Methodological summary

This summary serves to give an overview over how our estimate of the distributional impact of a range of climate policy instruments was calculated. First, in Section 1 we describe the datasets that were used in the analysis, next, preparatory adjustments are explained in Section 2 and finally, in Section 3 we shed light on how the results were derived.

1 Data

The research primarily made use of the 2017 edition of the *Mobilität in Deutschland* (MiD) dataset. Additionally, the *Mobilitätspanel* (German Mobility Panel, MOP) was used to estimate fuel efficiency.

The MiD survey is a household-level survey that was conducted for the third time in 2017. It contains data on more than 300,000 individuals, 150,000 households and almost one million individual journeys (Nobis & Köhler, 2018; Nobis & Kuhnimhof, 2018, p. 15). However, the MiD dataset lacks information on most of the characteristics of the households' vehicles, including, most importantly, fuel efficiency. A measure of fuel efficiency is essential for calculating the impact of different climate policy instruments.

The *Deutsche Mobilitätspanel* (MOP) is an annual household-level survey which has been commissioned by the German Federal Ministry of Transport and Digital Infrastructure since 1994. The survey collects information on everyday mobility patterns in Germany as well as car mileage and fuel consumption (Federal Ministry of Transport (BMVI), 2019). The latter aspect allows to fill the gap on fuel efficiency in the MiD dataset. The 2017 issue of the MOP survey is used in order to best match the MiD dataset.

To estimate fuel efficiency, a linear regression model was used with fuel efficiency as the dependent variable. The independent variables were chosen along two conditions, namely that they would serve as valid determinants for fuel efficiency, and had a corresponding variable in MiD. The second condition was the more limiting factor in this regard. Some variables that were available in MOP that were good predictors of fuel efficiency, such as engine displacement, were not available in MiD. Model selection was based on the adjusted R^2. The resulting linear regression model was set up as follows:

$$FE_{i,j} = \beta_0 + \beta_C C_{i,j} + \beta_D D_{i,j} + \beta_{CY} CY_{i,j} + \beta_{FT} FT_{i,j} + \beta_Y Y_j + \epsilon_{i,j}, \tag{1}$$

where $FE_{i,j}$ translates to the fuel efficiency of household j's ith car, $C_{i,j}$ is the car classification, $D_{i,j}$ the distance travelled in 2017, $CY_{i,j}$ the year of construction, $FT_{i,j}$ the fuel type, and Y_j the monthly household income.

2 Preparation of the analysis

2.1 Adjustments to the datasets

To be able to use the variables for fuel type and car classification, it had to be made sure the variable categories in both datasets match. Therefore, the seven observations of camper vans were dropped in MOP and, since methanol/hydrogen is not a fuel category in MiD and represents only one observation in MOP, it was also dropped. Moreover, households with more than three cars were excluded in the MiD dataset, as relevant variables were only collected on the households' first three cars. Including these households would have led to an underestimation of costs to those households. As only a small fraction of households falls into this category, the impact on our results is of small magnitude.

2.2 Estimating fuel efficiency

To compute estimates of the MiD cars' fuel efficiency, we estimated Equation 1 based on the MOP data. MiD fuel efficiency values were then predicted with the estimated coefficients. Some of the cars in MiD lacked information on the vehicle classification or fuel type. To impute for the missing values, we computed how classification and fuel type contribute to fuel efficiency on average over the whole car fleet in the estimation equation and inserted these terms, when information on either of the attributes was missing. Two observations that provided negative results had to be dropped, as those are not valid results for fuel efficiency. Electric vehicles are registered with a fuel efficiency of 0 gCO_2/km, as, in Europe, there is no accounting upstream carbon content in the electricity production in an electric vehicle's efficiency attribution (Lutsey, 2017). Fuel efficiency values were thus imputed as such. The results and distribution for the estimated fuel efficiencies of the vehicles in MiD are depicted in Figure 1.

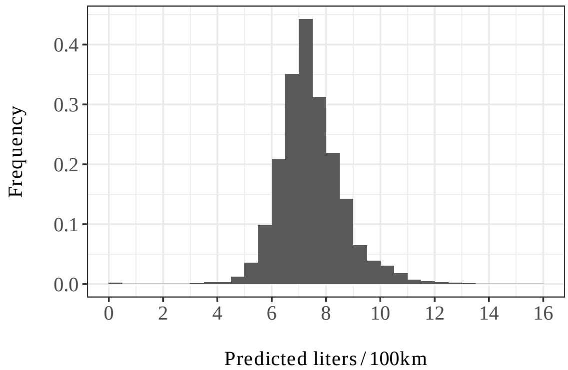

Figure 1: Distribution of predicted fuel efficiency in MiD 2017 in liters per 100 kilometers

Another indication that the fuel efficiency estimated in MiD is close to the actual values, is a comparison of fuel efficiency in MiD and MOP, as shown in Table 1. Concerning the location parameters, MOP and MiD estimates match very well. Dispersion-wise, the values lie a bit closer to the mean for the MiD estimates, which is unsurprising given the averaging procedure we applied when encountering missing values.

Table 1: Summary statistics of fuel efficiency in MOP and MiD

	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
MOP	3.1	6.1	7.1	7.4	8.3	26.2
MiD	0.1	6.8	7.4	7.5	8.1	15.6

3 Deriving results

To assess the distributional effect of any of the modelled measures, we divide households into income quintiles. If no valid response to the household income item was collected in the survey, MiD-implied values were used. We examine the transfers that households pay or receive relative to household income. To show the effect of a particular policy, we analyse the distribution of these relative transfers within income quintiles. All figures are calculated using survey weights.

3.1 Carbon price and inefficiency standard

The German emissions trading scheme foresees a fixed carbon price of €25/tCO_2 starting in 2021 rising progressively to €55/tCO_2 in 2025 and moving to a price corridor thereafter (The Federal Government, 2019b). We chose to base our calculations on a price of €55/tCO_2. Information on the carbon content of diesel and petrol[1] (Umweltbundesamt, 2016), and their density conversions

[1]For petrol, we use the mean emission factor for 'super' (page 32) and diesel is calculated by taking the mean of the emission factors of summer and winter (third column page 34 of the publication).

(Bundesverband der deutschen Bioethanolwirtschaft e.V., 2020) were used to convert liters of fuel to tons of CO_2. Most hybrid electric cars have petrol engines, we therefore applied the petrol emission factor, when calculating the amount of CO_2 emitted per liter of fuel.

Given respective fuel type and yearly kilometers driven, the annual cost per car was calculated based on the previous considerations. The inefficiency standard was computed using Levinson's (2019) approach. The sum of the incurring costs of the carbon price (i.e. the total tax revenue) was divided by the sum of the fuel efficiencies. This ratio determines the payment per unit of fuel inefficiency (in l/100km). We then multiply each car's fuel efficiency with the inefficiency tax to receive the cost per car. Finally, the results are aggregated at the household level.

3.2 Redistribution of carbon price revenue

We implement two possible ways of redistributing carbon price revenue: A lump sum transfer and a commuter allowance. The lump sum transfer equally reallocates the carbon price revenue to the households, including those with zero emission vehicles or without cars. The existing commuter allowance is a tax deduction of €0.30 per kilometre travelled to work. In the German climate action package, the Federal Government decided to increase the commuter allowance for every kilometer from the 21st kilometer onwards by five cents from 2021 – 2023 and eight cents from 2024 – 2026 (Gesetz Zur Umsetzung Des Klimaschutzprogramms 2030 Im Steuerrecht, 2019). Our calculations determined that an increase by €0.36 would result in a redistribution of all the revenue generated by the carbon price. To allow for a comparison of the two redistribution strategies, we base our analysis on that figure.

3.3 Feebate scheme

The concept of a feebate implemented here can be thought of as a yearly payment one has to pay for owning a car that depends on that car's fuel efficiency. We use the same emission factors as in Section 3.1 and our fuel efficiency estimates to derive a distribution of grams CO_2 per kilometer emitted by the cars. Payment under the feebate is proportional to the grams CO_2 per kilometer figure. The total amount of payments made by the less fuel-efficient households is equal to total revenue made under the carbon price. The total amount received by the more fuel-efficient households corresponds to that same amount, such that the policy is revenue neutral. Comparison with other redistributive policies (see Section 3.2) is valid under that property.

3.4 Driving ban

To analyse the distributional effects of a driving ban for combustion engines in metropolises, we rely on the regional classification 'RegioStaR' of the Federal Ministry of Transport (2020). We further base our calculation on the assumption that everyone who lives in the metropolitan area is affected by the ban, although realistically the ban could apply only to the metropolitan area and not to the surrounding areas. One way to think about this is that the vast majority who live in the metropolitan area commute to the metropolitan area. Since no information is collected on where people work, it is impossible to distinguish observations based on whether people work in the metropolitan area or not.

Before we compute the projected effects, we make some adjustments to the dataset. We exclude households with more than 4 adults. It is not very likely that more than four adults contribute significantly to monthly household net income. Therefore, including trips by households with more than four adults would inflate the opportunity cost to these households. All trips longer than 120 minutes were excluded. Anything above that is assumed to be too long a distance for a daily round trip. All figures are calculated for households actually affected by the driving ban, i.e. we only consider people who drive their own car or carpool to work.

The analysis uses information on how long it would take individuals to use public transport instead of commuting by private vehicle. Only the commute (both ways, to and from work) is analysed, which, as opposed to other journeys covered in MiD, can be regarded as the journeys that cannot easily be avoided. By subtracting the amount of time it takes to travel to work from the time required using public transport, the time lost or gained can be calculated. The total time loss was aggregated for the whole working month. On average, there are 20 working days per month in Germany, accounting for holidays and weekends. The additional travel time was then aggregated at a household level, in line with the other analyses conducted. Trips undertaken with electric vehicles were not considered as they would not be subject to an combustion engine ban.

To produce results consistent with previously analysed measures, we put a price tag on time. To determine the value of time, a myriad of factors could be considered, such as personal preferences, whether commuters are stuck in traffic jams or not, and the amenities provided in the private vehicle or the public transport (Small, 2012). A very simple approach is to assume that individuals are perfectly flexible to decide whether to spend more or less time on work or on other activities (including commuting). The time could be equal to income after taxes (Becker, 1965; Small, 2012). According to Small (2012), empirical observations show that time roughly has the value of one half of the gross income rate but does not rise in proportion to income. This analysis applies a simplified combination of these insights and values time as half of the net income of households. Hence, the total minutes lost (or gained) of a household are multiplied by half of what that household earns per minute. The opportunity costs are calculated per household, summing up the costs for each commuter in the household.