University of Oldenburg

Faculty V - School of Mathematics and Science

# Thesis

M.Sc. Umweltmodellierung

*Avoid, shift, improve - Coupling of a transport model with a car stock model to compare the effects of three main policy strategies in German passenger transport*

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**List of acronyms**

**BEV** battery electric vehicle

**CA** car availability

**CO2** carbon dioxide

**CO2e** carbon dioxide equivalents

**EU** European Union

**GHG** greenhouse gas

**ICE** internal combustion engine vehicle

**KSG** ‘Klimaschutzgesetz’

**LDV** light duty vehicle

**MID** ‘Mobilität in Deutschland’

**MIT** motorised individual traffic

**MMS** ‘mit Maßnahmen Szenario’

**MNL** Multinomial Logit

**PHEV** Plug-in Hybrid Electric Vehicle

**PKM** passenger kilometres travelled

**PT** public transport

**SHS** ‘sofortiges Handeln Szenario’

**TTW** tank-to-wheel

**VCC** variable cost of driving a car

**VIZ** ‘Verkehr in Zahlen’

**WTW** well-to-wheel

**Abstract**

Despite efforts to electrify the car fleet, the German passenger transport sector lacks behind in the decarbonization process.

To identify pathways to effectively reduce GHG emissions in passenger transport, I analyse potential effects of the three strategies *avoid*, *shift* and *improve* on car GHG emissions and the vehicle fleet. For this purpose, I couple the macroscopic passenger transport model quetzal_germany with the car stock model EUTRMpy in an interdependent manner.

I find all three strategies to strongly decrease energy demand and consequently GHG emissions from cars until 2040. The reduction arises either out of a decrease in vehicle activity (*avoid* and *shift* strategy), out of an increase in efficiency and the usage of BEV (*improve* strategy) or both. Additionally, the strategies impact the car fleet: Applying the *avoid* or *shift* strategies decreases the number of vehicles needed. Therefore, the car sales are reduced accordingly leading to car sales dropping to 40% of 2017 levels in the *avoid* scenario. When *improving* the car fleet a rebound effect is visible. This increase in passenger activity is caused by the reduced cost of driving resulting from usage of electric cars and efficiency increases in internal combustion engines. The rebound effect can be counteracted if additional to *improve* at least one of the other two strategies is applied. Since the *improve* strategy is already in place in EU legislation, while the other two are not yet covered, a focus on *avoid* and *shift* measures in future policy making is advised.

## 1. Introduction

In 2022, the transport sector's greenhouse gas (GHG) emissions made up for 19.8% of Germany's total emissions (1). Therefore, the reduction of GHG emissions of the transport sector is crucial to be able to stay withing the limits of the 1.5°C warming goal of the Paris Agreement. Nevertheless, GHG emissions have not yet decreased in German transport between 1990 and 2019 (2).

### *1.1. Mobility and car industry in Germany*

In 2017, in Germany 1,155 billion km were travelled by passengers and 79% of these by car (2).

The reason for this dominance of car usage in German mobility is closely linked to the importance of car industry in the German economy.

After WWII the German car industry grew strongly (especially in West Germany) and became the growth engine in German reconstruction. While 100,000 cars were produced in West Germany in 1949, 1.8 million cars left the factories in 1960 (3). Large numbers of vehicle sales in Germany and exports to other Western European countries created tax revenues and jobs in the car industry which acted as a catalyst to economic growth after WWII ('Wirtschaftswunder'). The car focus affected culture, spatial planning, settlement structure and thus collective mobility habits. Moreover, car industry set standards in labour policy (4).

4.1 million cars were produced in Germany in 2023 (3). Therefore, the car industry employs many workers. In 2019, 830,000 workers were employed in car industry. Additionally, workers are employed along the supply chain, and in related parts of the economy such as workshops and car shops (5).

The immense growth of the car industry would not have been possible without public-private-partnerships such as public investments in traffic infrastructure and car-friendly cities, supportive tax policies (e.g., commuting allowance 'Pendlerpauschale'), and specific aids in times of crisis (e.g., scrapping premium to cushion the effect of the financial crisis in 2009 and wage subsidies during COVID-19 pandemic) (4).

Relying on oil intensive means of transport comes with a cost. Disadvantages have been visible as early as 1973 and 1979 when the oil-crises shook the German economy while environmental concerns increased. After a rising demand in the beginning of 1990s due to the new markets in Eastern Germany and Eastern Europe, the sector was shaken by another crisis in 1992/1993. This lead to debates in labour unions regarding the future of the industry which included environmental concerns and conversion potentials at the core of debate. One example for this is the discussion process 'Zukunft Auto.Umwelt.Mobilität' initiated by the labour union IG Metall (6).

Nevertheless, these debates were not succeeded by a shift away from car focused mobility: In the 2000s, market pressures led to a shift in labour unions strategies, now aiming at good economic status of the companies and high sales to guarantee jobs (5).

### *1.2. Avoid, shift, improve - passenger transport and the environment*

While the number of cars registered in Germany increases, their negative impacts on people and nature cannot be neglected: To move vehicles, energy is needed, which comes from fossil fuels, from regrowing sources (biofuels), or from electricity which itself needs to be generated (e.g., from renewable energy, fossil fuels or nuclear, each with their respective impacts on people and nature). While usage of biofuels depend on crops competing with food production for land, burning of fossil fuels causes GHG emissions ultimately inducing climate change (7).

Other environmental impacts are caused in vehicle production, which needs energy and materials. Growing car market shares of battery electric vehicle (BEV) add demands on lithium, cobalt, manganese and other minerals destroying ecosystems, degrading water sources, and thus affecting people and nature in the respective mining areas (8).

Because of the broad range of (negative) impacts of the transport sector on people and nature, it is difficult to display all these impacts in detail in one research project. Therefore, this work will focus on climate impacts.

Today, humanity is at a point where measures need to be taken to strongly and fast reduce climate impacts to be able to restrict global warming to 1.5°C and prevent climate change to have devastating impacts on human well-being (7). Consequently, it is crucial to determine effective strategies to decrease these negative impacts, thus, reaching sustainable mobility.

An often-used framework is describing three strategies - namely *avoid*, *shift* and *improve* - which can be used to bring about the transport sector's transformation to climate neutrality (9). Firstly, transport is *avoid*ed i.e., reducing the kilometres travelled by goods and passengers. This strategy includes structural changes such as spatial planning, to enable people to satisfy their every day needs within a small radius, as well as cultural changes e.g., choosing closer vacation destinations. Additionally, this strategy comprises changes in work culture such as prioritising online meetings over face-to-face meetings. Secondly, transport is *shift*ed to modes with less environmental impact per kilometre travelled (e.g., from car to bike, from road to rail). Thirdly, vehicles are *improve*d by application of new technologies or increases in vehicle efficiency (e.g., changing from diesel to electric trains, using BEV emitting less CO2 per km travelled than internal combustion engine vehicle (ICE) and hydrogen cars) (9).

Adverse effects which can occur in all three strategies of sustainable transport are called rebound effects (10). A rebound effect occurs, for example, when efficiency increases are not (or not entirely) translated into a reduction in primary energy demand, since the increased efficiency decreases the price per energy service unit leading to an increased demand in energy service units. In the case of passenger transport rebound effects appear e.g., when a decreased price per km cause an increase in activity (passenger kilometres travelled (PKM)) or vehicle weights. This efficiency increase can occur due to higher engine efficiency or the usage of BEV which are more efficient than ICE (11).

Energy sufficiency is another strategy which can be used to reduce energy demands and hence CO2 emissions. This strategy aims at reducing the absolute number of energy-based services used, and thereby progressing towards sustainability (12). Thus, this 'enoughness' of energy demand lies between two limits: The planetary boundaries as an upper limit to energy use and GHG emissions, and a lower limit of basic human needs. With this in mind, the concept applies to mobility in an indirect manner, since mobility is not a need in itself but only a means to satisfy one's needs. While tempo-spatial mobility patterns depend on mobility culture, on the distribution of the points of interest at which people can meet their needs, on transport planning and the specific person, the need behind mobility is independent of these factors (13).

Zell-Ziegler et al. 2021 define two options to decrease energy consumption through sufficiency. On the one hand, sufficiency can be accomplished by lowering the number of utility units of energy service e.g., by reducing passenger activity. On the other hand, sufficiency can imply to alter facets of the energy service leading to no or reduced energy consumption e.g., walking instead of taking the bus (12). Applying the notion of energy sufficiency as described by Zell-Ziegler et al. 2021 to mobility, points to measures which can be assigned to *avoid* and *shift* strategies described above. Therefore, I will not look at energy sufficiency as a separate strategy.

### *1.3. Modelling German passenger transport*

Transport models are mathematical representations of reality, which can be used to compare identified measures and strategies in their effectiveness. In research various transport models exist. Importantly, they differ in usage, spatial resolution, time horizons and transport modes included.

One use-case of transport models is spatial planning, where they are utilised to generate insights on temporal and spatial patterns of transport, to find out which infrastructure is needed, how urban and rural spaces might be planned to fulfil mobility needs and enable the distribution of goods. To enable spatial planning high tempo-spatial resolution is crucial. An example of such a model is the model VISSIM (14).

The transport models I will have a detailed look at are used to inform policy making on potential outcomes of a given set of policy measures. Depending on the aim, a model could be designed to estimate various output variables such as effects on nature (e.g., effects on resource use, GHG emissions, air pollution, energy use, transport activity, vehicle stock development, water use in production and noise) or economy (e.g., cost of driving, needed infrastructure investments, tax revenues, production capacities and jobs).

In this project, the models used need to fulfil four requirements. Firstly, they need to fit to the scope of the project by representing German passenger transport. Secondly, they should enable the inclusion of future pathways until 2040. Thirdly, they should be easily accessible to make them usable for future research, and thus, be available open source. Finally, and most importantly, they need to enable the user to adequately implement the three strategies *avoid, shift* and *improve* including related potential rebound effects. I identified the two models quetzal_germany and EUTRMpy, which in combination are able to meet all these requirements.

I chose queztal_germany over other models depicting German passenger transport (e.g., DEMO described by Winkler et al. 2017 (15) and ASTRA-M described by M-FIVE 2023 (16)), since it is open source. The model quetzal_germany is a macroscopic passenger transport model aggregating passenger activity to zones. EUTRMpy is a model describing vehicle stock developments until 2050 in 30 European countries.

Using the two models I will answer the following research questions:

- *What is the potential impact of Avoid, Shift, and Improve measures in passenger transport on environmental effects such as GHG emissions?*
- *How do the car stock's size and composition differ between scenarios with Avoid, Shift and Improve strategies?*

To answer these questions I will, firstly, couple the two models quetzal_germany and EUTRMpy with respect to cars in Germany, the two models and the coupling methodology is described in Sec. 2. Secondly, I will develop scenarios that differ in terms of which of the strategies *avoid, shift* and *improve* they incorporate (Sec. 2.4). Thirdly, the scenarios will be compared regarding environmental impacts while driving by observing well-to-wheel (WTW) GHG emissions and effects on stock size and number of new vehicles sold (Sec. 3.2). Finally, I will compare results and behaviour to other models (Sec. 4.1) and the outcomes will be discussed (Sec. 4).

## 2. Method & Material

### *2.1. quetzal_germany*

The open-source[1] model quetzal_germany is a macroscopic transport model designed to depict the demand-side of medium- and long-distance passenger transport in Germany and has been developed by Marlin Arnz (17).

The model can be utilised to estimate passenger transport demands in Germany for a given year. To do so, quetzal_germany uses the model framework quetzal. In quetzal_germany traffic between 2225 zones in Germany is modelled split up by transport mode (i.e., long- and short-distance rail transport, buses, coaches, aviation, cars and non-motorised transport). The model is based on the four steps of macroscopic transport modelling consisting of (1) trip generation, (2) trip distribution, (3) mode choice and (4) traffic assignment.

The model differentiates 12 travel segments distinguished by six travel purposes (commuting, business, leisure, education, grocery shopping or medical executions, and accompanying trips) and car availability (i.e., whether a household owns a car or not). Mobility data by travel purpose comes from the national mobility survey 'Mobilität in Deutschland' (MID) (18). The estimation procedure depends on the segment. For each of the segments choice models are estimated respectively. The distribution of compulsory trips (commuting, education, business) is based on the share of students or workers of the population in each region and on the distribution of schools

[1] Available here: *https://github.com/marlinarnz/quetzal_germany*

or workplaces (13). Non-compulsory trips (leisure, grocery shopping or medical executions, and accompanying trips) are generated using multinomial logit techniques to estimate the number of trips per day in each zone. The distribution of trips regarding non-compulsory trips happens in two steps of which the first one uses a binary logit model to determine whether the trip goes beyond the border of the zone (inter-zonal) or stays within the zone (inner-zonal). Secondly, the destination zone for each inter-zonal trip is estimated using a multinomial logit in which each zone (other than the origin) is represented by a choice. Finally, another multinomial logit is used for mode choice (9).

In the step concerning mode choice, for each segment a model is estimated by applying Multinomial Logit (MNL) techniques. Each model describes the relationship between level of service attributes (e.g., price and travel time of all transport modes) and mode choice regarding all trips in this segment.

MNL models are statistical discrete choice models maximising the utility of each choice which depends on known and unknown parameters (19).

The probability for the person $n$ to choose an option $i \in J$ given all options $j \in J$ is defined by

$$P_{ni} = \frac{e^{\ \beta_i \ x_{ni}}}{\sum_j e^{\ \beta_j \ x_{nj}}}, \tag{1}$$

where $x_{nj}$ are the observed variables and $\beta_j$ is the parameter vector which includes a scale parameter reflecting the unknown parameters. Here, utility $U_{nj}$ of the choice $j$ is represented in the exponent:

$$U_{nj} = \beta_j x_{nj}. \tag{2}$$

The utility function differs between the four steps depending on the type of model used. A full description of these can be found in (9).

Since car availability in households splits the segments and thus the MNL models, it has a strong influence on mobility behaviour in quetzal_germany.

Based on the four steps the model estimates PKM travelled by each mode and finally, in a post-processing step GHG emissions are determined based on emission factors. Therefore, emissions from both public transport (PT) and motorised individual traffic (MIT) change proportionally to demand (17). By changing input parameters (e.g. costs, distribution of places for meeting daily needs, income, waiting time at PT stops, car availability) users are enabled to define scenarios.

### *2.2. EUTRMpy*

EUTRMpy is a python based model estimating greenhouse gas and air pollutant emissions of road transport including various modes of passenger and goods transport (cars, vans, trucks segregated by weight class, bus and coach) in 30 European countries and developing policy scenarios until 2050. The model has been implemented by Transport & Environment and is based on models of ICCT (GTRM) and Cambridge Econometrics (EUTRM) (20). EUTRMpy is focused on a detailed representation of vehicle fleet development in different policy scenarios including various drivetrains (petrol, diesel, petrol phev, diesel phev, cng, lpg, fuel cell and BEV), fuel types (petrol, starch ethanol, sugar ethanol, cellulosic ethanol, diesel, low-sulphur diesel, vegetable oil-based diesel, cng, lpg) and differentiating by emission standard applied. Transport activity is exogenously determined.

At the core of the model a turnover algorithm determines the changes in the stock from one year to the next (Fig. 1): when vehicles become older,

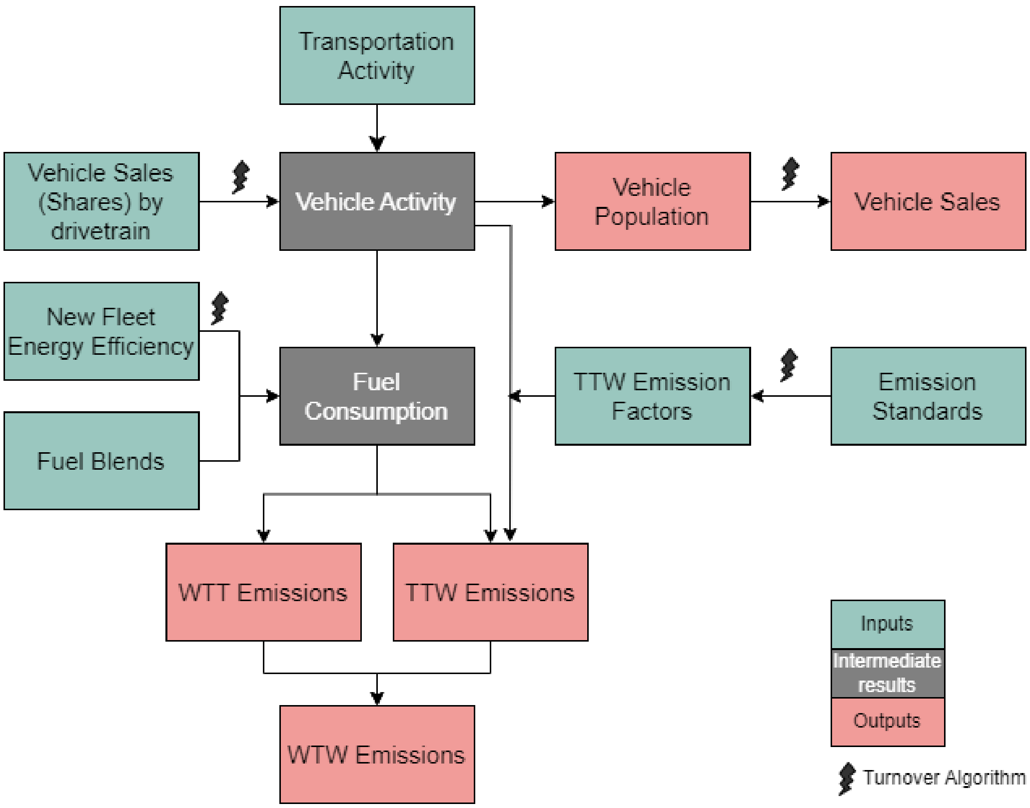



Figure 1: Overview of steps in EUTRMpy. Adjusted figure from (20). Turquoise boxes are input variables, grey intermediate results, and red final results. The arrows represent calculation steps, which are marked with a lightning-bolt if they are part of the turnover algorithm.

they will be used less, and they have a higher probability of leaving the stock. To meet traffic demand, cars need to enter the stock. These cars can be either new or enter from some other country via second hand trade. Vehicles entering from other countries have average characteristics (efficiency, drivetrain share, age) of the origin country's vehicles. Depending on the scenario new vehicles will have different characteristics regarding efficiency and drivetrain (calculation steps can be found in Appendix B).

To enable the usage of EUTRMpy for this project I updated the model to a new version (version 3.0) and released this version under an open-source licence[2]. The update includes the introduction of new features, changes in the calculation steps of the model and updates of the data used (a more detailed description of the updates can be found in Appendix A).

The detailed representation by drivetrain enables specific behaviour to apply only to one drivetrain. For example, it permits that in EUTRMpy BEV travel on average less km per vehicle than all other vehicles. In 2017 BEV travel 64% of the distance an average ICE travels. This share increases linearly reaching 100% in 2030. Whereas the weight of vehicles in stock is not included.

### *2.3. Coupling*

The two models include various datasets, which need to be consistent. Both models include data regarding passenger activity (in cars) and regarding the number of cars (Tab. 1). When adjusting this input data to match in the coupled version, a problem arose: The two models are in themselves

[2]Available here: https://zenodo.org/doi/10.5281/zenodo.11209354

not consistent in what they define as "car". The input data of EUTRMpy generally describes cars (in this model called light duty vehicle (LDV)), but the passenger activity data comes from the dataset ‘Verkehr in Zahlen’ (VIZ) and refers to MIT including cars and 2-wheelers. In quetzal_germany PKM refer to MIT, albeit being named "car", but car availability in households and the number of vehicles describe actual cars. In the coupled version, all data describing characteristics of vehicles (e.g., drivetrain, efficiency, survival) refer to cars, while all coupled data (PKM, car occupancy, new vehicles sales, stock) refers to MIT. Therefore, the model describes MIT activity with car efficiencies, leading to higher energy use and emissions than a true MIT stock would have. In German passenger transport cars make up for 91% of MIT vehicles and 99% of vehicle activity (2). Therefore, regarding PKM, energy consumption and GHG emissions can be omitted. Only when looking at the stock size, the difference between MIT and cars is relevant.

Table 1: Harmonizing the input data of the 2 models. EUTRMpy and quetzal_germany had different input data regarding PKM, vehicle occupation, vehicle sales and stock. In the coupled version these were adjusted regarding past years (right column). Inputs were changed to use data describing MIT instead of cars. The data is taken from the datasets MID 2017 (18), VIZ 2019 (21) or VIZ 2023 (2).

| | quetzal_germany | EUTRMpy | In coupled version |
|---|---|---|---|
| Pkm | MID 2017 (MIT) | VIZ 2019 (MIT) | MID 2017 (MIT) linearly interpolated |
| Car occupation (passenger/vehicle) | MID 2017 (cars) | Changed during calibration | MID 2017 (MIT) linearly interpolated |
| New vehicle sales | | VIZ 2019 (cars) | VIZ 2023 (MIT) |
| Stock | number of cars: VIZ 2019 (cars), car availability: MID 2017 | VIZ 2019 (cars) | VIZ 2023 (MIT, cars in quetzal_germany) |

There are multiple possible ways to couple the calculation steps of quetzal_germany and EUTRMpy. I identified three input variables which can be endogenously determined by the respective other model (Fig. 2): PKM, car availability (i.e., share of households owning at least one car) and variable cost of driving a car (VCC).

In a first step I implemented a simple way of coupling the two models using PKM estimated by quetzal_germany as an input to EUTRMpy. Hereby, quetzal_germany is used for its main purpose being detailed passenger transport activity calculation. EUTRMpy calculates the stock development with respect to number of vehicles and sales, drivetrain shares, age and efficiency. Since quetzal_germany only describes one year and the data used comes from MID 2017 (18), I take 2017's values as a basis. New policies proposed in the scenarios only apply to future yeas, thus, changes in activity only start in 2025. Therfore, quetzal_germany was run regarding 2017 and 2040 and when preparing the activity data for EUTRMpy, the value of 2017 was kept constant until 2024. From 2025 to 2039 activity is shrinking (or growing) logarithmicly.

Thus, PKM in year $y \in \{2025, 2026, ..., 2029\}$ is calculated as,

$$k_y = k_{2017} - \frac{k_{2017} - k_{2040}}{1 + \exp(-\kappa * (y - 2032))}, \tag{3}$$

where $\kappa$ is 0.5. Car occupancy $d_y$ is not estimated inside quetzal_germany but is a scenario variable. It stays constant from 2017 to 2024 and is interpolated linearly between 2024 and 2040.

A more complex coupling strategy is bidirectional coupling. The variables car availability (CA) and VCC are input variables in quetzal_germany but can instead be endogenously determined. Calculating these variables

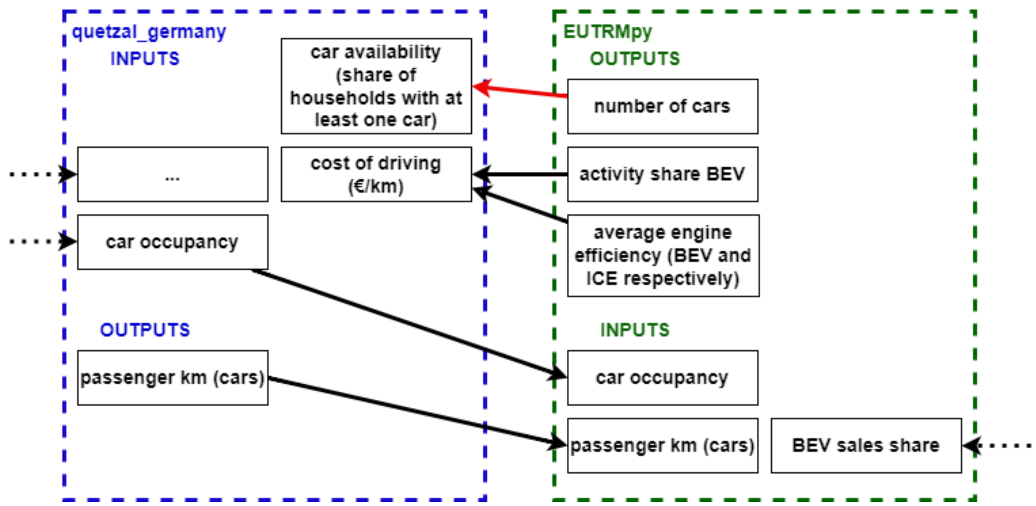



Figure 2: Coupling of the two models. Each box represents a variable, which is either output or input to one of the models. Arrows represent calculation steps in the coupled version. The red arrow represents a link which has been removed after testing the model (see Sec. 3.1). Dotted arrows represent scenario variables. The interaction of the models is bidirectional.

endogenously would close two gaps: Firstly, the calculation of CA inside the model enables the harmonizing of the stock size assumptions in the two models. Secondly, determining VCC based on changing shares of drivetrains and their respective costs allows the model to change the price in quetzal_germany based on the drivetrain scenario defined in EUTRMpy. This allows the model to include a rebound effect which might occur if higher efficiency (which can also occur due to higher shares of BEV) lead to a price reduction causing rising passenger activity.

Car availability is defined by

$$\text{CA} = \frac{N_{cars}}{N_{households} * \phi}, \text{ with CA} \in [0, 1], \tag{4}$$

where $N_{cars}$ is the number of cars, $N_{households}$ is the number of households and $\phi$ reflects the number of cars per household owning at least one car, with $\phi \geq 1$ . If I assume $N_{households}$ to be constant and no substantial changes in $\phi$, the number of cars and car availability change proportionally. Today $\phi$ is about 1.5.

In reality $\phi$ might buffer changes in $N_{cars}$ e.g., if taxation on car ownership increases, the number of cars might decrease. But in a first step, this only leads to a reduction in $N_{cars}$ while car availability stays the same, i.e., households reduce the number of cars they own but keep one car per household. Only in a second step, it leads to reduced CA, i.e., households selling their last car and strongly changing their mobility habits. For simplicity I keep $N_{households}$ and $\phi$ constant.

To calculate cost of driving, I adjusted the estimation in quetzal_germany.

Now VCC in 2040 is calculated as

$$\begin{aligned}\mathrm{VCC}_{2040} = \mathrm{VCC}_{2017} * (\mathrm{INFL}^{2040-2017}) * \frac{\overline{\eta}_{ICE,2040}}{\overline{\eta}_{ICE,2017}} * (1 - u_{BEV}) \\ + \overline{\eta}_{BEV,2040} * \mathrm{VC}_{BEV,2040} * (\mathrm{INFL}^{2040-2017}) * u_{BEV},\end{aligned} \tag{5}$$

where $\mathrm{VCC}_{2017}$ is the cost of driving in 2017 (in €/km), INFL is an inflation factor (set to 1.015 which equals an average inflation rate of 1.5%), $\overline{\eta}$ is the average fuel consumption estimated by EUTRMpy, $u_{BEV}$ is the share of vehicle activity travelled by BEV and $\mathrm{VC}_{BEV,2040}$ is the cost of charging set to 0.4 €/kWh, which is based on average values regarding home charging (17). This cost of charging is tested in sensitivity analyses (Sec. 3.4).

In quetzal_germany there are two VCC parameters: one refers to households with a car, the other refers to households without a car. Both values are calculated in the same way (but with different initial values). Additionally, this value also changes depending on the scenario. If *avoid* and *shift* assumptions are applied, 9 ct/km are added to VCC referring to the internalising of externalised costs.

Bidirectional coupling can be implemented in different ways: One option is to, (1) run quetzal_germany on a 2040 scenario, (2) interpolate the results between 2017 and 2040 (as described above), (3) run EUTRMpy (which includes all years 2017 to 2040), and (4) use EUTRMpy's results for the next run of quetzal_germany. These steps can be repeated multiple times. For testing I ran both models 10 times. In Sec. 3 I show how results change with the number of iterations. A second option is to run quetzal_germany on each year from 2017 to 2040, while after each quetzal_germany run EUTRMpy is used to generate the inputs for the next quetzal_germany run. In this project I implement only the first option (i.e. quetzal_germany is only run regarding 2040), since the quetzal_germany scenarios only describe the year 2040 and run time of the second option would be 2.5 times longer which was not feasible. The coupled version has been published under an open-source license and is available online[3].

### *2.4. Scenarios*

Table 2: Overview of scenarios. The combinations of two assumption sets impacting EUTRMpy and 4 assumption sets impacting quetzal_germany lead to eight scenarios in this project.

| | Assumption sets in quetzal_germany | | | |
|---|---|---|---|---|
| | *Reference* | *Avoid* | *Shift* | *Avoid+Shift* |
| Assumption sets in EUTRMpy | | | | |
| *State of Policy* | BAU | a | s | a-s |
| *Improve* | i | a-i | s-i | a-s-i |

The aim of this project is to show potential effects of policy making in passenger transport especially looking at the strategies *avoid*, *shift* and *improve*. Therefore, assumptions representing each of these strategies were used. The researchers who developed the models quetzal_germany and EUTRMpy used scenarios themselves to quantify the effects of policy making. To be able to compare the results of the coupled model to results of other researchers, I build on these scenarios which have already been applied to the models. Thus, each of these original sets of assumptions only affects one of the two models and only when the two models are coupled, they impact

[3]Available here: https://zenodo.org/doi/10.5281/zenodo.12520024

the behaviour of both models.

Two sets of assumptions affect EUTRMpy, one of them representing the strategy *improve* and the other describing the state of policy regarding vehicle efficiency and drivetrain shares. The state of policy refers here to the EU's Car CO2 regulation including amendments from 2023 (22). The assumption set describing *improved* transport additionally includes a faster ramp up of BEV in corporate car fleets: 50% of new corporate car sales are BEV in 2027 and 100% in 2030. Since around two thirds of newly registered cars in Germany are in this category, this has a major impact (23). The two sets only differ in their assumptions regarding drivetrain shares in new vehicles (Fig. 3). Importantly, the 'state of policy' assumptions incorporate *improvements* of the vehicle fleet, too: New vehicles are more efficient in later years and these assumptions include a ramp up of BEV.

Four sets of assumptions affect quetzal_germany. A reference pathway does not implement any policies regarding *avoid* and *shift* strategies, which is contrasted with three sets of assumptions.

Firstly, the *shift* pathway, which consists of radical pull measures and focuses on a strong reduction of car dependency through the improvement of PT and bike infrastructure. This strengthening is implemented in law (road traffic regulations giving priority to PT and bikes), in planning (shifting planning budgets to PT), in user costs (uniform PT tariffs) and in education.

Another pathway is the *avoid* pathway, in which the need for (long) trips is reduced through top-down and bottom-up changes. In a top-down approach spatial planning aims to densify towns and cities, and the improvement and diversification of these settlements to eliminate the need to go fur-

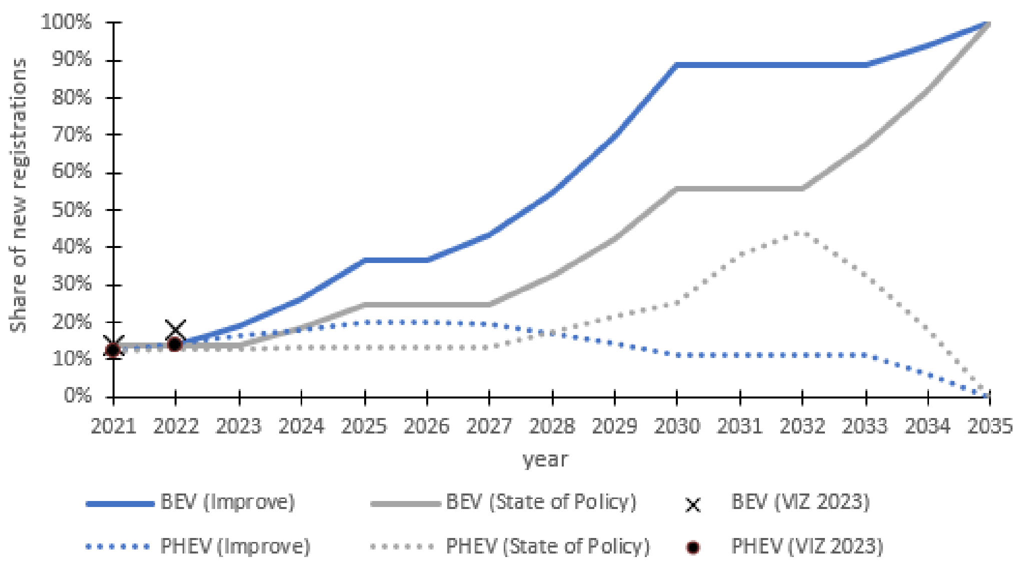



Figure 3: Sales shares of BEV and Plug-in Hybrid Electric Vehicle (PHEV) in EUTRMpy compared to real world data (VIZ 2023 (2)). When "State of Policy" assumptions are used, the share of BEV increases later than in the "Improve" assumption set.

ther than walking distance to fulfil daily needs. Additionally, in a bottom-up approach local initiatives and businesses enable local, restorative lifestyles, while social contacts over longer distances (both private and work-related) are mostly taking place in digital spaces.

Thirdly, the *avoid+shift* pathway comprises the afore-mentioned two pathways and adds a more radical change in transport planning and economic activity. This includes a shift of the population's mindset implying reduced importance of materialism and economic growth, while social justice, climate change mitigation and health become more relevant. Importantly, this shift is visible in transport planning and regulation, comprising the ban of car advertisement, the parting of car lobby and politics, car bans from cities and the car becoming an 'anti-status symbol'.

These three pathways are described in detail by Arnz & Krumm 2023 (13).

Based one theses sets of assumptions 8 scenarios are created as the combinations of them (Tab. 2).

## 3. Results

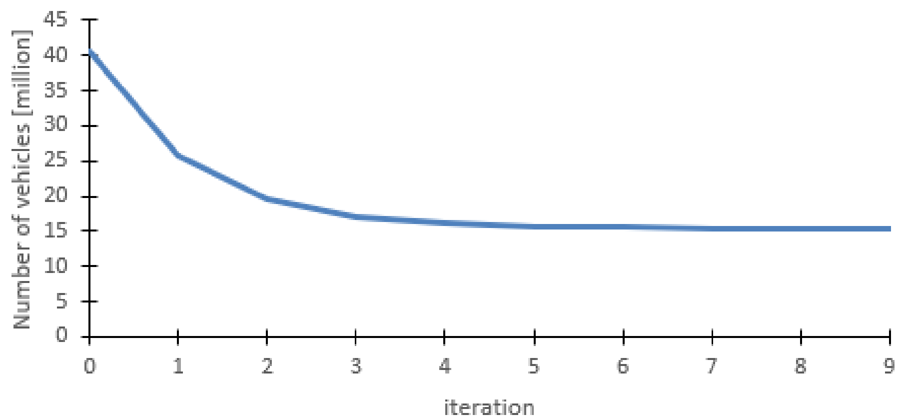
### *3.1. Bidirectional coupling*

When coupling the models bidirectionally and running them over 10 iterations, the PKM dropped by 50 % in some of the iterations and only stabilised after five iterations (Fig. 4a). This strong reduction in number of vehicles was associated with converging values of average mileage (per vehicle) in the two models (Fig. 4b).

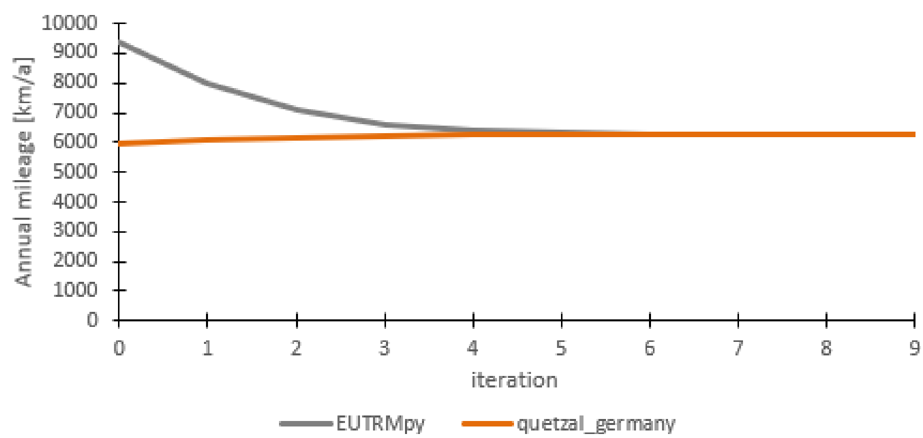
Average annual mileage is not explicitly included in the variables of quetzal_germany or EUTRMpy but can only be calculated in post-processing from stock size and vehicle kilometres. Importantly, in the initial conditions of the two models (0th iteration) average annual mileage differs between the two models (Fig. 5). Therefore, this coupled version optimises average annual mileage to agree between the two.

This leads to an unrealistically strong drop in the number of vehicles and PKM, which is caused by the link of CA (further explanation on this in Sec. 4.2). I therefore decided to erase the link via CA and run the model without. In the following, I will only refer to the results without this link.

In the resulting reduced coupling method, the step from iteration 0 to iteration 1 includes a change in the calculation method: To be able to endogenously calculate VCC the method needs more inputs (values on efficiency improvement and drivetrain shares), which are calculated in EUTRMpy and depend on the scenario assumptions. In subsequent steps of the iteration the calculation method stays the same. When inspecting the results, only negligible changes occurred after the first iteration. In the following, all results describe the first iteration (i.e., running the models twice).




(a) Number of vehicles in scenario ‘a-i’ (CA coupled)




(b) Annual mileage in scenario ‘a-i’ (CA coupled)

Figure 4: Number of cars (4a) and annual mileage (4b) in scenario ‘a-i’ changing over iterations when CA is coupled between the two models. Annual mileage converges aligning the assumptions of the two models, while stock size drops by over 60%.

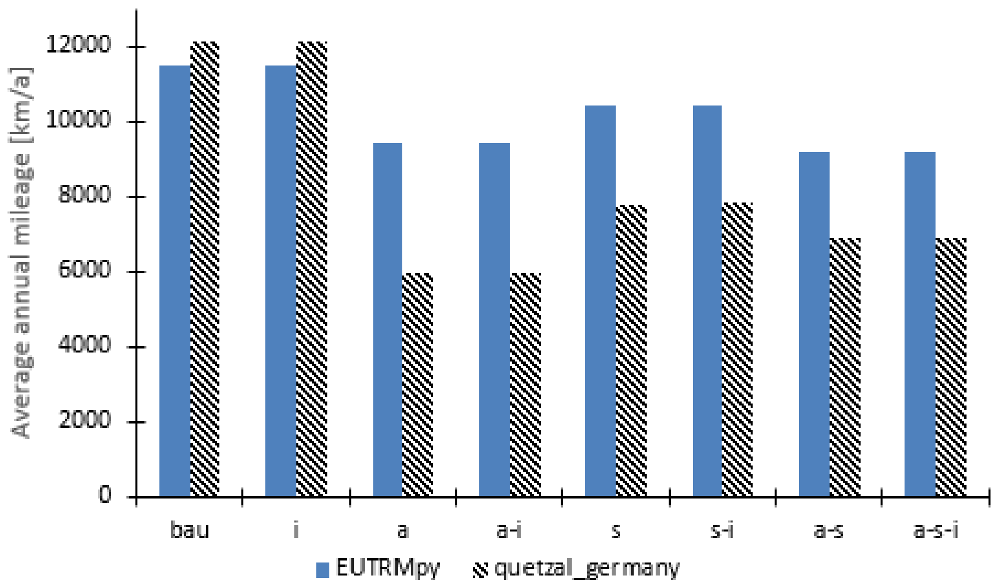



Figure 5: Average annual mileage in all scenarios comparing estimates by EUTRMpy and quetzal_germany in iteration 0. Average annual mileage is calculated in post-processing as vehicle km by stock. Vehicle km are estimated in quetzal_germany, EUTRMpy estimates stock size based on this estimate. quetzal_germany has its own assumption on stock size. Average annual mileage varies stronger between the scenarios in quetzal_germany than in EUTRMpy but in the same pattern: Whether *improve* assumptions are included does not make a difference to average annual mileage, the scenarios are ordered 'BAU', 's', 'a', 'a-s' in decreasing order.

Table 3: Central results of all 8 scenarios compared to values in 2017. *VCC is corrected for inflation to match 2017 €value.

| | 2017 | BAU | i | s | s-i | a | a-i | a-s | a-s-i |
|---|---|---|---|---|---|---|---|---|---|
| PKM 2040 [billion km] | 866 | 918 | 920 | 578 | 580 | 441 | 442 | 408 | 409 |
| WTW CO2e 2040 [Mt] | 133 | 45 | 38 | 34 | 29 | 25 | 22 | 24 | 21 |
| WTW CO2e 2030 [Mt] | | 99 | 92 | 92 | 86 | 80 | 76 | 79 | 75 |
| TTW CO2e 2040 [Mt] | 109 | 33 | 26 | 26 | 21 | 19 | 17 | 18 | 16 |
| TTW CO2e 2030 [Mt] | | 77 | 69 | 72 | 65 | 63 | 58 | 63 | 58 |
| Activity share BEV 2040 [%] | 0% | 57% | 67% | 50% | 59% | 43% | 51% | 42% | 49% |
| No. of BEV 2040 [million] | 0.1 | 31 | 36 | 19 | 22 | 11 | 13 | 10 | 12 |
| Avg. sales 2025-2040 [million] | 3.6 | 3.4 | 3.5 | 2.2 | 2.2 | 1.4 | 1.4 | 1.3 | 1.3 |
| No. of vehicles 2040 [million] | 50 | 53 | 53 | 37 | 37 | 26 | 26 | 24 | 24 |
| VCC 2040 [€/km] * | 0.110 | 0.075 | 0.071 | 0.077 | 0.075 | 0.081 | 0.078 | 0.146 | 0.143 |

### *3.2. Outcomes of the scenarios*

Large differences between the scenarios are visible in stock size estimates: In the scenarios ‘BAU’ and ‘i’ the number of vehicles increases slightly to 53 million vehicles in 2040 compared to 50 million in 2022 (Tab. 3). In all other scenarios the stock size decreases (to 37 million in ‘s’ and ‘s-i’, to 26 million in ‘a’ and ‘a-i’ and to 24 million in ‘a-s’ and ‘a-s-i’).

The scenarios with decreasing numbers of vehicles include changes in vehicle sales, as well (Fig. 6). In scenario ‘a-s’ on average (between 2025 and 2040) 1.3 million vehicles are sold per year. In contrast, in ‘BAU’ and ‘i’ 3.4 million vehicles are sold on average in the same time period, which is only slightly lower than the sales of MIT vehicles in 2017 which was 3.6 million (Fig. 6).

The number of BEV driven depends on the estimated sales and sales shares of drivetrains. Sales differ between scenarios depending on whether or

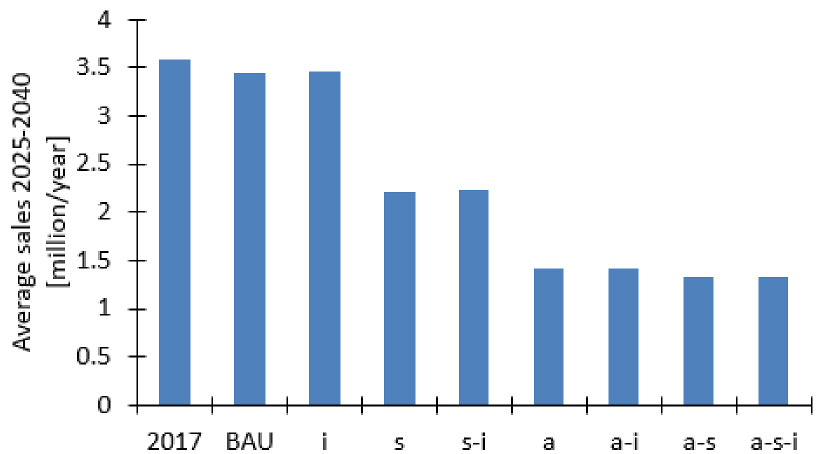
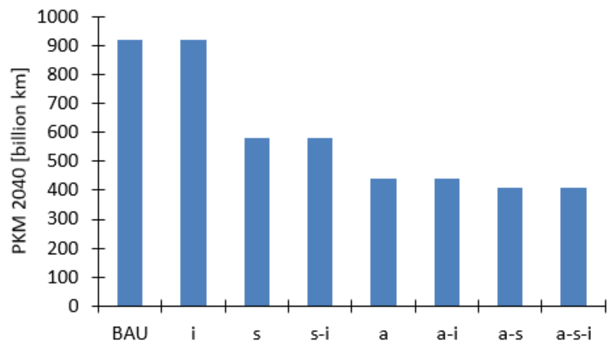



Figure 6: Average sales (2025-2040) in all scenarios compared to 2017 level. In the scenarios 'BAU' and 'i' sales are slightly lower than the 2017 value of 3.6 million vehicles. If the *shift* strategy is applied, sales drop to 2.2 million vehicles. In the scenarios including the *avoid* strategy sales drop to 1.4 million. If *avoid* and *shift* strategy are included, sales drop to 1.4 million vehicles. Applying the *improve* strategy has a negligible effect on the sales, which are increased by 1,800-5,000 vehicles, if this strategy is applied.

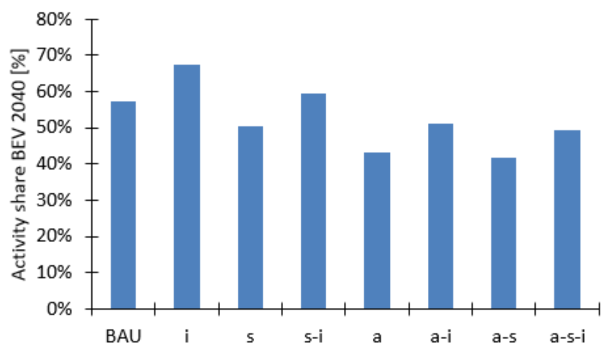
not *avoid* and/or *shift* assumptions are included. Sales shares of drivetrains differ depending on whether or not *improve* assumptions are included. Therefore, the number of BEV varies between all scenarios. However, it increases in all scenarios compared to the level of 2023 which is 1.01 million electric cars (2). The highest numbers of BEV are reached in 'i' and 'BAU' scenario (36 and 31 million BEV respectively). The scenarios 's-i' and 's' reach half of this level (22 and 19 million BEV respectively). While the scenarios 'a-i', 'a', 'a-s-i' and 'a-s' reach lower numbers of BEV (Tab. 3). Similarly, the activity share travelled by BEV also differs between scenarios (Fig. 7b).

Comparing PKM in 2040 between scenarios, whether or not the *improve* strategy is applied has a negligible effect (Fig. 7a). When the *shift* strategy is introduced passenger activity of MIT drops from 918 billion km ('BAU') to 578 billion km. If using the *avoid* strategy PKM is reduced to 441 billion km. If these two strategies are combined PKM even drop to 408 billion km (Fig. 7a).

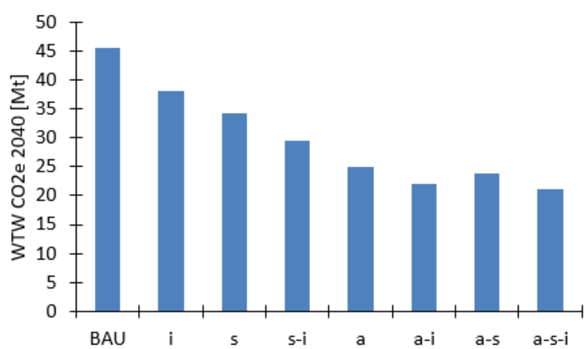
In all scenarios the GHG emissions from MIT reduce strongly until 2040 (Fig. 8). But there are large differences visible between the scenarios. The lowest emissions are reached in the 'a-s-i' scenario where tank-to-wheel (TTW) emissions drop to 15 Mt CO2e. In 'BAU' TTW emissions reduce to 33 Mt CO2e. So TTW emissions in 'a-s-i' scenario are only 48% of what would be emitted in 'BAU'. The 'Klimaschutzgesetz' (KSG) sets GHG reduction goals for each sector in Germany. In 2030 the German transport sector should not emit more than 85 Mt CO2e and in 2045 net 0 is supposed to be reached (24). Assuming emissions to decrease linearly between 2030 and 2040 and MIT to cause the same share of emissions as in 2022, equals goals




(a) Passenger activity travelled in 2040




(b) Activity share of BEV in 2040




(c) WTW CO2e emissions in 2040

Figure 7: Comparison of all scenarios in 2040. WTW CO2e emissions (7c) are lower in the scenarios with lower PKM (7a). If the difference between two scenarios is the application of *improve* assumptions, PKM differ only slightly, thus, the scenario with the higher BEV share (7b) is the one with lower emissions. The only exception to this is the comparison of scenarios 'a-i' and 'a-s'. The former has lower emissions, and the latter has lower PKM.

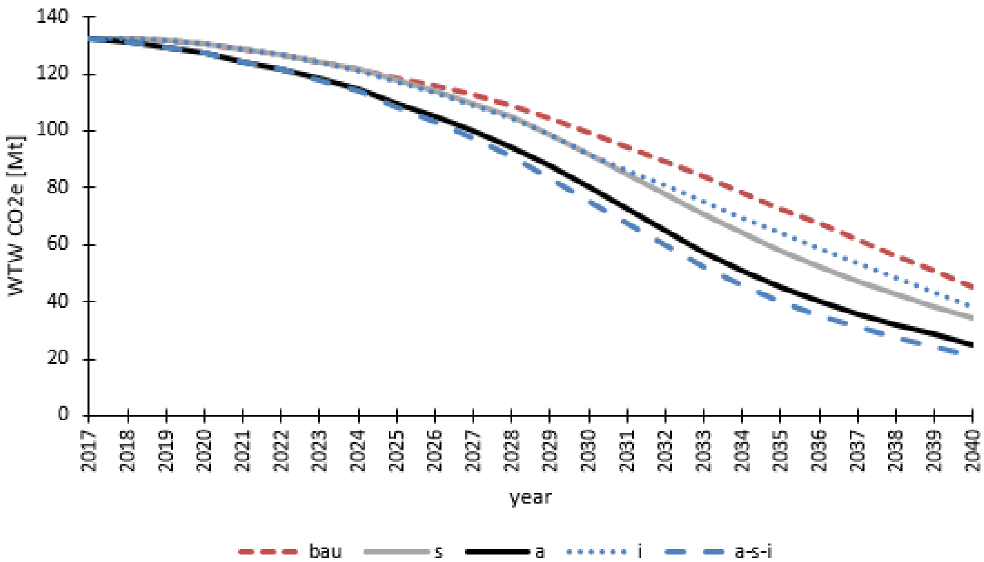



Figure 8: WTW carbon dioxide equivalents (CO2e) emissions in the scenarios 'BAU', 's', 'a', 'i' and 'a-s-i'. Emissions decrease strongly in all scenarios. In 2040 in scenario 'a-s-i' GHG emissions are less than half of 'BAU'.

of 55 and 18 Mt CO2e in 2030 and 2040. In 2030 this goal is met in none of the scenarios. In 2040 only the scenarios 'a-i' and 'a-s-i' meet this goal. When inspecting WTW emissions, which also comprises emissions along the energy conversion chain including emissions from electricity generation, the 'a-s-i' scenario reaches CO2e emissions of only 46% of what would be emitted in 'BAU' (Fig. 7c).

### *3.3. Effects on cost of driving (VCC)*

By coupling the two models potential rebound effects caused by improving engine efficiency or an increase of the share of BEV are included. In this model the efficiency of internal combustion engines increased steadily (in new sales) causing an average ICE in 2040 to consume only 80% of the average ICE in 2017 ('BAU'). In the same time period the share of the activity travelled by BEV increases to 57% in 'BAU' and even to 67% in 'i'. In 2040 the average ICE consumes 2.0 MJ/km compared to 0.6 MJ/km consumed by a BEV. These efficiency increases are visible in the price per km: In 2017 VCC is at 11.0 ct/km and until 2040 drops in 'BAU' and 'i' scenario to 7.5 and 7.1 ct respectively (all € values are corrected for inflation to fit 2017 € value). Here, I am only referring to VCC when owning a car. The price when not having a car has a smaller impact.

Meanwhile, PKM increases by 6.1% and 6.2% in 'BAU' and 'i' (Fig. 9). Here, the additional BEV in 'i' only slighly impact PKM (Fig. 7a). To check whether the share of BEV can make a difference regarding price and thus PKM, I created an additional scenario which is a copy of 'BAU' scenario but with BEV sales shares staying at 2020 levels for all future years. In this 'low BEV' scenario BEV make up for only 12% of activity in 2040. The VCC

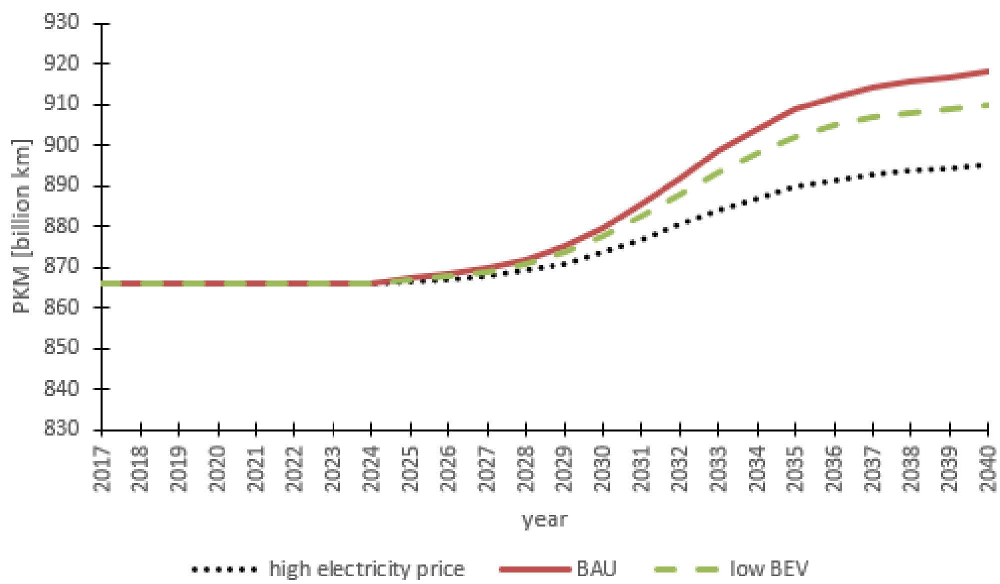



Figure 9: Passenger activity travelled (MIT) in 'BAU' compared to 'BAU' with doubled electricity price (in 2040) and a scenario ('low BEV') where drivetrain shares of vehicle sales remain at the level of 2020. PKM depend on the assumed electricity price and on the share of BEV of the stock. Between 2017 and 2040 PKM increase by 6.1% in 'BAU'. If the electricity price is doubled, PKM increase by only 3.4% i.e. reducing the rebound effect.

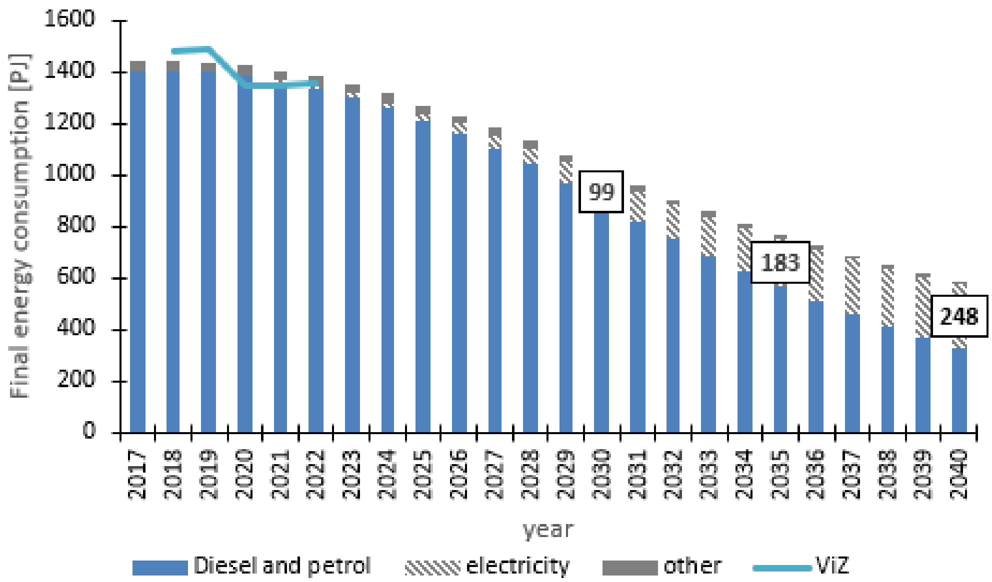



Figure 10: Final energy consumption by cars in scenario 'i' by energy source. The turquoise line represents consumption measurements from VIZ (2). The values in the boxes display the electricity consumption in the respective year. Until 2040 the total energy consumption decreases strongly, while the electricity consumption increases.

decreases to 8.5 ct/km and PKM increase by 5.1% (Fig. 9). Hence, the reduced share of BEV in the stock increases the price (compared to 'BAU' or 'i') and thus reduces the rebound in activity.

Importantly, even including the PKM increase of 6.2% in 'i' scenario, total energy consumption of cars drops by 59% (Fig. 10). The rebound effect counteracts only a small part of the energy demand reduction induced by the efficiency increase.

VCC increases in nearly all scenarios. Only the two scenarios, which combine *avoid* and *shift* strategies, show a price increase. Nevertheless, these two scenarios include an efficiency increase: In 2040 an average ICE consumes only 82% of its equivalent from 2018 and the activity share travelled by BEV increases to 42% in 'a-s' and to 49% in 'a-s-i'. Thus, the measures taken in these scenarios are able to counteract the efficiency improvement to not affect the price. In 'a', 's', 'a-i' and 's-i' PKM is decreasing while price is decreasing, too. Thus, in these four scenarios the potential increase in PKM induced by price decrease is counteracted by the measures taken.

### *3.4. Sensitivity*

In the process of developing the coupled model I made assumptions. To see the effect of these assumptions on final results, I tested the sensitivity of the results to changes in single assumptions. One parameter which links the two models is VCC. This parameter depends on the price of electricity. Doubling the (charging) electricity price in 2040 decreases the PKM estimates by 3% reducing WTW CO2e emissions by 2% (Fig. 9).

In EUTRMpy the annual mileage travelled by each vehicle at a certain age, is a variable determining how many vehicles are needed to meet transport demand. Therefore, if it is decreased, sales and fleet size are increased leading to an increased number of BEV entering the stock, to an increase in the activity share of BEV, and thus, to slight decreases in energy demand and GHG emissions while driving. Decreasing this mileage variable by 20% leads to 3% lower WTW CO2e emissions in 2040 (in 'a' scenario). While the stock size in 2040 is increased from 26 million to 32 million vehicles in 2040 (in 'a' scenario). In this test this mileage variable is linearly decreased to reach 80% of the 2017 value by 2035 (e.g., a new vehicle drives 12,000 km instead of 15,000 km per year).

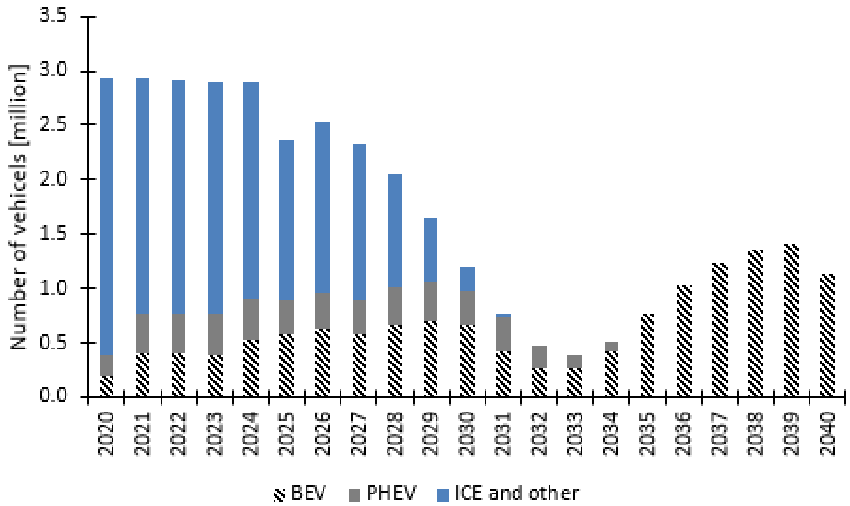
## 4. Discussion

### *4.1. Comparison to other models*

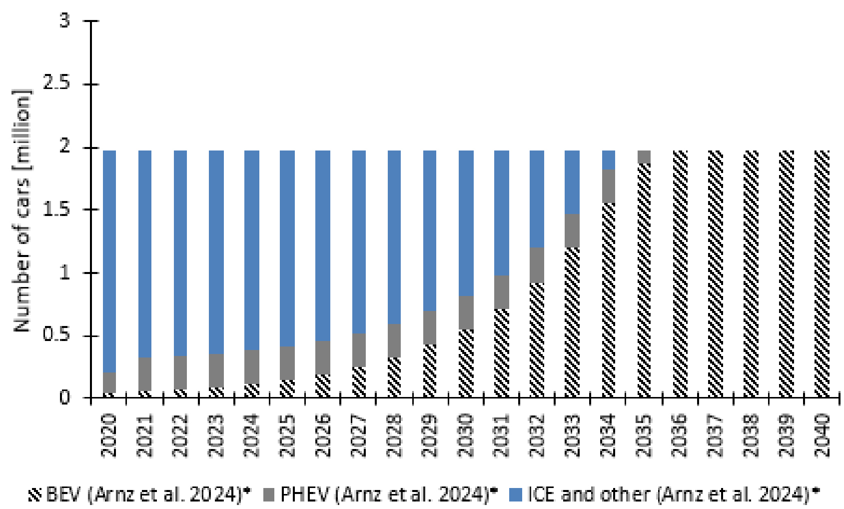
To ensure realistic results I will inspect estimates of PKM, BEV share of stock, total energy consumption and number of vehicles and compare them with other models' results. The German environmental agency commissioned multiple reports describing possible futures of the German transport sector. They describe one scenario including the policy measures, which are already in place as of summer 2022 named 'mit Maßnahmen Szenario' (MMS), which projects passenger activity (MIT) to reach 931 billion km by 2040 (25). Lower levels of passenger activity are reached in a scenario focused on immediate action called 'sofortiges Handeln Szenario' (SHS), which includes additional pull (e.g., investments in walking and biking infrastructure) and push (e.g., higher car taxation) measures. Here, PKM drop to 603 billion km in 2040 (24). Passenger activity as modelled in my project fits well with these results: PKM ranges between 913 km ('BAU' and 'i' scenario) and 408 billion km ('a-s' and 'a-s-i' scenario) in 2040. This stronger reduction of PKM in my model compared to SHS, is induced since the cultural change described by the *avoid+shift* pathway exceeds the strength of the measures taken in SHS (24).

In my scenarios vehicle sales is the variable changing between scenarios and over time to adjust the stock to the activity demand. Therefore, it varies over time. In scenario 'a-s' the number of vehicles sold drops as low as 380,000 vehicles for one year, while on average (between 2025 and 2040) 1.3 million vehicles are sold per year (Fig. 11)

Arnz et al. 2023 assume the number of cars to depend on the scenarios,




(a) Scenario 'a-s'




(b) Scenario 'a-s' Arnz et al. 2024

Figure 11: Sales by drivetrain in 'a-s' scenario (11a) compared to 'a-s' scenario as in Arnz et al. 2024 (11b) (9). In scenario marked with an asterisk only cars are included, otherwise MIT is covered. While Arnz et al. 2024 assume constant vehicle sales, the sales in Fig. 11a vary from year to year and are much lower between 2030 and 2035, when BEV sales shares are high.

therefore, it is decreased by a certain factor which has been determined in expert interviews (13). In the reference scenario it stays constant (levels of 2017). It drops to 29.5 million until 2040 if *avoid* and *shift* measures are taken (Fig. 12). Conversely, in the report by Umweltbundesamt 2024 the stock size is expected to be constant (levels of 2022) in all their scenarios (24). In my scenarios the number of vehicles is changing to match vehicle activity, while the annual mileage of vehicles (of a certain age) is the same in all scenarios. Thus, the number of vehicles (MIT) varies strongly between scenarios. In the scenarios 'i' and 'BAU' it increases compared to 2017 level, while it decreases in all other scenarios. Strikingly, the reduction in the number of vehicles is stronger in the 'a-s' scenario than in the respective scenario by Arnz et al. 2024 (Fig. 12).

The share of the stock per drivetrain depends in the models on sales shares, the number of sales and assumptions made on the stock size development. As seen above, in SHS the number of cars in stock is constant over time, and it includes larger BEV sales shares than the *improve* assumption set since it includes an additional car tax depending on the carbon dioxide (CO2) emissions of the vehicle. Here, BEV make up for 71% of the stock in 2040. Arnz et al. 2024 include BEV sales shares of 100% as early as 2027 in their 'improve' scenario (9). Thus, their simple stock model reaches 100% BEV by 2040 in their 'improve' scenario. In their scenario with *avoid* and *shift* measures 56% of vehicles are BEV in 2040. In my scenarios the number of BEV in 2040 ranges from 10 million vehicles or 42% ('a-s') to 36 million vehicles or 67% ('i'). Comparing 'a-s' to the respective scenario of Arnz et al. 2024, the lower share of BEV is explained by the smaller stock in this

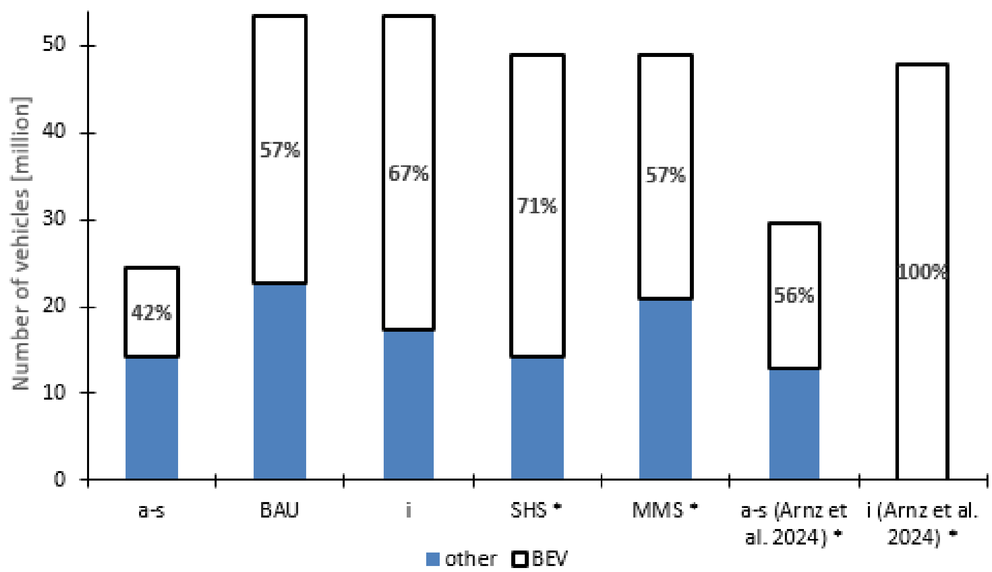



Figure 12: Number of vehicles by drivetrain in 2040 in different scenarios. The value inside the box signifies the share of BEV of the whole stock in the respective scenario. Scenarios 'a-s', 'BAU' and 'i' are estimates of the coupled model. SHS and MMS are scenarios by Umweltbundesamt (25) (24). 'a-s' and 'i' scenarios on the right-hand side are from Arnz et al. 2024 (9). In scenarios marked with an asterisk vehicles include cars only, otherwise MIT is covered. 'BAU' and MMS both describe the state of policy today and agree in their results regarding the share of BEV in the stock.

scenario: In my scenario vehicle sales are changed accordingly leading to a smaller number of BEV entering the stock (Fig. 11).

Finally, the coupled model estimates energy consumption. Comparing the total energy consumption estimates to real world data, the estimates fit well in past years (Fig. 10). The model estimated a total energy consumption of MIT in Germany of 1439 PJ and 1383 PJ in 2018 and 2022 respectively. In the same years 1478 PJ and 1359 PJ were described in VIZ (2). In scenario 'i' in 2040 total energy consumption is reduced by 55% compared to 2019 values which is mostly due to the high efficiency of BEV compared to ICE. In SHS total energy consumption of all German transport, which can give a hint on the order of magnitude, is reduced by 56%, thus, agreeing to my results (24).

### *4.2. Annual mileage*

A central question regarding the future development of passenger transport is the annual mileage travelled by each vehicle. Today, there are about 50 million cars in Germany. A transport system in 2040 might consist of half the number of cars but still the same number of passenger kilometres travelled, if each car was shared between households (car sharing) and car occupation would increase (ride sharing). This would mean an increase in average annual mileage. Another possible pathway is a constant car stock at decreasing PKM as described in SHS by Umweltbundesamt 2024 (24). Average annual mileage decreases strongly in such a scenario. Which of these pathways is closer to the German transport system in 2040 depends on the policy measures taken. From an energy sufficiency perspective, it would be beneficial to reduce passenger activity to a sufficient minimum meeting all mobility needs of all people, while the number of cars would be reduced to efficiently meet these activity demands through ride and car sharing. In this case, low activity levels and low numbers of cars would lead to reduced energy consumption while driving, and reduced material and energy consumption in production. Thus, an energy sufficiency-oriented transport system would be one with high annual mileage per vehicle.

The two models quetzal_germany and EUTRMpy do not explicitly include assumptions on average annual mileage of all vehicles. Comparing average annual mileage in the two models in all scenarios in 2040, mileage varies strongly between the scenarios in quetzal_germany, while it only varies slightly in EUTRMpy (Fig. 5).

When coupling the two models these differences need to be considered and in the best case harmonised. In a first version of the coupled model annual mileage was optimised to agree between the two models by linking CA. The following paragraph describes how this link influenced the model, and why it did not lead to realistic results.

In quetzal_germany the number of cars and car availability are input parameters. In the first coupled version they are changed by the same factor (as long as car availability is between 0 and 1). Car availability influences PKM by affecting generation, distribution and mode choice. Additionally, multiple other scenario parameters affect the PKM estimation. When iterating this coupled version, a behaviour is visible where PKM drops by the same order of magnitude as car availability does. Therefore, annual mileage in quetzal_germany changes only slightly while iterating (per scenario, see Fig. 4). In EUTRMpy average annual mileage is determined from the annual mileage travelled by a car at a certain age (which is kept constant over time) and the age distribution of the stock. Vehicles sales are changing to fit activity and stock. Meanwhile, sales can change the age distribution. Thus, in this coupled version, vehicle sales are strongly changed from iteration to iteration leading to the visible drop in sales and stock (Fig. 4). If the stock size of the two models is linked via CA, annual mileage is optimised via this change in stock size and sales, which does not imply a realistic stock size.

By deleting this link via CA this problem was solved. But at the same time, this project did not succeed in fitting the assumptions regarding annual mileage inside the two models. Future research could fill this gap by e.g., purposely changing annual mileage in EUTRMpy through its input variables, to fit to quetzal_germany's implicit assumptions. When erasing the CA-link, the resulting stock as estimated in this project fits with the annual mileage assumed by EUTRMpy (Fig. 5), the annual mileage does not significantly decrease compared to 2017 levels. Thus, it follows the idea of high annual mileage per vehicle aiming at energy sufficiency.

### *4.3. Stock and sales estimation in EUTRMpy*

EUTRMpy estimates the number of cars needed to fit vehicle activity. In this project I assumed the annual mileage travelled by each car at a certain age to be constant over time. This leads to a close relationship between stock size and vehicle activity. Sales change over time to adjust the stock size to match vehicle activity. Therefore, sales vary strongly over time and between scenarios and mostly depend on vehicle activity. Strikingly, this behaviour is different than it would be in reality, where vehicle sales depend on consumer choices, industry decisions, policy making and economic situation of a country (see Sec. 1.1) and is not directly linked to vehicle activity. A good example for this behaviour is the strong reduction of passenger activity caused by policy measures taken to reduce the spreading of the COVID pandemic in 2020 and 2021 (2). In this period of strongly reduced vehicle activity, people neither sold their cars nor stopped buying new vehicles. With the assumptions made in this project, sales should have dropped dramatically and the number of cars in Germany should have decreased by the same factor as vehicle activity did. This behaviour is not realistic at all.

In this project multiple scenarios include a reduction of vehicle activity. The car activity reduction is caused by pull and push measures, shifting activity to other transport modes, as well as reducing the need for (long) trips. Whether this activity reduction implies a reduction of the stock depends on the exact design of the measures. A change in the tax regime could be implemented in different ways. Whether car use, car ownership or car sales are taxed, implies different effects on the car stock. It could lead to either reduced annual mileage, changing survival rate or lower sales or a mixture of the three. Additionally, it makes sense to assume a certain 'car ownership threshold' implying that the reduction of the number of cars per household is politically easier achievable than convincing households to sell their last car i.e., changing their habits (26).

In this project annual mileage and survival are not changing inside the model leaving sales to be the only factor adjusting the stock to fit the changing activity. If these assumptions had been made differently, sales estimates would be different (as described in Sec. 3.4). Nevertheless, this model enables the estimation of car sales in various scenarios allowing future research to estimate effects on resource and energy use in production.

### *4.4. Avoid, shift, improve - effects on stock and emissions*

In the following paragraph I will answer the research questions by comparing and discussing the effects of the three strategies avoid, shift and improve on GHG emissions and vehicle stock.

To strongly reduce the GHG emissions in Germany and mitigate climate crisis, it is crucial to include all three strategies: When only applying the *improve* strategy, the German climate target of 2030 as set in KSG is missed by 26%. If all three strategies are used it is only missed by 6%.

As shown in Sec. 3.2, all scenarios including the *avoid* or *shift* strategies, showed a decrease in size of the vehicle stock and in the number of new vehicles joining the stock. On the one hand, reduced car production demands less energy and materials. On the other hand, car industry needs to be strongly restructured if the demand in cars decreases as strongly as depicted in scenario 'a-s-i'. In Germany today 830,000 people are employed in car industry (5). Therefore, it's advised to already now work on the solutions to develop long-term strategies to ensure incomes for people working in car industry today. Related strategies have been discussed in trade unions, environmental movements, and research since the 1990s. Central ideas in this debate are the conversion of the car industry to produce different goods, working hour reduction, growth potentials in other 'Mobility industries' (e.g., production of buses, trams) creating related industrial jobs and better working conditions (including higher wages) in non-industrial mobility jobs such as bus drivers (27) (28). Thus, transforming mobility to reduce its negative impact on climate, people and nature implies a large scale metamorphose not only regarding mobility habits and spatial planning but also regarding the spheres of society, industry, and labour.

Although, the strategies are additive and lead to a GHG emission reduction while driving, it is important to notice that the strategies do not add up completely. One example are WTW CO2e emissions, which are decreased to 75% (of 'BAU') if *shift* is applied and to 55% if *avoid* is applied. Combining the two does not lead to a reduction to 41% as a simple multiplication would imply, but only reduces the emissions to 52% of 'BAU'. This is not surprising, to illustrate, the *improve* strategy (as implemented in this model) only affects a share of vehicle sales, if one of the other strategies reduces vehicle sales, the impact of the *improve* measures is reduced.

In the scenarios 'bau' and 'i' I was able to show a rebound effect, which is caused by ICE efficiency increase and a higher share of BEV in the vehicle stock. Thus, this rebound effect and its rising activity demand already occurs with the policies in place today. Additional policy measures increasing vehicle efficiency and the share of BEV as described in SHS might even enhance the rebound effect and further increase activity demand.

But, as seen in Sec. 3.2, both strategies *avoid* and *shift* applied on their own or in a combined manner are able to counteract this rebound effect. Therefore, the implementation of *avoid* and *shift* measures to halt rebound effects caused by efficiency increases is crucial in any policy path.

In this work, the only rebound effects I looked at are increases in PKM caused by internal combustion engine efficiency improvements and the increased usage of BEV. Hereby, I omitted other rebound effects such as rebound effects related to sufficiency increases (10). Moreover, I did not include a rebound effect which is clearly visible in today's car market: Efficiency improvements in engines do not manifest in reduced fuel use per km but in higher vehicle weights or increased horse power (29). Future research should close this gap by including vehicle weights into the stock model and incorporating this rebound effect.

My results show that all three strategies reduce GHG of German passenger transport and can therefore help to mitigate climate crisis. However, the model focuses on MIT and thus did not take into account climate (or other environmental) effects from PT. Since both EUTRMpy and quetzal_germany can also model other modes of transport than MIT, future research can further improve the coupling of the two models to also include PT.

Moreover, I did not consider the environmental and societal costs regarding other emissions, resource and energy use in vehicle production, space needed, health and social justice. Regarding these concerns *shift* and *avoid* strategies have positive side effects, by e.g., reducing energy and resource use in production, the space needed for mobility services, the number of deaths in traffic, while increasing human well-being (30). Especially with rising numbers of BEV, the energy and resource demand of (battery) production need to play a role when deciding how to combine the strategies described above. This project did not cover estimates of energy and resource use in production. Nevertheless, I was able to show that the number of new vehicles entering the stock decreases strongly in scenarios where *avoid* and *shift* measures were applied, which will certainly lead to lower energy and resource demands than when only applying *improve* measures.

Therefore, aiming at a transformation of passenger transport to reach a sustainable future a combination of the three strategies *avoid*, *shift* and *improve* with a clear focus on the first two strategies is advantageous. This would imply large societal changes as described in the 'Avoid&Shift' pathway by Arnz et al. 2023, which includes a shift in people's mindsets towards minimal car ownership, transport and spatial planning shifting their focus to equity, health and diversity and the decoupling of prosperity from growth (13).

## 5. Conclusion

To identify pathways to effectively reduce GHG emissions in passenger transport in Germany until 2040, this work compares the effects of the three strategies of sustainability transformation in transport: *avoid*, *shift* and *improve*.

Within this project, the macroscopic passenger transport model quetzal_germany is coupled with the stock model EUTRMpy enabling the quantification of the vehicle stock's size and composition and GHG emissions from MIT. The two models are linked bidirectionally. Passenger activity modelling by quetzal_germany is used as the basis of the stock modelling and emission estimates by EUTRMpy, while the engine efficiency improvements, and car stock composition (by drivetrain) modelled by EUTRMpy influence the cost of driving in quetzal_germany.

In all scenarios energy demand decreases over time. This happens either due to an decrease in vehicle km (if *avoid* or *shift* strategy is applied) or due to an increase in engine efficiency and broader use of BEV (*improve* strategy) or both. Although, all strategies reduce the WTW GHG emissions from cars, *avoid* has the strongest reduction impact (compared to 'BAU') when comparing single strategies. Even in the most ambitious scenario, which includes all three strategies, TTW CO2e emissions from MIT are higher in 2030 than the estimated KSG goal. In 2040, in two scenarios the policy measures accomplish to reduce GHG emissions satisfactory: If *avoid* and *improve* strategies are applied or all three strategies are used, the goal is met.

If either *shift* or *avoid* strategies are applied, sales drop to 60% and 40%

respectively, while the vehicle stock decreases to 37 and 26 million respectively (compared to 50 million in 2017). If both strategies are applied, sales decrease even to 37% of 2017 levels, while the vehicle stock shrinks to 24 million vehicles. This is the case, since annual mileage per vehicle stays at today's levels in these scenarios intending high usage of each vehicle and, thus, aiming at sufficiency on the production side. To enable the reorganization of car industry caused by low sales, it is central to plan industry conversion and new income opportunities in mobility.

The number of BEV increases in all scenarios and to up to 36 million BEV in 2040 (if only *improve* strategy is applied). Importantly, the *improvement* of the vehicle stock via the large scale introduction of BEV and engine efficiency improvements is fostered through European Union (EU) legislation already today. If the vehicle stock is *improved* - through today's policies or additional measures - the consequent price decrease per km travelled cause a rebound effect, which leads to an increase in passenger kilometres. This rebound effect can be counteracted by application of *avoid* or *shift* measures. Therefore, it is crucial to focus on *avoid* and *shift* measures in future policy making including a new orientation of transport and spatial planning and society at large aiming at minimal car ownership.

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## Appendix A. Update of EUTRMpy to Version 3.1

### *Appendix A.1. New features*

The new version includes new features, mainly

- Possibility to adjust the variable "annual distance accumulation" (i.e., a factor to describe how much a vehicle aged x travels compared to a new vehicle) for future years by setting a goal value for a specific year and linearly interpolating between today and this goal year.)
- Possibility to adjust the variable "survival rate" (i.e. the share of vehicles surviving until age x) for future years by setting a goal value for a specific year and linearly interpolating between today and this goal year.
- I introduced a new input variable "annual mileage new vehicle". In the baseline scenarios this might be constant. If increased this leads to increased mileage of all vehicles (This value multiplied by "annual distance accumulation" equals to the annual mileage of each vehicle at age x).
- There is now the possibility to install EUTRMpy as a package using pip. Thus, it can be installed inside the quetzal_germany environment.
- I reduced the datasets to only include Germany as a country and changed how vehicles are traded between countries. Before, 6% of the vehicles entering the German stock were second hand vehicles from other European countries. Now, the same share enters the stock as second-hand vehicles but have characteristics regarding age, efficiency

and drivetrain as if they were from German second hand market (i.e., 100% of bilateral trade entering Germany, come from Germany).

*Appendix A.2. Changes in calculation steps*

To include these new features, I had to change some of the calculation steps. Main changes inside the model:

- Various values were calculated regarding one baseline year (i.e., the last year with sufficient data) and would then be used for all future years. These are now calculated for each year (after the baseline year).
  - "Share vehicle km older x" (see below)
  - "Average distance at age x" (annual mileage of a vehicle aged x; see below)
  - "Stock age" (the number of vehicles which are age x in absolute values)
- The calculation of "Average distance at age x" has been simplified ("annual distance accumulation" * "annual mileage new vehicle").
- There was some odd behaviour regarding the calculation of "Share vehicle km older x" (i.e., the share of km travelled by all vehicles being at least x years old): The value was calculated twice with different results and the second calculation was supposed to overwrite the first results. But the outputs of the two calculation steps were stored in separate variables leading to a behaviour where not all values were overwritten, and the model was not consistent in the values used in subsequent steps. In version 3.0 only the newer version of the calculation step is

used. Changing this behaviour slightly affected TTW emissions (e.g. in Germany increases of max. 0.4% where the gap decreases over time).

*Appendix A.3. Updated data*

Table A.4: Updated data in EUTRMpy

| Name of dataset | Source |
|---|---|
| CO2 Emission factor grid electricity | UBA CO2 Emissionsfaktor Strommix (31) |
| Age distribution | NMP task C (average 2005-2018) (32) |
| Survival | NMP task C (average 2005-2018) (32) |

## Appendix B. Calculation steps EUTRMpy

*Appendix B.0.1. stock and sales estimation*

The average distance travelled at age $a$ in year $y$ and region $r$ is defined as

$$M_{y,r,a} = M_{y,r,0} \cdot A_{y,r,a}, \tag{B.1}$$

where $M_{y,r,0}$ is the annual mileage of new vehicles in year $y$, region $r$ and $A_{y,r,a}$ is the annual distance accumulation (i.e. how much a vehicle aged $a$ travels compared to a new one), where $a \in \{0, 1, 2, ..., 39, 40\}$.

The marginal survival rate $Z_{y,r,a}$ (i.e. how large is the share of vehicles surviving from age $a$ to age $a + 1$) can be calculated from the survival rate $S_{y,r,a}$ (i.e. how many vehicles survive until age $a$) as

$$Z_{y,r,a} = \frac{S_{y,r,a+1}}{S_{y,r,a}}. \tag{B.2}$$

The absolute age distribution $E_{y,r,a}$ (number of vehicles aged $a$) is defined as

$$E_{y,r,a} = b_{y,r} \cdot G_{y,r,a}, \tag{B.3}$$

where $G_{y,r,a}$ is the age distribution (share of vehicles aged $a$) and $b_{y,r}$ is stock size.

The average mileage of additional sales $c_{y,r}$ (i.e. how many km are on average travelled by each vehicle entering the stock (comprising new vehicles and second hand vehicles)) is calculate as

$$c_{y,r} = p_r(\sum_i M_{y,r,i-2} \cdot Q_{r,i}) + (1 - p_r)M_{y,r,0}, \tag{B.4}$$

where $i$ are age groups with $i \in \{5, 10, 15, 20\}$ (5: aged 1 to 5 years, 10: 6 to 10 years,...), $Q_{r,a}$ is the share of second hand sales in this age group and $p_r$ is the share of second hand sales of all sales in region $r$.

The absolute age distribution after survival before adding sales $E^*_{y,r,a}$ is defined as

$$E^*_{y,r,a} = E_{y-1,r,a-1} \cdot Z_{y,r,a}. \tag{B.5}$$

From this residual PKM $l_{y,r}$ (i.e. PKM not met by surviving stock, need to be travelled by sales) can be calculated as

$$l_{y,r} = k_{y,r} \cdot 1000 - ((\sum_a E^*_{y,r,a} \cdot M_{y,r,a}) \cdot d_{y,r}), \tag{B.6}$$

where $k_{y,r}$ are passenger kilometres travelled in year $y$, region $r$ and $d_{y,r}$ is the occupation rate (load factor).

Vehicle sales by age $V_{y,r,a}$ are defined as

$$V_{y,r,a} = \begin{cases} \dfrac{(1-p_{y,r}) \cdot l_{y,r}}{c_{y,r} \cdot d_{y,r}} & \text{if } a = 0 \\ \\ \dfrac{p_{y,r} \cdot l_{y,r}}{c_{y,r} \cdot d_{y,r}} \cdot Q_{r,a+2} & \text{if } a \in \{3, 8, 13, 18\} \\ \\ 0 & \text{else.} \end{cases} \tag{B.7}$$

Thus, $V_{y,r,0}$ are sales of new vehicles.

Now the stock size $b_{y,r}$ is calculated as

$$b_{y,r} = \sum_a E^*_{y,r,a} + V_{y,r,a}, \tag{B.8}$$

the absolute age distribution $E_{y,r,a}$ is updated to

$$E_{y,r,a} = E^*_{y,r,a} + V_{y,r,a}, \tag{B.9}$$

and age distribution $G_{y,r,a}$ is updated to

$$G_{y,r,a} = \frac{E_{y,r,a}}{b_{r,y}}. \tag{B.10}$$

Now the share of vehicle kilometres travelled by all vehicles aged $a$ $H_{y,r,a}$ is defined as

$$H_{y,r,a} = \frac{G_{y,r,a} \cdot A_{y,r,a}}{\sum_a G_{y,r,a} \cdot A_{y,r,a}}. \tag{B.11}$$

The share of vehicle kilometres travelled by all vehicles aged $a$ or older $O_{y,r,a}$ is defined as

$$O_{y,r,a} = \sum_{j=0}^{40} H_{y,r,a} \cdot \epsilon_{a,j}, \tag{B.12}$$

where $\epsilon_{a,j}$ is defined as

$$\epsilon_{a,j} = \begin{cases} 1 & \text{if } a \leq j \\ 0 & \text{else .} \end{cases} \tag{B.13}$$

Hiermit versichere ich an Eides statt, dass ich diese Arbeit selbstständig verfasst und keine anderen als die angegebenen Quellen und Hilfmittel benutzt habe. Außerdem versichere ich, dass ich die allgemeinen Prinzipien wissenschaftlicher Arbeit und Veröffentlichung, wie sie in den Leitlinien guter wissenschaftlicher Praxis der Carl von Ossietzky Universität Oldenburg festgelegt sind, befolgt habe.

Kikan Eleonore Nelle

Oldenburg, den 5.Juli 2024