utility relates to a (dis)utility related to the time spent in transportation means, that does neither come the distance it allows to cover (which in the first element), nor from the time lost in transportation (which is in the second element); hence it does qualify to measure discomfort.

The program of the household implies maximizing (7) with respect to x, t and d_j, subject to the budget constraint, obtained using equations (3)-(5):

$$w.t = x + \sum_j d_j * L_j$$

The first order conditions with respect to x and d_j (t is provided by the budget constraint) are respectively:

$$\frac{1-\gamma}{x} = \frac{\delta}{w}\left(t + \sum_j \frac{d_j}{s_j}\right) \tag{8}$$

$$\frac{\gamma\alpha_j}{\sum_j \alpha_j d_j} = \frac{\delta}{s_j}\left(t + \sum_j \frac{d_j}{s_j}\right) + L_j\frac{\delta}{w}\left(t + \sum_j \frac{d_j}{s_j}\right) + \frac{\beta_j(d_j)}{s_j} + \frac{\partial\beta_j(d_j)}{\partial d_j}\frac{d_j}{s_j} \tag{9}$$

Equation (9) shows the transportation - consumption arbitrage. The marginal utility of traveling, as it contributes to the leisure good (left hand side of Eq.(9)), equals the "value of travel time" (VOTT) usually studied in the literature (right hand side of Eq.(9)).

[9]Note that this type of survey is already available for all EU countries, thus, the estimations can be replicated for all EU countries.

[10]It is assumed to be equal to the intertemporal elasticity of substitution (or the inverse of the risk aversion)

However, we distinguish here clearly the different components of VOTT. It encompasses the opportunity cost of time in terms of utility (first term on the right hand side), the user cost in terms of utility (second term on the right hand side), discomfort per hour and per kilometer (third term on the right hand side) and the contribution to per hour discomfort of the next km (fourth term on the right hand side).

The elasticity of the distance traveled with respect to the levelized cost of 1km can then be computed analytically (one could compute the one with respect to each component of VOTT as well):

$$\frac{\Delta d_j/d_j}{\Delta L_j/L_j} = -\frac{(1-\gamma)/x + g(L_j,x,d_j)d_j}{\gamma(\sum_j d_j L_j)^{-2}\alpha_j^2 + f(\beta_j,d_j) + g(L_j,x,d_j)\left(\frac{w}{s_j}+L_j\right)}\frac{L_j}{d_j} \tag{10}$$

where $g(L_j,x,d_j) = \frac{1-\gamma}{x^2}\left(\frac{w}{s_j}+L_j\right))/(1+\frac{w^2}{\delta}(1-\gamma)x^{-2})$
and $f(\beta_j,d_j) = \partial\left(\frac{\beta_j(d_j)}{s_j} + \frac{\partial\beta_j(d_j)}{\partial d_j}\frac{d_j}{s_j}\right)/\partial d_j$.

After calibration one can make comparative statics on price for instance, using the first order conditions and the budget constraint:

$$x = \frac{(1-\gamma)w}{\delta\left(t+\sum_j \frac{d_j}{s_j}\right)}$$

$$t = (x + \sum_j d_j L_j)/w$$

$$d_j = \frac{s_j}{2\beta_j}\left[\frac{\gamma\alpha_j}{\sum_j \alpha_j d_j} - \frac{1-\gamma}{x}\left(\frac{w}{s_j}+L_j\right)\right]$$

that needs to be solved simultaneously, with $j \in 1;6$ which are respectively: 1) Foot, 2) Bike, 3) Car, 4) Motorbike, 5) PT - public transportation inner city (City Bus, Tram/Metro and urban train) and 6) Trains (trains inter regions).

2.4 Calibration

Parameters α_j, s_j, β_j and L_j depend on the transportation mean j. Based on the data, the above mentioned parameters and w are heterogeneous across households. δ is common across time and agents and taken equal to 0.0005.[11] All the other parameters are estimated from our data at household level and vary across time and households. Parameters α_j, s_j, and L_j and w are directly taken from the data described in section 3. γ is calculated from our sample and its means is used homogeneously across our sample. The function $\beta_j(d_j)$ needs to be specified. Assuming $\beta_j(d_j) = \beta_j d_j$ (hence $\frac{\partial\beta_j(d_j)}{\partial d_j} = \beta_j$), we adopt the following calibration strategy: the jth equation (9) provides the β_j:

[11] Since this parameter is common to all agents, we have chosen one characteristics of the model to fit observed data. In particular, $\delta = 0.0005$ allows the theoretical model to reproduce the average value of the price elasticity of travels by train -which depends on δ, see equation (10) -obtained with two econometric models that are relatively robust in the sense that they differ according to their control variables.

$$\beta_j = \frac{s_j}{2d_j}\left[\frac{\gamma\alpha_j}{\sum_j \alpha_j d_j} - \frac{1-\gamma}{x}\left(\frac{w}{s_j} + L_j\right)\right] \tag{11}$$

Therefore, we obtain an endogenous measure of discomfort per hour, that is determined by the model. In addition, γ is calibrated such that the consumption-leisure arbitrage (equation (8) is satisfied. The summary statistics for parameters γ and β_j that will be used for policy simulation can be found in Table 1.

It already shows the great heterogeneity of per hour discomfort within our sample. The ranking of the βs is in line with the existing literature on Germany (Follmer & Gruschwitz (2019)) or other countries (see Raymundo & Reis (2017) for Japan), particularly regarding the relatively high comfort associated with car and motorbike use. In our case, trains emerge as the most comfortable mode, followed by motorbikes and cars. This supports literature suggesting that long-distance or regional rail is perceived as more reliable and less stressful, especially compared to crowded urban transit systems (Tirachini et al., 2016, 2017; Li & Hensher, 2011). We found that public transportation (inner city) ranks poorly. Indeed, crowding in public transportation is a major issue in particular for commuters.[12] However, we find that walking and biking exhibit the highest levels of perceived discomfort. The relatively high discomfort associated with walking and biking is also consistent with studies highlighting the physical effort or infrastructure constraints involved in active modes (Heinen et al., 2010; International Transport Forum, 2021). Additional details can be found in the Appendix Tables 12 and 13, where we report the estimated β values for walking and biking by region and year. These tables highlight significant spatial and temporal variation across the sample, reinforcing the importance of local infrastructure conditions that is an issue also emphasized in the OECD/ITF report on improving active mobility (i.e., walking and biking) infrastructure (International Transport Forum, 2021).

Table 1: Calibration parameters

Parameter	γ	β_{foot}	β_{bike}	β_{car}	β_{moto}	β_{pt}	β_{train}
Mean	0.4648	0.0714	0.0671	0.0151	0.0068	0.0273	-0.0079
SD	0	0.1534	0.1153	0.0661	0.1707	0.0940	0.1090

Notes: γ is homogeneous and calculated from the sample. The higher the β the larger the discomfort per hour. The data presented in this table are the parameters used for the policy simulations presented in Section 5. Missing data (for speed and share of amenities over work related trips) were replaced by yearly-regional averages.

[12]See Haywood et al. (2017) for an empirical study based on a survey made in Paris, Tirachini et al. (2017) for a survey and stated choice study of users of Santiago's subway system, Tirachini et al. (2016) for a study based observed behavior of a subset of metro users in Singapore or Li & Hensher (2011) for a review of public transport crowding valuation research, using a number of primary studies conducted in the UK, USA, Australia and Israel.

2.5 Income Gini, Mobility Gini & Emission Mobility Gini indices

The Gini indices are calculated following (Jenkins, 2021)[13] and are given by:

$$Gini = 1 + \frac{1}{N} - \left(\frac{2}{m * N^2}\right) * \left(\sum_i (N - i + 1) * var_i\right) \tag{12}$$

where var_i is any variable we want to study the distribution of. Households are ranked in ascending order of var_i and i representing a household, N the total number of households in the sample and m the arithmetic mean of var_i. Keeping the Gini equation (12) in mind, we successively consider different variables for var_i.

First, using the data detailed in Section 3, we calculate the Income Gini for the sample studied, where var_i represents monthly income.

Second, we build a Mobility Gini index (MGini) that represents inequality in transportation cost, accounting not only for the monetary cost of using transportation means to travel distances d_j (that is, $L_j * d_j$) that is paid by the household, but also the value of travel time of the household, that is approximated through the time spent in the transportation means and the wage of the household (that is, $w * d_j/s_j$), such as:

$$var_i^{MGini} = \sum_j d_{ji} * r_{ji} = \sum_j d_{ji} * \left(L_{ji} + \frac{w_i}{s_{ji}}\right) \tag{13}$$

Do note that MGini also captures differences of use of transport and access to mobility (through d_j) and accounts for heterogeneity in households across a given time and region.

Third, an Emission Mobility Gini (EMGini) is built from the Mobility Gini (MGini) by adding a cost in terms of GHG emissions related to the transportation modes. The GHG emission intensities e_{kj} are based on the k different GHG pollutants: CO_2, CO, CH_4, NO_x and $PM10$ reported in emission per kilometer of each transportation means j. As the National Travel Survey details the type of vehicle used by the household, we are able to compare petrol versus diesel cars and allocate their respective emission costs as needed.[14] Emissions' cost is added to the other costs, using their value p_{ek} to convert it into euros. The EMGini can shed light with regards to disparities in access to "clean" transport in a given time/region combination, hence showing how climate policy might affect this source of inequality.

$$var_i^{EMGini} = \sum_j d_{ji} * \left(\sum_k e_{kj} * p_{ek} + r_{ji}\right) \tag{14}$$

Finally, we are also interested in understanding whether changes in inequality are driven by changes in the loss of time inequality or transport cost inequality. Hence, we also

[13] We used the ineqdeco package of STATA

[14] As we have data until 2018, our sample is limited in the number of electric vehicles so we refrain from drawing conclusions regarding these vehicles.

decompose MGini into a cost part, MGini$_C$ that is related to the inequality in $C_i = \sum_j d_{j,i} L_{j,i}$ and a time part, MGini$_T$ that is related to the inequality in $T_i = \sum_j \frac{d_{j,i}}{s_{j,i}} w_i$:

$$MGini = 1 + \frac{1}{N} - \frac{2}{N^2} \frac{\sum_i (N-i+1)(C_i + T_i)}{\frac{\sum_i C_i + T_i}{N}} = 1 + \frac{1}{N} + MGini_C + MGini_T \quad (15)$$

with

$$MGini_C = -\frac{2}{N^2} \frac{\sum_i (N-i+1) C_i}{\frac{\sum_i C_i + T_i}{N}} \quad \text{and} \quad MGini_T = -\frac{2}{N^2} \frac{\sum_i (N-i+1) T_i}{\frac{\sum_i C_i + T_i}{N}}$$

3 Data

We exploit the German Mobility Panel (MOP) survey for the years 2004 to 2020. The data is provided by the German Aerospace Center - Institute for Transport Research (DLR) and has been collected annually since 1994. The survey relies on rotating panels every three years to limit the bias in respondent's answers.[15] Interviewees are asked to fill seven-day travel diaries once per year. The seven-day travel diaries record the purpose, the transportation mean chosen, the travel time, the distance traveled and the number of trips taken.

The survey includes different purposes for traveling, such as, for work, to work, to go to school, for errands or shopping, for hobbies, to pick up or drop off someone and other private activities. For the purpose of this study, we have combined most of the purposes under a newly created category: "amenities". Amenities account for all travels excluding those related to or for work. It includes travels to go to school, for errands or shopping, for hobbies, to pick up or drop off someone and other private activities. Figure 1 (in Section 1) represents graphically the daily average and maximum distances traveled for amenities by an individual in each region of Germany.

In addition, the survey includes an exhaustive list of possible methods of transport. However, we focus on the most commonly used methods of transport, such as foot, bike, car, motorbike, citybus, tramway, urbanrail and longtrain. We group public transport methods into two subgroups i) inner-city public transport (citybus, tramway, urbanrail), that hereafter is named "pt", which are all accessible by purchasing a public transport card and ii) inter-city public transport (inter region/cities), hereafter named "train" which is accessible by purchasing a forfait (bahncard).

The remaining of this section is divided in three main parts to explain in detail the data sets used for transport trends, transport pricing and labor related variables used in the article.

[15] In other words, a household will not participate in the study for more than three consecutive years.

3.1 Transportation trends

Table 2 presents weekly distances traveled[16] for our full sample vs. for users only.[17] For each transportation modes, the travels are decomposed between the ones for amenities (all non-work related trips) and for work.[18]

Table 2: Weekly distance by method and purpose for households

	Full sample					*Users only*				
Method	N	Avg.	SD	Min.	Max.	N	Avg.	SD	Min.	Max.
Panel A: To amenities										
Foot	7,011	1.2	2.47	0	20.45	4447	1.9	2.88	0	20.45
Bike	7,016	0.99	3.35	0	34	2049	3.38	5.5	0.01	34
Car	6,994	57.76	71.44	0	431.43	5931	68.12	72.89	0.02	431.43
Moto	6,968	0.04	0.35	0	6	154	1.7	1.69	0.02	6
Innercity PT	7,042	2.28	13.5	0	722.4	1681	9.53	26.35	0.01	722.4
Train	6,976	0.59	3.52	0	42.17	326	12.66	10.64	0.09	42.17
Panel B: To work										
Foot	6,544	0.2	0.72	0	6	1208	1.06	1.37	0.01	6
Bike	6,548	1.27	4.2	0	31.2	1030	8.06	7.58	0.03	31.2
Car	6,559	56.59	73.17	0	390	4943	75.1	75.59	0.04	390
Moto	6,550	0.08	0.76	0	12	107	4.82	3.61	0.04	12
Innercity PT	6,385	4.79	16.01	0	128.57	1126	27.19	29.08	0.1	128.57
Train	6,551	1.48	10.93	0	145	211	46.1	40.7	0.22	145

Notes: The table presents distances traveled by each mode of transport j for amenities (Panel A) and for work (Panel B). We present statistics corresponding to the full sample and for users only (excludes households who do not use a given method for the specific purpose). Reading: The average household in our sample travels about 1.2km by foot to reach amenities and 0.2km by foot to reach work. If we exclude households who do not walk as their main transport mode, the households walk, on average, 1.9km and 1.05km to amenities and to work, respectively.

From Table 2 we observe the most common method of transport is by car, regardless of the purpose of the journey. The share of total distance traveled per transportation mode, α, can be found in Appendix. While "train" covers a large share of the distance traveled for certain households, the number of households using this method of transport is relatively small compared to other methods of transport like car, foot or bike, as shown in the last column. The top three most used methods of transport are car, foot and bike. The least used methods of transport are motorbike and train.

[16] The distances shown in Table 2 are logged one way only. For instance, the distance to work is measured only from home to work. A trip to and from work would account for $4.72 \times 2 = 9.44$ km/day. However, individuals do not always go to work and come back directly to their home. Thus, distance is logged one way and the variable "to go back home" accounts for all the distance traveled to go home in a given day.

[17] Meaning those who actually use the mode of transport j for their travel to either amenities or to work.

[18] All variables used in calculations were winsorized at 1% level.

3.2 Transportation costs

One important aspect for the calculation of the Mobility Gini and the calibration exercise is to obtain values for the levelized cost for each method of transport (L_j). In order to quantify regional differences in transportation pricing, we exploit several databases to obtain the levelized cost for each transportation method. For instance, to calculate the purchase price of private cars we exploit a 1.5 million data set[19] of second-hand car advertisements including variables such as the make, model, year, fuel type and city. In addition, to calculate the purchase price of motorbikes, bikes and public transportation we exploit regional data and use CPI indices for transportation to calculate for other years. Table 3 and Table 4 summarize respectively the main variables used in the calculation of the L_j and of the costs for the emission mobility Gini (EMGini) for each method of transport selected.

The L_j is a particular relevant measure as not accounting for all expenditures related to asset-ownership (i.e., car) can result in an underestimation of the burden on the household (Eisenmann & Kuhnimhof, 2018; Rangel Guevara, 2024).[20]

Table 3: Per kilometer transportation costs (L_j)

Variable	N	Avg.	SD	Min.	Max.	Source	Heterogeneity
Panel A: Fuel/Elec. prices							
Petrol price (liter)	7066	1.41	0.11	1.13	1.63	MOP	Y,R
Electricity price (kWh)	7068	0.29	0.05	0.19	0.33	EUROSTAT	Y
Panel B: Purchase prices							
Bike	7068	360.04	153.71	84.36	672.05	de.statista.com	Y, R
Car	3770	14508.7	9132.69	0	47421.12	Leparking.fr	Y,R,HH
Moto	7068	18045.09	9967.4	1009.95	37824.38	Motoservices.com	Y, R
PT innercity	7068	64.75	11.47	28.2	104.47	genesis.destatis.de	Y, R
Train	7068	410.71	26.64	346.3	443.61	fahrkarten.bahn.de	Y
Panel C: L_j calculated							
L_{car}	6190	0.39	0.16	0.13	1.86	own calc.	Y,R,HH
L_{bike}	2136	0.88	1.07	0.04	6.7	own calc.	Y,R,HH
L_{moto}	186	4.88	3.97	1.65	29.44	own calc.	Y,R,HH
$L_{innercity}$	1462	4.92	5.99	0.09	57.08	own calc.	Y,R,HH
L_{train}	247	15.22	10.07	4.31	59.11	own calc.	Y,R,HH

Notes: The table above presents summary statistics for all variables (prices of petrol & electricity and purchase price of the asset) used in the calculation of L_j. L_j represents the average cost for one kilometer traveled by mode j. *See Appendix A for formulas. We assume a one year lifetime for public transport tickets and ten years for other assets. Heterogeneity in transport pricing could be due to time effects (Y) and/or region effects (R) and/or household effects (HH) based on the data sources used.*

[19] Given by leparking.fr

[20] In the case of L_{car} results are in line with those reported by Eisenmann & Kuhnimhof (2018) who use a similar methodology to input Total Cost of Ownership (TCO) for a smaller sample of the MOP survey.

Table 4: Emissions level and pricing

Pollutant	Price (€/kg)	E(car(G)) (g/km)	E(car(D)) (g/km)	E(bike) (g/km)	E(e-bike) (g/km)	E(moto) (g/km)	E(train) (g/km)	E(PT) (g/km)
CO2	0.21	166.21	145.81	5	8.5	133.19	33.36	104.09
CO	0.109	1.18	0.06	-	-	4.86	0.04	0.05
PM10	39.4539	0.12	0.46	-	-	0.17	0.17	0.24
NOx	50.7102	0.001	0.004	-	-	0.07	0.003	0.002
CH4	1.98975	0.03	0.03	-	-	1.24	0.01	0.03

Note: The level of emissions are from Byrne et al. (2021). We differentiate between gasoline versus diesel cars and between bike versus e-bike. CO2 prices correspond to the Social Cost of Carbon (SCC) recently published by U.S. Environmental Protection Agency (2023) at around 190USD/ton or 182€/ton. All other prices per pollutant are the middle price estimates extracted from Environmental Prices Handbook 2017 of CE Delft, and they are for 2017. The price are then calculated according to the CPI for 2015 and extrapolated for the other years. CO2 estimates for bike and e-bike are estimated considering their production process.

3.3 Labor related variables

There are two key variables related to the labor needed for this study, income and hours worked for the household. The MOP survey used in this paper includes more than 24,000 households with adults from 18-90 years old being either students, retired, employed part or full time, or people who stay at home. Due to the nature of this study, and the needs of our model, we focus the empirical application on the households with employed adults

over the age of 18 and below the age of 65 who report being employed either part time or full time. Originally, we gather 9,160 observations who meet these criteria but due to missing values in distances traveled, we end up with a final sample of about 7,000 households.

We estimate the total number of hours worked per individual and per household from our sample. Figure 3 shows the distribution of total monthly hours worked for the sample. On average a household works 164 hours per month.

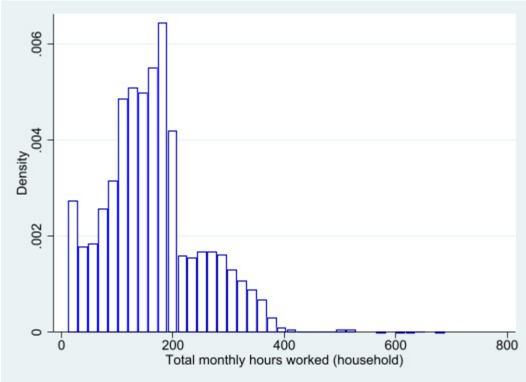
Net income is presented by the MOP survey as a categorical variable based on income brackets. To overcome this limitation, for a given household belonging to each income bracket, we randomly assign a net income assuming a normal distribution inside the income bracket. Thus, we guarantee that the household will have a net income inside the income bracket it announced.[21] Table 5 presents summary statistics for key labor variables used in this study.

Finally, Figure 4 portrays the distribution of the average wage per hour of the households in the sample. The average wage per hour per household is 32€[22] and the total wage per household per hour is 44€.

[21] See Appendix D for step by step process.

[22] This is higher than the average hourly wage in Germany as provided by the OECD Database which is about 12€for our sample (over 15 years).

Figure 3: Monthly hours worked (household).



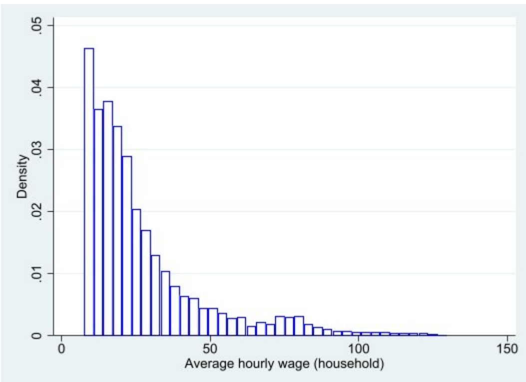
Notes: The figure presents total monthly hours worked per household. The average for the sample is 164 hours per month per household - which is in adequation with the OECD Data for Germany that mention a weekly average of 34hours

Table 5: Labor related variables

Variable	Min.	Avg.	Max.	SD.	N
Monthly income	1060.92	2601	5760.58	1087.48	7474
Monthly hours worked	12.2	163.95	688.83	85.5	7474
Average wage per hour	7.57	31.61	138.95	29.52	7474
Total wage per hour	7.57	43.92	458.74	43.62	7474

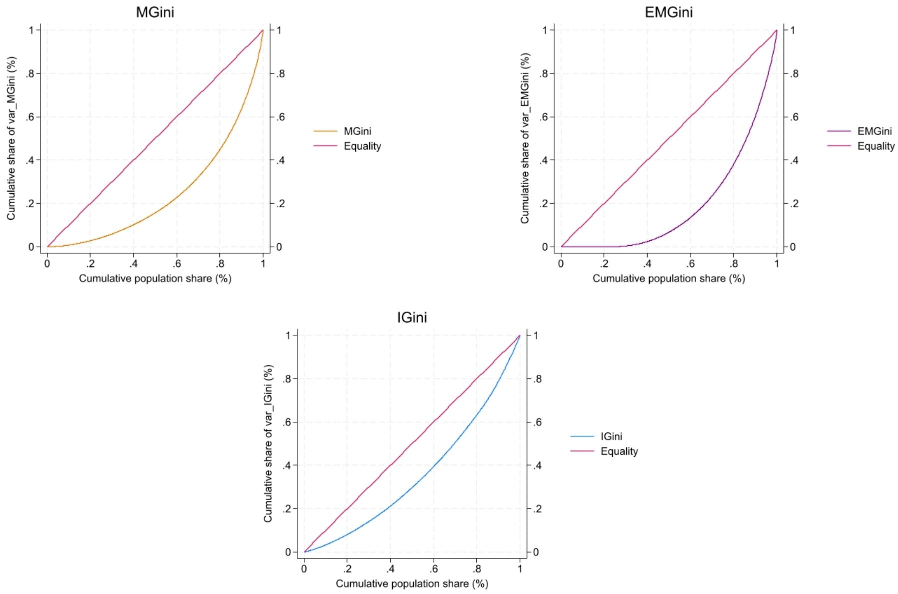
Note: The table presents statistics at the household level for fully employed households, i.e. households whose adults report being in the labor force. The average wage refers to the mean hourly income of working household members within the same household, while the total wage represents the sum of all individual hourly wages earned by household members.

Figure 4: Average hourly wage (household).



Notes: The figure presents the average wage per hour for a household taking into account all employed individuals. The average wage per hour is 32€.

Figure 5: Differences in Lorenz curves



4 Results on Ginis

We conduct our analysis both at the national and the region-year level. The latter level allows us to account for spatial and temporal heterogeneity, hence to capture subnational variation in mobility inequality. Table 6 presents summary statistics for the main Gini indices. We present here the results that are weighted for the population.[23]

From the yearly Gini indices computed with our country sample, we observe that income inequality is lower than both measures of transport inequality (Table 6). On average, IGini is around 0.21 while the MGini and the EMGini are around 0.5 and 0.62, respectively. Do note that the EMGini exhibits larger variation (SD) than the MGini. A similar story occurs when accounting for the heterogeneity in regions and years.[24] The average IGini is around 0.19 while the MGini and the EMGini are around 0.46 and 0.58, respectively. Figure 5 illustrates the difference in the corresponding three Lorenz curves showing that the bottom 40% of the population contribute very few to the transportation costs, in particular once pollution costs are accounted for: people who spend the less on transportation basically do not contribute at all to emissions.

Regarding the decomposition of the MGini proposed in equation (15), we find that the results are driven by both time and cost with a larger role played by time: $MGini_T = -0.31$ and $MGini_C = -0.18$ (see Table 11 in Appendix).

When analyzing data across time and regions, we obtain that there is a smaller difference between the MGini and the EMGini than between the IGini and MGini. This may be due to the current relatively low value associated with carbon and other air pollutions.

[23] We do so to account for the weight of the different types of household in the German population which is needed to compute a meaningful Gini index. This is done using the extrapolation factor at household level of the survey accounting for place of residence, household size, car ownership.

[24] Do note that two regions have been dropped due to lack of data.

Table 6: Gini indices

Index	Dimension(s)	Obs	Mean	SD	Min	Max
MGini	Y	15	0.5	0.01	0.48	0.53
EMGini	Y	15	0.62	0.05	0.58	0.73
IGini	Y	15	0.21	0.03	0.17	0.25
MGini	Y,R	210	0.46	0.08	0.13	0.68
EMGini	Y,R	210	0.58	0.11	0.26	0.86
IGini	Y,R	210	0.19	0.05	0.04	0.3

Note: The table summarizes our calculations of Mobility, Emissions-Mobility & Income Gini indices. The first three rows present Gini indices calculated by year for the whole country. The last three rows present Gini indices calculated for each region/year combination (note that two regions have been dropped due to lack of data).

Table 7 shows the correlation results for income, mobility and emission mobility inequalities and in the appendix, Figure 6 illustrates the distribution of the three Gini indices. Regression results show a statistically significant positive correlation between the Gini indices; in particular, there is a 48% correlation between the Income Gini and MGini, and a 71% correlation between the Income Gini and the EMGini. However, the Granger causality test indicates that there is no causality between neither the MGini and IGini[25] nor the EMGini and IGini.[26] Therefore, policies that reduce income inequality will not automatically reduce mobility inequality (and vice versa) and targeted interventions are needed.

Table 7: Correlation of MGini, EMGini and IGini

Dependant Variable:	*MGini*	*EMGini*
IGini	0.477***	0.709***
	(0.181)	(0.239)
Year FE	Y	Y
Region FE	Y	Y
N	210	210

Note: Standard errors are reported below the estimates. The significance levels are indicated such as * p $<$ 0.10, ** p $<$ 0.05,*** p $<$ 0.01. There is a positive correlation between our Mobility Indices and the income Gini (IGini).

In line with the works of Levinson & Silva (2019) for electricity, we come to the conclusion that income cannot explain all the choices a household makes regarding transportation (such as car purchase, method of transport, distances driven). For the case of Germany,

[25] H_0: IGini does not Granger-cause MGini & H_1: IGini does Granger-cause MGini for at least one panel (region). Lag(1). $\bar{W} = 1.1531$. $\bar{Z} = -0.3868$, $p = 0.6989$. $\tilde{Z} = -0.6672$, $p = 0.5046$

[26] H_0: IGini does not Granger-cause EMGini & H_1: H1: IGini does Granger-cause EMGini for at least one panel (region). Lag(1). $\bar{W} = 0.8538$. $\bar{Z} = 0.4052$, $p = 0.6853$. $\tilde{Z} = -0.1251$, $p = 0.9004$

policies for the transition require other dimensions for their impact to be investigated. Consequently, the Gini indices explained in Section 2.5 take us a step further and combine household socio-economic characteristics, travel discomfort, emissions and all transportation pricing for a given region into a more comprehensive Gini regarding the impact on transportation.

We analyze the evolution of transport inequality in Germany between 2004 and 2018. As shown in Figure 7 (Appendix B), the Lorenz curves for both the MGini and EMGini highlight distinct trends. While the MGini remains relatively stable - with a slight increase in inequality driven by rising transport costs for the bottom 70% - the EMGini shows a clear decline, indicating reduced inequality in emissions-related transport burdens. Notably, in 2018, the bottom 40% of the population accounts for an almost negligible share of pollution costs, suggesting significant progress in the distributional equity of cleaner mobility.

We also exploit the panel design of our sample. First, we show the regional heterogeneity in inequality patterns in 2018 on Figure 8 (Appendix B). Second, we quantify the changes in inequality ranking of the years 2010 versus 2018: Figure 9 (in Appendix B) presents the ranking of inequality indices and shows that the most unequal regions in terms of income, are Saxony-Anhalt (in 2018) and Saxony (in 2010). The most unequal regions in terms of mobility (MGini) are Hamburg (in 2018) and Saxony-Anhalt (in 2010). Including emissions (EMGini), the most unequal region was and remains Hamburg (2018 and 2010).

5 Climate policy implications: shocks to transport costs

In this section, we take advantage of the theoretical model in section 2.1 to appraise the effect of climate policies affecting the cost of transportation means, taking work location and living place as given. For one given transportation means (e.g. car), we simulate the impact of an exogenous shock affecting the cost per km of that means, (e.g. L_{car}), on each of the distances driven using each transportation means (i.e. foot, bike, car, motorbike, public transportation and train) which provides information on how the households substitute among different transportation means. As a method of transport i becomes more or less costly, the households can adjust distances traveled using each transportation method $\{1, ..., n\}$, its consumption of other goods x, and the number of hours worked t, with substitution and income effects at play. We then derive the effect of these shocks on mobility inequality, as given by the MGini and the EMGini.

Table 8 portrays the results in percentage change with respect to the values without the shock. Columns (2) and (3) show the change in mobility inequality as appraised by the MGini and EMGini. Columns (4) to (10) detail the allocation of households' resources between the other goods x and the distance driven by transport method d_j.

First, we simulate the impacts of an increase in the carbon price that would rise the cost of ICEVs through a 20% increase in the levelized cost per km of cars. Do note that substitutions between ICEVs and EV are not accounted for in the model; for this reason, we rather measure a short run effect.

Our result stands in the cost effect of an increase in carbon tax that tends to reduce mobility inequality. The mechanism goes through a substitution of travels for consumption as households reduce their mobility but consume more goods. Specifically, we observe that a 20% increase in L_{car} leads to a reduction of 3.7% in MGini. Following an increase in L_{car} of 20%, the households decrease the distance traveled by private car by 5.52%, by train by 2.07% by foot by 2.04%, by bike by 0.47%, by motorbike by 0.31%, and by public transport by 0.24%. As such, they free up resources and increase their consumption of other goods x by 0.29% (*i.e.* the income effect prevails). Hence we can conclude that an increase in the cost of driving cars (for instance through carbon price on ICEVs emissions) cannot be held responsible for increasing the mobility inequality.

Following the shock on L_{car} we also obtain a decrease in EMGini by 2.6%, *i.e.* smaller than the one for MGini. Recall that the EMGini includes the emission's footprint of a household and its respective cost. Hence, having a smaller decrease in EMGini compared to that in MGini means that following a carbon tax, emissions of the bottom population (in terms of costs) decrease less than those of the upper part, which is a desirable feature.

To check whether there exist a linear effect of the cost of driving cars, we simulate a symmetrical shock on the cost of one km driven by car and test the response of households to a reduction of the same magnitude (20%) in L_{car}. Interestingly, it is indeed not the case as a decrease in L_{car} decreases mobility inequality as well. However, mechanisms and magnitudes differ. First, we find that responses are not perfectly symmetrical as a decrease of 20% in L_{car} leads to a decrease in MGini of 1.7% (compared to 3.7% for a 20% increase in L_{car}) and a decrease in EMGini of 1.2% (compared to 2.6% for a 20% increase in L_{car}). Second, even if substitutions occur towards more travels while consumption is reduced (consistent with what is observed for an increase in L_{car}), magnitudes are not similar: following a decrease in L_{car} of 20%, households increase distance traveled by car by 2.44%, by public transport by 1.96%, by foot by 1.69%, by train by 1,4%, and by bike by 1.18%. At the same time, the households reduce distance traveled by motorbike by 0.44% and decrease the consumption of other goods x by 0.29%. Hence, the only perfectly linear reaction comes from consumption, implying that the wedge between the two simulation exercises occurs through the substitution effects between the different modes of transportation. Do note that the result of this simulation exercise suggests that the current mobility cost system is not minimizing mobility inequality (and may not be far from maximizing it).

The last policy tested concern subsidies to soft mobility (-15% for L_{bike}). Interestingly it shows that bikes are substitutable with walk, car and train, while they are complementary with motorbike and public transportation. Finally, the income effect prevails for the impact on consumption, which rises: there is an increase in x of 0.05.

Table 8: Changes in behavior and inequality due to climate policy shocks

Policy	MGini (%Δ)	EMGini (%Δ)	x (%Δ)	d_{foot} (%Δ)	d_{bike} (%Δ)	d_{car} (%Δ)	d_{moto} (%Δ)	d_{pt} (%Δ)	d_{train} (%Δ)
L_{Car} +20%	-3.7	-2.6	0.29	-2.04	-0.47	-5.52	-0.31	-0.24	-2.07
L_{Car} -20%	-1.7	-1.2	-0.29	1.69	1.18	2.44	-0.44	1.96	1.4
L_{Bike} -15%	-2.6	-1.8	0.05	-0.03	0.81	-0.23	0.03	0.24	-0.45

Notes: Columns two and three present the average percentage change of MGINI and EMGINI following selected policies. Columns four to ten present percentage changes in other goods consumed x and distances traveled for each method of transport following selected policies.
Reading: The increase of L_{car} by 20% leads to a decrease in mobility inequalities for both the MGini and EMGini by -3.7% and -2.6% respectively. This is due to the adjustment of the household in terms of x and d_j where the household decreases the use of car by -5.52%, the use of train by -2.07%, the use of foot by -2.04% and increases x by 0.29%.

6 Conclusions

Meeting climate targets for the transport sector in the years to come will require a mix of policies. Each household, once its living location fixed, chooses between a mix of transportation means, time in transportation and consumption goods. We build a theoretical model to quantify how households make these choices, taking into account heterogeneous costs from different methods of transportation, household's socio-economic characteristics and preferences. With this model we complete the existing literature on the value of travel time by estimating the heterogeneous discomfort of households in using different transportation modes. We show the importance of accounting for heterogeneity in travel discomfort for the calculation of VOTT. As such, we attempt to build regional Mobility Gini indices including transport pricing for all methods of transportation, the travel discomfort of households based on their socio-economic characteristics, their own preferences, and the pollution emitted by their transportation choices. Empirically, using the German Mobility Panel Survey, we build Mobility Gini (MGini) and Emission mobility Gini (EMGini) indices for the sample period of 2004 to 2018.

We identify the regions that are most unequal in terms of overall costs of transportation and compare the results to the traditional Income Gini. Furthermore, our results do not display causality between the income Gini and the Mobility Gini, suggesting the need to use such Mobility inequality index for evaluating the impacts of climate policies. We evaluate how these indices evolve when different climate policies are applied. The Mobility Gini indices allow policymakers to identify distributive effects of public policies for the clean transition in the transport sector.

The methodology proposed here allows to disentangle how policy shocks for the transport transition affect household decision making in terms of allocation of resources between distances traveled by each method of transport and other goods consumed. The changes in behavior quantified here are key to understanding how mobility inequality will change after the introduction of policies for the transport transition in the years to come. A first extension of this work would consist in investigating the impact on different types of households, in particular on car-dependent households, as defined in Rangel Guevara (2024). Following the recent findings of OECD (2025), another extension could be to investigate the drivers of change in inequality patterns, i.e., infrastructure, accessibility, reliability, discomfort of transport modes. Last but not least, another interesting extension of this work would be to study the longer run effects, that allow for working and living locations to be adjusted endogenously through the household's choice.

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A Appendix A L_j calculation

A.1 L_j for car and motorbike and e-bike

$$L_j = \frac{\sum_{t=1}^{n}[\frac{Purchaseprice_t + OM_t + Fuel_t}{(1+r)^t}]}{\sum_{t=1}^{n}[\frac{Km_t}{(1+r)^t}]} \tag{16}$$

Where we account for all future cashflows for a period of $n = 10$ years [27] and calculate the net present value of the project. Then, we divide by the net present value of total kilometers driven over the period. This calculation gives us the levelized cost of driving one kilometer after accounting for all future payments and benefits related to the car. When a car was not owned by the household, the cost was considered as null as all maintenance and fuel costs ca be removed from the taxes. For e-bike the fuel costs were calculated based on electricity prices per region adjusted yearly to electricity CPI, and kWh consumption.

A.2 L_j for bike

$$L_j = \frac{\sum_{t=1}^{n}[\frac{Purchaseprice_t + OM_t}{(1+r)^t}]}{\sum_{t=1}^{n}[\frac{Km_t}{(1+r)^t}]} \tag{17}$$

Where we account for all future cashflows for a period of $n = 10$ years and calculate the net present value of the project. Then, we divide by the net present value of total kilometers driven over the period. This calculation gives us the levelized cost of driving one kilometer after accounting for all future payments and benefits related to the bike.

A.3 L_j for public transportation

For public transportation methods the L_j is calculated using the following formula:

$$L_j = \sum_{t=1}^{n} \frac{Ticketspurchaseprice_t}{Km_t} \tag{18}$$

In this case, the calculation is done for a period of $n = 1$ year due to the fact that tickets can be purchased for a maximum of one year.

A.4 L_j for walking

We assume that this $L_j = 0$ for walking and thus the transportation cost of walking c_m (m for march) can be written as the distance traveled by walking d_m times the ride cost of walking r_m. It can be expressed as follows:

$$c_m = d_m * r_m \tag{19}$$

[27] The average holding period of the asset, for the sample

The ride cost r_m of walking is simply the individual wage w, and the speed s_m of travelling by walking and can be written as follows:

$$r_m = \frac{w}{s_m} \tag{20}$$

B Appendix B: Regional and Temporal Heterogeneity MGini & EM-Gini

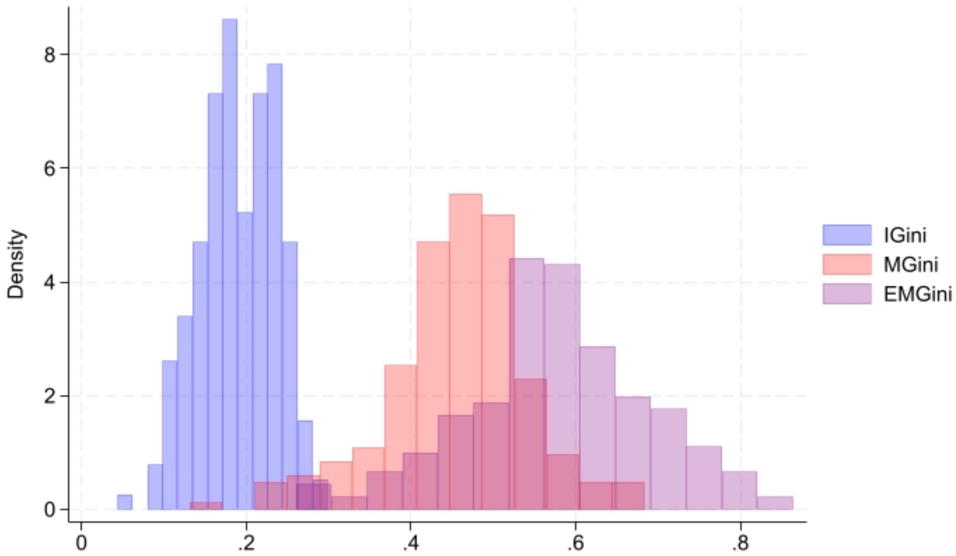
Table 9: MGini by region and year

Region/Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Schleswig-Holstein	0.31	0.43	0.27	0.6	0.33	0.28	0.41	0.47	0.56	0.5	0.48	0.47	0.43	0.38	0.5
Hamburg	0.4	0.44	0.33	0.4	0.54	0.49	0.48	0.49	0.48	0.5	0.47	0.45	0.33	0.49	0.56
Lower Saxony	0.44	0.37	0.54	0.51	0.51	0.44	0.51	0.43	0.46	0.43	0.42	0.48	0.52	0.5	0.51
North Rhine-Westphalia	0.52	0.48	0.49	0.45	0.47	0.53	0.46	0.43	0.49	0.48	0.47	0.55	0.49	0.45	0.52
Hesse	0.58	0.44	0.37	0.39	0.42	0.43	0.47	0.47	0.42	0.47	0.49	0.45	0.51	0.44	0.47
Rhineland-Palatinate	0.35	0.29	0.46	0.38	0.54	0.5	0.25	0.22	0.45	0.4	0.48	0.42	0.48	0.57	0.51
Baden-WÃŒrttemberg	0.44	0.49	0.45	0.5	0.41	0.44	0.42	0.6	0.5	0.53	0.65	0.54	0.43	0.52	0.48
Bavaria	0.54	0.47	0.5	0.49	0.53	0.42	0.49	0.45	0.46	0.55	0.49	0.49	0.53	0.45	0.48
Berlin	0.35	0.5	0.26	0.54	0.46	0.38	0.39	0.51	0.52	0.48	0.5	0.52	0.45	0.32	0.41
Brandenburg	0.41	0.52	0.47	0.44	0.42	0.44	0.51	0.57	0.42	0.54	0.44	0.64	0.38	0.48	0.41
Mecklenburg-Vorpommern	0.54	0.59	0.13	0.39	0.4	0.24	0.34	0.46	0.56	0.23	0.64	0.56	0.68	0.62	0.5
Saxony	0.61	0.54	0.36	0.57	0.43	0.38	0.43	0.44	0.49	0.5	0.47	0.4	0.46	0.4	0.53
Saxony-Anhalt	0.48	0.38	0.43	0.46	0.43	0.48	0.58	0.37	0.28	0.41	0.48	0.5	0.35	0.44	0.47
Thuringia	0.42	0.38	0.28	0.49	0.34	0.4	0.31	0.35	0.48	0.66	0.52	0.35	0.6	0.38	0.41
Avg. Yr.	0.46	0.45	0.38	0.47	0.45	0.42	0.43	0.45	0.47	0.48	0.5	0.49	0.47	0.46	0.48

Table 10: EM-Gini by region and year

Region/Year	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Schleswig-Holstein	0.44	0.73	0.59	0.79	0.27	0.44	0.54	0.48	0.59	0.62	0.57	0.58	0.42	0.53	0.67
Hamburg	0.56	0.53	0.46	0.57	0.63	0.71	0.76	0.68	0.69	0.54	0.54	0.53	0.47	0.61	0.7
Lower Saxony	0.72	0.66	0.69	0.72	0.62	0.58	0.7	0.55	0.5	0.47	0.59	0.55	0.59	0.61	0.58
North Rhine-Westphalia	0.69	0.74	0.72	0.69	0.57	0.55	0.55	0.55	0.65	0.6	0.57	0.6	0.58	0.56	0.59
Hesse	0.8	0.66	0.64	0.63	0.44	0.59	0.54	0.69	0.52	0.55	0.56	0.43	0.61	0.49	0.62
Rhineland-Palatinate	0.66	0.64	0.69	0.58	0.74	0.63	0.38	0.38	0.45	0.4	0.51	0.49	0.48	0.61	0.53
Baden-WÃŒrttemberg	0.75	0.75	0.64	0.62	0.63	0.54	0.54	0.58	0.65	0.69	0.59	0.6	0.55	0.62	0.46
Bavaria	0.81	0.77	0.68	0.6	0.62	0.55	0.59	0.61	0.53	0.56	0.52	0.53	0.57	0.59	0.55
Berlin	0.56	0.61	0.47	0.54	0.49	0.58	0.68	0.41	0.67	0.48	0.47	0.57	0.51	0.4	0.66
Brandenburg	0.51	0.55	0.47	0.78	0.56	0.49	0.43	0.66	0.4	0.64	0.61	0.69	0.54	0.53	0.53
Mecklenburg-Vorpommern	0.35	0.26	0.29	0.77	0.54	0.33	0.52	0.46	0.73	0.63	0.58	0.65	0.86	0.71	0.45
Saxony	0.8	0.76	0.7	0.6	0.53	0.52	0.66	0.63	0.59	0.55	0.66	0.49	0.54	0.58	0.54
Saxony-Anhalt	0.84	0.35	0.81	0.5	0.76	0.52	0.56	0.41	0.64	0.31	0.76	0.44	0.57	0.49	0.63
Thuringia	0.6	0.68	0.29	0.58	0.59	0.59	0.39	0.36	0.44	0.58	0.56	0.55	0.67	0.48	0.36
Avg.Yr.	0.65	0.62	0.58	0.64	0.57	0.54	0.56	0.53	0.58	0.54	0.58	0.55	0.57	0.56	0.56

Figure 6: Comparison distribution of selected Gini indices.

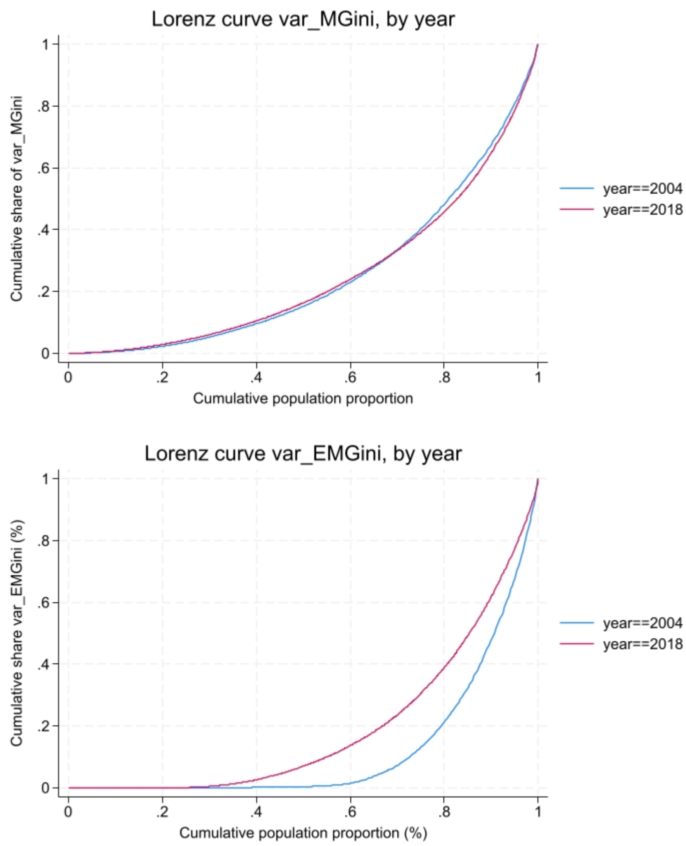


Note: Distribution of Gini indices for fully employed households. The MGini shows heterogeneity in transport cost accounting for distances, L_j and value of time. While the EMGini also accounts for emissions and pricing of emissions.

Table 11: Values of Gini Components and Weights

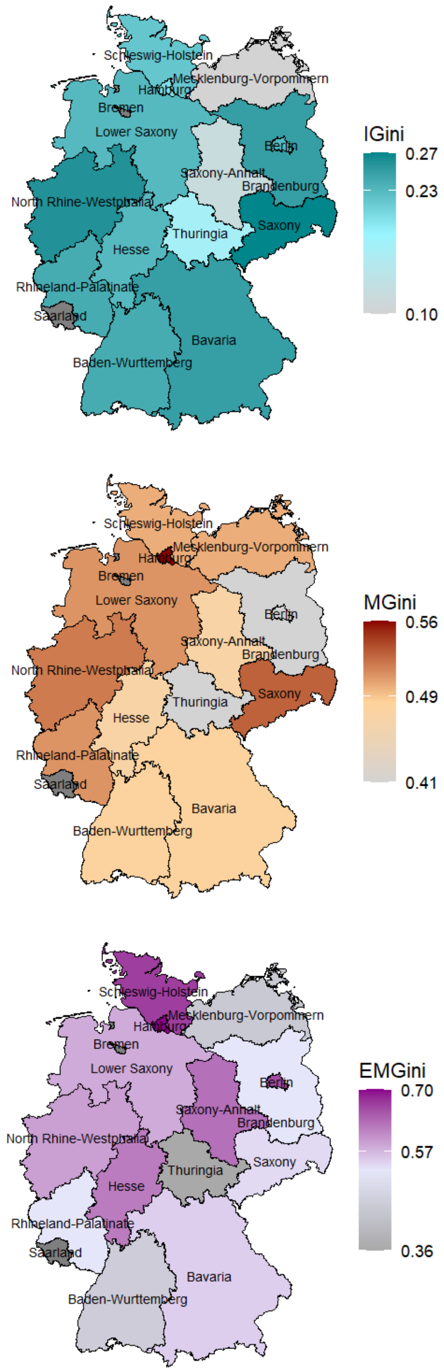
Variable	**Value**
MGini	0.5081
MGini_C	-0.1786
MGini_T	-0.3134

Figure 7: Differences in inequality, selected years



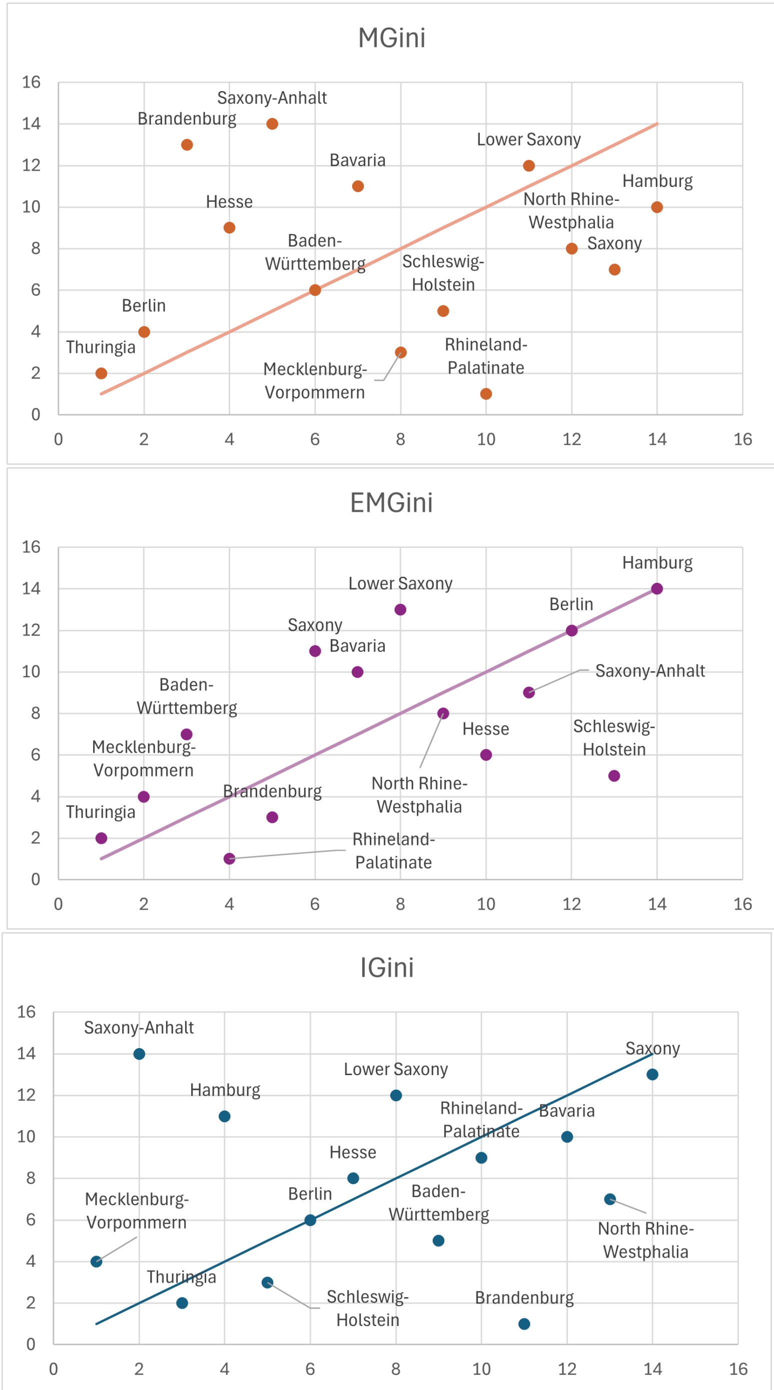
Note: Figure portrays Lorenz Curves for the sample. Two selected years are presented 2004 and 2018 which correspond to the first and last years observed.

Figure 8: Regional heterogeneity in inequality patterns in 2018



Note: Scales differ by index: numbers in scale represent min., med., and max. for each index. Numbers are for the year 2018. Higher index represents higher inequality, where 1 would represent perfect inequality and 0 would represent perfect equality.

Figure 9: Changes in rankings of Gini Indices, by region (2010 vs. 2018)



Note: All rankings are based on indices. Two regions are dropped due to data limitations. Regions are ranked by ascending order. Lowest rank means lowest inequality, highest rank means higher inequality. Dots above (left of) the line represent regions that have improved their ranking while dots below purple(right of) the line represents regions whose ranking has deteriorated.

C Appendix C: Transportation variables

Table 12: Summary Statistics of β `walking (foot)` and β `biking` by `regions`

Regions	β **foot**			β **biking**		
	Mean	SD	N	Mean	SD	N
1	0.0596	0.1600	253	0.0813	0.1188	253
2	0.1024	0.1602	216	0.1062	0.1775	216
3	0.0868	0.1597	685	0.0693	0.1341	685
4	0.1202	0.2064	70	0.0449	0.1030	70
5	0.0693	0.1481	1383	0.0769	0.1194	1383
6	0.0695	0.1531	516	0.0853	0.1119	516
7	0.0423	0.1365	283	0.0750	0.1211	283
8	0.0460	0.1283	933	0.0516	0.0868	933
9	0.0722	0.1557	1122	0.0542	0.0854	1122
10	0.0200	0.1012	74	0.0972	0.1413	74
11	0.1153	0.1800	339	0.0744	0.1321	339
12	0.0930	0.1581	277	0.0565	0.1217	277
13	0.0852	0.1671	121	0.0627	0.0980	121
14	0.0639	0.1527	408	0.0430	0.1068	408
15	0.0858	0.1595	207	0.0455	0.0935	207
16	0.0626	0.1588	181	0.0930	0.1567	181
Total	**0.0714**	**0.1534**	**7068**	**0.0671**	**0.1153**	**7068**

Table 13: Summary Statistics of β `Walking (foot)` and β `Biking` by Year (`jahr`)

Year	**β foot**			**β biking**		
	Mean	SD	N	Mean	SD	N
2004	0.0721	0.1500	324	0.0417	0.0998	324
2005	0.0654	0.1659	316	0.0886	0.1315	316
2006	0.0733	0.1615	300	0.0456	0.1029	300
2007	0.0869	0.1676	301	0.0295	0.0806	301
2008	0.0663	0.1349	375	0.0739	0.1080	375
2009	0.0563	0.1350	328	0.0729	0.1165	328
2010	0.0703	0.1551	340	0.0521	0.0752	340
2011	0.0813	0.1617	342	0.0861	0.1239	342
2012	0.0934	0.1707	391	0.0453	0.0932	391
2013	0.0759	0.1478	588	0.0946	0.1296	588
2014	0.0725	0.1472	672	0.0521	0.1147	672
2015	0.0526	0.1302	693	0.0830	0.1233	693
2016	0.0600	0.1503	681	0.0949	0.1293	681
2017	0.0791	0.1455	733	0.0505	0.1138	733
2018	0.0764	0.1800	684	0.0640	0.1082	684
Total	**0.0714**	**0.1534**	**7068**	**0.0671**	**0.1153**	**7068**

D Appendix D: Labor variables

In order to calculate net income, wage per hour and hours worked the following steps were taken.

1. For each bracket, randomly estimate an income inside the bracket with normal distribution
2. divide over number of people who are employed per household
3. use panel FE regression to calculate wage per month based on socio-economic characteristics like age, gender, number of children, hours worked, type of household, region and year fixed effects.
4. Then predict for employed without wage (2700 obs)
5. Replace this prediction into wage for those with missing values. Thus the wage is now

   For those with a bracket of income : random draw inside the bracket

   For those with no bracket of income : FE regression prediction
6. Last step is dividing over hours worked per person to get a wage per hour.

There were cases in which an individual reported working between [0,1] hours per month. In this case, we used a panel FE regression to calculate the hours of work this individual should have reported based on socio-economic characteristics like age, gender, number of children, hours worked, type of household, region and year fixed effects.