Developing an integrated transport model framework

Report in the context of the Energy technology modelling framework for POlicy support towards a Cost-effective and Sustainable society in 2030 and 2050 – EPOC 2030-2050

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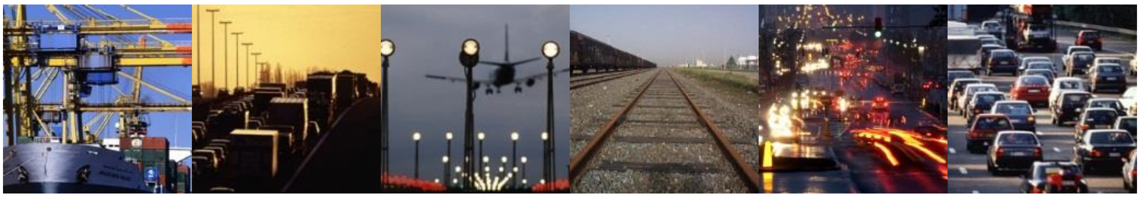

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Abbreviations, symbols and units

CES	Constant Elasticity of Substitution – a framework to represent transport demand using a mathematical function that simulates the trade-off between several inputs.
CNG	Compressed natural gas
CO_2e	CO_2 equivalent
BET	Battery electric truck
BEV	Battery electric vehicle
CO2	Carbon dioxide
CO_2e	CO_2 equivalents
DIV	Dienst Inschrijvingen Voertuigen (Federal agency for the registration of vehicles)
EAFO	European Alternative Fuels Observatory
EC	European Commission
EU	European Union
EV	Electric vehicle
HDV	Heavy duty vehicle
ICEV	Vehicle with Internal Combustion Engine
FCEV	Fuel cell electric vehicle (hydrogen)
FCT	Fuel cell truck
GHG	Greenhouse gas
LCV	Light commercial vehicle
LDV	Light duty vehicle
LEZ	Low emission zone
LPG	Liquefied petrol gas
Km	Kilometre
Ktonnes	1000 tonnes
OVG	Onderzoek Verplaatsingsgedrag (Survey on Flemish mobility choices)
PHEV	Plug-in hybrid electric vehicle
V2G	Vehicle To Grid
WTP	Willingness-to-pay

1 Introduction

1.1 Setting the scene

The European Climate Law (Regulation (EU 2021/1119) sets the objective of a climate-neutral European Union (EU) by 2050 and a collective, net, greenhouse gas (GHG) emission reduction target (emissions after deduction of removals) of at least 55 % in 2030 compared to 1990 (EU, 2021). For transport, there is no corresponding legally enshrined sector specific reduction target. However, the European Green Deal states as an ambition that in 2050 the GHG emissions from transport should be 90 % lower than in 1990 in order to achieve climate neutrality for the economy as a whole (EC, 2019).

The importance of decarbonizing the Belgian vehicle fleet for the energy transition and climate change mitigation efforts can therefore not be ignored. Transport is one of the main greenhouse gas emitting sectors. Domestic transport emitted about 23 860 ktonnes CO_2 equivalents (CO_2e) in 2021, or 21.5 % of the total GHG emissions in Belgium[1]. In 2021 the total GHG emissions from transport in Belgium were 14 % higher than in 1990. Together with tertiary heating, transport is the only sector in which emissions increased compared to 1990. Over time the CO_2 emission intensity of transport has decreased but at the same time transport demand has increased, leading to a net increase in emissions. The years 2020 and 2021 saw lower emissions than in 2019, due to the COVID-pandemic. In 2021 car transport emissions amounted to 12 013 ktonnes of CO_2e, which corresponded with 50.3 % of domestic transport emissions in Belgium.

Both at the EU level and in Belgium a range of policy instruments are in place in order to decarbonise road transport.

Mandatory EU fleet-wide targets apply for new cars, which have been tightened gradually over time. Providing battery electric vehicles (BEVs) to the market is one of the strategies that car manufacturers can take to comply with these targets. Over the last years, an increase in the uptake of these cars is observed. According to the European Alternative Fuels Observatory (EAFO, 2023)[2], at EU level the share of BEVs and plug-in hybrid electric vehicles (PHEVs) in new car sales increased from 3 % in 2019 to 21.6 % in 2022. This corresponds to a growing though still modest share in the vehicle stock of 0.46 % in 2019 and 2.3 % in 2022. Up to now sales in Europe are concentrated in high income countries (ACEA, 2021). There is also a strong correlation between the market share of EVs and the policy incentives that are provided (Wappelhorst, 2021; ACEA, 2021).

In Belgium, the share of EVs in new car sales grew from 3.2 % in 2019 to 26.8 % in 2021 (10.3 % BEVs + 16.5 % PHEVs). The share of electric vehicles (EVs) in the Belgian car stock was 4.64 % in 2022, compared to 1 % in 2019.

In the future, EVs are expected to play a growing role in the decarbonisation of road transport, given the further strengthening of the CO_2 performance standards. Regulation (EU) 2019/631 (EU, 2019), which covers both new passenger cars and vans, sets the following targets compared to

[1] https://klimaat.be/in-belgie/klimaat-en-uitstoot/uitstoot-van-broeikasgassen/uitstoot-per-sector

[2] https://alternative-fuels-observatory.ec.europa.eu/transport-mode/road

2021: a 15 % reduction from 2025 onwards and a 37.5 % reduction from 2030 onwards for cars and 31 % for vans. Moreover, in view of the ambitious climate neutrality target set in the Climate Law, the Fit-for-55 package of the European Commission (EC) included a proposal for even more stringent CO_2 emission performance standards. The proposal sets the 2030 CO_2 emission limits for new passenger cars and vans registered in the EU respectively 55 % and 50 % lower compared to the emission limits applicable in 2021. In addition, all new passenger cars and vans should have zero emissions by 2035 (EC, 2021a). In October 2022 the Council and the European Parliament reached a provisional agreement on these stricter CO_2 emission performance standards. After further negotiations, the Council gave the final approval in March 2023. In a statement accompanying the vote, the EC has committed to submit proposals to enable the registration of cars and vans exclusively running on carbon-neutral fuels after 2035, as stipulated in the adopted Regulation[3].

The electrification of the car fleet comes with several challenges. The purchase cost of BEVs is currently very high, while the autonomy of the cars is still more limited than their fossil fuel counterparts. This is holding back mass adoption of the cars by private households. The Federal government of Belgium is taking steps to accelerate the decarbonization of the vehicle fleet. The market segment of company cars is used as leverage in this effort. As of 2026, only fully electric company cars will still be able to benefit from a tax advantage. This government intervention is expected to result in a swift electrification of the company car segment. In addition, in the Vision note on the additional measures to the Flemish Energy and Climate Plan 2021-2030 published in November 2021, the Flemish government has indicated that it will ask the Federal government to phase out the purchase of fossil combustion engines of passenger cars and vans from 1 January 2029. Moreover, for cars, vans and minibuses, diesel vehicles will no longer be allowed in the low-emission zone of the Brussels Capital Region from 2030 onwards. From 2035, petrol, LPG and CNG vehicles will also no longer be allowed. In Flanders the Flemish government decided in December 2022 that from 2031 onwards diesel cars can no longer enter the Flemish low-emission zones and that from 2035 cars and vans can only enter the low-emission zone if they drive electrically or on hydrogen. The legislative process for these provisions in Flanders is still ongoing[4] .

While the policy objective of increasing electrification of the fleet is obvious, quite little is known on the overall impact of a large increase in EVs on the Belgian roads. Multiple questions need to be addressed.

- What is the impact of EVs on (intertemporal) electricity demand?
- How should fiscal policy change in case of large-scale adoption of BEVs, as these cars currently pay little to no taxes on vehicle ownership and use.
- What are the equity impacts of electrification, as the purchase costs of BEVs have remained higher than those of vehicles with an internal combustion engine (ICEVs) or hybrid vehicles?
- How is the fleet of company cars going to evolve in the next years, facing changes in fiscal stimuli of company car ownership to zero emission vehicles.
- Is there a difference in uptake of electric vehicles between urban and rural regions?

[3] https://climate.ec.europa.eu/news-your-voice/news/fit-55-eu-reaches-new-milestone-make-all-new-cars-and-vans-zero-emission-2035-2023-03-28_en

[4] https://www.vmm.be/nieuws/archief/lage-emissiezones-worden-nog-socialer-en-gaan-richting-zero-emissie-vanaf-2035

- How does one mitigate the negative impacts that remain even with EVs, namely the external cost of congestion, accidents and pressure on public space?

The main objective of this report is to describe the steps we undertook in the EPOC project to develop an integrated assessment model that allows shedding light on these questions. Building on the model results described in this report, we can start to answer at least some of these questions. This will enable a smoother transition to EVs and help Belgium to achieve the goals set out in the European Climate Law.

1.2 Structure of the report

In this report we describe the development of a model to assess the impact of the electrification of the fleet. We build from the existing TREMOVE model, that was developed by Transport & Mobility almost 20 years ago (De Ceuster et al., 2007). The model architecture is updated and integrated with different modules to improve its overall functioning. From the original TREMOVE model the elements of the demand tree are adapted. This is referred to in the document as Module I. The vehicle stock module is updated as a separate model now and is referred to as Module II. Additionally, the model is both regionalized and split up using micro-data originating from a.o. Statistics Belgium, the Federal Planning Bureau and the Flemish survey on mobility behaviour (Onderzoek Verplaatsingsgedrag, OVG).

A comprehensive methodology has been developed to clean datasets from different sources and to generate representative agents. We label this micro-model as Module III of the model. Adding representative agents to the model can help to assess a broad range of transport policies and analyse population level differences of policies. For example, in the case of electrification the differential uptake of BEVs can be studied on the level of the population. This enables a study of inequality in uptake and distribution of car fleet.

In parallel with Module III, Module IV has analysed the distribution of car use during the day to simulate the impact of car use on the grid level. In addition to this Annex reports on further explorations of the OVG data. Linking regression analysis with data from the OVG and other data sources we explored the possibility to construct a database of the car fleet on household level. Using the data from the OVG on daily trip distribution, we also aimed to construct the distribution of trips on a highly disaggregate level. The trip distribution matrix can then be used for grid level analysis, for example to enable researchers to predict network load of electrification in vehicle-to-grid (V2G) analysis, to complement the survey of the potential uptake of V2G by the consumers which was carried out during the EPOC project by TML and which is reported in a separate EPOC report (Vanpée and Mayeres, 2022).

The structure of the rest of the report is as follows.

- Section 2 discusses the overall structure of the model and provides more detail on the different modules as well as how this integrates with the rest of the EPOC project.
- Section 3 discusses the structure of the Demand module (Module I).
- Section 4 discusses the Vehicle stock module (Module II).
- Section 5 discusses the microdata and the imputation of new data characteristics in the micro data, as well as the generation of representative agents (Module III)
- Section 6 treats the generation of grid level data and analysis of trips (Module IV)
- Section 7 presents a number of model simulations, focussing on two aspects. One, the equity of the electrification of the car fleet. Second, the fiscal impact of the electrification

of the car fleet. For this we use projections of the vehicle stock performed during the EPOC research.

- Finally, section 8 concludes.

The Annexes present the methodology and sources for the data collection, as well as some further exploration of the OVG data.

2 Structure and use of the model

The overall structure of the model and the different modules presented below result from intensive discussion at the beginning of the project. Researchers from Transport & Mobility Leuven and the other EPOC research partners discussed how the model should be developed and what type of data should be fed in the TIMES model and any other models of the EPOC project.

In the end we agreed on the following aspects to tackle during EPOC:

- Module I: Demand Module
- Module II: Stock Module
- Module III: Microsimulation
- Module IV: Grid level data and trip distribution

The model developed during the EPOC project consists of these four main modules. However, despite our aim to create a fully integrated model, the different modules are not yet fully linked by the end of the EPOC project. They should be seen as separate aspects of the same model, that can be linked through their outputs. A researcher will still need to do manual work in translating the output from one module to the other, especially in what concerns Module III and IV. While this is a disadvantage, the manual checking and updating of the data inputs/outputs does allow for additional checks in the assessment and helps to avoid the 'black box' nature of more integrated assessment models.

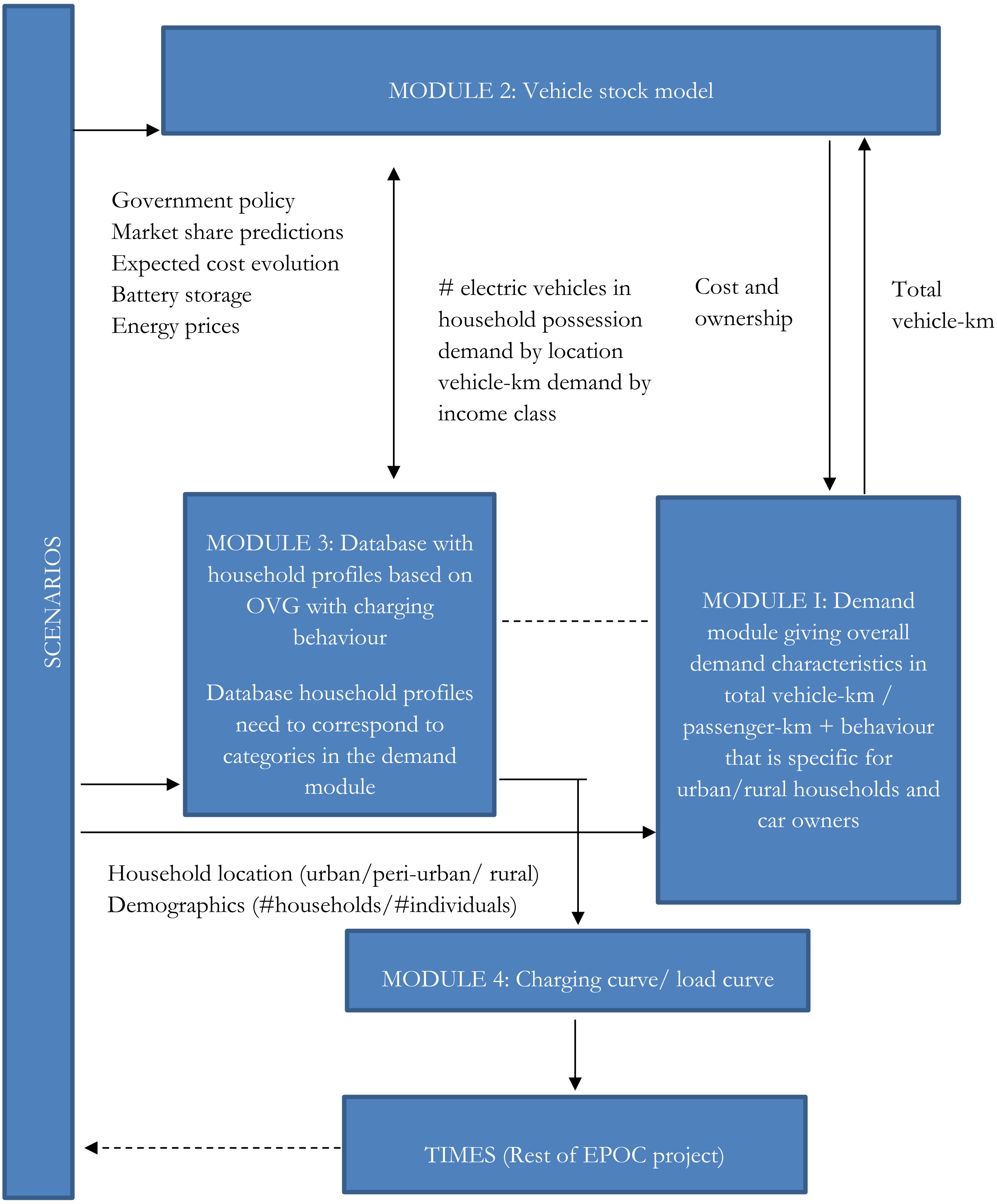
The modules have been built on consistent datasets, and much of the data generating process is automated in Python scripts that are described in Chapters 5 and 6 of this report.

Below, we discuss the overall process of analysis using the different modules and how they should be used in combination. The next figure visualizes the overall model integration and the input/output flows between different modules.

Module I is the demand module. This aspect of the model is the closest to the original TREMOVE model developed by TML (De Ceuster et al., 2007). However, it is largely rebuilt from scratch to increase flexibility and introduce novel elements in the demand module. For example, the original TREMOVE model did not have E-bikes or Speedelecs, Mobility-on-demand or carpooling. Given the changes in mobility of the last decade, this was considered a serious drawback.

The idea of Module I is to use monetary costs, fiscal policy, taxes and overall ownership from the vehicle stock module as input. The vehicle stock module (Module II) is mainly a cost model and does not predict overall transport demand or modal shift. This output needs to be taken from Module I. The two models are therefore closely related. Any shift in overall demand (Module I) can be translated in a shift in generalized costs (Module II), which can then enter the demand module again.

Figure 2-1: Overview of elements from the different modules



Modules II and III are integrated in a much looser way than Modules I and II. Vehicle ownership by income class and type were aligned in both models. However, the data in Module III are much more flexible and much more detailed than those in Module II. The main feedback going from Module II to Module III is the ownership of electric vehicles and the overall projection of the vehicle fleet. Data processing methods developed in Module III are then used to project the number of electric vehicles per income class and ownership level. Additionally, besides income, the level of urbanization can be distinguished. Also other aspects of households can be assessed in combination with electrification, for example the composition of the household or the availability of a second or even third car in the household. For example, it can be assessed how many families have both a vehicle with an internal combustion engine and an electric vehicle.

Another aspect of Module III is its ability to generate representative agents for either a region in Belgium or for the entire population. Such a synthetic population can be useful to study the equity aspects of different policies and may help to improve our understanding of social resistance to electrification and other aspects of the Green Deal. The approach to generate a synthetic population was developed during the EPOC project, but was eventually not used in the analysis due to a lack of time. It remains a valuable aspect of Module III however, that can be useful for subsequent research.

Module IV builds further on Module III. In this module procedures were developed that clean the OVG datasets and combine this with Belgian statistics at national and regional level. The original objective of Module IV was to predict the electricity use of electric vehicles on the grid level. For this data on daily travel use on household level was required. Processing of these data has also led to a corrective regression analysis (Annex 3). Data on household level did not match well with other statistics, namely with respect to car ownership and the availability of company cars. As company cars are currently the fastest moving segment in the BEV stock, such a correction in data was deemed necessary. The grid level dataset in itself can be disaggregated in multiple ways. Temporal (weekdays), regional, by income class, by car type and by degree of urbanization.

In practice - during the EPOC project - Module II was used to predict the overall impact of the electrification of the fleet on the cost structure of car transport. Feedback from Module I was rather limited, as the EU policy and national policy (as it stood during the research on EPOC) did not allow for many alternatives to full electrification of the fleet.

In fact, much of the electrification of the fleet is policy driven, as sales of ICEVs will be prohibited in the near future in the EU. This is an important challenge for car manufacturers, but also for researchers in this issue. Putting a hard restriction on the sale of ICEVs breaks a number of assumptions that are generally made when modelling car sales. This comes down to restricting consumer choice to a largely different set of vehicles than those that are used today. BEV technology, but also alternative zero-emission technology like hydrogen cars may have a number of unknown aspects that could drive consumer demand.

For the modelling of electrification therefore, we combined projections of the overall increase in stock with predicted changes in electricity prices and purchase costs. The projections were made on the basis of the best available data in 2020-2021, but could not be adapted to the changes in the geopolitical situation encountered in 2022. While it is unclear how the situation will evolve in the next years, the electrification of the car fleet is a *conditio sine qua non* for attaining the objectives set out in the EU Climate Law. Throughout EPOC we have operated under the assumption that Belgium will achieve the emission reductions set out by the EU.

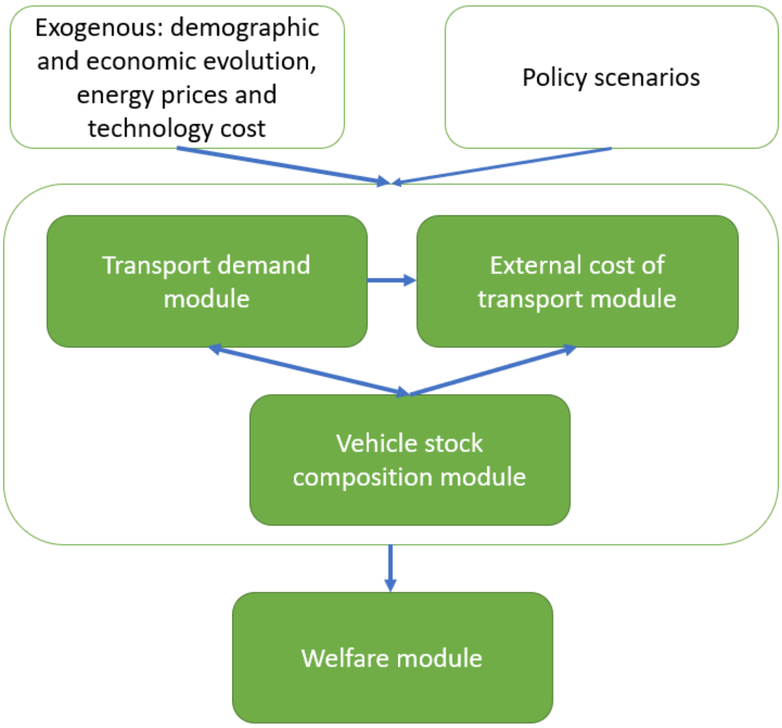
3 Module I: Transport demand model TREMOVE

3.1 Overall structure

The overall structure of the model is similar to TREMOVE. The figure below details its overall structure, similar to Figure 2-1. A lot of the information entering the model is largely exogenous and comes from the assumption of the policy scenario or from other modules. For example, the demographic and economic evolution is based on Module III. The evolution of energy prices and technology cost is based on projections from policy scenarios.

Used by the TREMOVE module are the projections from Module II (Vehicle stock) as a direct input to the cost of car transport. The resulting impact on external costs and welfare are the main outputs from TREMOVE.

Figure 3-1: Structure of the travel demand module and interaction with vehicle stock and 'external cost' calculation



3.2 Model components

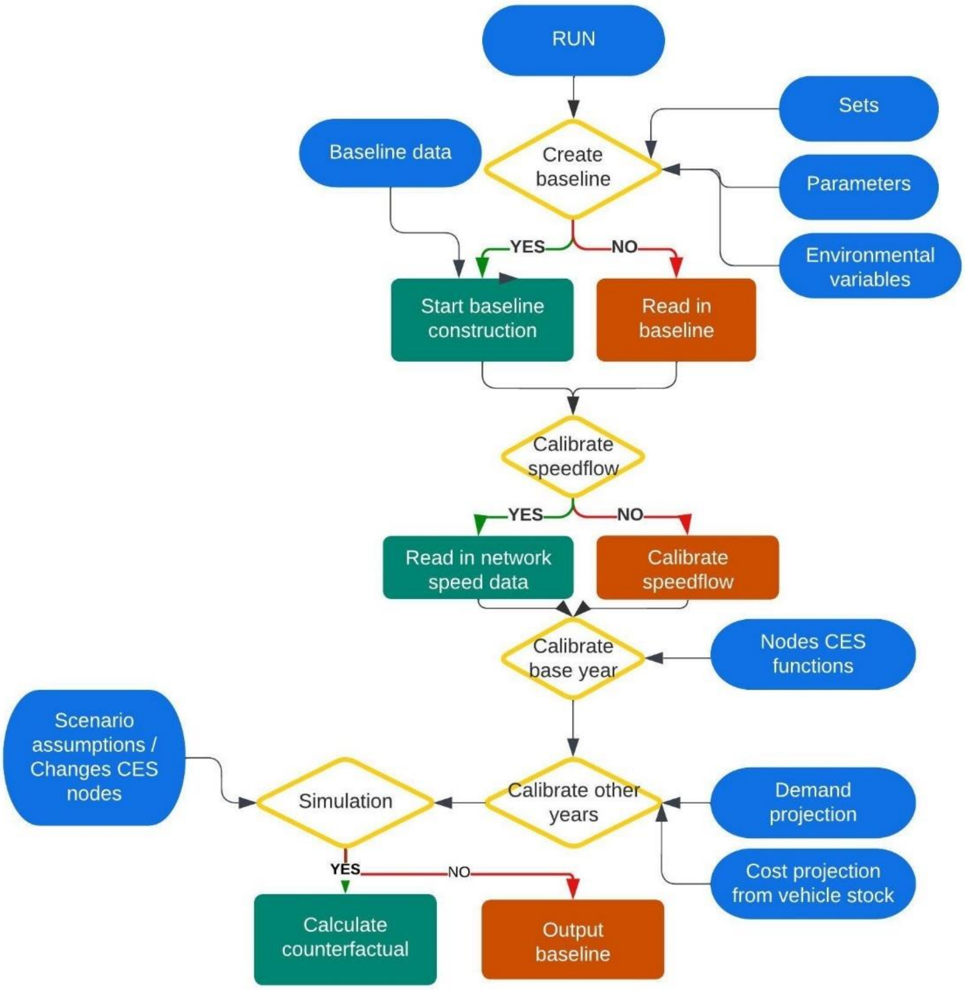
3.2.1 Running and use of the model

The demand module has a relatively simple and flexible structure. The model has broadly four phases.

- The **init** procedure reads in the basic data used to calibrate the model. This entails the travel demand, socio-demographic data, capacity of the network and external cost of transport. The baseline of the model is constructed within the model. The user can opt to change specific assumptions on how the baseline is constructed or introduce new data. If no new data are added, a previously constructed baseline can be read into the model directly.

- The **calib** procedure calibrates the nested demand functions of the model. These are generally (but not necessarily) defined as CES functions (Constant Elasticity of Substitution) functions. The CES functions are calibrated on the initial value or expenditure shares from the data and a substitution parameter. The calib function makes sure that the baseline is reproduced if no changes are made to the initial costs. Within the calib function there is an option to recalibrate the speed-flow functions of the network. This procedure estimates the impact of changes in travel demand on the time cost of the network. Correct calibration of this function is necessary to adequately simulate congestion.
- The **sim procedure** makes a counterfactual simulation of the network. The user should insert new costs or (if necessary) a new cost or demand function that is relevant for the simulation. In the absence of a simulation, the model should reproduce the baseline.
- The **output** procedure translates the model output to user defined variables that can be analysed in excel or other data processing and analysis software. Standard the output is provided in pivot table ready format.

Figure 3-2: Overview of transport demand implementation TREMOVE



3.2.2 Novel elements

The running and use of the model is not spectacularly different from the original TREMOVE model. However, the structure is much more flexible than the original demand module.

The first is that all CES functions have been programmed in a flexible way, using a baseline structure that is exactly similar, independent from the complexity of the nested function. Users can therefore easily reprogram the demand structure of the model, without the need of in depth and time intensive recoding. This was considered necessary due to the strong evolution of new types of mobility. Among others: Mobility on Demand, Ride sharing, Fast electric bikes, E-steps. Also added to the model is the 'zero distance' travel or home-based activity (see Section 3.2.3).

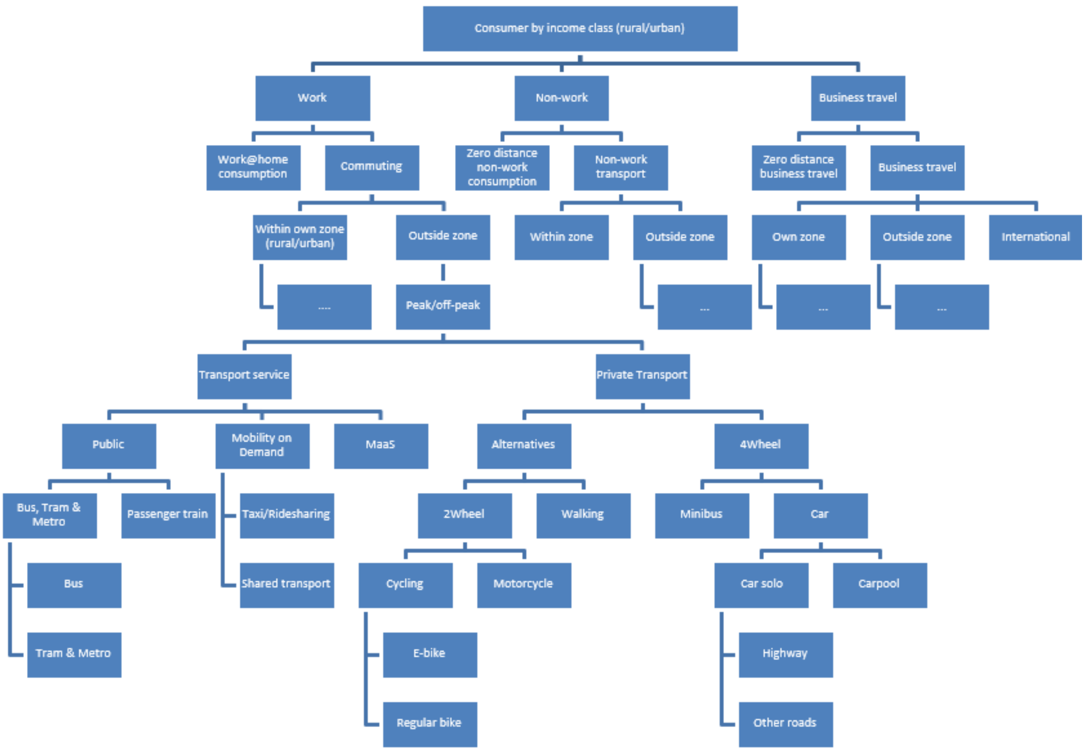
The second is that a complex optimisation procedure has been developed to calculate the elasticity and cross-elasticity of demand directly from the demand trees. The optimisation tries to reproduce a set of given (exogenous) elasticity parameters for car, active and public transport. It does this by changing the elasticity of substitution parameters within the demand tree. The result is a much more transparent impact of the model, that can be compared with other (partial) transport demand models, even when they do not share the exact same model structure.

The third element is the output linkage of results from the demand model to the micro-simulation module and grid-level based module. Using this linkage makes it possible to disaggregate the results of the transport demand module to many representative travel agents. This can enable more detailed analysis of transport policy, for example of road charging and electrification.

3.2.3 Passenger demand

The passenger demand of Module I is represented schematically below. This is the 'base' structure of the demand, but it can be adapted in function of the interest of the researcher. Representative consumers are distinguished by urbanization level and income class. These classes are based on data coming from Module III and IV.

Figure 3-3: Overview of representative demand module households



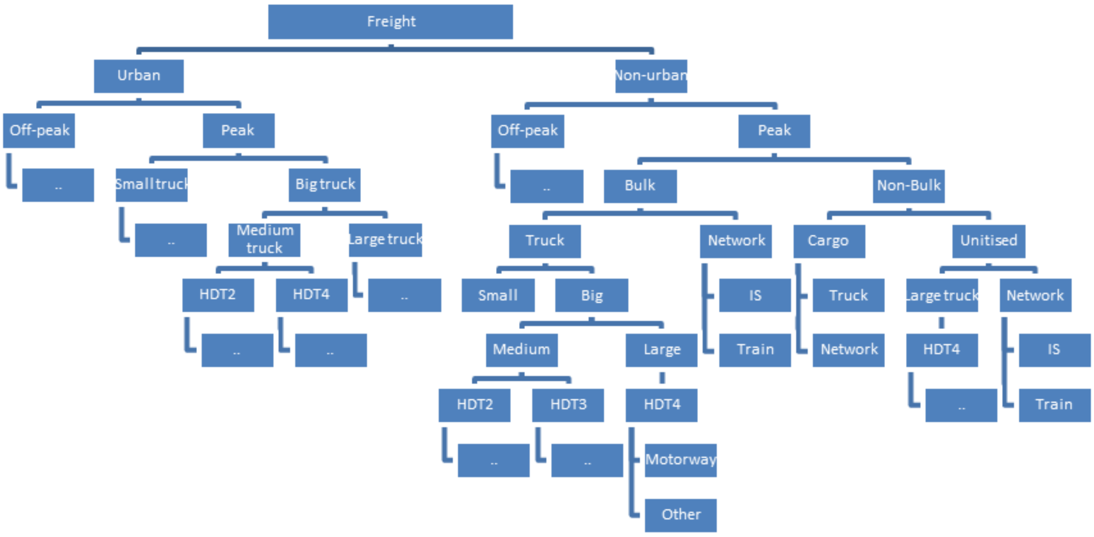
Travel demand distinguishes between

- Zero distance travel
- Peak / off-peak travel
- Public / Private and Semi-public transport (Ride sharing, MoD)
- Several active transport modes (two-wheelers)
- Several types of cycling

3.2.4 Freight demand

The freight demand part of the module has not changed significantly from the original TREMOVE model as the focus of our work in EPOC was largely on private demand.

Figure 3-4: Overview of freight demand module



4 Module II: Vehicle stock module

4.1 Objective of the vehicle stock module

The vehicle stock model determines the total number of cars in any given year t and the composition of the fleet. In this chapter we first describe the approach that was eventually taken for the EPOC project to make projections for the vehicle fleet up to 2050. Then Section 4.3 reports on a new method that was explored to determine the size of the vehicle stock. Based on the tests of this new approach it was decided, however, that it could not yet be integrated in the TREMOVE model and should be explored further.

4.2 Determining the vehicle fleet composition up to 2050

We distinguish the following vehicle types:

Table 4-1 Vehicle and fuel types considered

Code	Description	Fuel types
PCAR	Privately owned car	CNG, diesel, diesel hybrid, electric, hydrogen, LPG, petrol, petrol hybrid
CCAR	Company car	CNG, diesel, diesel hybrid, electric, hydrogen, LPG, petrol, petrol hybrid
LDV	Light duty vehicle	CNG, diesel, diesel hybrid, electric, hydrogen, LPG, petrol
HDV	Heavy duty vehicle	CNG, diesel, electric, hydrogen, LPG, petrol
MC	Motorcycle	diesel, electric, petrol
MP	Moped	diesel, electric, petrol
COACH	Coach	diesel, electric, petrol
UBUS	Urban bus	diesel, electric, petrol
BIKE	Bicycle	electric, none

4.2.1 Current vehicle stock

The vehicle stock in the base year (2018) is based on data from DIV (Federal Agency for the registration of vehicles). The following table shows the vehicle stock in Belgium in 2018 for the different vehicle categories and fuel types. Vehicles can be distinguished further based on age, size or Euro-norm.

Table 4-2 Belgian vehicle stock 2018

	Brussels	Flanders	Wallonia
CAR	**444 866**	**3 436 142**	**1 724 827**
car_CNG	596	9 645	940
car_diesel	249 551	1 829 543	958 000
car_diesel_PHEV	86	1 429	165
car_BEV	1 321	7 953	1 641
car_FCEV	0	0	4
car_LPG	517	8 728	3 727
car_petrol	190 334	1 556 433	757 028
car_petrol_PHEV	2 461	22 411	3 323
Light duty vehicle (LDV)	**63 121**	**492 108**	**234 633**

	Brussels	Flanders	Wallonia
LDV_CNG	222	2 156	292
LDV_diesel	59 202	460 435	219 643
LDV_diesel_PHEV			
LDV_BEV	270	620	102
LDV_FCEV			
LDV_LPG	357	7 801	3 422
LDV_petrol	3 070	21 096	11 174
Heavy duty vehicle (HDV)	**9 936**	**117 160**	**39 477**
HDV_CNG	17	314	36
HDV_diesel	9 901	116 553	39 319
HDV_BEV	6	7	2
HDV_FCEV			
HDV_LPG	5	106	38
HDV_petrol	7	180	82
Motorcycle (MC)	**33 417**	**262 857**	**158 629**
MC_diesel	26	191	59
MC_BEV	203	1 183	303
MC_petrol	33 188	261 483	158 266
Moped (MP)	**7 563**	**126 743**	**47 763**
MP_diesel	161	3 287	4 120
MP_BEV	1 121	19 228	918
MP_petrol	6 281	104 228	42 725
COACH	**972**	**12 130**	**4 248**
coach_diesel	971	12 100	4 205
coach_BEV	1	2	0
coach_petrol	0	28	43
Urban bus (UBUS)	**908**	**4 256**	**2 622**
ubus_diesel	900	4 247	2 619
ubus_BEV	8	8	0
ubus_petrol	0	1	3

Source: DIV

For the vehicle type CAR, we make a distinction between company cars (ccar) and private cars (pcar). This distinction is necessary because of the different taxation of the two types of cars. According to data for 2018, the share of company cars in the total transport demand (vehicle-km) of cars is estimated to equal 27.5% in Flanders, 9.8% in Wallonia and 24% in Brussels.

4.2.2 *Formula vehicle stock evolution*

The future vehicle stock is projected based on the following formulas:

$$stock_T = stock_{T-1} - scrappage + new\ vehicles$$

$$stock_T \times mileage_{T0}[km/veh/year] = transport\ demand_T[vkm/year]$$

Where

- T = the current year
- T-1 = the previous year
- T0 = year used as starting point for the projections (here T0 = 2018).

Hence, the projection model requires the following input:

- $stock_{T0}$: Stock for the most recent year available
- $scrappage$: based on survival curves
- $transport\ demand$: projections for vehicle-km
- $mileage_{T0}$
- The market share of new vehicles per category and fuel type

4.2.3 Mileage (transport demand)

For the reference scenario the vehicle-km for each combination of vehicle type, size, fuel and euronorm are calculated based on the following three inputs:

- the vehicle stock
- the total vehicle-km per vehicle type from traffic statistics/outlooks
- info on the average yearly kilometres driven from GOCA/CARPASS.

The dataset contains actual vehicle-km driven and the actual vehicle stock (from DIV) up to 2019. The future vehicle-km driven per vehicle type are based on scenario projections. The following scenarios were used:

Brussels

For the period 2020-2030, the Good-Move scenario is used, which assumes a decrease of 24% of the total vehicle-km per vehicle type in Brussels compared to the 2018 reference year.[5] As of 2030 we use the projected travel activity from the European Reference Scenario 2020 (EC, 2021b) for the transport sector as shown in Table 4-3.

Flanders

For the period 2020-2030, we use the scenario as projected by the Flemish Air Management Plan 2030.[6] The plan contains a series of measures to improve the air quality in Flanders on a short, mid (2030) and long (2050) horizon. For the period 2030-2050 we use the projected travel activity from the European Reference Scenario 2020 for the transport sector.

Wallonia

For Wallonia, we use the projections based on the European Reference Scenario 2020 for the transport sector in Belgium.

[5] https://mobilite-mobiliteit.brussels/nl/good-move

[6] https://www.vmm.be/publicaties/vlaams-luchtbeleidsplan-2030-voortgangsrapport#

Table 4-3 Belgium: Reference Scenario 2020 (REF2020) – transport activity growth rates

Transport activity	2018-2025	2025-2030	2030-2035	2035-2040	2040-2045	2045-2050
Passenger transport activity (Billion passenger-km)	+15.12%	+4.49%	+1.88%	+1.92%	+1.61%	+1.72%
Buses and coaches	+28.63%	+0.70%	-0.85%	+0.83%	+0.56%	+0.36%
Passenger cars	+5.63%	+3.63%	+1.38%	+0.88%	+1.15%	+1.27%
Powered two-wheelers	+13.22%	+16.65%	+9.01%	+8.62%	+4.52%	+4.42%
Rail	+63.35%	+5.78%	+4.67%	+3.75%	+4.04%	+3.86%
Intra-EU aviation	+73.03%	+12.22%	+4.51%	+7.36%	+2.95%	+3.42%
Inland waterways and domestic maritime	+74.50%	+3.20%	+4.54%	+3.03%	+2.73%	+2.64%
Freight transport activity (Billion tonne-km)	+13.60%	+4.05%	+2.98%	+2.87%	+3.33%	+3.03%
Heavy goods and light commercial vehicles	+11.92%	+1.94%	+1.25%	+1.95%	+2.29%	+1.99%
Rail	+22.78%	+17.25%	+10.00%	+7.03%	+7.44%	+6.99%
Inland waterways and domestic maritime	+16.03%	+5.01%	+5.56%	+3.61%	+4.50%	+4.07%

Source: Good Move scenario Brussels Capital region, Flemish Air Management Plan, EU reference scenario 2020 (EC, 2021b)

The number of kilometres driven per year per vehicle type is equal to the total vehicle-km per vehicle type divided by the number of vehicles. Because there are small variations year-by-year, we average the kilometres driven per year over the period 2018-2030 and round to the closest thousand (hundred for motorcycles and mopeds). This results in the following annual mileage per vehicle type:

Table 4-4 Average annual mileage per vehicle type

	km/year
CAR	15 000
LDV	16 000
HDV	50 000
Motorcycle	2 400
Moped	2 600
COACH	13 000
Urban bus	43 000

Source: Own calculations

The average lifetime of a vehicle is calculated based on the average vehicle stock, new vehicles and scrappage in the DIV database over the period 2012-2019. We first compute the survival function l(x), which corresponds to the number of vehicles in the fleet with an age equal to x years. Then, the scrappage in the interval (x, x+1) for all vehicles of age x can be calculated as

$$d(x) = Max\big(0, l(x) - l(x+1)\big)$$

Next, we calculate the following parameters:

- L(x), the number of vehicle-years lived by the cohort from year x to x+1. This is the sum of the years lived by the l(x+1) vehicles who survive the year and the d(x) vehicles that were scrapped during the year. The former contribute exactly one year each, while the latter contribute on average half a year. This assumes that scrappage occur, on average, halfway during a year. Hence, $L(x) = l(x+1) + 0.5 * d(x)$.
- T(x), the total number of vehicle-years lived by the cohort from age x until all vehicles of the cohort have been scrapped. More specifically, $T(x) = \sum_{x}^{x\_max} L(x)$.

The average expected lifetime of a new car, $life$, can then be calculated as:

$$life = \frac{T(0)}{l(0)}$$

The average lifetime per vehicle type is shown in the table below. For buses, we use the expected lifetime from the guidelines for cost benefit analysis used by De Lijn. In these guidelines, urban buses have an expected lifetime of 10 years, while coaches have an expected lifetime of 14 years.[7]

Table 4-5 Average life expectancy for new vehicles in year per vehicle type

	Average life (in years)
CAR	11
LDV	10
HDV	9.5
Motorcycle	19
Moped	10
Coach	14
Urban bus	10

Source: Own calculations

4.2.4 New vehicle sales

To estimate the market shares of new vehicle sales, we take into account the following policy measures and assumptions in the reference scenario:

For the three regions:

- In May 2021, the federal government decided to limit the tax deduction of company cars to 100% electric cars only as of 2026. Tax deduction of fossil fuel cars is gradually phased out as of 2023.[8] We assume that the market share of new zero emission company cars in total company car (ccar) sales increases to 70% by 2025 and 100% by 2026.
- Fuel cell electric vehicles (FCEV) are expected to remain a niche market in the passenger car and LDV segment due to their higher costs. By 2050, we project 1% of the new sales in passenger cars and 5% of LDV to FCEVs. This corresponds to what is foreseen in the EU Reference Scenario 2020.

[7] http://docs.vlaamsparlement.be/pfile?id=1197684

[8] https://financien.belgium.be/nl/ondernemingen/vennootschapsbelasting/voordelen_van_alle_aard/bedrijfswagens

- We foresee no long-term growth path for PHEVs because most studies expect BEVs to replace plug-in hybrids passenger cars in the long term (Rietman et al., 2020; EVvolumes, 2022)
- For privately-owned passenger cars (pcar), we assume a steep and fast decline in the market share of new diesel cars, which is a continuation of the observed trend since 2016, after Dieselgate. Sales of diesel cars are expected to drop to 5% of total pcar sales in 2025 and to drop to zero in 2030. We also project a strong decline in the sales of petrol cars, although less swift than for diesel. The proportion of petrol cars in new car sales is expected to decline gradually from 10% in 2035 to zero in 2040.
- Following the EU Reference Scenario 2020, we expect only a moderate shift from diesel to other power trains in the HDV segment. The market share in sales of CNG trucks is expected to rise to 10% by 2030 and 20% in 2050. According to the EU Reference Scenario, the market share of battery electric (BET) and fuel cell (FCT) trucks remains small at respectively 3 and 1 percent. Other studies on zero-emission trucking predict larger shares for BET and FCT. For example, PWC (2020) projects market shares in sales to be at 28% for BEV and 18% for FCT by 2035. Ruf et al (2020) estimate FCT sales at roughly 17% of all trucks sold in Europe by 2030, based on a strong technology cost reduction path. We compromise among the projections at a market share in sales of 3% for BET and 10% for FCT by 2050[9].
- Following the targets set in the EC's Clean Vehicles Directive, we take into account a faster and more significant uptake of battery electric buses compared to HDV.[10] We project all new sales of urban buses to be electric by 2050. For the coach category, new sales of fully electric vehicles are assumed to be much lower, 35% by 2050. This is because these buses drive long distances.

For Brussels:

- On June 24, 2021, the regional government of Brussels approved the timeline for the low emission zone (LEZ) in Brussels. This implies that fossil fuel passenger cars are banned from the LEZ as of 2030 (diesel and diesel hybrid) or 2035 (petrol, CNG, LPG, petrol hybrid). Hence, we assume no new sales of diesel cars in Brussels as of 2030 and zero sales of other fossil fuel cars as of 2035. Diesel-powered vans are prohibited in the Brussels region as of 2033 and other fossil fuel vans as of 2035. Diesel-powered mopeds and motorbikes are no longer allowed to drive in Brussels as of 2025.

For Flanders and Wallonia:

- We use two sources to project new sales of BEVs, a recent study by BloombergNEF and Transport & Environment (2021) and Rietmann et al (2020). BNEF predicts plugin hybrids to represent 28% of all sales by 2025 in Europe. For BEVs in Europe, the study estimates the share sales to be 50% by 2030 and 85% by 2035. Higher adoption rates are expected in the Nordics and other countries leading BEV adoption. Rietman et al. (2020) model the EV inventory by fitting a logistic growth function (S-shape) with country-specific parameters. For Belgium, fast EV penetration is expected. The market share of EVs in Belgium is expected to be 50% of the total car fleet by 2030 and 83% by 2035.

[9] This statement and the original assessment date from early 2021. This was an expert assessment based on the data and numbers available to us at that moment. However, the market on HDV and electric trucks is moving very rapidly. Updated projections show that the EU reference scenario is much too conservative and that projections of Ruf et al (2020) and PWC (2020) may even be surpassed.

[10] https://ec.europa.eu/transport/themes/urban/clean-vehicles-directive_en

Note that this comprises BEV and plug-in hybrids. Based on these reports, we project the share of BEV sales in total car sales to be 72.5% by 2030, increasing to 97% by 2050.

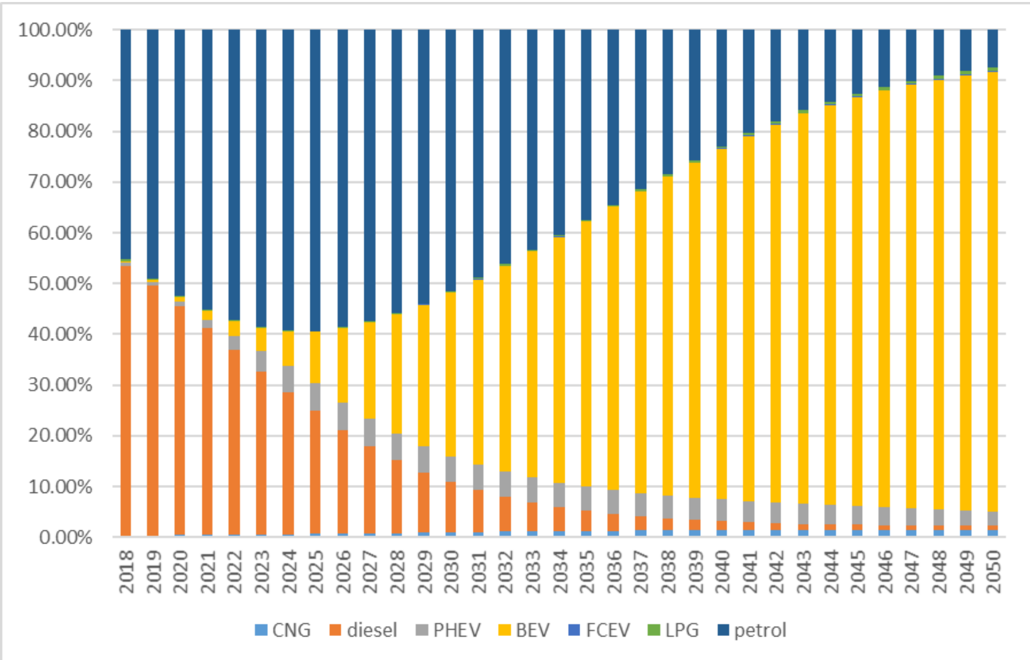
When the projections were made, the new EU regulation for the CO_2 emission performance standards for cars and vans was not yet adopted officially by the EU. Hence it is not yet taken into account in the outlook below. In addition, at the time when the outlook was made, the literature was still less optimistic about the cost evolution of electric HDVs than it currently is. The outlook for HDVs that is presented below is therefore very conservative.

4.2.5 Composition of the vehicle fleet

The assumptions made on the future sales of new cars and the average lifetime of a vehicle have direct repercussions on the projected composition of the vehicle fleet in Belgium.

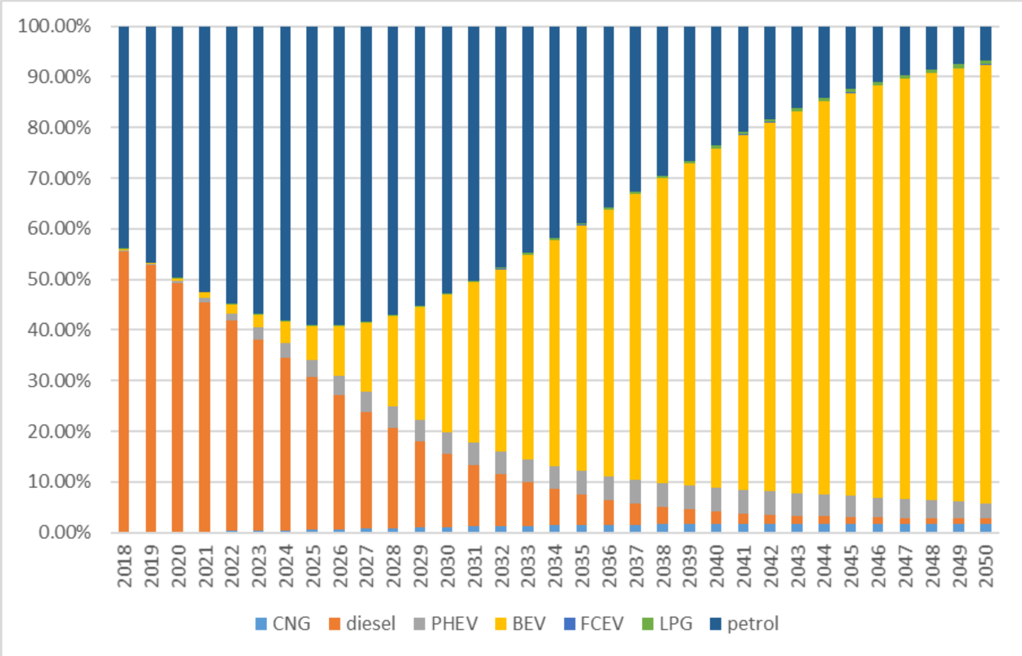
The next three figures show the projected composition of the car fleet for the three regions. All figures show a gradual replacement of diesel and petrol cars by BEVs. The pace of this transition is regional specific. In Brussels, we project a more rapid shift to BEV as a consequence of the upcoming fossil fuel ban. By 2030, the share of BEV in the total car fleet is expected to be 32% in Flanders, 27% in Wallonia and 65% in Brussels. By 2050 the respective market shares are estimated at 87% for Flanders and Wallonia and 99% for Brussels.

Figure 4-1: Composition of the car fleet Flanders



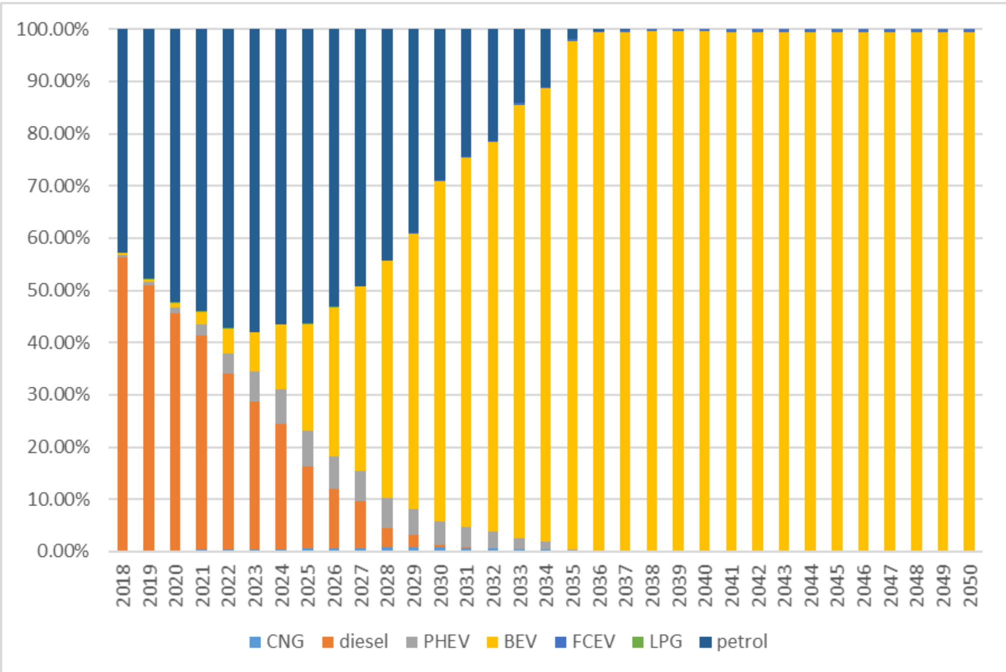
Source: Own calculations

Figure 4-2: *Composition of the car fleet Wallonia*



Source: Own calculations

Figure 4-3: *Composition of the car fleet Brussels*

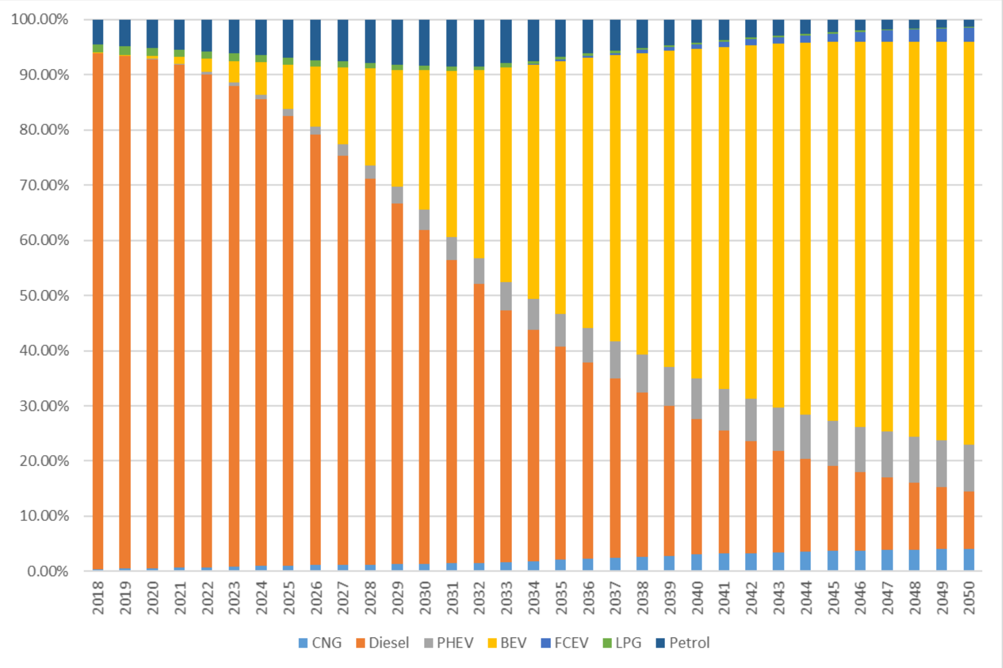


Source: Own calculations

The regional differences between the other vehicle types are less pronounced than for cars. For conciseness, we show the projected fleet composition for the other vehicle types at Belgian level.

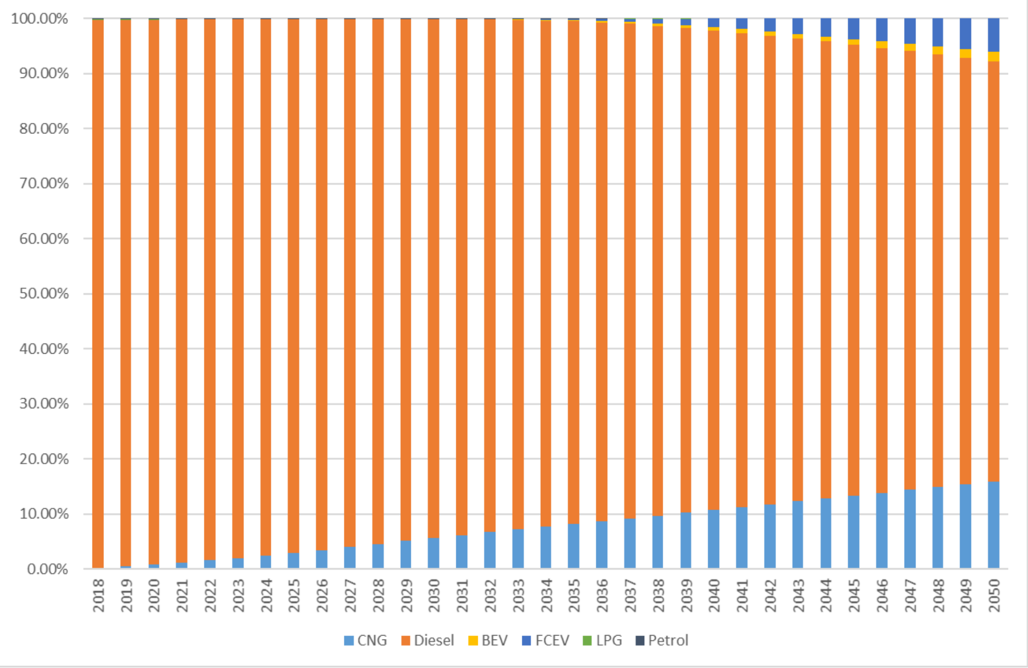
The next two figures show respectively the projected fleet for LDV and HDV. The LDV fleet, which is currently dominated by diesel-powered vehicles, is expected to experience electrification although at a slower pace than what is expected for passenger cars. In line with the expectations from the EU Reference Scenario 2020, we expect no strong electrification pathway for the HDV segment. There is a modest growth in market share for CNG-powered and FCEV in the HDV segment. As indicated in the previous section, the outlook for HDVs is conservative in view of recent developments.

Figure 4-4: Composition of the LDV fleet – Belgium



Source: Own calculations

Figure 4-5: Composition of the HDV fleet - Belgium



Source: Own calculations – conservative assumptions

4.3 Exploration of a new approach to determine the size of the vehicle stock in TREMOVE

Most models will first determine the aggregated demand for cars in year t, also called the desired stock, and determine the composition in a later step. From the desired stock, the number of new sales can be deduced by subtracting the expected number of scrapped cars. In a later step the composition of either the stock or the new sales is determined (see also Section 4.2.2).

There are several ways to determine the number of cars (or the level of car ownership) that makes up the vehicle stock at any given year *t*[11]. Some models derive the desired stock directly from a transport model that determines the demand for vehicle-km (MINIMA-SUD, PLANET), other models estimate the level of car ownership directly. When the stock is estimated directly, this can be done either on an aggregated level using Gompertz curves (CASMO, ITPS) which uses the GDP per capita as input or on a household level (UKTCM, NATCOP, DYNAMO, NLTDM).

Most models operating on household level estimate a logit function, one of the exceptions being the UKTCM model who defines three ownership groups depending on the minimum of cars they own and determine the share of the population belonging to each category (Brand, 2010; Brand et al., 2017). It is assumed that levels of car ownership for each category will continue to grow until a saturation point is reached. The share of the population that belongs to a category follows an S-shaped function with inputs, the income, vehicle purchasing price and ownership elasticity. The maximum number of cars owned varies over time and depends on various variables such as, the number of diving licence, the number of households with more than one person, the level of public transport use in rural areas and parking availability in urban areas.

The advantages of this methodology compared to the estimated logit functions is that it is less data intensive. Compared to the Gompertz curves used in other models, it has the advantage to be explicitly sensitive to the vehicle purchasing price and allows for an evolution in the maximum ownership. In the following sections we will describe the exploration of this approach for use in the TREMOVE model.

4.3.1 *The theoretical model*

Following the methodology of the UKTCM (Brand et al., 2017) we define the following key variables for modelling household car ownership:

- household structure (number of adults and children).
- household disposable income (by year).
- average new car price.
- household location (urban and non-urban), linked to public transport availability.
- car ownership saturation level (urban and non-urban).

All are exogenous variables except average new car price – new car price in n+1 is derived based on the average price in year n weighted by the vehicle-km for each technology in year n.

The households are divided in three "ownership groups":

- owning at least one car
- owning at least two cars

[11] For an extensive literature review we refer to Franckx (2019)

- owning more than two cars or having a business car

Moreover, the distinction is made between households living in an urban or rural environment. Together this amounts to a total of 6 household types. The distinction between urban and rural households is important as the need for a car due to longer trips or commute can be different. Also, the accessibility to public transport can differ for both types.

Following UKTCM we use the subscript $c \in C = \{1,2,3\}$ to denote the different households owning at least *c* cars. As said, a distinction is made between households living in an urban or rural environment. To denote the environment in which the household lives we use the subscript $l \in L = \{1,2\}$.

The total car ownership in year y denoted by V_y and is equal to:

$$V_y = \sum_{\substack{l \in L \\ c \in C}} P_{c,l,y} * NumHH_{l,y}$$

where $NumHH_{l,y}$ is the number of households for each year and location and $P_{c,l,y}$ is the share of households that falls in category (c,l) in year y. While the number of households for each year is an exogenous variable, the shares $P_{c,l,y}$ are determined endogenously by the model.

The way to compute the share of households owning at least one or two cars is different from the way we compute the share of households that owns three or more or a company car. We first start with the households owning at least one or two cars.

The share of households owning at least one or two cars is assumed to be given by the following expression:

$$P_{c,l,y} = MaxOwn_{c,l,y} * \left[\frac{\left(f_y^1\right)^{e_{c,l,y}}}{\left(f_y^1\right)^{e_{c,l,y}} + f_{c,l,0}^5}\right], \qquad c = 1,2; l = 1,2; \ \forall y.$$

Where $MaxOwn_{c.l.y}$ is the maximum level of ownership of a household of type c living in l in year y. We will discuss later how these are determined. f_y^1 is the household income I_y divided by the average purchasing price of a new car R_y : $f_y^1 = \frac{I_y}{R_y}$, While the incomes are exogenous, the average purchasing price is determined by the TREMOVE model. Finally, the variable $f_{c,l,0}^5$ is given by:

$$f_{c,l,0}^5 = \left(\frac{MaxOwn_{c,l,0}}{P_{c,l,0}} - 1\right) * (f_0^1)^{e_{c,l,0}}$$

where $e_{c.l,y}$ is related to the price elasticity and is a calibrated variable.

The shares $P_{c.l.y}$ are S-shaped and bounded by the maximum ownership level. Changes in the shares will depend on the relative change in income and the average purchasing price. If incomes increase at a higher rate than the average purchasing price, the share of households owning at least one or two cars will increase.

The share of households owning three cars or more, or a business car is determined by the relative change in the share of households owning at least two cars and is again bounded by the maximum ownership level for three cars or more:

$$P_{c=3,l,y} = MaxOwn_{c=3,l,0} - \left(P_{c=3,l,y-1} - MaxOwn_{c=3,l,0}\right) * f_y^6$$

$$f_y^6 = -\frac{P_{c=2,l=2,y} - MaxOwn_{c=2,l=2,y}}{P_{c=2,l=2,y-1} - MaxOwn_{c=2,l=2,y-1}}$$

If the share of households owning at least two cars increases, the share of households owning at least three cars or a company car will increase too but more moderately.

The maximum level of ownership is determined as follows. The main driver for owning at least one car is the possession of a driving licence. The higher the proportion owning a driving licence, the higher the maximum level of ownership of a t least one car:

$$MaxOwn_{c=1,l,y} = MaxOwn_{c=1,l,0} * f^2, \quad f^2 = \frac{D_y}{D_0}$$

With D_y denotes the share of the population in possession of a driving licence in year y.

The dominant decision variables for households when choosing to buy a second car are assumed to be the size of the household and the accessibility to public transport (note: this is a slight variation to the UKTCM model where for urban households, it is the availability to parking that drives the maximum level of ownership. Due to lack of data and the Belgian context, we consider for both rural and urban households the accessibility to public transport instead).

$$MaxOwn_{c=2,l,y} = MaxOwn_{c=2,l,0} * f^3 * f^4 \quad with \quad f^3 = \frac{mop_y}{mop_0}, \quad f^4 = \frac{PK_{l,0}}{PK_{l,y}},$$

mop_y being the share of households with more than one person and $PK_{l,y}$ is the total vehicle-km travelled by public transport and is determined endogenously within the transport model:

$$PK_{l,y} = PKM_{bus,l,y} + PKM_{rail,l,y} + \cdots$$

Finally, the maximum level of ownership for 3 or more cars is assumed to be constant

$$MaxOwn_{c=3,l,y} = MaxOwn_{c=3,l,0}$$

4.3.2 Data

The next table summarizes the data needed for the model.

Table 4-6: Main variables for vehicle stock module

Notation	Definition
D_y	Share of population able to drive in year y
mop_y	Proportion of households with more than one person in year y
I_y	Disposal income for each household in year y
R_y	Average new purchase price in year y
$PKM_{PT,y}$	Passenger-km public transport in non-urban areas in year y
$NumHH_{l,y}$	Number of households for each year and location
$P_{cl,0}$	Share of households with at least *c* cars in location *l* in year 0
$MaxOWn_{c,l,0}$	Maximum level of ownership per household type in year 0
$e_{c,l,y}$	Car ownership elasticity in year y
g	Calibration parameter

The next table gives the data used to calibrate the model, i.e. data between 2001 and 2019 for Flanders. Similar datasets are used for Wallonia and the Brussels Capital Region.

Table 4-7: Main data for vehicle stock module of Flanders 2001-2019

year	able to drive [%]	proportion of households with more than one person [%]	Passenger-km public transport urban (index)	Disposable Income I(y) – [euro]	Average purchasing price R(y) – (index)	Passenger-km public transport rural (index)	pop shares urban [%]	# of households [thousands]
2001	67	72.31	93	39 175	81.13	81	89.7	2416
2002	67	72.01	93	39 324	82.08	91	89.7	2437
2003	67	71.62	90	39 357	83.04	97	89.7	2460
2004	67	71.25	88	39 876	84.01	106	89.7	2482
2005	67	71.00	89	41 137	85.00	109	89.7	2504
2006	67	70.74	89	42 928	86.00	109	89.7	2528
2007	67	70.51	90	44 698	87.00	111	89.7	2552
2008	67	70.29	88	46 809	87.77	115	89.7	2581
2009	67	70.09	88	46 466	88.49	118	89.6	2605
2010	67	69.82	88	46 461	88.47	117	89.6	2629
2011	67	69.76	87	47 335	89.08	115	89.6	2652
2012	67	69.52	85	48 227	89.09	110	89.6	2675
2013	67	69.35	90	48 516	89.25	106	89.6	2692
2014	67	69.19	93	48 803	89.90	104	89.6	2708
2015	67	68.93	98	49 345	91.82	103	89.6	2731
2016	67	68.80	100	50 295	94.80	102	89.6	2748
2017	67	68.63	100	51 917	96.47	100	89.6	2769
2018	67	68.37	100	53 121	97.43	100	89.58	2792
2019	67	68.14	100	55 087	100.00	100	89.52	2816

For the data after 2019 that are used to compute the future desired vehicle stock, we will use the passenger-km and vehicle purchasing prices that are computed by the transport model. The other exogenous data are:

Table 4-8: Additional exogenous data for vehicle stock module of Flanders 2019-2050

year	% people able to drive [%]	proportion of households with more than one person [%]	Disposable Income I(y) – [euro]	population shares urban %	# of housholds [thousands]
2019	67	68.14	55 087	89.52	2816
2020	67	67.89	55 590	89.52	2841
2021	67	67.69	57 108	89.53	2853
2022	67	67.51	58 160	89.53	2869
2023	67	67.30	59 743	89.54	2889
2024	67	67.08	61 425	89.55	2908
2025	67	66.86	62 939	89.57	2927
2026	67	66.65	64 600	89.58	2945
2027	67	66.46	64 607	89.59	2963
2028	67	66.26	64 613	89.61	2980
2029	67	66.04	64 620	89.62	2996
2030	67	65.83	64 626	89.64	3013
2031	67	65.64	64 632	89.66	3028
2032	67	65.44	64 639	89.67	3045
2033	67	65.24	64 645	89.69	3060
2034	67	65.05	64 652	89.71	3076
2035	67	64.86	64 658	89.73	3091
2036	67	64.68	64 664	89.74	3106
2037	67	64.50	64 671	89.76	3120
2038	67	64.32	64 677	89.78	3134
2039	67	64.15	64 684	89.80	3147
2040	67	63.98	64 690	89.82	3159
2041	67	63.82	64 696	89.84	3171
2042	67	63.66	64 703	89.86	3181
2043	67	63.50	64 709	89.88	3191
2044	67	63.35	64 716	89.91	3201
2045	67	63.19	64 722	89.93	3210
2046	67	63.04	64 728	89.95	3218
2047	67	62.90	64 735	89.97	3226
2048	67	62.76	64 741	90.00	3233
2049	67	62.62	64 748	90.02	3239
2050	67	62.49	64 754	90.05	3246

4.3.3 *Calibration and model reactivity*

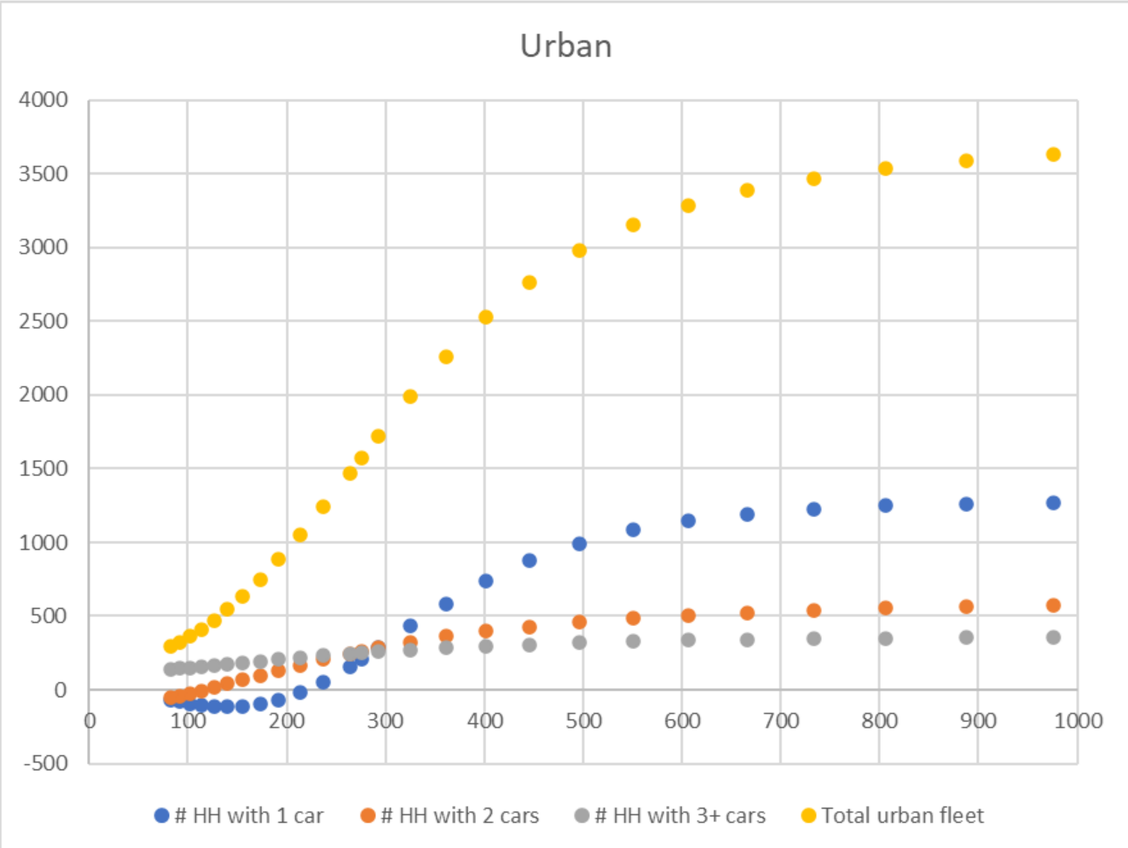
For the calibration we take 2019 as reference year and, using the historic data, we construct the historic vehicle stock from 2001 – 2019. This is then compared with the actual historical stock.

There are two types of parameters that can be used to fit the model: the maximum ownerships (for owning at least 1, 2 or 3 or more cars), the parameters $e_{c,l,y}$ for $c = \{1,2\}$ and the parameter *g* which determines the evolution of $e_{c,l,y}$ over time.

In order to get sensible results when the model is used for simulations it is important to get an insight how the model reacts to a change in income or vehicle purchasing price and how variables determined during the calibration will influence these.

First, we show the evolution of the number of households with 1, 2 or 3 and more cars in an urban environment to a change in the ratio between income and vehicle purchasing price. The maximum ownership has been set at 90, 40 and 15 resp. The elasticity is set to 3.5 for the first car and 2 for the second car.

Figure 4-6: Model reactivity for urban households – change income vs vehicle purchasing price – high

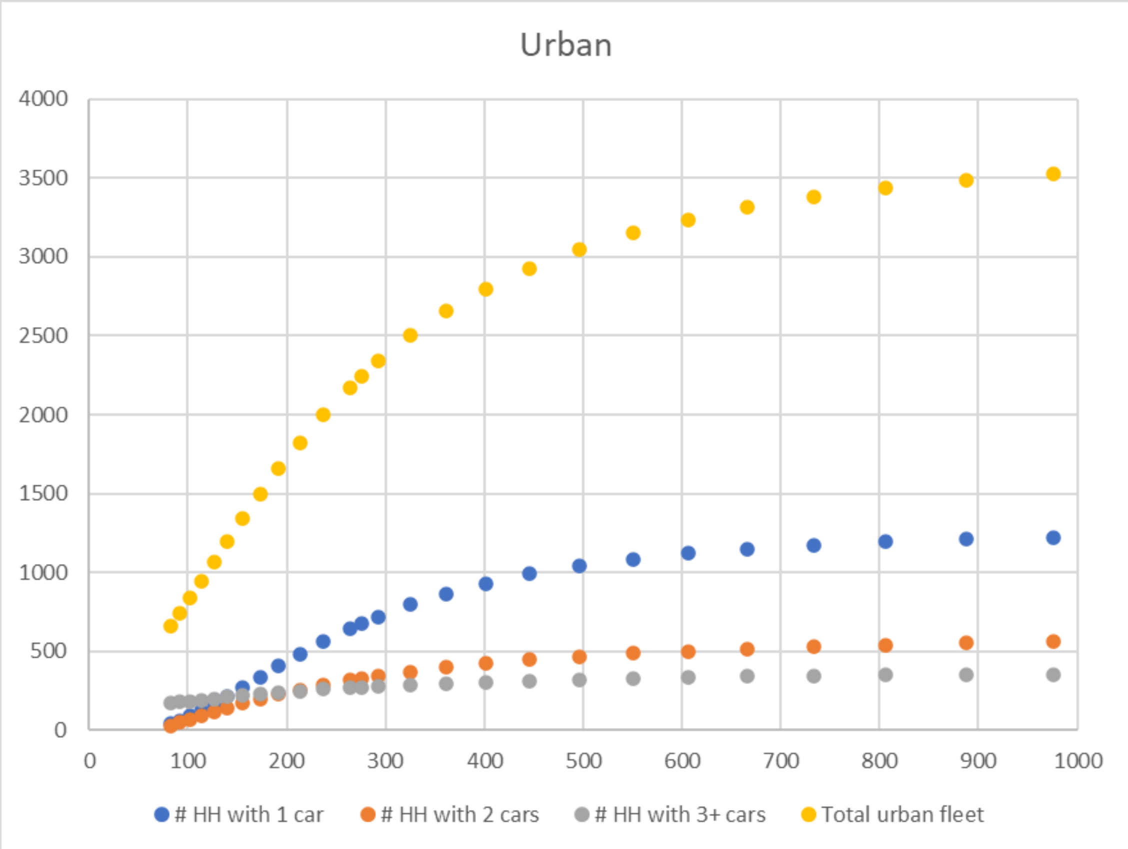


Source: Prototype of vehicle stock module

We see that we have an S-shaped function with the difference that it can become negative which is not the case with a Gompertz curve. We also see that we need to be careful about inconsistencies for large changes. In the above example, the number of households with 1 car becomes negative when purchasing price doubles (or income halves - the current income over vehicle purchasing price lies at 550.87).

For smaller elasticities (2 for 1 car and 1.5 for second car) we get

Figure 4-7: Model reactivity for urban households change income vs vehicle purchasing price – low elasticity



Source: Prototype of vehicle stock module

The conclusion is that the model will not be able to cope with large changes if the elasticities are set too high.

Secondly, we examine the influence of Maximum ownership on the results. To illustrate the sensitivity of the model to the maximum ownership we show the share of the (urban) population that owns at least 2 cars with a maximum ownership of 70 and 45 (interpretation: we assume that there will never be more than 70% or 45% of the urban population that will own at least two cars). The elasticity is taken to be 2.

Figure 4-8: Sensitivity analysis of model for a higher maximum ownership

Source: Prototype of vehicle stock module

The higher the assumed maximum ownership, the more sensitive the shares will be to a change of income or vehicle purchasing price. The current shares are 35%.

The conclusion is that to be able to deal with relative important changes, the maximum ownership cannot be too far from the current ownership.

4.3.4 Test calculations

Flanders

Keeping these two restrictions in mind the following Maximum ownerships and elasticities give the best results:

Table 4-9: Maximum ownership of cars

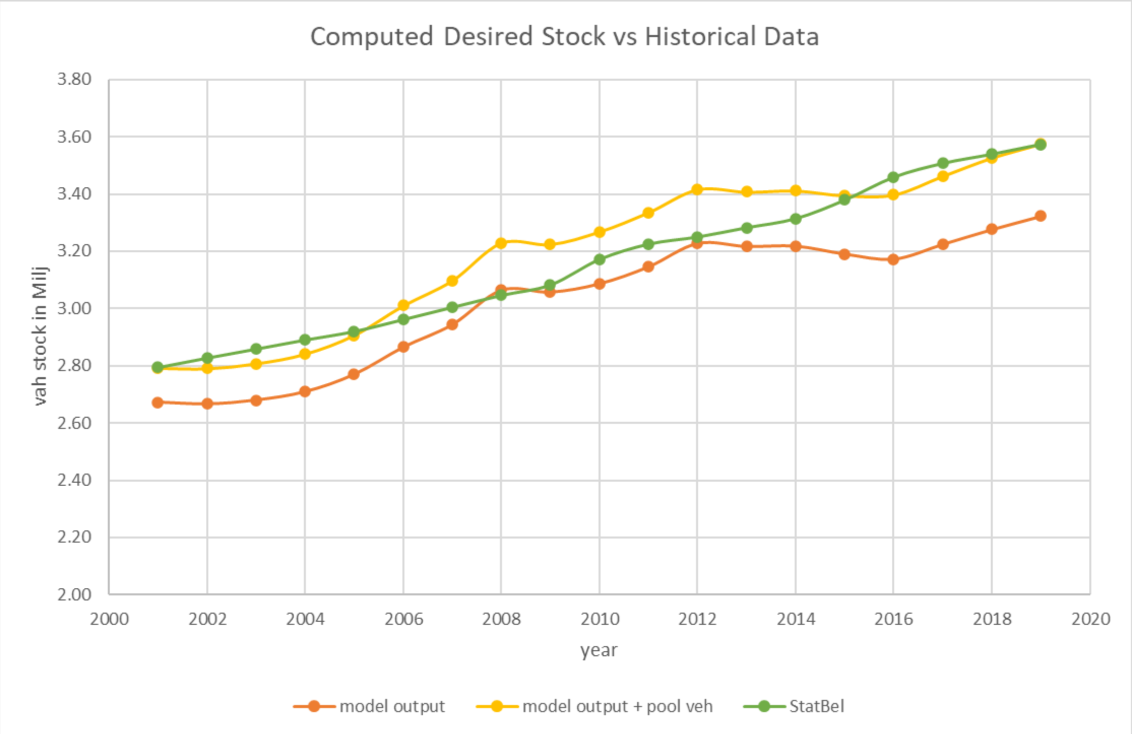
Maximum share of population with	location	
	urban	rural
At least 1 car	90	95
At least 2 cars	40	50
3 or more cars	15	20

Table 4-10: Elasticity of car ownership

e_{y11}	3.5
e_{y12}	2.5
e_{y21}	2
e_{y22}	1.500
g	0

In the next graph we show the desired vehicle stock computed by the model and the historical data for the above values.

Figure 4-9: Desired vehicle stock vs historical data – Flanders – comparison of test simulation



Source: Prototype of vehicle stock module

As mentioned above, the elasticities could lead to problems if the changes are too important. Lower elasticities, however, give an evolution of the stock that is not reactive enough and the vehicle stock projected in the base year is too high. To get an acceptable match, the (inverse) evolution of the elasticities need to be adjusted (i.e. g needs to be different from zero)

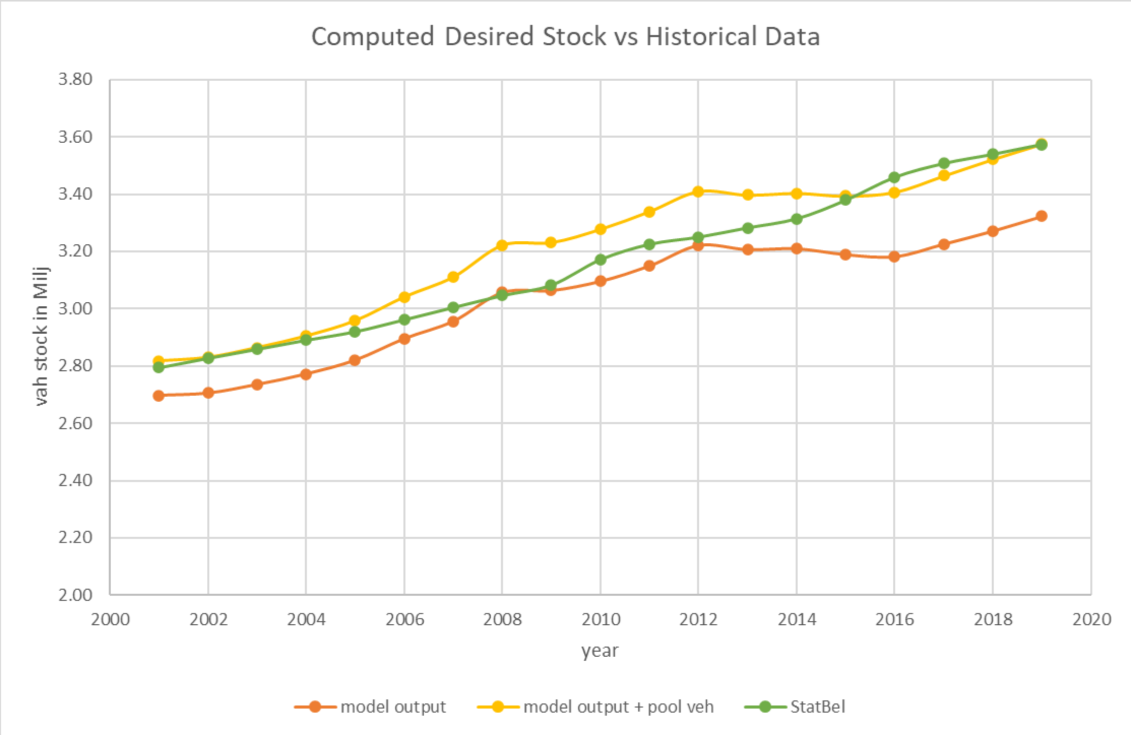
e_{y11}	2.2
e_{y12}	1.8
e_{y21}	1.5
e_{y22}	1.2
g	-0.1

In 2001 this gives us the following elasticities

e_{y11}	2.177
e_{y12}	1.799
e_{y21}	1.494
e_{y22}	1.195

The match with the historical data is given in the next graph.

Figure 4-10: *Desired vehicle stock vs historical data - Flanders*

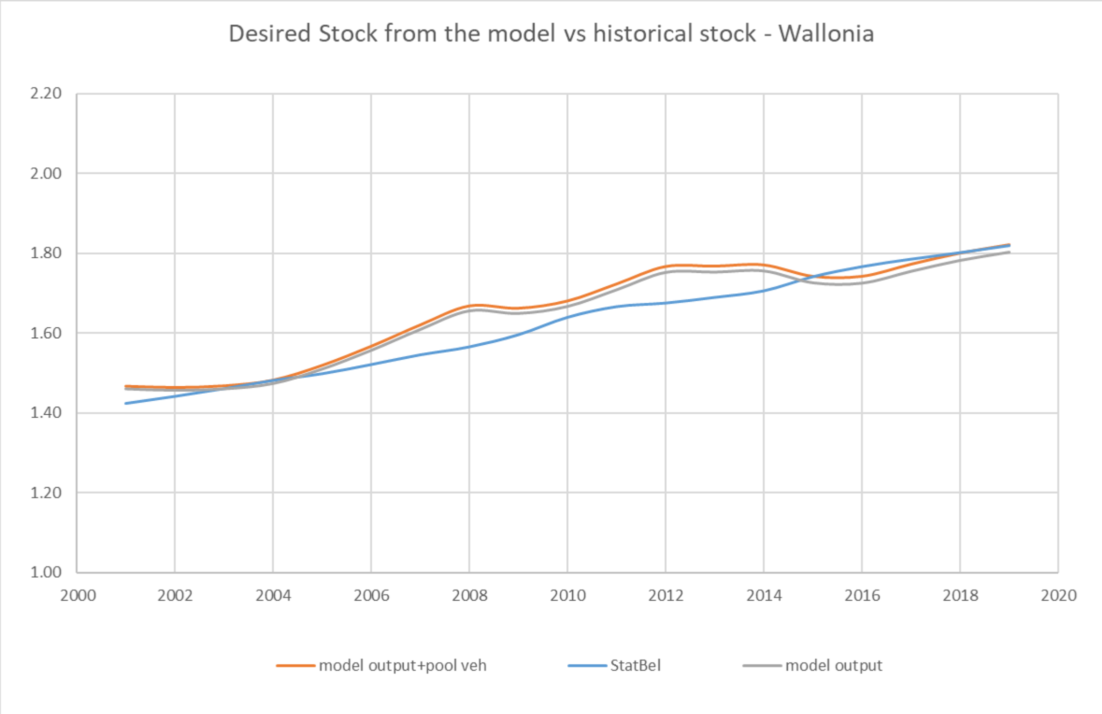


Source: Prototype of vehicle stock module

Wallonia

e_{y11}	3
e_{y12}	2
e_{y21}	2.2
e_{y22}	1.8
g	0

Figure 4-11: Desired vehicle stock vs historical data - Wallonia



Source: Prototype of vehicle stock module

Brussels Capital Region

Two observations for the data about Brussels:

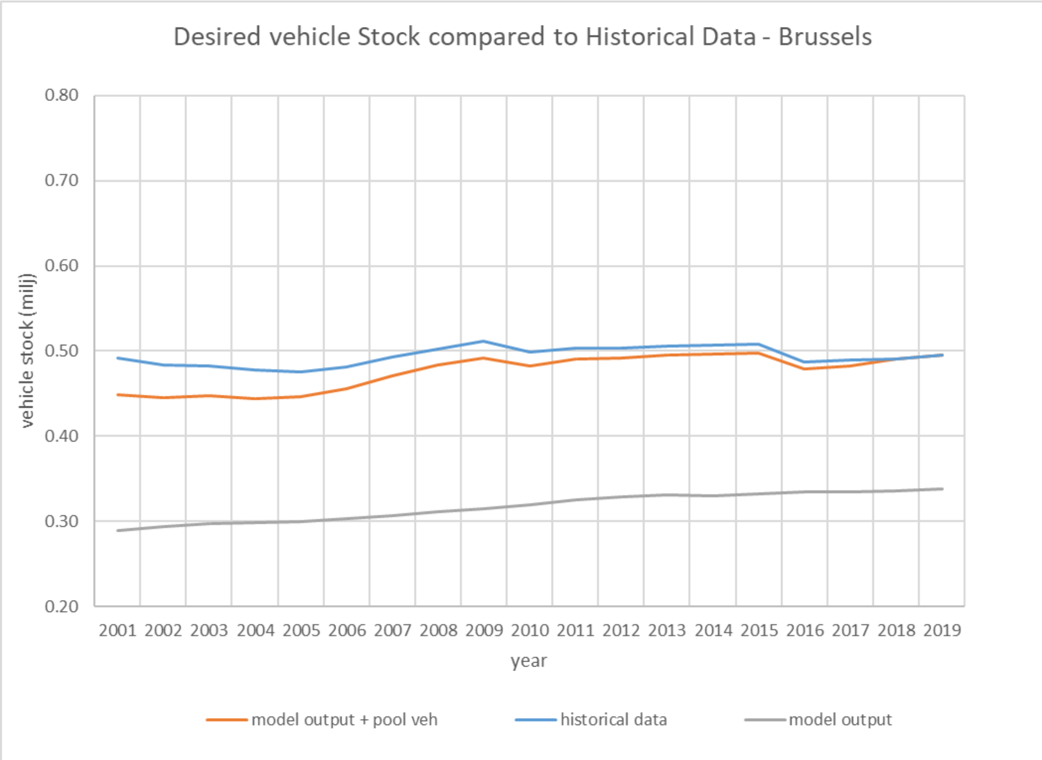
- The vehicle stock for Brussels is nearly constant over the years: in 2001 there were 0.49 million cars registered in Brussels, in 2019 0.5 million.
- The proportion of pool vehicles is much larger than in the other regions, probably because a lot of companies are registered in Brussels.
- There is no rural location in this region.

The constant fleet means that the elasticities need to be taken very low for Brussels.

e_{y11}	0.1
e_{y12}	0.1
g	0

The match between model output and historical data is as follows:

Figure 4-12: *Desired vehicle stock vs historical data - Brussels*



Source: Prototype of vehicle stock module

4.3.5 *Test simulations for Flanders*

To illustrate the sensitivity of the calibrated models we simulate a couple of scenarios for Flanders.

We take the following values for the "elasticities".

e_{y11}	2.200
e_{y12}	1.800
e_{y21}	1.500
e_{y22}	1.200

We report some simulation results in the following table, where we keep everything constant (even population) and only make the changes mentioned. We report the percentage change in number of households with 1 car, 2 cars and 3 or more (urban and rural) and the total fleet (which includes the company cars and pool vehicles which are kept constant too)

Table 4-11 Test simulations

		2% increase in rural passenger-km	2% increase in vehicle price	Doubling of vehicle price	2% increase in households with more than 1 person
# HH 1 car	Urban	0.00	-0.90	-46.97	-1.38
	Rural	1.61	-0.50	-29.76	-1.64
# HH 2 cars	Urban	0.00	-0.66	-27.52	3.56
	Rural	-3.67	-0.53	-21.02	3.74
# HH 3+ cars	Urban	0.00	-0.99	-41.00	-0.89
	Rural	1.05	-0.92	-36.59	-1.07
Total fleet		-0.04%	-0.77%	-34.94%	0.37%

The impact of a 2% rise in passenger-km in rural environment will only be felt for rural households: a decrease of 3.67% in the number of households owning 2 cars and an increase of 1.61% of households owning 1 car and an increase of 1.05% of households with three or more cars. The total desired fleet decreases very slightly.

The impact of a 2% increase in the vehicle purchasing price is the strongest for the households with 3 cars. Less households will be wanting a second car. In rural areas, some of the households with previously two cars will switch to one car, hence a less severe decrease of households with one car in rural areas. In urban areas, where we assume higher price elasticities, the number of households with one car will also decrease substantially.

If there is a 2% rise in households with more than 1 person, more households will opt for a second car and the number of households with two cars increases, while households with only one car decrease.

4.3.6 Taking the number of company and pool vehicles as exogenous

If we treat all company cars as exogenous, as they are not under the control of the households, we need to adjust the percentage of households with at least 1,2 or 3+ cars in 2019. The shares for Flanders are:

Table 4-12 Car ownership with company cars taken as exogenous

	location	
	urban	rural
>1	67.78	74.28
>2	24.74	30.42
>3	5.51	7.47

If company cars are taken out of the modelling exercise, there is no reason anymore to treat the households with 3+ cars differently. The shares are now all computed with the following formula.

$$P_{c,l,y} = MaxOwn_{c,l,y} * \left[\frac{\left(f_y^1\right)^{e_{c,l,y}}}{\left(f_y^1\right)^{e_{c,l,y}} + f_{c,l,0}^5}\right], \qquad c = 1,2,3; l = 1,2;\ \forall y.$$

We still assume that for 3 or more cars, the maximum ownership remains constant. Note, that we now also need to calibrate the parameters e_{y31} and e_{y23}.

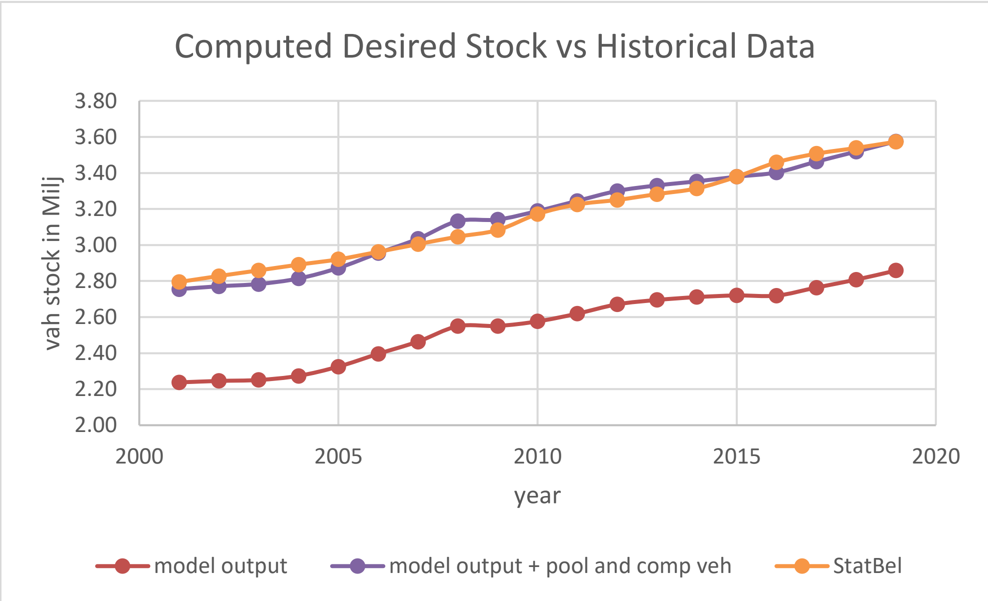
The results for the calibration are now:

Table 4-13 New elasticities for Flanders with exogenous company car fleet

e_{y11}	2.2
e_{y12}	1.8
e_{y21}	1.5
e_{y22}	1.2
e_{y31}	1.1
e_{y32}	1
g	-0.1

The fit is as follows:

Figure 4-13: Computed stock vs historical data



Source: prototype of vehicle stock module

In this case the test simulations give the following result.

Table 4-14 Test simulations with exogenous number of company cars

		2% increase in rural passenger-km	2% increase in vehicle price	Doubling of vehicle price	2% increase in households with more than 1 person
# HH 1 car	Urban	0.00	-1.06	-50.43	-1.15
	Rural	1.36	-0.68	-36.12	-1.39
# HH 2 cars	Urban	0.00	-1.18	-43.15	2.57
	Rural	-2.60	-0.91	-33.77	2.65
# HH 3+ cars	Urban	0.00	-0.98	-33.90	0.00
	Rural	0.00	-0.99	-33.43	0.00
Total fleet		-0.05	-0.85	-34.71	0.50

4.3.7 Test evaluation

Based on these tests it was decided that the update of the vehicle stock module should be studied further before it can be incorporated in TREMOVE. Hence, for the simulations that are reported in Chapter 7 the original vehicle stock module is still used.

5 Module III: Micro-simulation

5.1 Objective

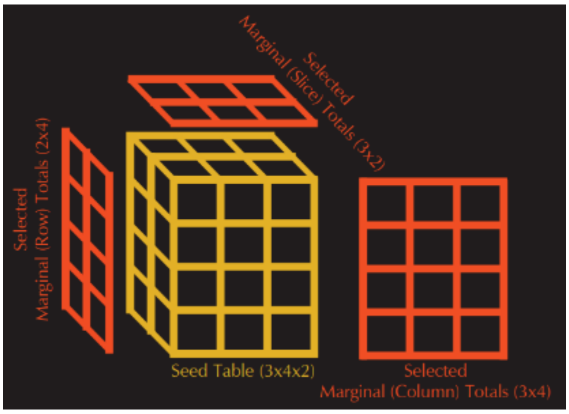
The objective of this module is to construct a synthetic population representing the population living in a given area in Belgium with personal and household characteristics and associate them with the trips generated by the trip distribution. Generating population at the agent level enables to increase the accuracy of the transport demand model since the transport choice depends highly on different personal and household characteristics.

5.2 Methodology

Iterative proportional fitting

The population is synthesized thanks to a n-dimension Iterative Proportional Fitting (IPF) algorithm which requires the knowledge of total marginals (socio-demographic data available at a specific geographic resolution) and an initial solution (coming from surveys results) which gives the combination of characteristics which makes sense and implicitly those which are nonsense. Afterwards, in the features expansion part, extra interesting variables are added (for example, in this case, the binary variable indicating if the agent has or does not have a driving license is determined). Finally, the trips of the OD matrix are assigned to the agents generated. This assignment is realized thanks to an IPF algorithm where the initial solution is determined based on the distance of the trip and on the characteristics of the agents.

The Iterative Proportional Fitting (IPF) algorithm: the IPF is, in 2D, an iterative algorithm which takes as input an initial 2-dimensional matrix and two 1-dimensional vectors, called marginal totals, which provide the sum of each row or line. The algorithm normalizes iteratively the rows and the columns of the matrix and converges when the sum of the rows and columns of the matrix reach the marginal totals. The initial matrix is thus "*iteratively and proportionally*" fitted with the marginal totals.



This principle might be generalized for *n* dimensions. In that case, the initial matrix used must be a *n* dimension matrix and the maximum dimension of the marginal totals is *n-1*.

The flowchart below includes the main steps required to synthesize a population and associate the agents created with an OD matrix.

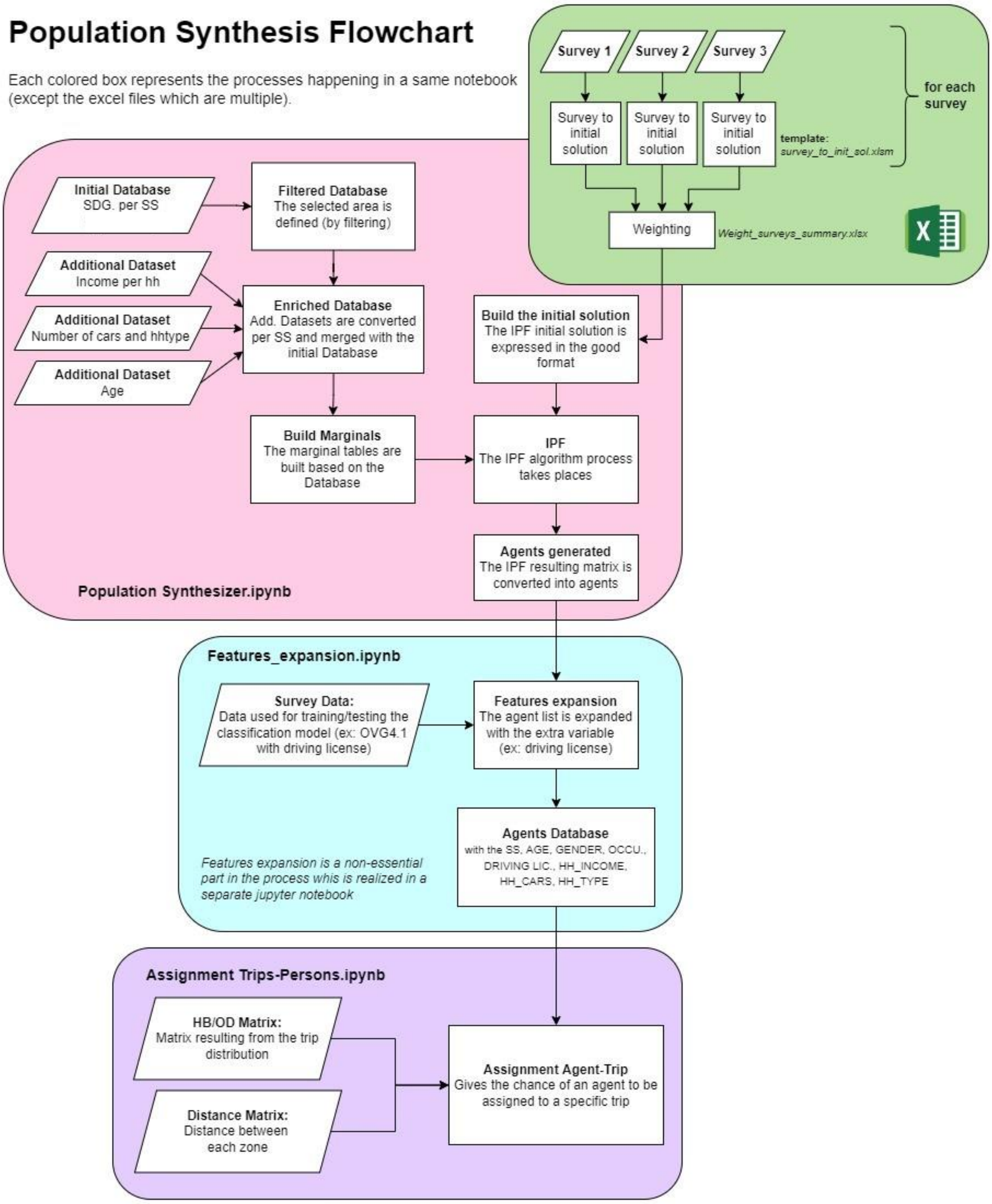
The pink rectangle is the most important one, where the population is synthesized in a given geographical area (a municipality) using a set of features (in this case, eight features: the socio-economic status, the age, the gender, the income per household, the occupation, the type of household and the number of cars per household). An IPF algorithm is used to respect the socio-demographic data.

This IPF algorithm needs both total marginals (socio-demographics data) and an initial solution (telling the algorithm which combinations of features are possible or not) to run properly. This initial solution is obtained thanks to surveys (see **green**).

Then, in **turquoise**, additional features of the persons are added using the already implemented variables, survey data and classification model. Owning of driving license has for instance been inferred from the other variables.

Finally, each trip contained in the OD matrix resulting from the trip distribution is assigned to the population generated (see last **purple** rectangle)

Figure 5-1 Population synthesis flowchart



Files Structure

Here below the description and the purpose of each file/folder is presented:

- Population Synthesis
  Main jupyter notebook which includes the entire process of population synthesis: build a socio-demographics database per statistical sector, define the geographical area, provide the inputs of the IPF algorithm (marginal totals and initial solution), run the IPF algorithm and generate the agents resulting into a .csv file.
- Expansion of features
  The jupyter notebook which is used to add an extra variable by using the already implemented variables, survey data and classification models. For example, the possession of a driving license is a variable which has been inferred from the other variables thanks to a classification model trained and tested on a survey data.
- Trip assignment
  This notebook takes as inputs the OD matrix generated after the trip distribution, the related distance matrix and the population synthesized. Its purpose is to calculate for each person synthesized the chance that he/she goes to each destination. This estimation is resulting from an IPF algorithm.
- Social demographic folder
  This folder gathers the files containing and treating the socio-demographic variables used as agents' features.
- IPF initial solution folder
  This folder includes all the files used to determine the IPF initial solution. This includes the surveys, their conversion into the IPF matrix, the file weighting the matrix generated by each survey and finally the initial solution matrix.
  - *1_Survey_to_init_sol.xlsm*
    This excel file is the template used to transform the survey results into a IPF matrix with one row for each unique combination of the variables.
  - *2_Weights_surveys_summary.xlsx*
    This excel file has been realized to weight the IPF matrices coming from the surveys. This enables us to give more or less weight to each survey.

- Outputs folder
  This folder is composed by the different agents' list synthesized. The characteristics of each agent are also included.

- Feature expansion folder
  This folder contains the files used in the features expansion notebook, namely the file used to train/test the classification model.

- Trip assignment folder
  This folder includes the files used in the assignment Trips-Person notebook, i.e. the OD-matrix, the distance matrix.

Datasets used

Different surveys are used to provide an initial solution to the IPF algorithm. Among those surveys, they are MOBWAL 2017, Leuven stadsmonitor, OVG, MONITOR 2017. Each of those surveys has first to be transformed to fit with the format of the IPF initial matrix. This is the purpose of the template file *survey_to_init_sol.xlsm*. Each survey can then be weighted to equilibrate the importance of each survey in the *Weight_surveys_summary.xlsm* file.

Population synthesis

The first important step in the process of Population synthesis is the merging of each socio-demographic dataset into one unique database, giving each feature as a categorical variable, per percent of the population and per statistical sector. Some data manipulations have thus been required to convert the different sources into this specific format:

- Incomes: Data coming the official fiscal declarations from STATBEL have been modified into fixed income categories as we only know the values of each quartile for each socio-economic status
- Cars per household and type of household: From STATBEL, we know the number of households per municipality which is of a given type and with a given number of cars. Values from municipalities have thus first been translated into socio-economic status data. Then, number of households have been converted to a number of persons. However, the average number of people per households highly depends on the household's type (*e.g.*, households of couples without children are composed by 2 members)

After the creation of one comprehensive dataset, the total marginal tables must thus be extracted. The process is a bit different depending on the dimension of the marginal tables.

Then, the IPF algorithm is run, and a list of agents is generated. The weight representing each agent (i.e., the number of agents per real human being) is by default equal to 1 but might be changed. However, in the *Assignment Trips-Persons.ipynb* notebook only 1-weighted agents have been tested.

Feature expansion

The driving license is a socio-demographics information that we did not find per statistical sector or municipality, and which is sometimes not included in the surveys. Moreover, this is a variable quite correlated with the other existing variables such as the age, the number of cars per household or the income level. To guarantee that the agents generated make sense, a classification model has been developed to infer the state of the driving license of each individual based on the known characteristics.

Trip assignment

The assignment between the trips contained in an OD-matrix and the agents generated is not an evident task. In most cases, the agents generated in an area are just randomly assigned to the trips starting in this area, without any other concerns. However, it is not impossible to imagine that certain agents have a higher probability to be assigned to specific trips. In order to go one step further than just the random assignment, we have decided to calculate the probability of an individual to be assigned to a specific destination, based on its personal characteristics and on the trip distance. Our intuition was that a person with a driving license and with a car at disposal would have a higher chance to travel further than someone without driving license.

From the OVG survey, one can thus parameterize a distribution which, for each specific type of agents, gives the trip distance distribution. Two variables have been used to define the types of agents: the driving license status (Yes/No) and the number of cars in the household (0/1/2/2+), which makes 8 types of agents for which one distribution must be parameterized each time. By analyzing the distance distribution of the trips performed by each of those 8 types, one distribution seems to match particularly often: the LogNormal distribution. If one uses the logarithm of the distance, the appropriate distribution is thus a normal distribution. A specific notebook has been used for this. The objective of this notebook is to find the distribution (and its parameters) which fits the best with a given set of points.

Thanks to the parametrized distributions and their probability density function, it is possible to calculate for each agent-trip couple a value. That value is a first estimation used to fill the initial matrix of the IPF algorithm.

Indeed, to find the probability that a given agent chooses a specific destination, a 2-dimensional IPF is run with as one axis all the persons coming from one zone and as second axis all the possible destinations. As marginal totals, one knows that the sum of probabilities along the first axis must be equal to 1 (for one person, each time) and along the second axis, the appropriate value from the OD matrix. The table below gives an example for one specific origin zone the initial matrix and the corresponding marginals totals solved through the IPF. To find an appropriate first estimation for the No Travel column, we have determined the percentage of the people living in an area which do not travel. This might be easily found by comparing the population of a zone and the total number of trips started in that zone in the OD matrix.

Table 5-1 Example

Destination Agent	Zone 1	Zone 2	Zone 3	No Travel	**Marginals**
Agent #1	1.4	2.5	1.6	9.7	**1**
Agent #2	0.9	5.4	1.5	8.5	**1**
Agent #3	3.5	1.4	5.4	10.2	**1**
Agent #4	2.4	2.4	3.5	12.5	**1**
Marginals	**0.6**	**0.9**	**1.1**	**1.4**	**4**

This kind of 2-dimensional IPFs must be solved for each origin zone.

The philosophy of this assignment is to calculate the chance of each agent to travel to a defined destination. The origin is however well defined for each agent, it is the zone where the agent is generated (and thus where he/she lives). This assumption is acceptable during the morning peak hours. For the evening peak hours, the symmetric assignment can be made by calculating for each agent the probability that he/she travels from a specific zone to his house.

6 Module IV: Grid level data

This chapter describes how information from the Flemish mobility survey (Onderzoek Verplaatsingsgedrag or OVG) was processed to provide information that is relevant for the EPOC analyses at grid level. The main purpose was to derive daily traffic curves. In addition to this, the share of trips and mileage by the degree of urbanisation of the origin and destination of the trips was also derived.

6.1 Derivation of daily traffic curves

6.1.1 *Initial processing of the OVG data*

Annex 1 gives a general description of the OVG dataset that was used for the analysis. For the derivation of the daily car traffic curves, we used the data in the trip diaries that each respondent filled in for one day. In this trip diary, one trip (or "*verplaatsing"*), e.g. a trip from home to work, can contain multiple legs using different modes of transport, e.g. a ride with the car to a P+R park, and then a ride on the train, then finally a walk (longer than 100 meters to be recorded as a separate leg). This is then one single trip made out of three legs. Since our goal was to make daily traffic curves of car trips, we wanted to have all trips disaggregated into legs based on the mode of transport, so we could also look at these trip-legs separately. There are plenty of trips that only consist of one leg, but there is also a very large portion of multi-legged trips, so not taking this into account would have distorted the final results.

A relatively complex algorithm was required for this, as there are plenty of exceptions that we had to be able to handle due to often irregular data structures, but for each leg the following new variables were calculated using available data:

- vertrek_time (departure time)
- aankomst_time (arrival time)
- vertrek_dayofweek (departure day of week, e.g. Monday)
- vertrek_month (departure calendar month)
- kmperminute (km travelled by minute)

The last variable was calculated as a sanity check, it is used at a later stage to filter out erroneous data (so we do not get biased by potential outliers in our statistics).

6.1.2 *Methodology*

To create car traffic curves (for all days, for weekdays and weekends, and for each of the seven days of the week respectively), we applied the following method. We calculated for each minute of the day (from 00:00 to 23:59) the number of cars that have been on the move using the disaggregated trip-leg data. The aggregated leg data is filtered by transport mode (car driver or passenger selected), time of the day, and the appropriate day(s) of the week and then the selected entries' weights are summed up to create the totals for each minute of the day, and this process is repeated for every minute of the day. (We sum the weight and not the actual numbers, because this is the right way to take each trip's weight properly into account. Also a filter of 3.33 km/minute is applied, to discard all car trips with an impossibly high average speed. These outliers would introduce excessive vehicle kilometres in the statistics.)

It should be noted that minute-by-minute resolution traffic curves suffer from reporting bias: people tend to report start and end times rounded up to the closest hour, half hour, quarter, or ten minutes, which creates false structure in the data. This is why it is better to look at the hourly aggregated data, which is produced by simply aggregating the minute resolution data for each hour.

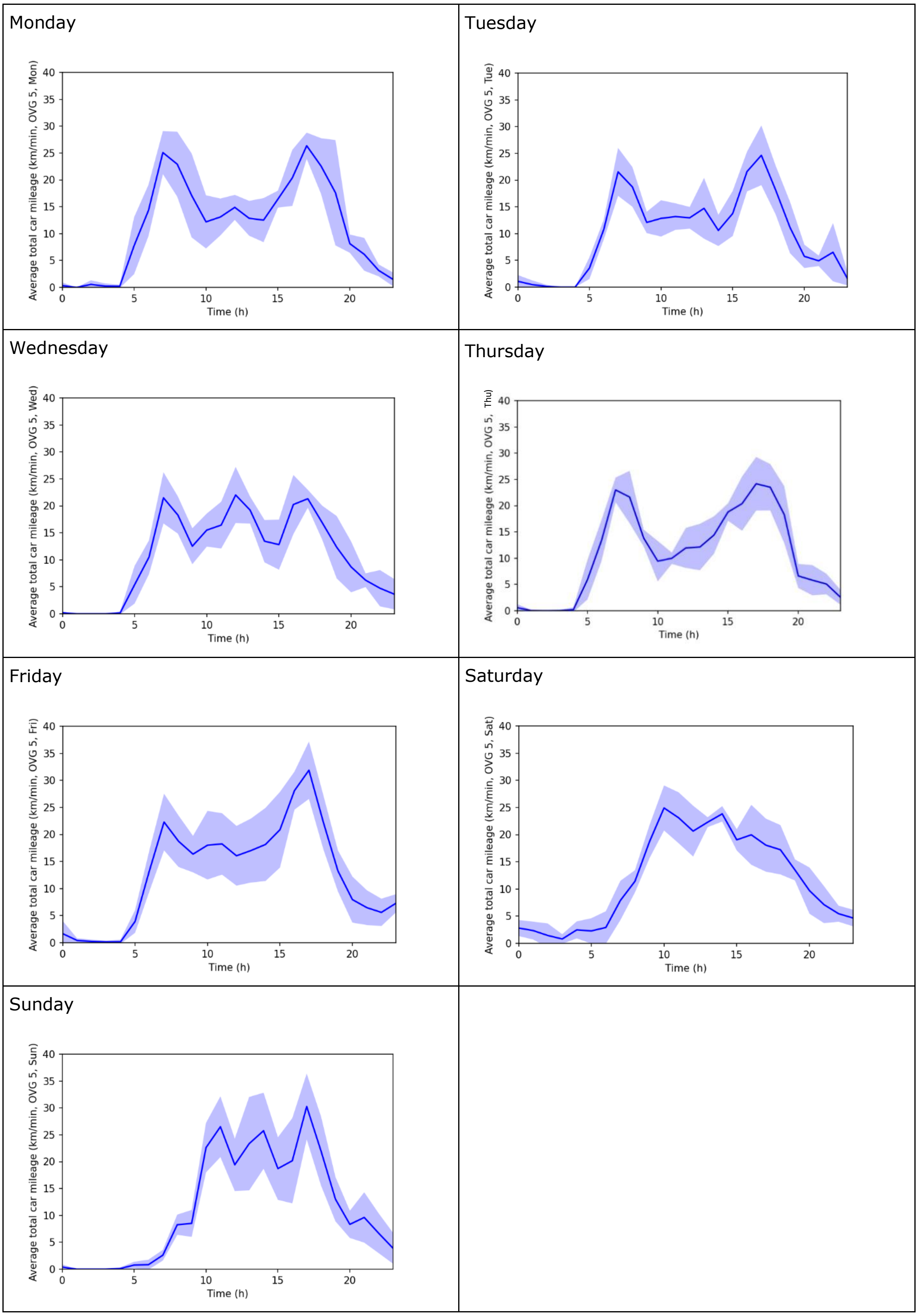
6.1.3 *Daily car traffic curves*

After the initial data cleaning, harmonisation, and processing steps, we have calculated the average (car) traffic curves (based on trip legs where the reporting person was driver or passenger in a car – as this filter was already applied during the calculation of the aforementioned on the move numbers) for the seven days of the week separately, and also for weekdays, weekends, and for an average day, respectively, by simply averaging the traffic curves of the separate OVG editions. Only the "per hour" data are used (since as mentioned the per minute data suffers from reporting bias). The separate OVG editions are given the same weight, and daily curves are normalised before averaging them together (this is needed to give the separate OVG editions really the same weight, otherwise different mileage over, e.g. Mondays over the editions would influence the weight of various editions when calculating the average Monday traffic curve).

Further notes on this data: The data file contains average - non-scaled (see note later) - car traffic curves derived from the five years of OVG 5 (OVG 5.1-5.5) data. The curves represent the vehicle-km produced by people in cars as drivers of as passengers in an hourly resolution, separately for the seven days of the week. Average values and standard deviations are given, where average is an average of the five years, and the standard deviation is the standard deviation of the five years' data, and can be used as an approximation of the 1 sigma uncertainty of the average. Before the average and standard deviation were calculated the daily curves were normalized, to give the same weight to each OVG edition.

After the average values were calculated, the traffic curves were scaled back up using the average normalization factor (to restore the original mileage ranges). For each hour the average kilometre/minute is given (since the hourly values are calculated from a minute resolution raw data table), so to calculate the hourly total vehicle-km one would multiply the given values by 60. In any case the absolute values are slightly arbitrary (they are representative to the average sample of respondents in these 5 years of the OVG), therefore we provide a further processing suggestion: to recreate a proper year, one would fill the 365/366 days of the year with hourly values sampled from these average curves according to the day of the week (Sundays can be taken for holidays too), then a general scaling factor would need to be applied to make the sum of the yearly vehicle-km equal the Belgian (or Flemish) yearly vehicle-km totals. This yearly scaling factor would be different for each year, according to the changes in the observed and projected yearly vehicle-km data.

Figure 6-1 Representative travel curves based on OVG 5 for each day of the week



Source: Own calculations based on OVG 5

6.2 Distribution of trips according to the level of urbanisation

For the OVG dataset, that is limited (mostly) to Flanders, we are also curious about the distribution of trips across urban/rural areas, or with other words, we would like to know what percentage of trips starts in a rural area and ends in a rural area, and how many are rural-urban, urban-rural, urban-urban.

Urbanisation data are based on a dataset of urbanisation level by postcode used by Afdeling Beleid, MOW Flanders. Postcode data are derived from a matching using NIS codes from another database. We merged levels 2 and 3, creating only urban and rural (or better to say "less urban" in Flanders) categories to increase the sample size.

The logic of figuring out the postcodes for each leg is the following. We determine each consecutive trips from the same person leaving from a previous endpoint. The first trip leaves most likely from home, so if there is a homewards journey somewhere (people tend to go home at one point every day), we can get the postcode of the home too. There are some caveats, for example if the first trip of a given person is a homewards journey, that could not have started from home, so in such case we cannot guess the departure postcode either.

We also want to know what is the dominant leg (i.e. the main mode) in a trip where it contains multiple legs, and we do this by looking at the disaggregate data. The main leg is chosen to be the longest one in distance. Very rarely two legs have the same distance, then both these legs are chosen as the main leg (and the remaining legs are non-main legs). This is an interesting statistic because sometimes we want to look at trips without disaggregating them to trip legs but we still want to know what was the main mode of the trip.

The next table presents car mileage and car trip (leg) numbers between the urbanisation zones 1 and 2. We label zone 1 as urban and zone 2 as rural[12]. (Individual trip weights are being taken into account, assuming that all OVG editions have the same weight – meaning that no extra weights are applied on top of the trip weights of individual OVG editions)

Table 6-1: Car mileage and trips by urbanization level for origin - destination

O – D	car mileage	%	car trips	%
urban to urban	10757	6.03	1043	7.67
urban to rural	24228	13.57	967	7.11
rural to urban	24761	13.87	980	7.20
rural to rural	118 762	66.53	10615	78.01

Source: Own calculations based on OVG 5

To calculate further statistics, for example to include income levels in the statistics of the origin-destination trip-subdivisions, we need to further process the personal and household data, as there are a lot of people who did not give all their information.

[12] Note that 'rural' in Flanders as stated above is still relatively dense compared to rural regions in other countries. In practice it is a mix of peri-urban and relatively densely populated rural regions.

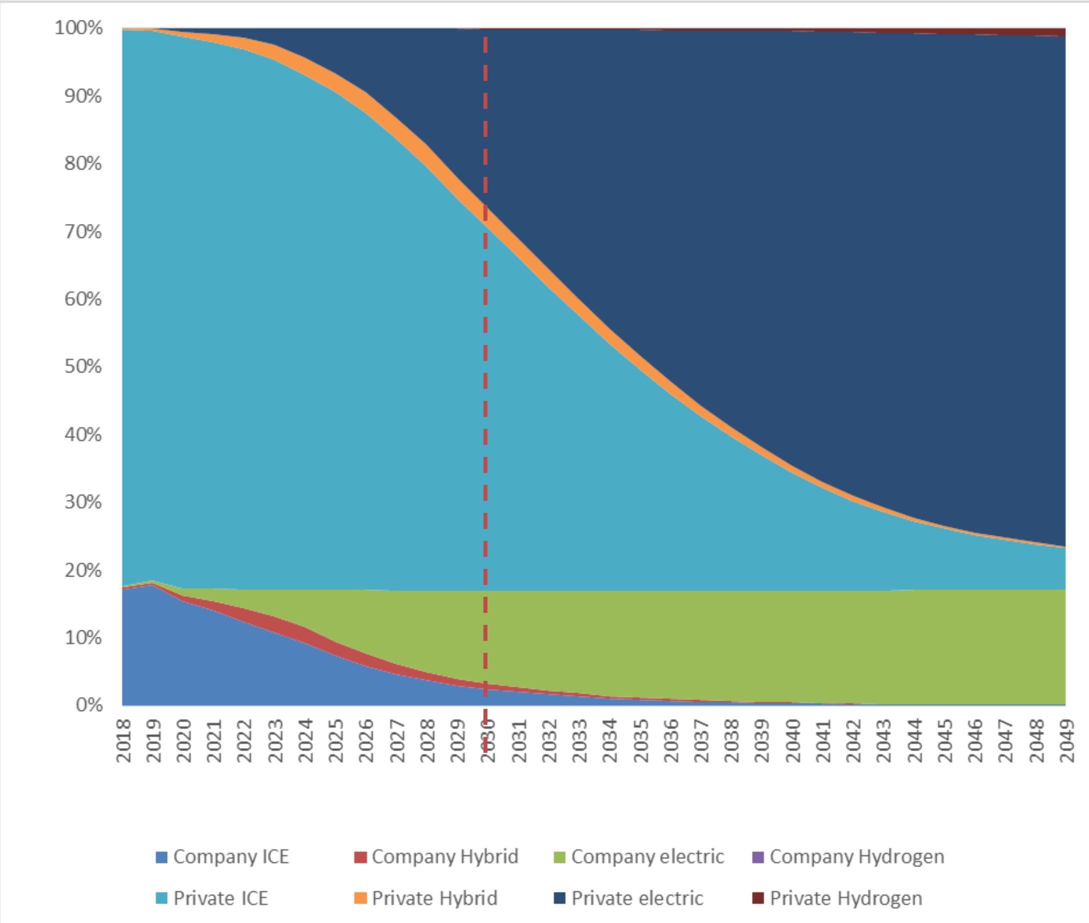
7 Scenario analysis and simulation

7.1 Projected growth of electric vehicle fleet up to 2050

Electrification of the fleet is expected to increase rapidly in the next years. Due to difference in fiscal rules between private cars and company cars, the electrification of company cars is expected to increase rapidly. Changes in the Belgian Tax code in 2021 lead to a phase out of tax deductibility of all cars, except zero emission vehicles. By 2026 the deductibility of fossil fuel cars will be effectively zero. This is expected to lead to a majority of new electric vehicles among company car sales in 2023 already (Franckx, 2022). In Europe, the sale of new cars on fossil fuels will be banned after 2035. Flanders has revealed plans to ban cars on fossil fuels even earlier, before 2030 (see also the policy context described in Chapter 1).

Based on DIV[13] data we made a forward projection of the changes in fleet composition, that are in line with regional and national policies (see Figure 7-1). Around 2030, this would lead to electrification of nearly 90% of the fleet of company cars and around 22% of the fleet of private passenger cars. The share of hybrid cars and cars on hydrogen is expected to be very limited in this scenario. Section 4.2 gives more detail about the construction of this scenario.

Figure 7-1 Forward projection of electrification fleet until 2050 distinguishing company and private cars

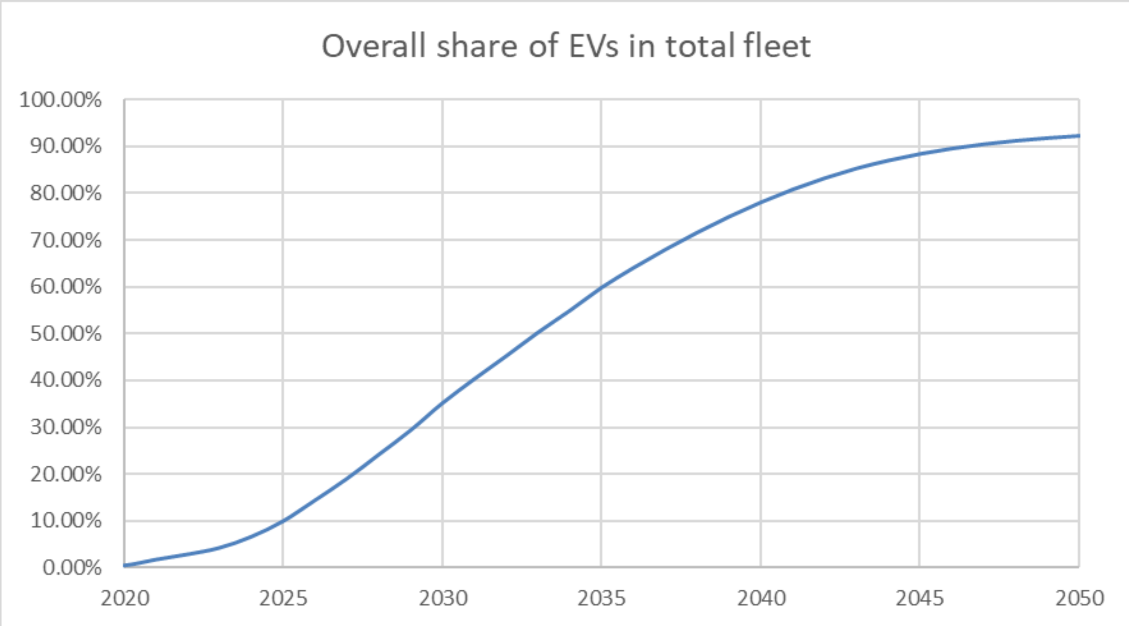


Source: Own calculations

[13] Dienst voor Inschrijving Voertuigen (nl) – Department for Vehicle Registration (en)

Looking at the share of EVs in the overall fleet, this comes down to 35% of the overall fleet in 2030. By 2035 – when European car sales of conventional fossil fuel cars would be formally banned – 50% of the car stock would have transitioned to electricity.

Figure 7-2 Overall share of EVs in fleet

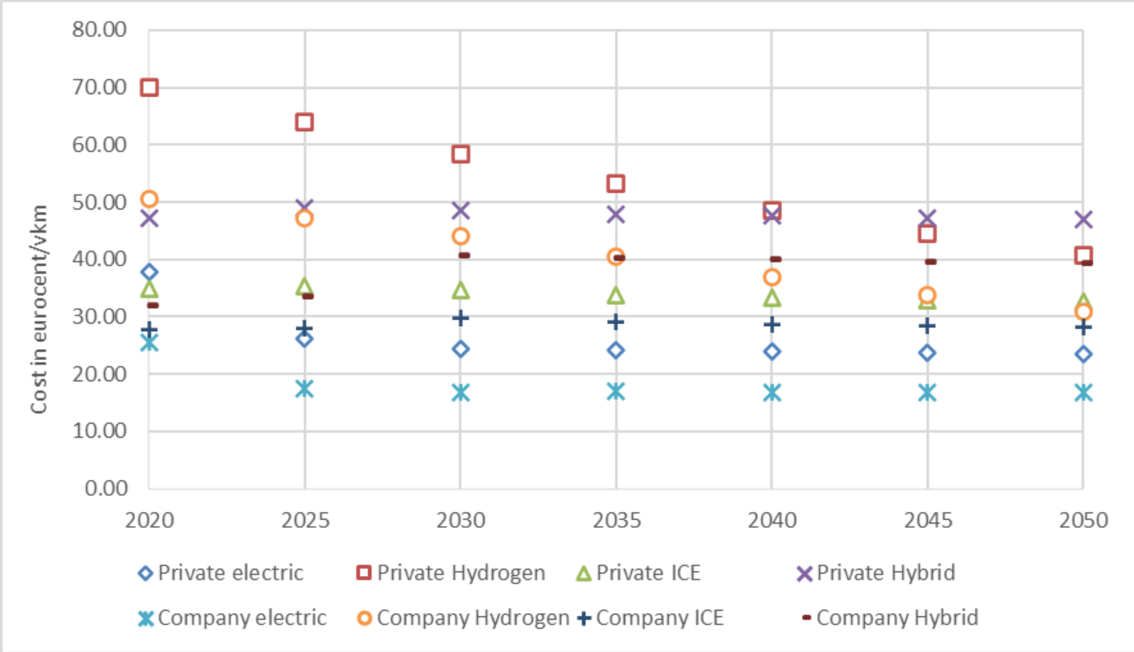


Source: own calculations

Despite many misgivings surrounding the higher purchase cost of electric vehicles, the total cost of ownership (TCO) of a number of electric vehicles is already largely on par with alternatives on fossil fuels (see for example the webtool of the Flemish government[14]). Studying the cost electric cars in the future, we expect purchase price to considerably decrease in the next few years. By 2026 the electric alternative is expected to be on the same level as fossil fuel cars.

[14] [Vergelijk milieuvriendelijke en conventionele wagens op kosten | Vlaamse Overheid (vlaanderen.be)]

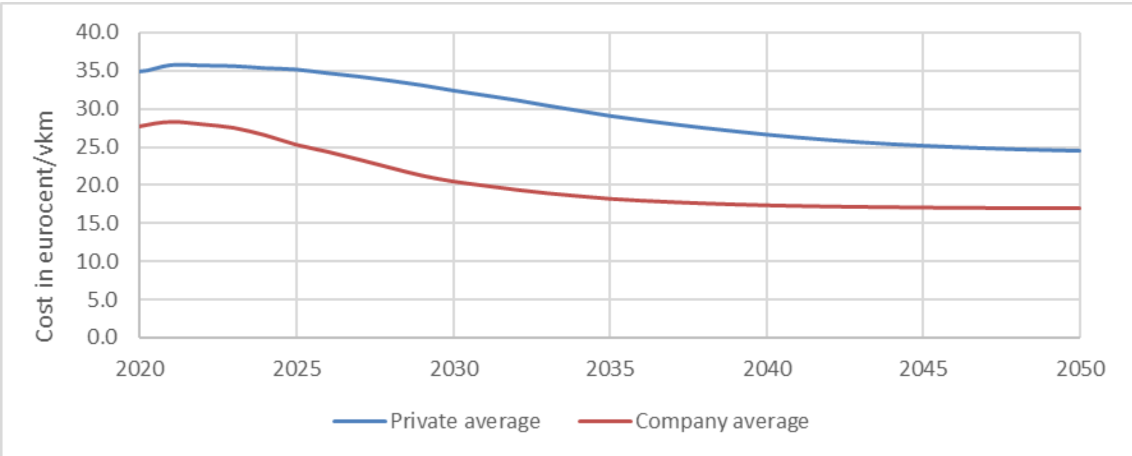
Figure 7-3 Forward projection of vehicle cost in eurocent per vehicle-km



Source: Own calculations

The forward projection of vehicle cost after 2026 is especially interesting. Looking at the overall cost per vehicle kilometre for the average fleet, we expect the cost to fall considerably beyond 2026. The average cost of using a car would drop by 5 eurocents per vehicle kilometre by 2035 and another 5 eurocent per vehicle kilometre by 2045. Of course, this is only the case if current excise taxes as well as ownership & registration taxes are unchanged. Thus, without any change to fiscal policy, the monetary cost of driving a car would drop considerably up to 2035.

Figure 7-4 Expected change in average cost for private and company cars (EUR-cent/km)



Source: own calculations

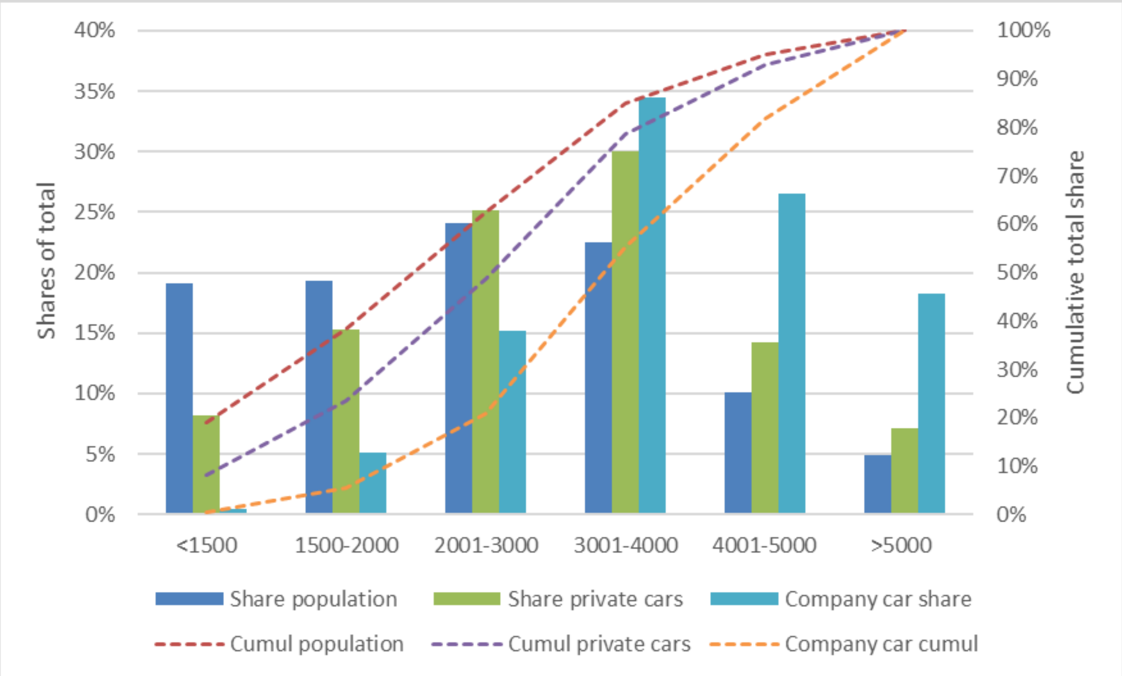
7.2 Extrapolation of ownership electric vehicles by income class

7.2.1 Car ownership of private and company cars in the reference dataset

Using the socio-economic data processed from the OVG surveys (see Chapters 5 and 6 and Annex 3), we can estimate the division of car ownership by income level as well as distinguish company cars and private cars. In Figure 7-5 below we give an overview of vehicle ownership in the general population according to OVG income categories (in line with OVG 5). In Table 7-1 we give an overview of car ownership distinguishing income and the number of cars owned.

As we can expect from the 'cleaned and processed' dataset, the overall level of car ownership/availability by household is divided in an inequitable way. Slightly more than half of the households with incomes below EUR 1500/month have no car. Car ownership rises quickly with income level. Ownership of company cars is strongly associated with high to very high levels of income. As such, more than half of the company car fleet is owned by households earning over EUR 3000/month. The fleet of private cars is divided in a less unequal way, but still more unequal than income itself. The reason is that households with higher levels of income are more likely to own 2 or even 3 cars, with possible addition of 1 or more company cars.

Figure 7-5 Vehicle ownership/availability and income versus total



Note: Horizontal axis: monthly income categories
Source: Own calculations based on OVG 5

Table 7-1 Car ownership versus income

Type	Monthly income	No Car	One car	Two Cars	Three Cars
Company car	<1500	99.7%	0.2%	0.1%	0.0%
	1500-2000	95.8%	4.2%	0.0%	0.0%
	2001-3000	90.5%	9.0%	0.6%	0.0%
	3001-4000	78.5%	18.5%	3.0%	0.0%
	4001-5000	65.3%	27.6%	6.4%	0.7%
	>5000	53.3%	34.8%	10.9%	0.9%
Private car	<1500	57.3%	40.0%	2.3%	0.3%
	1500-2000	23.9%	68.4%	7.2%	0.5%
	2001-3000	11.6%	67.2%	19.5%	1.6%
	3001-4000	7.1%	46.0%	44.3%	2.5%
	4001-5000	9.7%	40.6%	38.6%	11.0%
	>5000	12.7%	36.2%	36.1%	15.0%

Source: Own calculations based on OVG 5

7.2.2 Extrapolating the growth of the EV fleet to income level

Little data are available on the ownership and uptake of electric vehicles according to income level and household characteristics in Belgium. Is it possible to estimate how quickly electric vehicles will be taken up by the Belgian population with limited data availability?

We were not able to distinguish electric vehicle uptake in the vehicle stock module described in Chapter 4 directly. However, inspired by the vehicle stock module we propose a relatively simple process that can be used as an ad-hoc model to analyse uptake of electric vehicles, based partially on the logic of the vehicle stock model in Section 7.1

We start by defining a weight matrix W that sets the inherent likeliness that an electric vehicle will be owned by a household according to income level and as either the 'first', 'second' or 'third' vehicle. We distinguish this weight by either private ownership or company car.

$$W_{i,n_{car}}^{own}\begin{pmatrix} W_{11} & .. & W_{13} \\ .. & .. & \\ W_{61} & .. & W_{63} \end{pmatrix}$$

We assume that the weight matrix increases linearly with income and decreases linearly in the number of vehicles owned by the household. In practice, this means that high income households are twice as likely to switch to EVs as middle-class households. Middle class households are in their turn twice as likely to switch to EVs as poor households. The second car of a high-income household is then about as likely to switch to EV as the first car of a middle-class household. While additionally data could improve the

Next, we define the potential stock of electric vehicles owned by each household on the basis of the present stock of vehicles.

$$S_{i,n_{car}}^{EVmax}\begin{pmatrix} S_{11}^{max} & .. & S_{13}^{Max} \\ .. & .. & .. \\ .. & .. & S_{63}^{Max} \end{pmatrix}$$

Each year we assume that households will replace an ICEV or hybrid car with an EV. Households that already have an EV are assumed to buy a new EV. The likeliness that households buy an EV is their respectively 'weight' multiplied with a factor that corrects the weight for the actual ownership of EVs versus their potential ownership. The actual weight ($\widetilde{W}_{i,n}$) is therefore

$$\widetilde{W}_{i,n} = Max\left\{0, W_{i,n}.\left(1 - \frac{S^{EV}{}_{i,n}^{t}}{S_{i,n}^{EVmax}}\right)\right\}$$

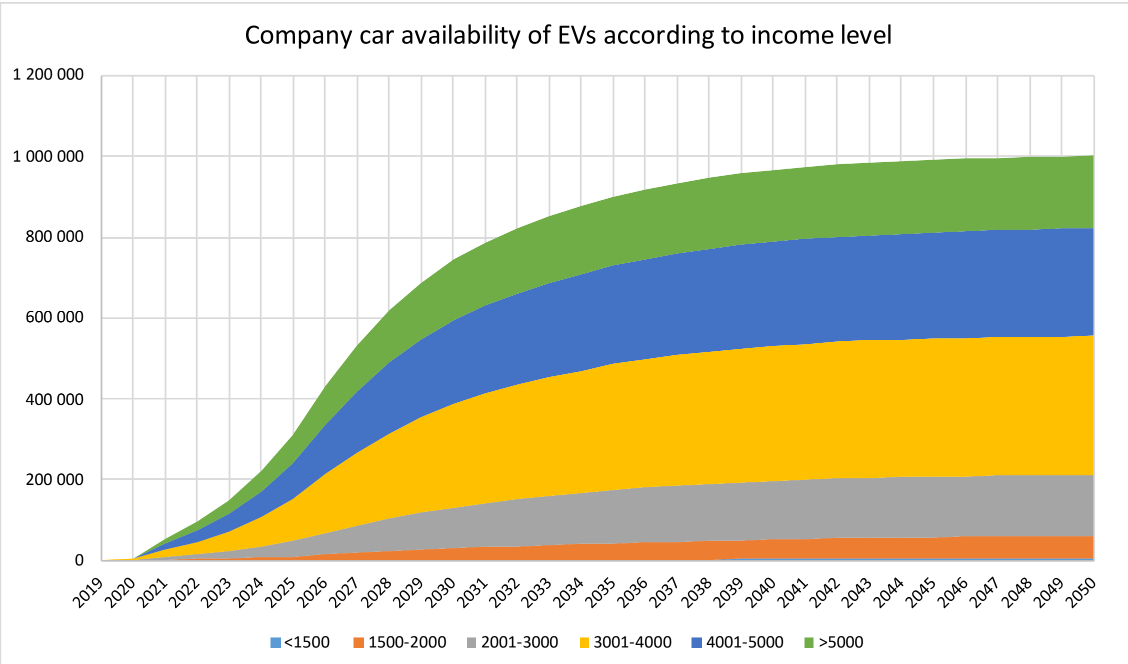
Each year we look at the growth in the total stock of EVs. New EVs are distributed among households according to the weights and the total stock (ICE and other) held by the households.

In practice this means that each year the stock of new EVs per household is divided as

$$S_{i,n}^{EV,t} = S_{i,n}^{EV,t-1} + S^{EVnew}\frac{S_{i,n}\widetilde{W}_{i,n}}{\sum_{i,n} S_{i,n}\widetilde{W}_{i,n}}$$

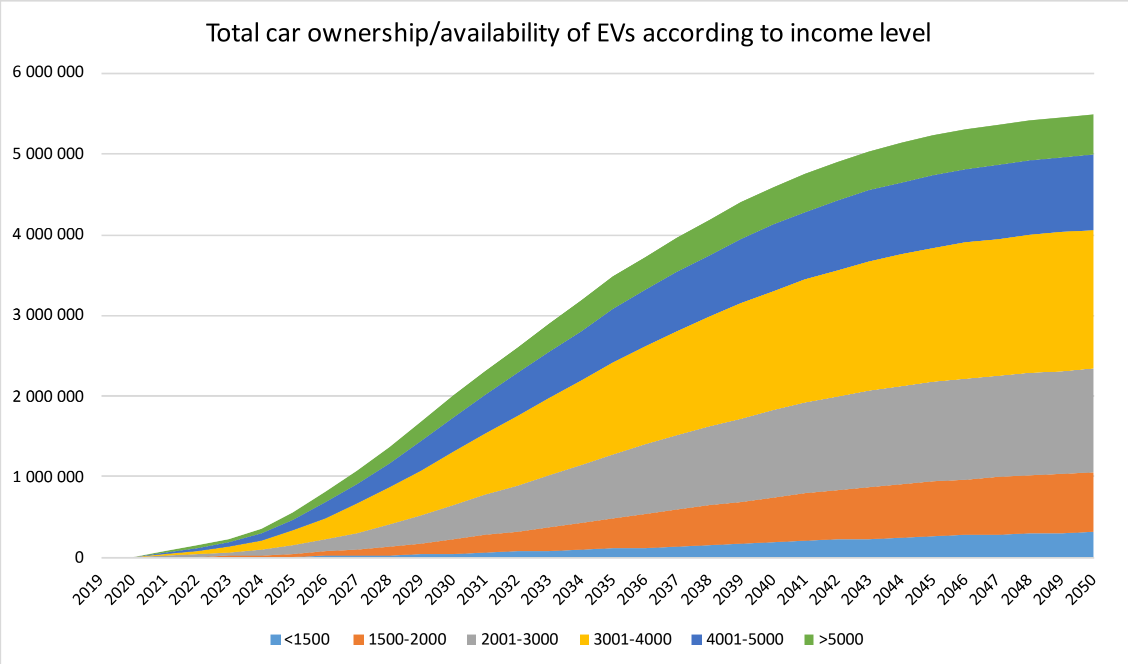
Using this simple formula, in combination with the weights leads to a realistic ad-hoc distribution of new EVs according to the initial distribution of the stock and assumed weights and preferences. If all weights in matrix W are set to one, this model will proportionally divide new EVs according to the initially observed stock. The higher the initial weight according to income, the stronger initial uptake of EVs according to income will be biased towards the high end of the income spectrum.

Figure 7-6 Projection of company car availability according to income level



Source: Own calculations based on income matched vehicle stock projection

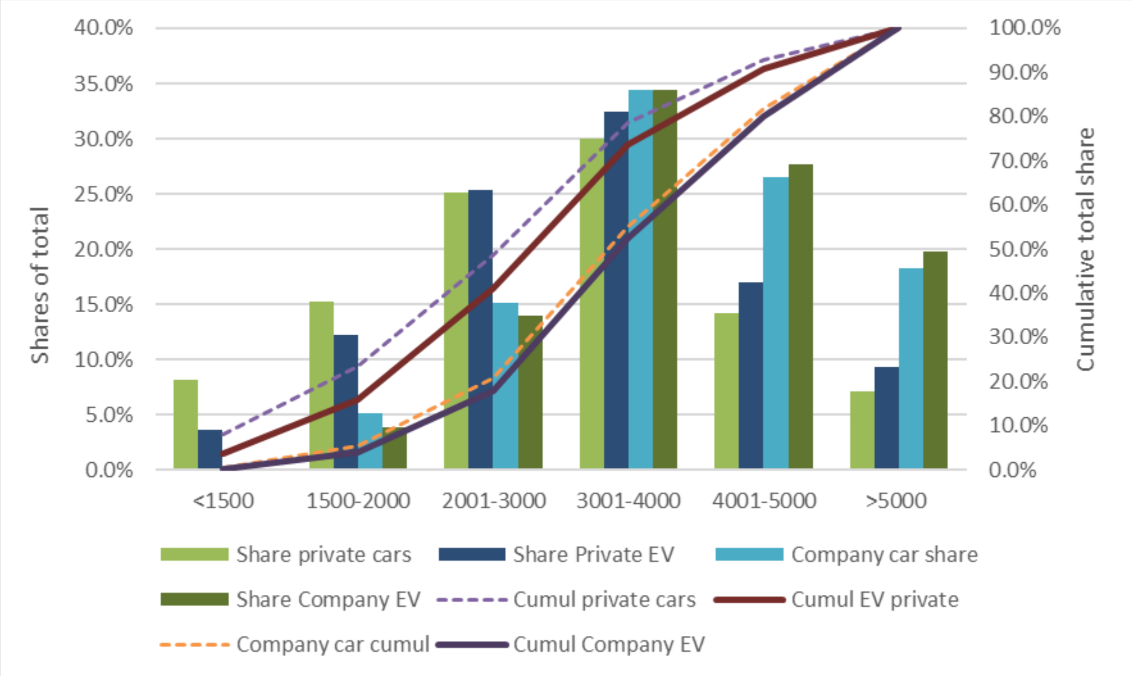
Figure 7-7 Total car ownership/availability according to income level



Source: Own calculations based on income matched vehicle stock projection

Given our projection - in combination with the income data - by 2030 slightly below 80% of company cars will be fully electrified. The availability of these EVs is highly biased towards upper income classes. For private cars the transition will be slower, but also biased towards richer households. In the figure below we compare overall private and company car ownership in 2030 with our projection of EV car ownership. Private EV car ownership is expected to lag somewhat for the lower two income categories (representing about 40% of the population). Especially for the lowest income class, EV car ownership will represent less than a third of all cars. However, the pick-up of EVs along the entire population is a lot less inequal than overall ownership of company cars. This projection and the overall growth in the stock suggest that after 2030 EV ownership will be rather common in the entire population, except for the lowest income class.

Figure 7-8: Projected EV ownership/availability according to income category



Source: Own calculations based on OVG 5

Based on the distributions shown above, we can calculate a Gini-index of inequality. This index ranges from 0 to 1, where 0 means perfect equality (everybody owns the same or receives the same income) and 1 perfect inequality (1 person holds all property or income). We compare the income inequality in our initial dataset with the distribution of private and company car ownership. This is also compared with data from 2030.

Income inequality in our dataset is slightly below official statistics of income inequality in Belgium which report values between 0.24 and 0.26[15]. Private car ownership is distributed more or less as (un)equally as income. This is not true for company cars, which are heavily tilted towards top income earners. Our projection for 2030 states that the distribution of both the private EV as well as the company EV fleet will be distributed slightly more unequally compared to the current fleet.

Table 7-2: Gini indices for distribution of income and cars

Distribution	Gini indices
Income inequality	0.23
Private cars 2022	0.20
Company cars 2022	0.53
Private EV 2030	0.30
Company EV 2030	0.56

Source: own calculations

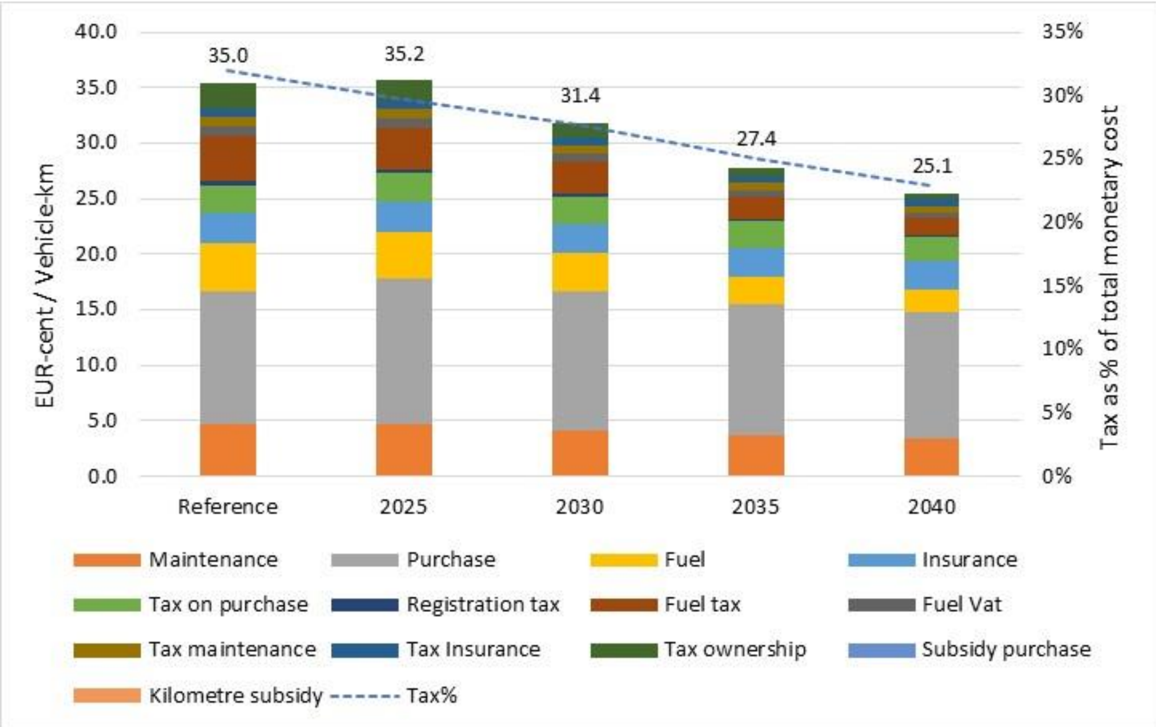
[15] https://www.indicators.be/nl/i/G10_GIN/Inkomensongelijkheid%3A_Gini-index_%28i52%29

7.3 Impact of electrification of the fleet on demand

7.3.1 Impact of electrification in the absence of changes in fiscal policy

In the previous section we analysed the micro-economic effect of the electrification of the fleet, in this section we study the impact on the network level. For this we use the TREMOVE demand module (Module I). In contradiction with popular intuition, our projection is that electrification in combination with current fiscal policy will lead to a drop in overall cost of car transport by 2030 (see Annex 2).

Figure 7-9 Overview of average cost (in EUR-cent per vehicle-km) of car transport, price of 2021

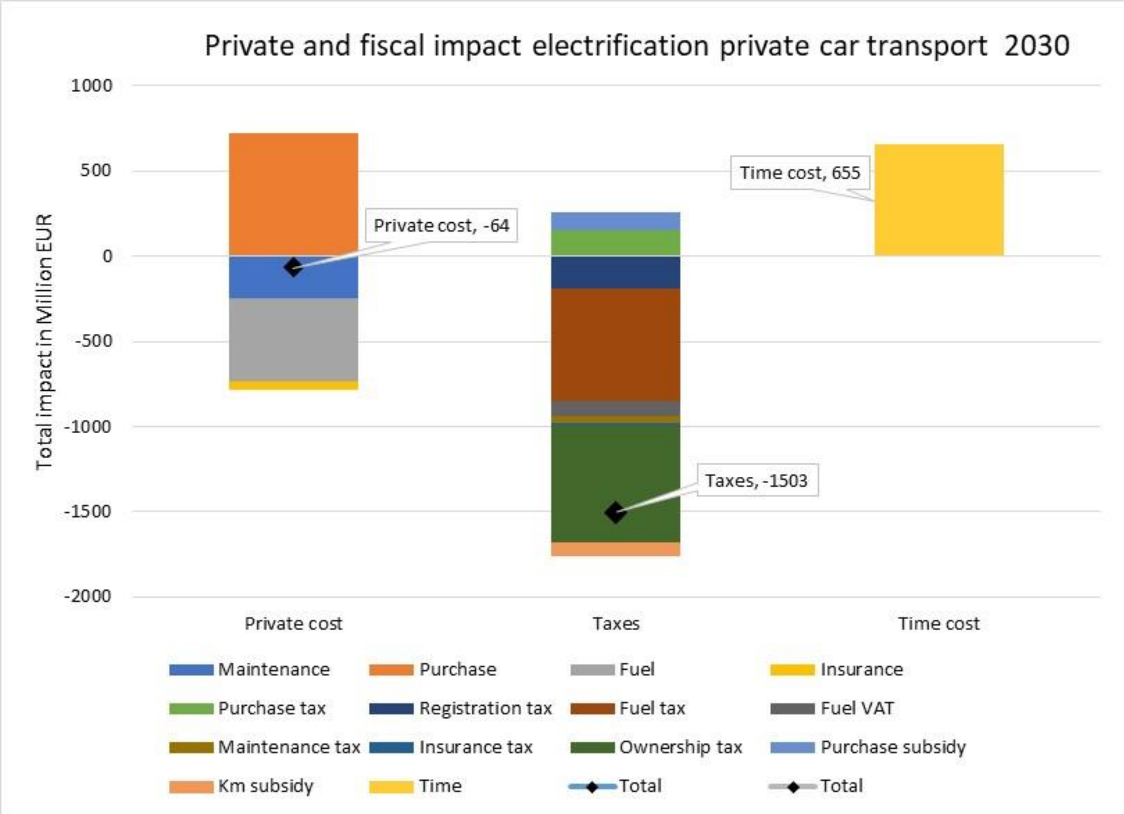


Source: Own calculations

The cost of car transport is expected to increase slightly in real terms until 2025. In absence of any additional policy, real term costs will decrease with almost 10 EUR-cent/vehicle-km by 2040. The reason is that purchase cost of electric vehicles is expected to drop rapidly after 2025. A large part of the drop in cost is due to differential taxation of electric cars versus ICE cars. As such the share of taxes in overall monetary cost drop from 32% to 23%.

For the whole of Belgium this will lead to an increase a decrease in fiscal revenues and an increase in congestion by 2030. In Figure 7-10 we show the resulting impact on fiscal revenues for private car transport by 2030. By that year, lower usage cost of EVs is expected to completely offset the higher purchase cost of EVs, independent of taxes. Combined tax revenues from vehicle ownership, registration, excise taxes and VAT are expected to drop with about EUR 1.5 billion. Time costs for private car transport will increase with EUR 655 million.

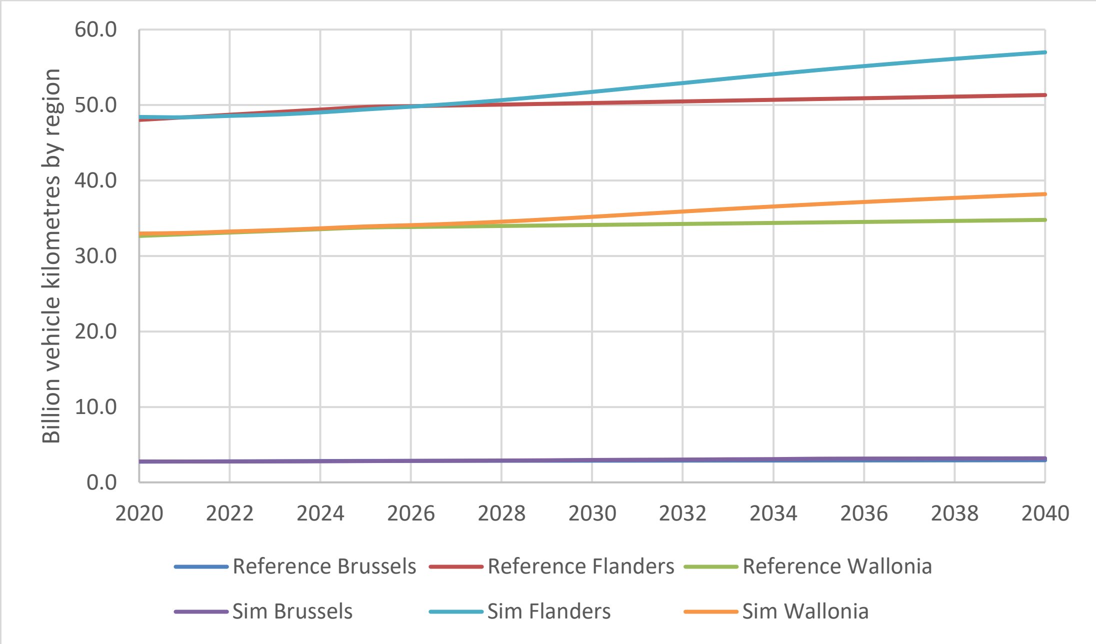
Figure 7-10 Overall impact electrification of private car transport on private cost and fiscal revenues in 2030



Source: Own calculations

In the absence of new fiscal policy, the drop in car transport cost may lead to an increase in vehicle kilometres and reverse modal shift (a shift from public transport, cycling and other modes to private car transport). Based on our projections, we can make a prediction when the positive impact of electrification of transport could start to outweigh the negative impact of losses in tax revenues and additional car kilometres. We first have a look at the possible increase in vehicle kilometres up till 2040 in the absence of additional policy. It is very hard to make a counterfactual to electrification of transport, as the sales of fossil fuel cars will be prohibited in the future. Therefore, we have chosen to fix the monetary cost of car transport in our reference scenario to the reference value. As such we attempt to isolate the impact of electrification on car transport demand. The result is illustrated in Figure 7-11.

Figure 7-11 Impact of electrification on vehicle demand (in billion vehicle-km) in the absence of fiscal reform



Source: Own calculations

The figure shows that demand for private car transport is expected to rise quickly after 2026, especially in Flanders. Table 7-3 shows that this could potentially lead to an additional 2.6 billion vehicle-km in 2030, 6.5 billion vehicle-km in 2035 and even 9.3 billion vehicle-km in 2040.

Table 7-3 Total demand for private car transport in billion vehicle-km (5 year intervals)

Year	Reference	Simulation	Difference
2025	86.4	86.2	-0.2
2030	87.3	89.9	2.6
2035	88.1	94.6	6.5
2040	89.0	98.4	9.3

Source: Own calculations

While it is improbable that stimulus for electric vehicles would be maintained up till 2040, these results give an indication that around 2030 a change in fiscal policy would be needed. Next, we look what this would mean in terms of modal share.

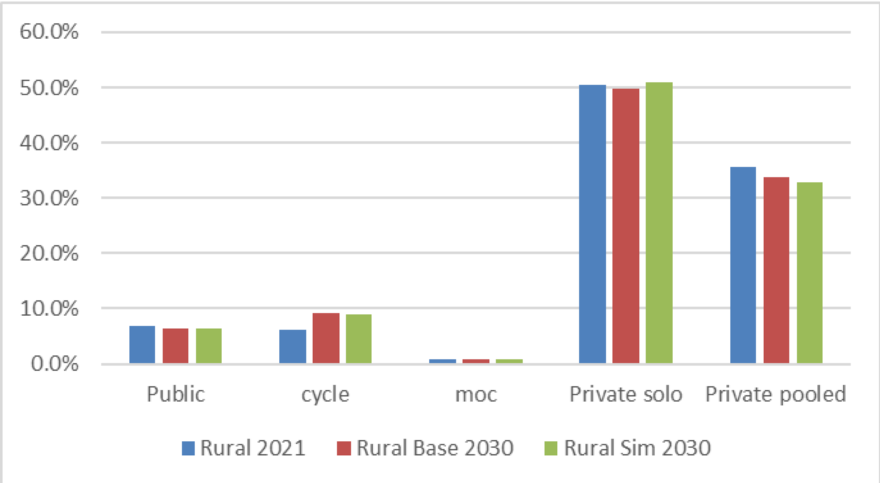
Table 7-4 Modal share reference vs 2030 in total passenger-km

	2021	2030	
Mode	**Reference**	**Reference**	**Simulation**
Passenger train	3.9%	3.7%	3.6%
Bus	4.7%	4.4%	4.2%
Cycle	6.8%	10.1%	9.7%
Motorcycle	0.7%	1.0%	0.9%
Car (solo)	43.0%	42.4%	45.8%
Car (pool)	30.0%	28.1%	26.0%
Van (solo)	6.3%	6.2%	6.0%
Van (pooled)	4.4%	4.1%	3.9%

Source: Own calculations

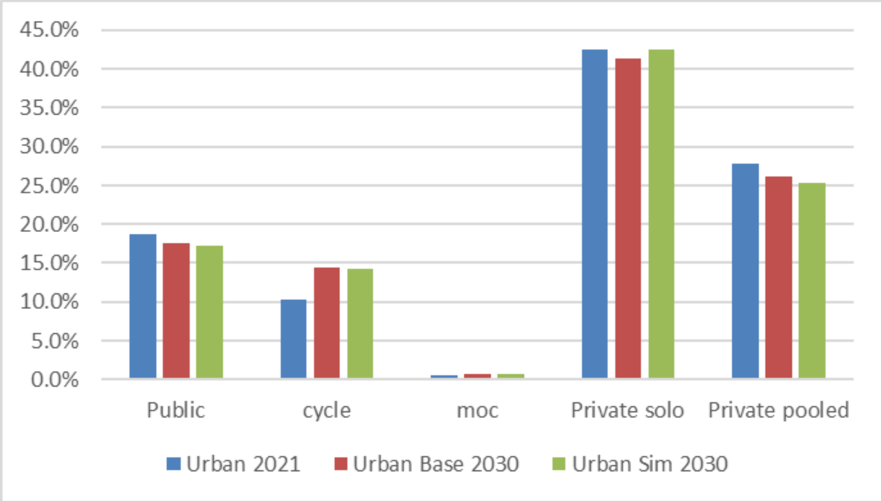
Table 7-4 shows how modal share is expected to shift by 2030. We find that without additional policy, electrification will increase the share of private car transport from 63% of all passenger kilometres to 72%. This is remarkable, as the modal share is expected to drop to 60.5% otherwise. Most of the shift in passenger kilometres comes from pooled car transport and public transport. The share of cycling would only marginally drop. This is also illustrated below, in Figure 7-12 and Figure 7-13. These figures distinguish the reference and simulated modal share in 2021 and 2030 for rural and urban regions.

Figure 7-12 Impact on modal share in rural regions in Belgium



Source: Own calculations

Figure 7-13: Impact on modal share in urban regions in Belgium



Source: Own calculations

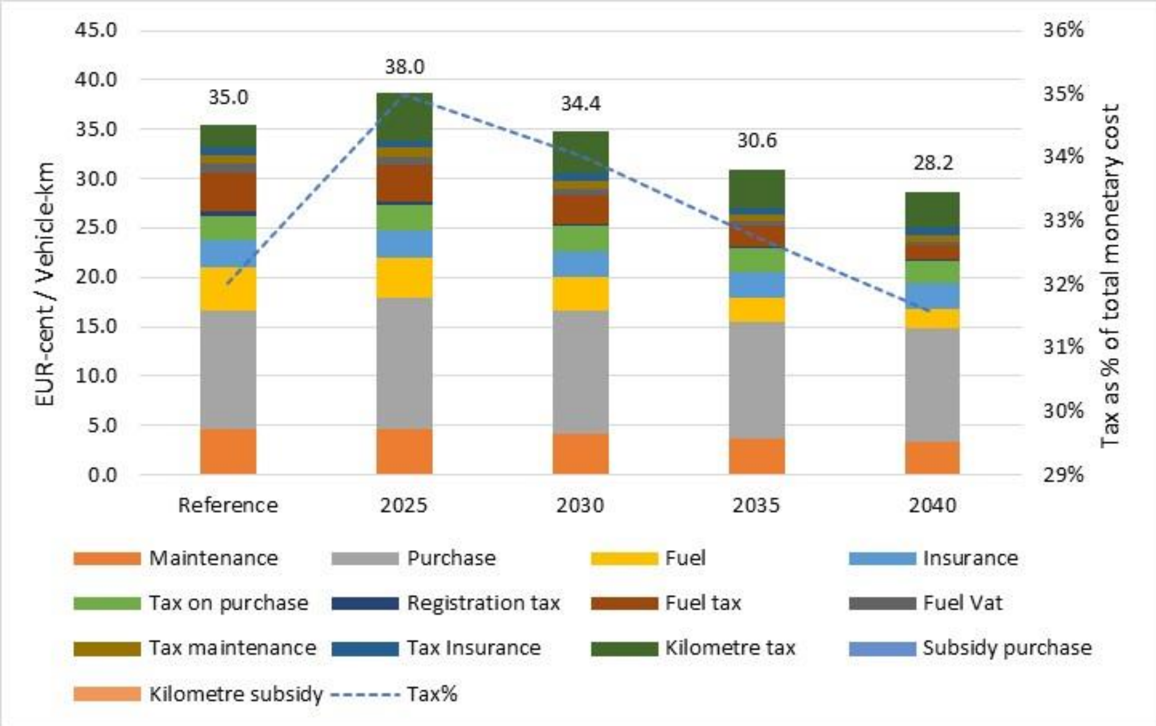
7.3.2 Impact of electrification in combination with a peak road charge

Electric vehicles cause little to no direct environmental damages. However, they do generate other externalities that are common for car transport. Notably: congestion, accidents and pressure on public space. While vehicle ownership taxes or a network registration tax could be a fiscal means to internalize damages, transport economists have proposed to introduce peak road charges. We show the impact of such a road charge that could reduce externalities of EVs. This should be interpreted as a test of the model and not a final scenario analysis of taxation of electric vehicles.

We test the impact of an indiscriminate 10 eurocent per vehicle-km peak road charge. The off-peak charge is zero. We make no distinction between motorways or other roads. Our results are illustrative only, but could be worked out to improve tax policy and add to the scientific literature.

In Figure 7-14 we give an overview of the cost of car transport when such a peak road charge would be introduced in 2025. This can be compared with a similar figure in the previous section Figure 7-9. We see that the peak road charge would increase the average cost of car use above the reference in 2025, but by 2030 the cost would be comparable to the reference period (2021). Beyond we see a similar drop in prices as in Figure 7-9, which means that beyond 2030 the peak road charge would need to be increased to level off the reduction in other fiscal revenues. For the rest of this section we take 2030 as the reference year for the simulation, like in the previous section.

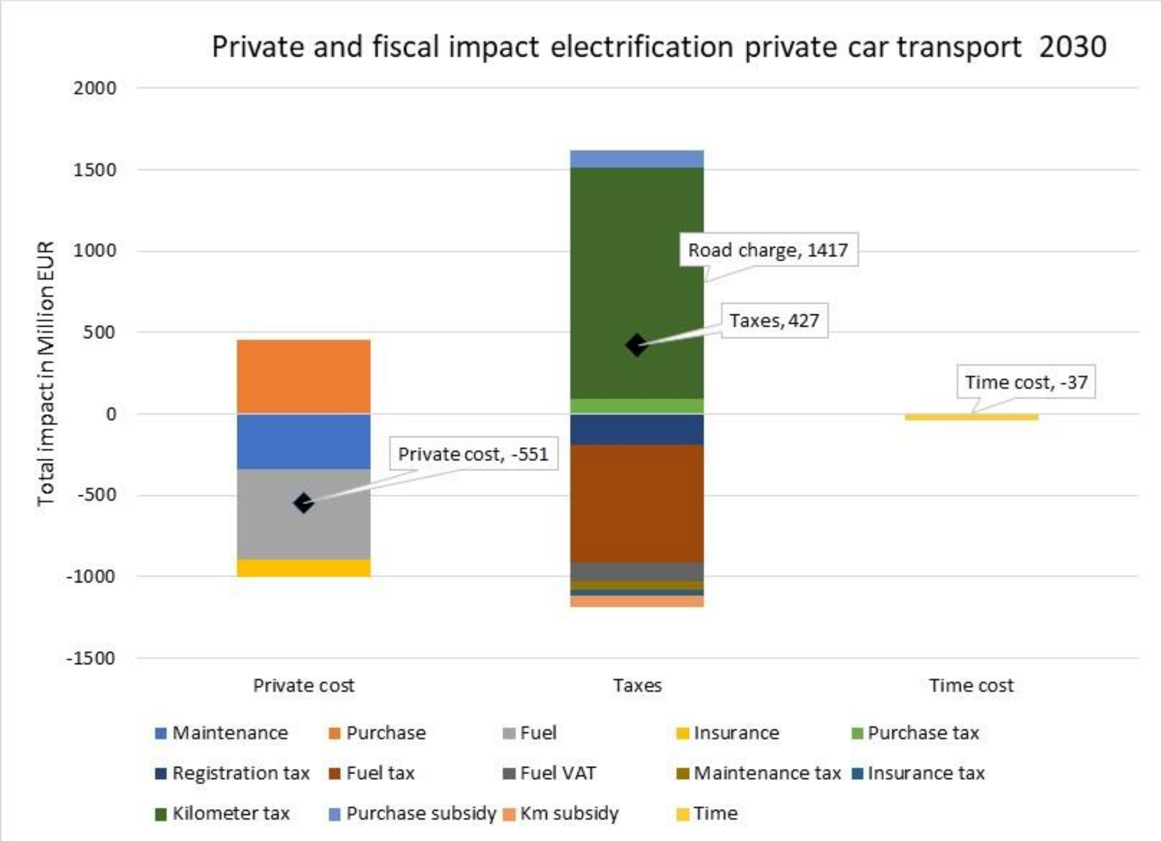
Figure 7-14 Overview of average cost (in EUR-cent per vehicle-km) of car transport with peak road charge of 10 EUR-cent/km (price level 2021)



Source: Own calculations

Figure 7-15 shows the overall impact of the peak road charge on private costs and public revenues. We find that the road charge almost perfectly compensates for the loss in fiscal revenues and even generates a net EUR 427 million compared to the reference case. This is line with Figure 7-14. Use of car transport is reduced compared to the base case scenario, which results in an overall reduction of total private cost of car transport. This should be interpreted as a reduction in car purchases and car use compared to the reference scenario.

Figure 7-15 Overall impact electrification in combination with peak road charge in 2030



Source: own calculations

In terms of modal shift, the results are rather unsurprising. The proposed peak road charge avoids the reverse modal shift from public transport and cycling to private car transport almost completely. This is shown in Table 7-5, the results from the previous section are added for comparison.

Table 7-5 Modal share reference vs 2030 in total passenger-km

	2021	2030		
Mode	**Reference**	**Reference**	**No road charge**	**Peak road charge**
Passenger train	3.9%	3.7%	3.6%	3.7%
Bus	4.7%	4.4%	4.3%	4.4%
Bicycle	6.8%	10.1%	9.7%	10.2%
Motorcycle	0.7%	1.0%	0.8%	0.8%
Car (solo)	43.0%	42.4%	43.6%	42.7%
Car (pool)	30.0%	28.1%	27.7%	28.0%
Van (solo)	6.3%	6.2%	6.1%	6.2%
Van (pooled)	4.4%	4.1%	4.1%	4.1%

Source: Own calculations

8 Conclusions

This report discusses how we approach the research questions in EPOC. After initial discussion, we decided to develop an integrated assessment model consisting of four mayor modules.

The first module consists of a transport demand module based on the original TREMOVE model, with a number of novel elements to improve flexibility of the model. Most notably a flexible demand structure, processes to improve calibration and transparency of the model and an improved input/output structure to integrate results better with other elements of the assessment chain.

The second module is a vehicle stock module which has been used to project the size and composition of the vehicle stock in the future and which is used in TREMOVE to derive the associated changes in the cost of transport. TML also explored a new approach for this module, that will be elaborated further in the future.

The third module is a set of data and procedures that allow to construct a synthetic population of representative consumers, consistent with different levels of aggregation in the Belgian dataset. Additionally, datasets from different sources, like city level data, the OVG datasets, Beldam and other statistical sources can be integrated to add new (simulated) features to the population. While we were unable to use all features of Module III within the time set out by EPOC, we were able to use the microdata to improve the calibration of the TREMOVE model and define a new set of representative households.

The fourth module extends upon Module III by providing procedures for trip analysis and grid level research. This module also cleans out existing datasets and extends certain characteristics of the OVG dataset that are now considered unreliable. In particular it allows a better modelling of company car ownership and private car ownership (Annex 3). Results from module IV can also be used to analyse the charging behaviour of EVs on the network.

Eventually, the different modules were not fully integrated, but integrated in a rather loose way. Input and output of the different modules were combined in two trial simulations for the EPOC project. The first is a combination of the vehicle stock module (Module II) with the microdata and grid level data (Modules III & IV). In this simulation we analyse the growth of the EV vehicle stock up till 2030 and beyond and analyse equity effects of electrification. We find that the purchase cost of EVs will decrease rapidly beyond 2026, which leads to a very quick transition towards 2030. Electrification up till 2025 is expected to go through the company car fleet however, which is distributed in a highly inequitable way. Any additional subsidy or stimulus to the company car fleet will therefore benefit high income households much more than low income households. After 2026 the growth in stock is so rapid that by 2030 the EV car fleet is expected to be distributed almost as equitable as the current ICE fleet. This means that we find relatively small differences in the distribution of EVs according to income or location, when compared with the present fleet of cars.

The second simulation combines elements of Module II, III and IV in Module I. In this simulation we start from the same premise of rapid electrification as above. However, we now go into detail on the fiscal and social impact of electrification. We take 2030 as a reference year for our simulation, which we compare with the base year of our simulation (2021). We see that the rapid reduction of the purchase cost of EVs will lead to lower overall costs for car transport by 2030. In the absence of any mitigating fiscal reform, tax revenues from car transport are expected to rapidly decrease. We estimate that the tax revenue from private car transport can decrease with EUR 1.5 billion by 2030. As EVs only have small environmental external cost, but similar or higher other external cost (congestion, accidents, pressure on public space) our research illustrates the need to reform the taxation of car ownership and use. In the absence of any reform, the strong electrification of the fleet will additionally lead to a reverse modal shift and higher congestion costs on the network. Although we do not go into detail on how a reform of EV taxation should look like, we illustrate the impact of a peak road charge of 10 EUR-cents on the entire transport network of Belgium. This charge compensates for losses in tax revenue in 2030. Additionally, it reduces congestion on the network substantially. Beyond 2030 we stress the need for additional reform, either by increasing the road charge or increasing ownership & registration taxes for EVs.

Next steps in the development of the model are to improve the integration between the different modules and further tackle questions surrounding electrification of transport. While the results of the model look promising, they may overly depend upon optimistic projections of the growth in the EV fleet. These projections were made before the mounting geopolitical tensions in 2022, and the possible disruptions of supply lines in EV manufacturing and battery supply. On the other hand, the growth in the EV fleet is a prerequisite to achieve the objectives set out in the EU Climate Law and follows from the recently adopted CO2 emission performance standards for cars and vans. Rapid electrification of the car fleet is generally considered the only realistic way to reduce overall dependence of transport on fossil fuels. As such, our results are in line with the EU and national objectives of emission reduction.

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Annex 1: Data collection

Data availability

One of the goals of the data collection was to have the data to introduce different types of representative consumers **by location** (city, city periphery, suburbs, open development) in the travel demand model (Module I). Each representative consumer should have distinct mobility patterns by location.

We initially proposed a classification of the territory of Flanders used by Vermeiren et al (2019). This study also gave clear differences in modal split: the urban (city) level used over 50% modal share of public transport & active transport combined with relatively low levels of car ownership (<40%) compared to the rest of Flanders. Open development on the other hand has over 90% car ownership and car use, with marginal levels of public transport.

In addition to location, the aim is to have different types of representative consumers **by income**.

We identified different possible sources, but two datasets were assessed as most promising. The EU SILC dataset (Statistics of Income and Livelihood Conditions), which was also used in the macro-economic model developed by TML (EDIP), and the dataset of the Flemish survey on mobility choices (Onderzoek Verplaatsingsgedrag, OVG). The SILC database offers panel data for the whole of Belgium.

Mobility data on Wallonia and Brussels do not have the same level of detail as the OVG. For this we needed to rely on more general data or older datasets. Mobel (1998) and data from Beldam[16] (2011) are the most recent comparable studies to OVG that provide data on the Belgian level, especially for Wallonia and Brussels. Other datasets that we relied on were available either via Statistics Belgium (Statbel) or the Federal Planning Bureau. This refers mainly to data on car use and modal share.

Onderzoek Verplaatsingsgedrag (OVG)

General

The *Onderzoek Verplaatsingsgedrag Vlaanderen* (Traffic Survey Flanders)[17] or OVG produces a set of linked datasets that provide a wealth of information on the respondents' mobility behaviour. We were given access to ten years of OVG data. There are about 1600 individual surveys per year (75% out of 2200 individuals surveyed). The five editions of OVG 4 (4.1-4.5) cover the survey periods from September 2008 to September 2013, while the five editions of OVG 5 (5.1-5.5) cover the survey periods from January 2015 to January 2020. The data given to us for each of the ten OVG editions consist of four separate (Excel) data tables: 1) *Gezinsvragenlijst* (a household questionnaire), 2) *Personenvragenlijst* (a personal questionnaire), 3) *Verplaatsingboekjes* (the broader trip questionnaire or travel diary), and 4) *Verplaatsingen* (the trip data). The last two are connected to the same questionnaire in the survey, but are split into two data tables.

[16] BELDAM Belgian Daily Mobility | Research Portal

[17] https://www.vlaanderen.be/mobiliteit-en-openbare-werken/onderzoek-verplaatsingsgedrag-vlaanderen-ovg

The questionnaires themselves are available (and were downloaded) from the website of the OVG, along with a very detailed documentation on data cleaning protocols that were used in the preparation of the data tables. Proper weighting is important to make the measured data representative for the whole population. The protocol documents also contain the weights that needed to be applied during the statistical analysis of the provided data tables (which had to be manually entered per category in the processing stage, as these weight tables are not available as a separate download).

We were given access to a limited but still quite broad set of parameters, only the most sensitive personal information was removed from the raw data, meaning that by doing the processing ourselves, we could extract information from the OVG that was not available in the otherwise excellent and extensive published results, b) or which combined multiple OVG editions in order to achieve a better sample size that was necessary for some of our objectives (e.g. hourly resolution traffic curves per weekday).

For information, for the travel diary a number of basic principles hold:

- Travel must take place on the public road (not on a private property).
- Trip should be more than 100 metres.
- Intermediate trips are not taken into account (e.g., the walking between train and bus), even if longer than 100 m.

A few important things should be noted related to the travel diary:

- Many times the end point of a trip becomes the departure point for the next journey.
- A trip chain can be noted as several separate trips, except when it is specifically noted as a shopping trip.
- Within one trip, multiple modes can be used.
- Waiting times are always included in the total duration.
- Car availability: this means that a respondent could have taken the car, or could have been driven by a household member by car at that very moment. So, e.g., if a student goes to school and at the time of his/her departure one of the parents is still home and was available to drive the car, then the car was "available" at that moment. But for example, on the way back, assuming both parents are at work, there was no car available.
- The main mode is always the one that was longest in distance (or if that equals, then in time).
- Vans are considered cars (and not freight transport or trucks).
- Hybrid cars are defined as 'other types of transport modes'.
- A temporary driving license does not match with 'having a license' in the questionnaire.

Data processing

Weight tables were manually entered and saved each with ten separate sheets for the ten OVG editions. Important to note that OVG 4.1 used a different weight encoding (different categories). The delivered OVG data were not completely homogeneous, lacked weights, and a lot of data columns had non-descriptive names. A python script was written to homogenize the data.

Data column names were harmonised and categories were documented based on the OVG documentation. This was the most time-consuming time to do, as every OVG edition had to be checked separately to make sure the same script can be ran for every edition in the future. An example of this is e.g. the personal data files had a column name of "V8a." which got consistently renamed to "diploma", and the encoding (the "keys") is provided as:

diploma = {
1:"geen",
2:"lager onderwijs",
3:"middelbaar onderwijs: algemeen vormend: niet volledig afgewerkt",
4:"middelbaar onderwijs: andere (technisch, beroeps, kunst, sport…): niet volledig afgewerkt",
5:"middelbaar onderwijs: algemeen vormend: volledig afgewerkt",
6:"middelbaar onderwijs: andere (technisch, beroeps, kunst, sport…): volledig afgewerkt",
7:"hoger niet-universitair onderwijs", 8:"universitair onderwijs"}

Time entries (e.g. start of a trip written as 945) were converted to proper time variables (09:45). Non-entries were removed (e.g. postcode of 9999 was cleared and left empty). Weights were added to each data table based on a complex lookup function, that collected the necessary information from multiple sources when necessary. When necessary, missing weights were assumed to be 1 (e.g. in some cases the sex of the head of the household is unknown, but it is needed for the weight lookup). The number of cases where weights could not be properly looked up but had to be assumed is very limited (not more than 1% of all).

Data used

From the household level questionnaire we used

- The number of cars, e-bikes, motorbikes, and other modes
- The average monthly net income
- The number of persons in the household

From the person questionnaire we use:

- Birth year
- Gender
- Ownership of a driving license
- Highest educational attainment
- Employment status
- In possession of a fixed work / school address
- Monthly personal net income

From the trip diary we used

- Made a trip on the present day (Boolean)
- Motivation to leave home
- Motivation not to leave home
- Point of departure (postcode/locality)
- Trip data
    - Mode
    - Duration
    - Distance
    - Amount of people in car
    - Arrival time
    - Car available?

Selection of other data sources

Statistics Belgium

- Vehicle stock
- Share of people holding a driving license as share of overall population
- Structure of the population – number of households by statistical unit. Gives us the number of households per municipality until 2021
- To determine which of the municipalities are urban and rural we use the EU-28 urban codes and consider 1 and 2 as urban, while category 3 is rural
- Car availability per household. This gives the number of vehicles per household per municipality for the year 2019. There are, however, methodological problems as the number of vehicles in this database does not match the total vehicles in the Belgian fleet at that time. In the database, 5 311 000 vehicles are attributed to households (this is for the whole of Belgium). The share of households with 0, 1, 2 or more than 2 cars is given in the next table.

Table A 1: Households according to car availability (2019)

	Share of households (%) with			
Urban/Rural	**0 cars**	**1 car**	**2 cars**	**More than 2 cars**
Urban	28.57	46.58	19.47	5.38
Rural	17.38	48.84	25.96	7.82

Source: Statbel

Company car ownership: From the 5 311 000 vehicles in the dataset above, 613 603 are identified as company cars, this is an underestimate of approx. 150 000.

Federal Planning Bureau

- Number of households per region and composition 1992-2020 and forecasts
- Disposable household income, regional economic projections 2021-2026 per region
- Report for the Committee on Aging (Vergrijzingscommissie) of July 2021; Projection of growth rate of gdp/capita until 2050 (used to extrapolate household income data forward until 2050)
- Car stock, by type of ownership, region, type of car, fuel, motor type and age
- Vehicle-km by public transport divided by public transport company 2001-2017.
- Vehicle kilometres on regional level with car, light duty vehicles, heavy duty vehicles and busses on regional level 2001-2017.

National Bank of Belgium

- Consumption price index

Annex 2: Transportation costs projections

The MIRA external cost study of transport of 2010 and 2016 of Transport & Mobility Leuven (Delhaye et al. 2017) makes a detailed analysis of the composition of the car fleet and the private and external costs per vehicle type. These data were used as a basis for the cost of different transport modes and as a baseline for the transport demand in Module I.

For this project we need the projections on the vehicle fleet composition and the private costs per vehicle type. We updated the MIRA study to the base year 2018 and made projections up to 2050.

Vehicle costs

As in MIRA (Delhaye et al., 2017), we consider the following cost categories:

- purchase costs,
- maintenance costs,
- insurance,
- technical inspection,
- personnel costs,
- taxes & subsidies,
- fuel costs.

We refer to Delhaye et al. (2017) for a technical explanation on each cost item. All costs items were updated to the year 2018. For future years, we used the relevant tax reforms up to the year 2022.[18]

For cars a distinction is made between private cars and company cars. This distinction is important because company cars enjoy tax deductibility.

To calculate the average purchase cost of cars and LDVs, we collected data on the most frequently sold vehicles per fuel type in Belgium in 2020 and computed the average purchase price. For LPG cars, we found only eight pure LPG models available in Belgium. However, most LPG vehicles are petrol cars that are transformed into LPG-enabled cars. The installation costs vary between EUR 1500 and EUR 3000.[19] Therefore, we estimate the average price of LPG cars by adding EUR 2250 to the average purchase price of petrol cars. Because CNG cars are significantly cleaner than LPG cars in terms of particulate matter (PM), LPG cars have become less popular in Belgium. Gas-fuelled vehicles are mainly CNG cars. For hydrogen cars, the available data are even more limited, with only two models currently available on the Belgian market.

An overview of the average purchase price (excluding VAT) is shown in the table below.

[18] Car registration taxes and yearly vehicle taxes were reformed during the period 2016 – 2019. We also updated the Viapass charges for HDVs to the most recent tariffs.
[19] https://autogas.be/nl/

Table A 2 Average purchase price of passenger cars and LDV in 2020, excluding VAT

Fuel	Description	Average price 2020	Average price 2018	Source
CAR				
CNG	Average of 22 CNG cars available in Belgium in 2020	€ 20 182	€ 19 334	Egear
Diesel	Average of 20 most frequently sold models in Belgium	€ 22 123	€ 21 850	HLNDRIVE
Diesel PHEV	Average of 13 most frequently sold models in Belgium	€ 34 447	€ 34 023	Egear
BEV	Average of 20 most frequently sold models in Belgium	€ 34 646	€ 34 219	Egear
FCEV	Average of 2 models available in Belgium	€ 57 632	€ 56 922	Egear
LPG	Average of 8 models available in Belgium	€ 20 326	€ 19 670	Egear
Petrol	Average of 20 most frequently sold models in Belgium	€ 18 076	€ 17 854	HLNDRIVE
Petrol PHEV	Average of 13 most frequently sold models in Belgium	€ 34 447	€ 34 023	Egear
LDV				
Diesel	Average of 10 most frequently sold models in Belgium	€ 23 727	€ 23 434	Febiac
BEV	Average of 20 most frequently sold models in Belgium	€ 45 300	€ 44 743	Egear
Petrol	Average of 10 most frequently sold models in Belgium	€ 19 037	€ 18 803	Febiac

The VAT on passenger cars in Belgium is 21% of the purchase price. For LDVs, a VAT rate of 21% also applies, but companies can deduct this up to 85%.

For projections of the purchase price in the future we assumed the following:

- The purchase price for fossil fuel cars is expected to follow the expected inflation rate.
- For BEV, we follow the Electric Vehicle Outlook 2021 by BloombergNEF and Transport & Environment (2021) that investigates scenarios and trends for electrification of road transport up to 2050. According to this study, the purchase price of BEV will gradually decrease from 2020 to 2030. The prices of BEV and fossil fuel cars are expected to hit parity in 2026.
- Several studies foresee an only limited role for FCEV in the passenger car segment. This is because the technology is relatively expensive, and especially for small cars, BEV will suffice. Scenarios where hydrogen vehicles can potentially compete with other vehicle types are mainly for vehicles with long range requirements (>500 km between refuelling) and heavy-duty vehicles (Hydrogen Europe, 2019; Hydrogen Council, 2020). Therefore, we assume a constant price for hydrogen passenger cars.

The costs of company cars are tax deductible in Belgium. The tax deductibility of company cars is undergoing a major transformation. As of January 1st, 2018, tax deductibility depends on the CO_2-emission of the vehicle. The costs of 100% battery electric (BEV) company cars enjoy 120% tax deductibility.

As of January 1, 2020, the tax benefit for fossil fuel company cars is phased out. The percentage of costs that can be deducted from the tax base is equal to:

$$Tax\ deductibility\% = 120\% - (0.5\% \times CO2\ emission \times fuel\ type\ coefficient)$$

The fuel type coefficient is equal to 1 for diesel cars, 0.95 for petrol cars and 0.90 for CNG cars.

As of 2026, only costs of BEV company cars will be tax deductible. For fossil fuel cars, tax deductibility will be phased out. The maximum percentage of deductible costs for fossil fuel cars is equal to 75% in 2025, 50% in 2026, 25% in 2027 and 0% as of 2028. For BEV company cars, tax deductibility will be 100% in 2026, but this will gradually decrease over the years as follows:[20]

Table A 3 Tax deduction rate for BEV company cars as of 2026

Income year	Deduction rate
2026	100%
2027	95%
2028	90%
2029	82.5%
2030	75%
2031	67.5%

The VAT paid on company cars cannot be fully deducted. As of 2013, a maximum of 50% of the VAT can be deducted and this depends on the proportion of the mileage driven of professional purposes. There are three calculation methods for the deduction of VAT: (1) based on the actual driven kms for professional purposes, (2) a fixed percentage of 35% and (3) a mix between the first two methods. Because we have no statistics on the division between private and professional use of company cars, we use the fixed percentage of 35% of VAT deduction for company cars.

For a discussion on the other cost items, we refer to Delhaye et al. (2017).

Fuel and electricity prices

Electricity prices for households and industry up to 2020 are obtained from Eurostat[21] and VREG.[22]

Table A 4 Electricity price and its components in Flanders, 2018 (EUR/kWh)

Average electricity price 2018	Household	Industry
Energy cost	0.097	0.092
Distribution cost	0.110	0.120
Transmission cost	0.020	0.020
Excise duties	0.010	0.010
VAT	0.050	
TOTAL EUR/KWh	**0.287**	**0.242**

Source: VREG

Electricity price projections are taken from the EU Reference Scenario 2020 (EC, 2021b), which uses the PRIMES model to calculate electricity prices for the EU. Electricity prices differ per sector (households vs. industry). Therefore, we apply the percentage growth rate of the average electricity price to the electricity price for households and industry in the three regions.

[20] https://www.leaseplan.com/nl-be/autofiscaliteit-in-2021/

[21] https://ec.europa.eu/eurostat/web/energy/data/main-tables

[22] https://www.vreg.be/nl/evolutie-energieprijzen-en-distributienettarieven

Table A 5 Electricity prices in Europe

	2015	2020	2030	2040	2050
Annual capital cost	23	29	33	29	23
Fixed costs	25	23	23	25	27
Variable cost	1	1	1	1	1
Fuel costs	18	17	16	15	14
Grid costs	27	29	32	35	34
Tax on fuels and ETS payments	7	6	7	8	10
Excise and VAT on electricity	20	19	20	21	20
Price of electricity before tax (€ 2015/MWh)	94	99	105	105	99
Price of electricity before tax (€ 2018/MWh)	101.1	103.8	107.2	105.0	97.9
Percentage change		+2.69%	+3.31%	-2.09%	-6.79%

Source: EU Reference Scenario 2020, PRIMES (EC, 2021b)

Fuel price projections are also taken from the EU Reference Scenario 2020.

Table A 6 Energy prices 2018

	unit	price net	excise tax	VAT	price total
CNG	€/kg	0.68	0.00	0.14	0.83
Diesel	€/l	0.64	0.60	0.26	1.50
Electricity	€/kWh	0.23	0.01	0.05	0.29
H2	€/kg	8.03	0.00	1.69	9.71
LPG	€/l	0.45	0.00	0.10	0.55
Petrol	€/l	0.61	0.60	0.25	1.47

Source: EU Reference Scenario 2020 (EC, 2021b), Eurostat and VREG

The table below shows the annual percentage price changes as used by the EU Reference Scenario 2020. The EU Reference Scenario does not report price projections for hydrogen. Therefore, we assume no price change for hydrogen.

Table A 7 Annual energy price changes

	2021-2025	2026-2030	2031-2035	2036-2040	2041-2045	2046-2050
CNG	8.69%	6.04%	1.86%	3.26%	1.62%	0.28%
Diesel	8.57%	5.98%	2.45%	1.50%	1.63%	2.23%
Electricity	0.53%	0.33%	-0.21%	-0.21%	-0.70%	-0.70%
LPG	8.69%	6.04%	1.86%	3.26%	1.62%	0.28%
Petrol	8.57%	5.98%	2.45%	1.50%	1.63%	2.23%

Source: EU Reference Scenario 2020 (EC, 2021b)

Fuel efficiency

Fuel and energy consumption of new cars and motorcycles in 2018 is obtained for the Federal Planning Bureau (FPB, 2019). The reference year in that study is 2015. We use the projected efficiency gains of the FPB to compute the energy consumption of cars per fuel type in 2018. For energy consumption projections after 2018, we use the EU Reference Scenario 2020 (values for medium cars, baseline projection).

Table A 8 Current energy consumption and projections

	Unit	2015	Expected by 2025 relative to 2015	Expected by 2050 relative to 2015
CAR_CNG	kg/100km	7.8	-10.0%	-13%
CAR_diesel	l/100 km	6	-9.4%	-20%
CAR_diesel_PHEV	l/100 km	4	-5.0%	-54%
	kWh/100km	5.7	-5.0%	-27.0%
CAR_BEV	kWh/100km	17	-10.0%	-27.0%
CAR_H2	kg/100km	1	NA	-5.0%
CAR_LPG	l/100 km	10.9	-10.0%	-13.0%
CAR_petrol	l/100 km	8.9	-8.5%	-13.0%
CAR_petrol_PHEV	l/100 km	5.9	-4.5%	-56.1%
	kWh/100km	5.7	-4.5%	-27.0%
MC_petrol	l/100 km	4.8	-6.1%	-8.33%
MP_petrol	l/100 km	2.9	NA	-2%

Source: Federal Planning Bureau (2019) and EU Reference Scenario 2020 (EC, 2021b)

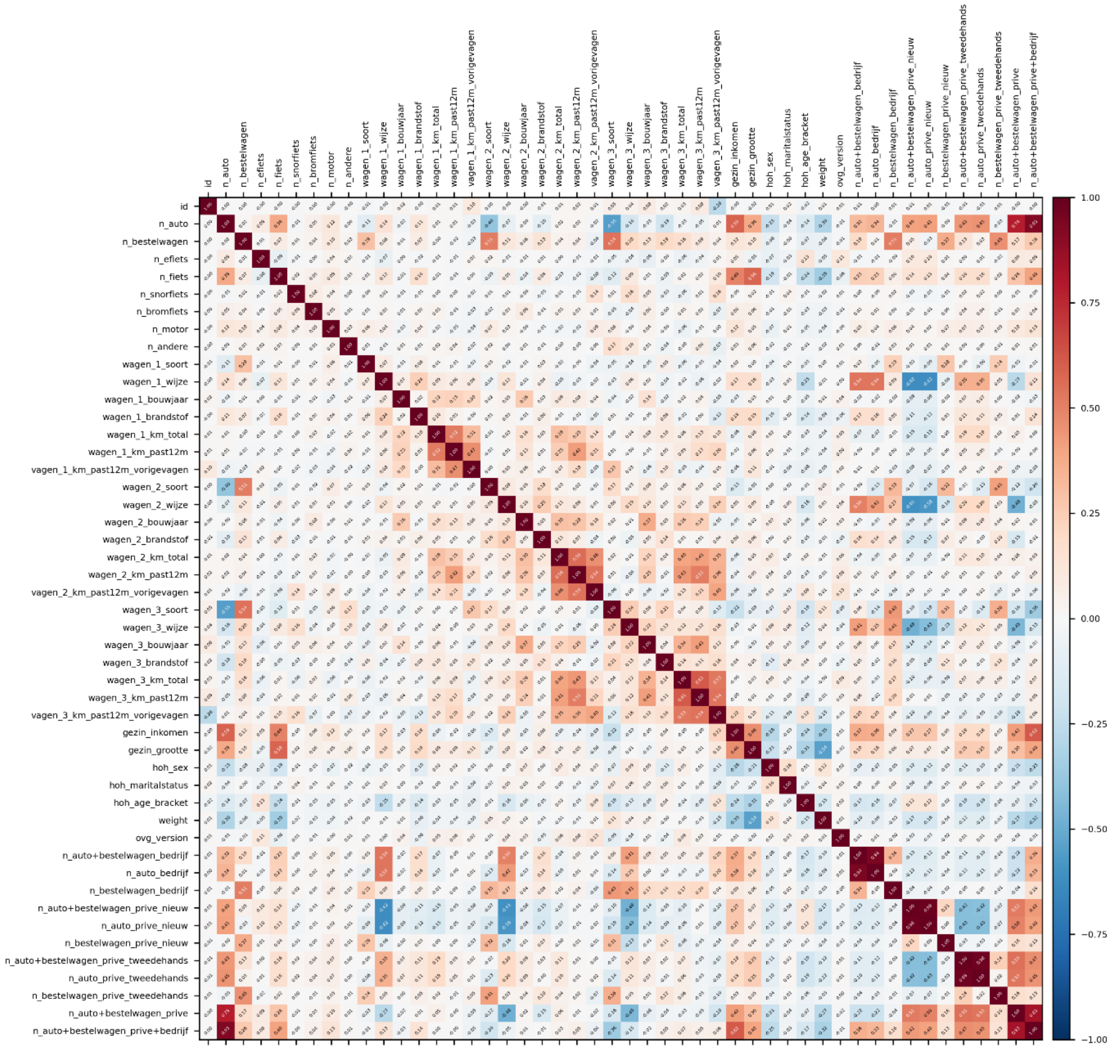
Annex 3: Further explorations of the OVG data

In addition to the results reported in Chapter 6 we explored the OVG data further to see whether we could make statistics with more than the location and mileage involved, for example including the income classes, but there are a lot of OVG travel diaries with incomplete or missing income data (or data that are not available to us). Basically, we need to find correlations between parameters that are preferably available throughout the whole OVG dataset, and parameters that are not. For example, if we can find correlations between the income category and parameters A, B, C (which are available for a majority of respondents), then we can estimate the non-disclosed income category for respondents from the available A, B, C parameters of these respondents. This process is carried out step by step – from the initial data discovery to the final multivariate model – using the following script.

First, we calculated some extra parameters that were possible to be derived from the available household level data, which we thought might be interesting when modelling the income classes. These were: the number of company cars, number of newly bought private cars, number of used bought private cars, number of company vans "*bestelwagens*" (light commercial vehicles or LCV), number of newly bought private LCV, number of used bought private LCV, and the sum of company, used private, and new private vehicles.

Then we proceeded with correlation tests of both personal and household data (only looking at the part of the dataset that actually had reported income categories). This way we got to see the correlation matrix of household data in the next figure.

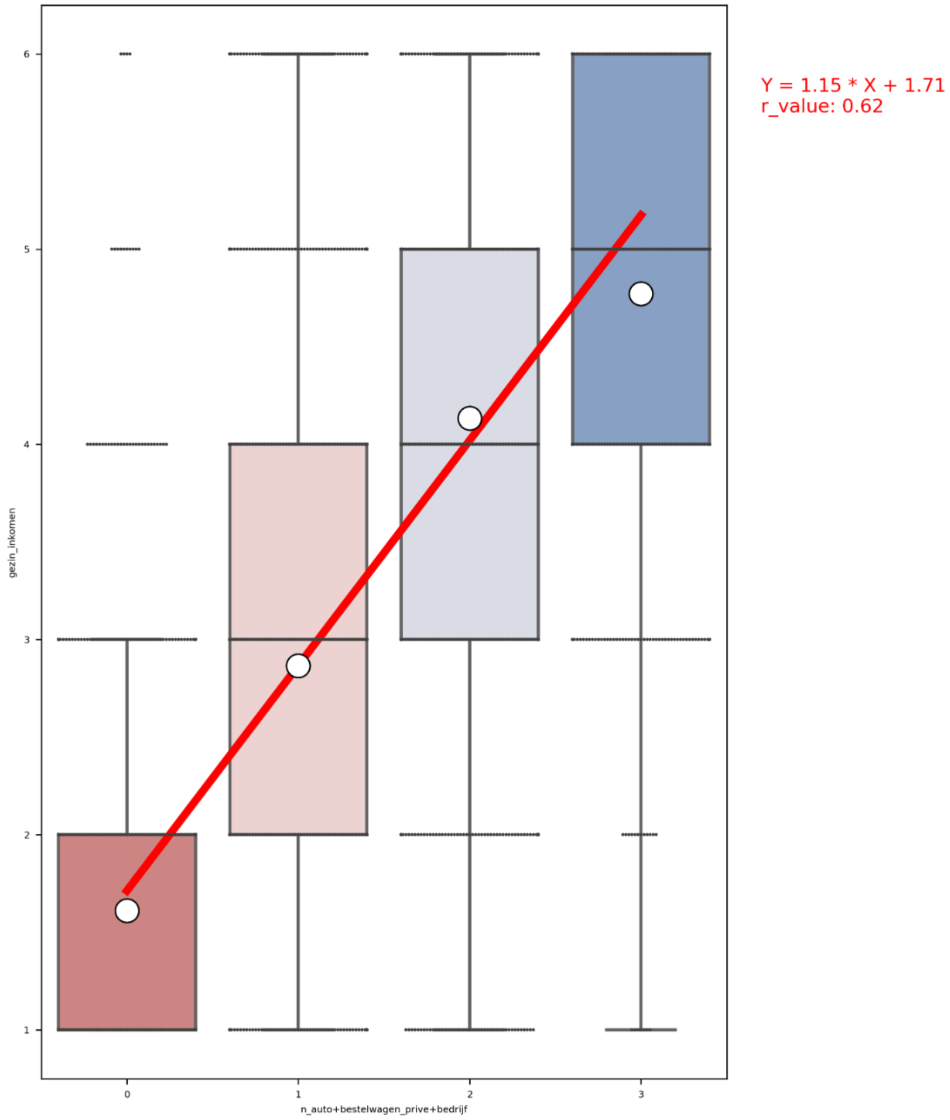
Figure A 1: Bivariate correlation - vehicle ownership and household characteristics



Source: Own calculations based on OVG 5

To visualise these correlations beyond the R value (being curious about the distribution of data points per bin, and the potential deviation from a linear correlation). We also created one-by-one correlation plots, e.g. between the household income and some motor vehicle ownership numbers. In general, we used this step to hand-pick the most influential parameters for the upcoming multivariate model estimation of the income category.

Figure A 2 Observation plot of vehicle ownership vs. reported income



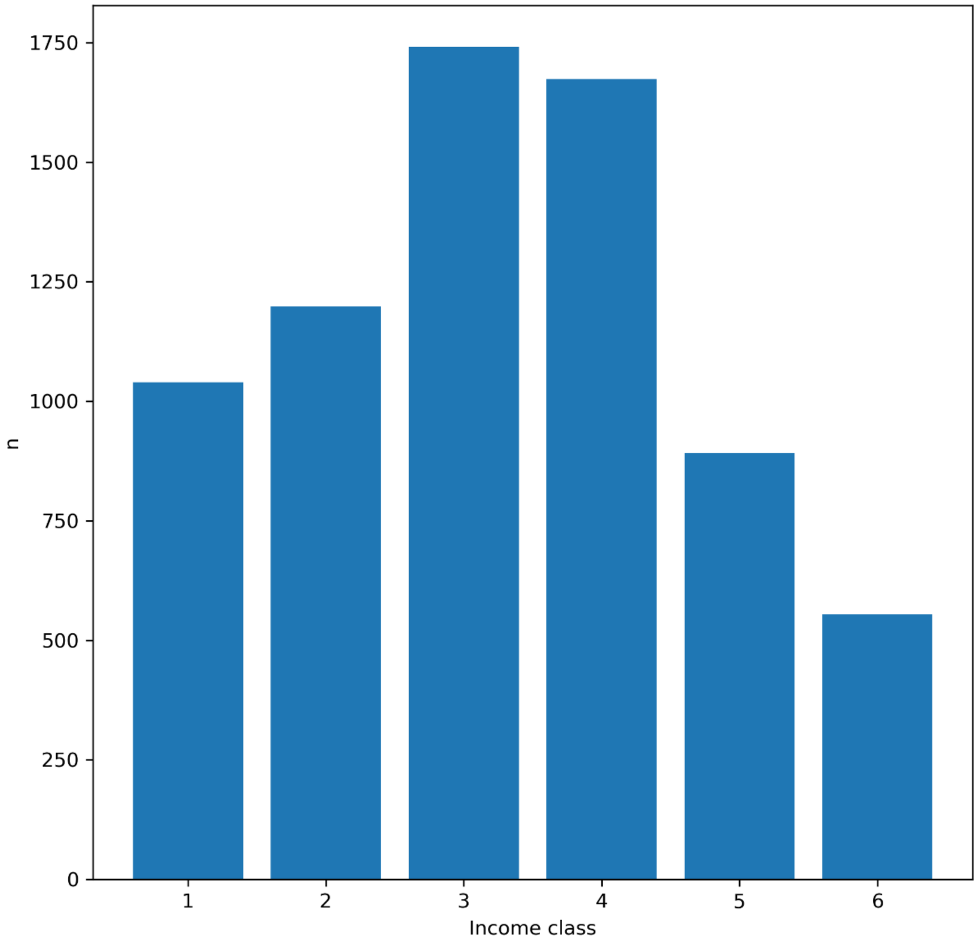
Source: Own calculations based on OVG 5

The next step was a creation of a simple multivariate model (of the household-level income groups) using selected parameters, in this case *'n_auto+bestelwagen_prive+bedrijf'* and *'gezin_grootte'* (so it is just a two parameter model – we cannot include too many parameters, because some parameters show no or very weak correlations, while others have also missing data issues).

We tested multiple aspects of this implementation. First of all, we were curious if the distribution of income bins in the training data and in the modelled data was similar, as it would have been an interesting find if these distributions were very different (e.g.) if it turned out that most people who did not report their income categories came from the highest or lowest income groups.

So we first plotted the distribution in the training group (see below)

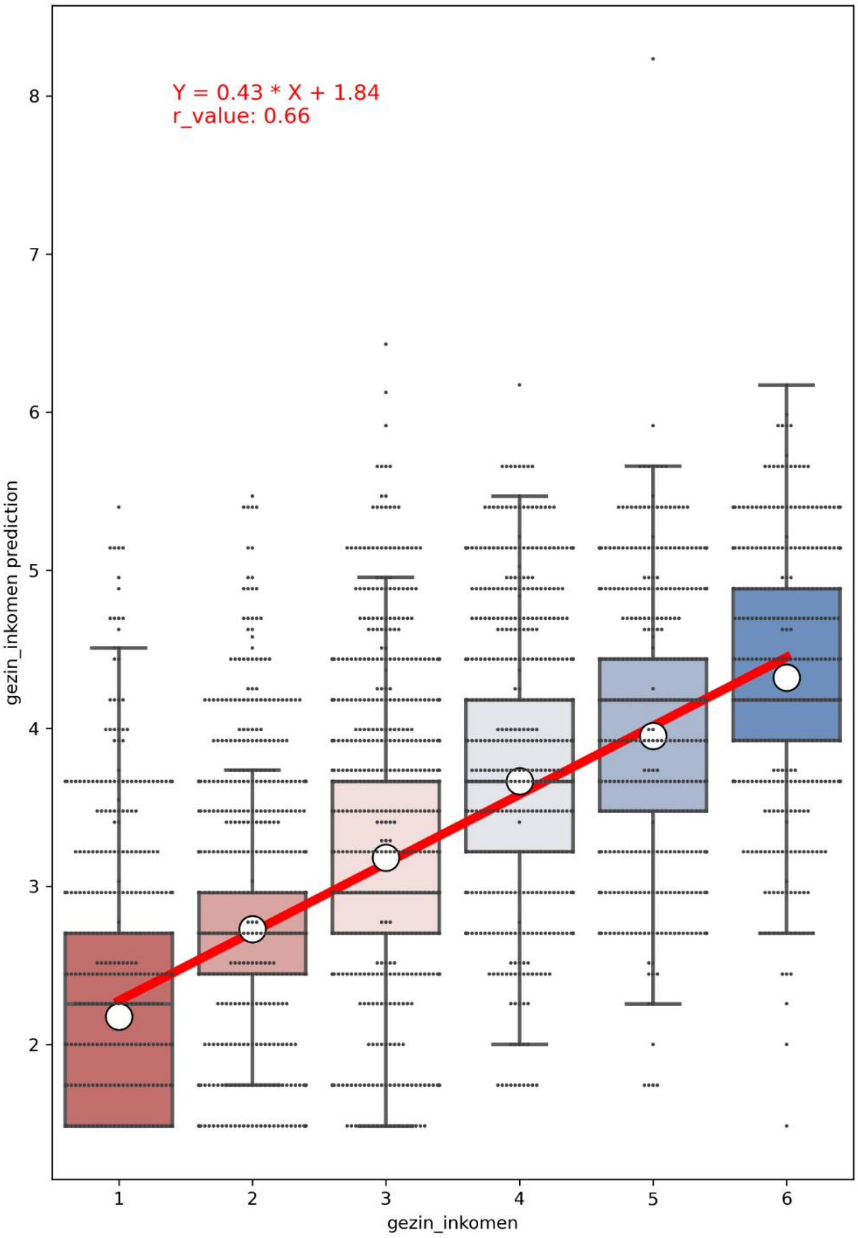
Figure A 3 Predicted income class using vehicle ownership as proxy



Source: Own calculations based on OVG 5

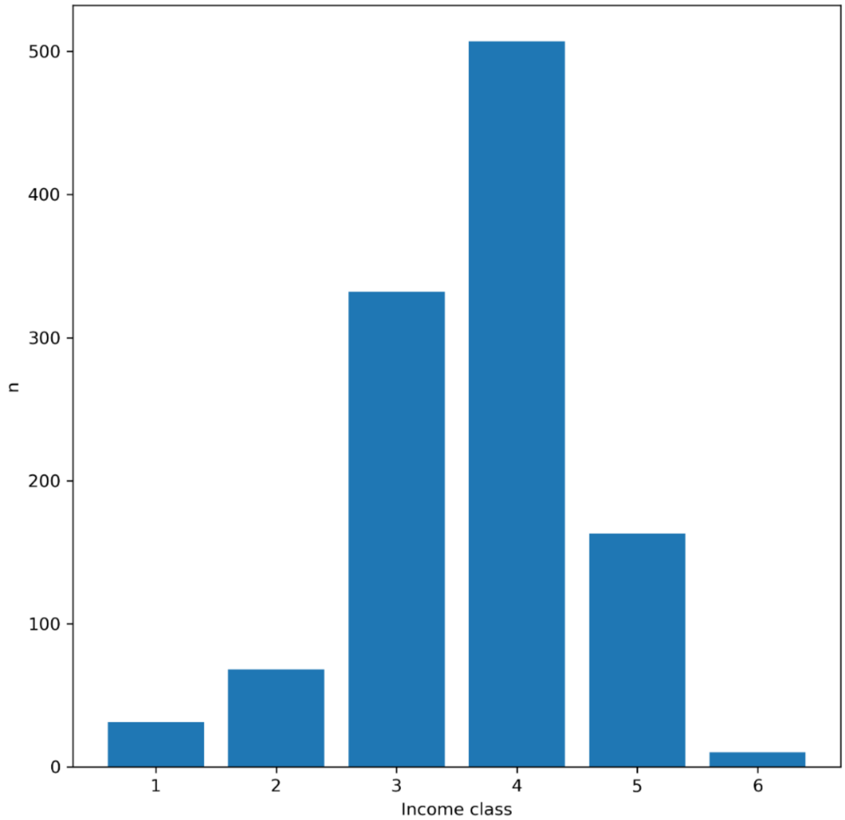
Then we fitted our multivariate linear regression model, and evaluated the model on the distribution of predicted income classes for those respondents who did not report the income class.

Figure A 4 Predicted income versus reported income class using vehicle ownership as proxy



Source: Own calculations based on OVG 5

Figure A 5 Missing values versus reported income class

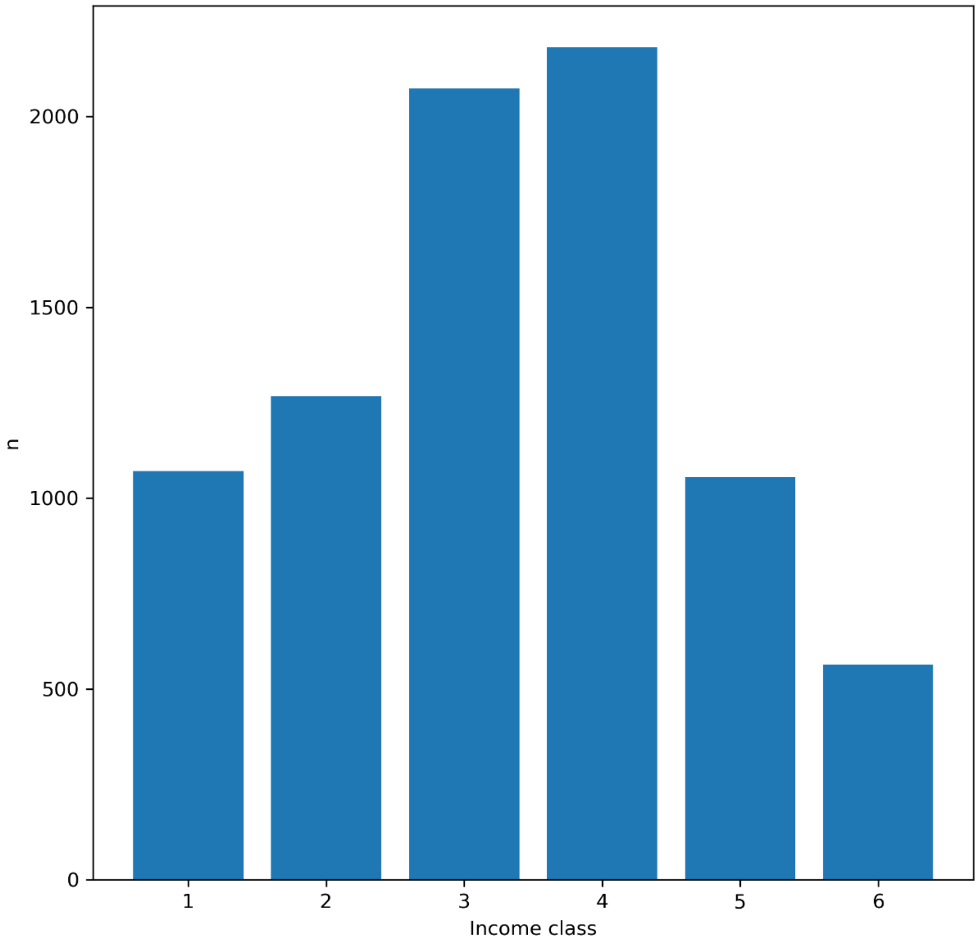


Source: Own calculations based on OVG 5

There is a clear excess in the middle classes, but some of this will be artificial as the model is unlikely to predict classes 1 and 6 (as it is illustrated by the figure showing the evaluation of the model, where observed class 1 incomes are mostly predicted to be class 2 and observed class 6 is predicted to be class 5). In any case, this is the best we can do, and it is definitely not far from our expectations.

Then to create the final data set, we evaluated the data on the full data set, and created a merged income class column which was given the original observed income class when that existed, and the predicted income class, when no reported data was available. This is the logic that is used later on with other models too.

Figure A 6 Final dataset using vehicle ownership as proxy for missing income class

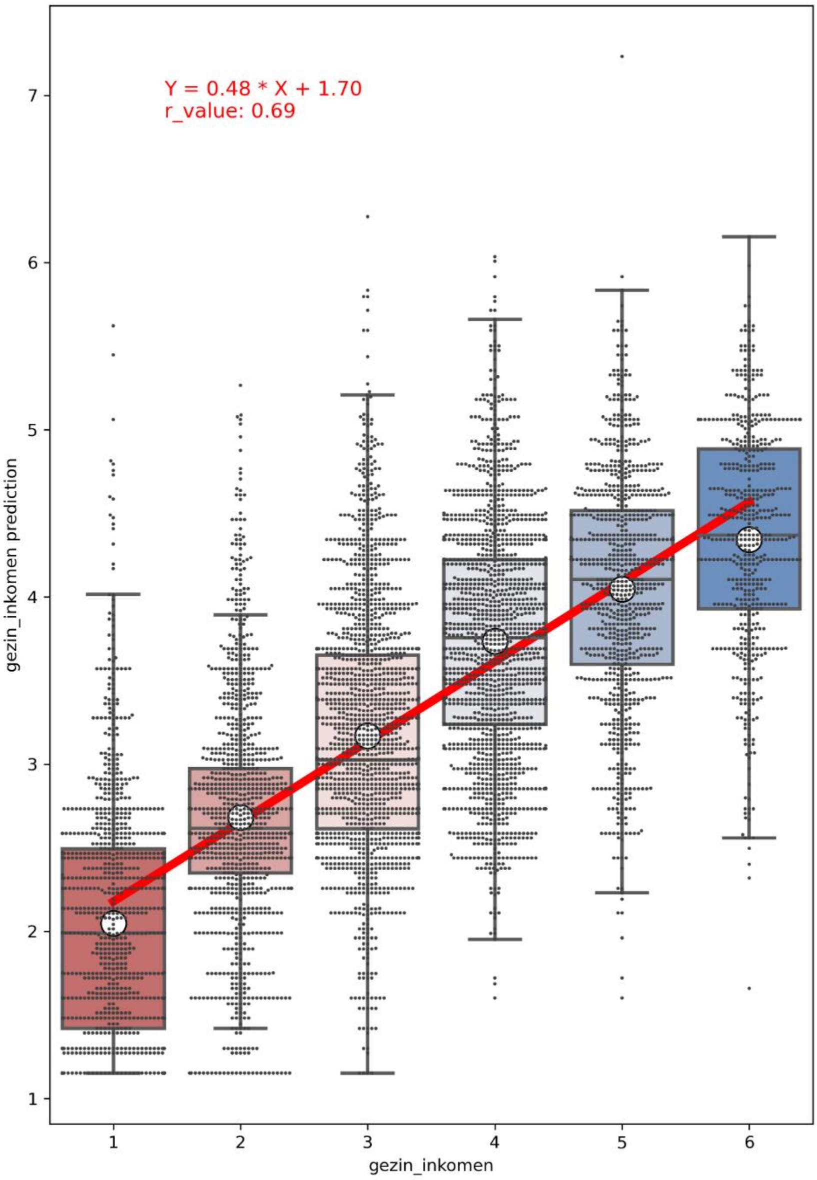


Source: Own calculations based on OVG 5

After this we repeated this process but with a few modifications, creating further model data sets. **The first such test data set took the weight also into account**, but overall, we think weights should not be applied when trying to model missing data, as we should take all actual reports with equal weights in this case.

The second of these tests took more parameters into account, namely 'n_auto+bestelwagen_prive+bedrijf', 'gezin_grootte', 'n_fiets', 'hoh_age_bracket', 'hoh_sex', and the resulting model was indeed better (not surprisingly as a result of more variables used), although only marginally. We took this as the final household data.

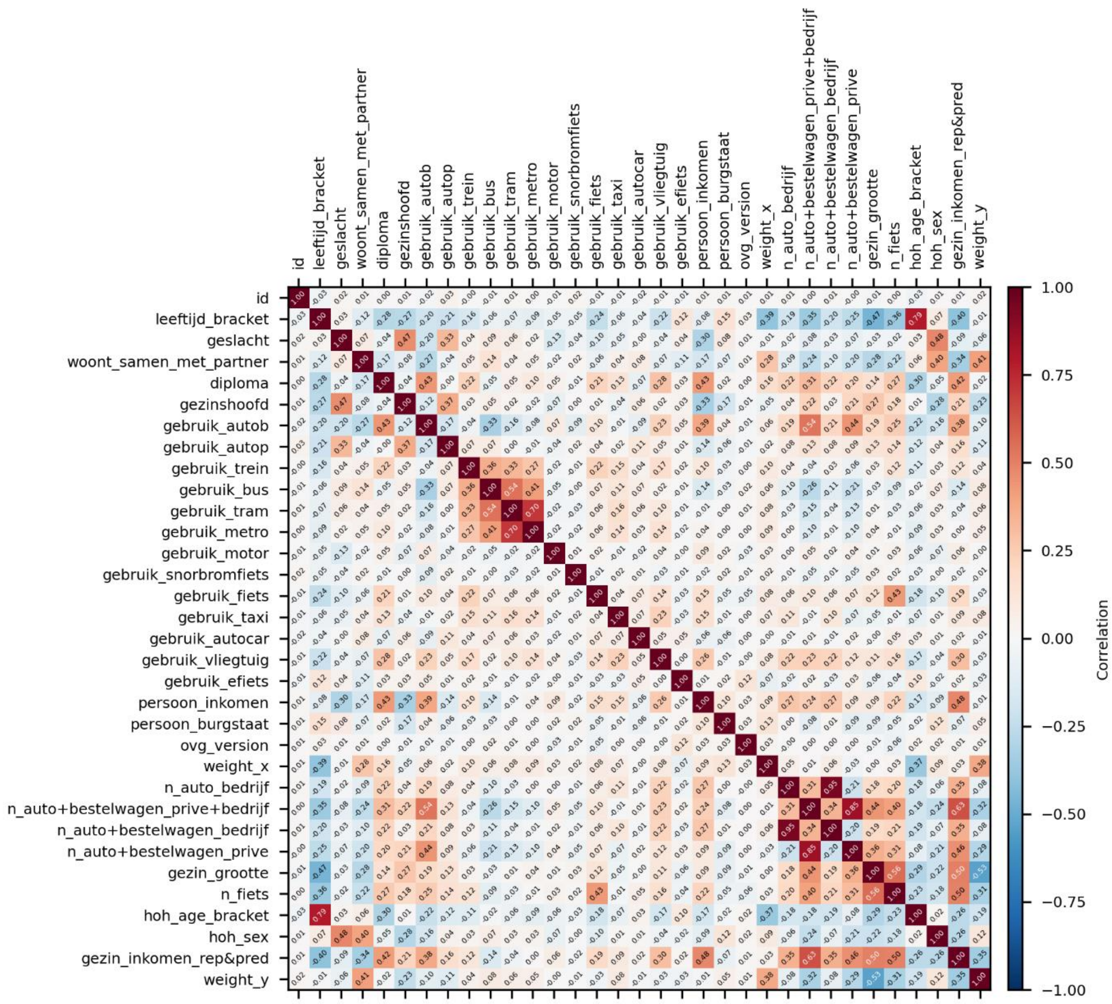
Figure A 7 Prediction income class versus reported income class using larger set of parameters as proxy



Source: Own calculations based on OVG 5

After this, we wanted to merge the now complete household data to the personal data (using the respondent ID, and OVG version fields, that are present in both data sets), to see if we can use parameters from both reports to create an even better income prediction on a personal level. Just as with the household data, we visualised all pairwise correlation below.

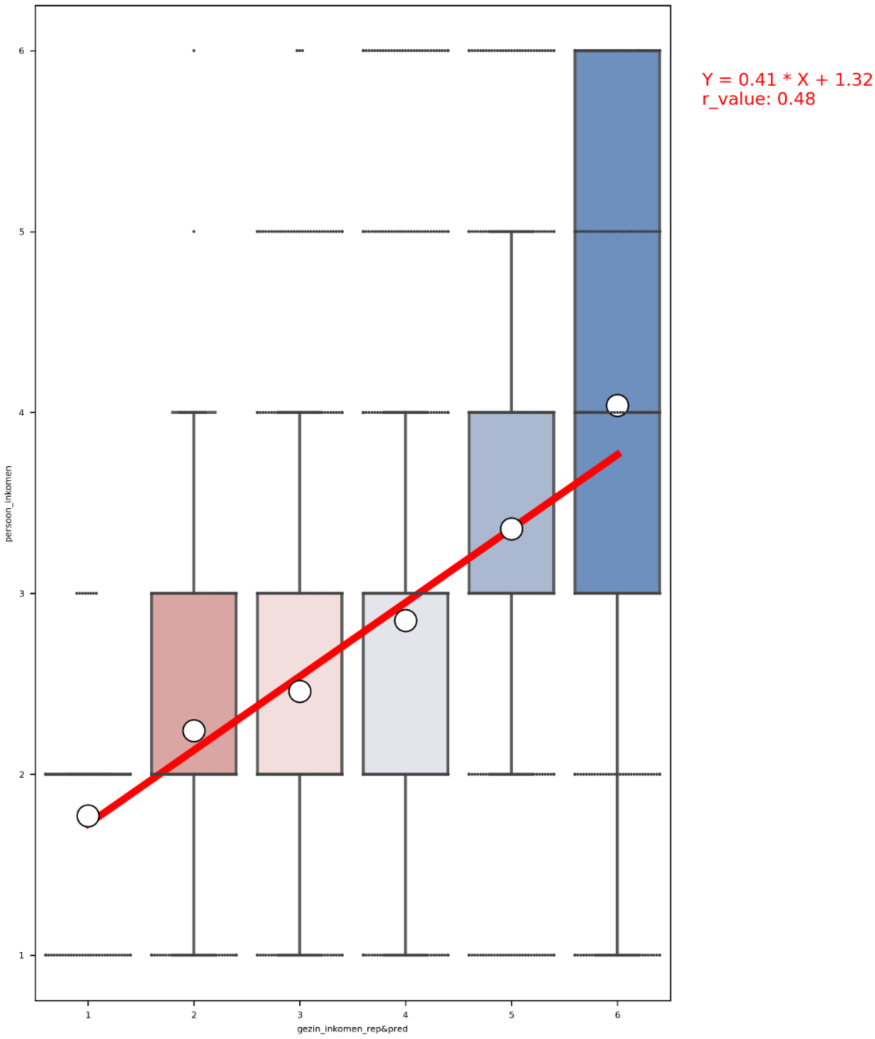
Figure A 8 Bi-variate correlation plot of OVG responses by income level – extended



Source: Own calculations based on OVG 5

There definitely is a correlation between reported personal income and the reported and modelled household income levels, but not strong/secure enough, that we should be using only this to model the missing data.

Figure A 9 Overview of regression model of income level according to characteristic

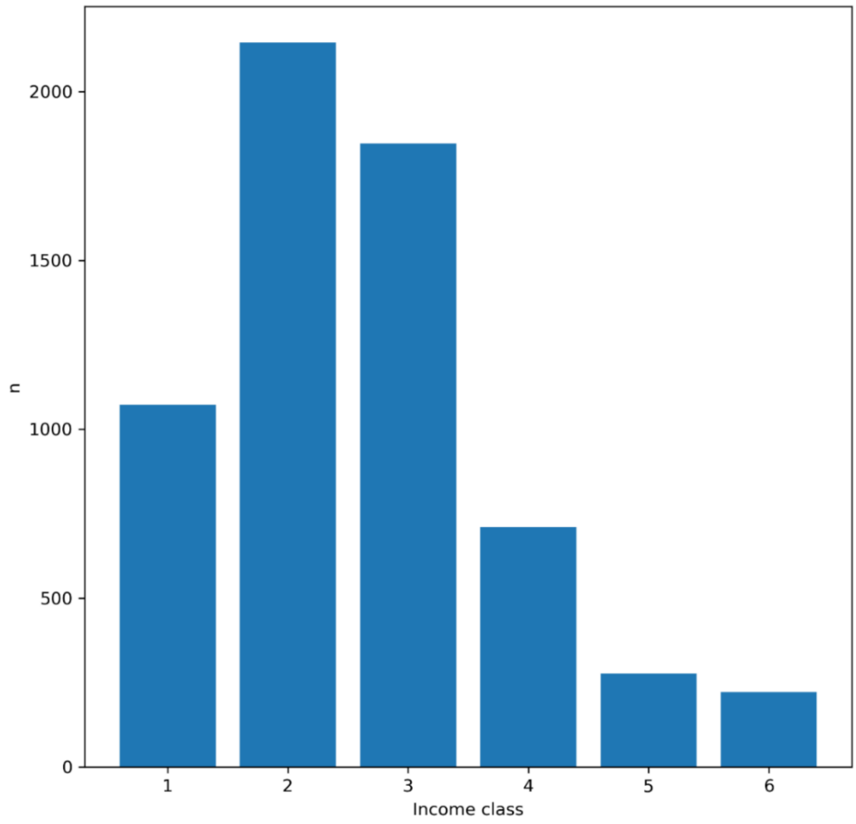


Source: Own calculations based on OVG 5

Instead, we go again with a multivariate regression model, unfortunately this case things will get more complicated because of missing data issues.

In the first step we constructed a model (of 'persoon_inkomen') using the following parameters: 'geslacht', 'diploma', 'gezinshoofd', 'gebruik_autob' ,'gebruik_vliegtuig', 'n_auto+bestelwagen_prive+bedrijf', 'gezin_inkomen_rep&pred'. As before, we choose the most influential parameters based on the initial pairwise plot. The distribution of income categories in the training set is shown below.

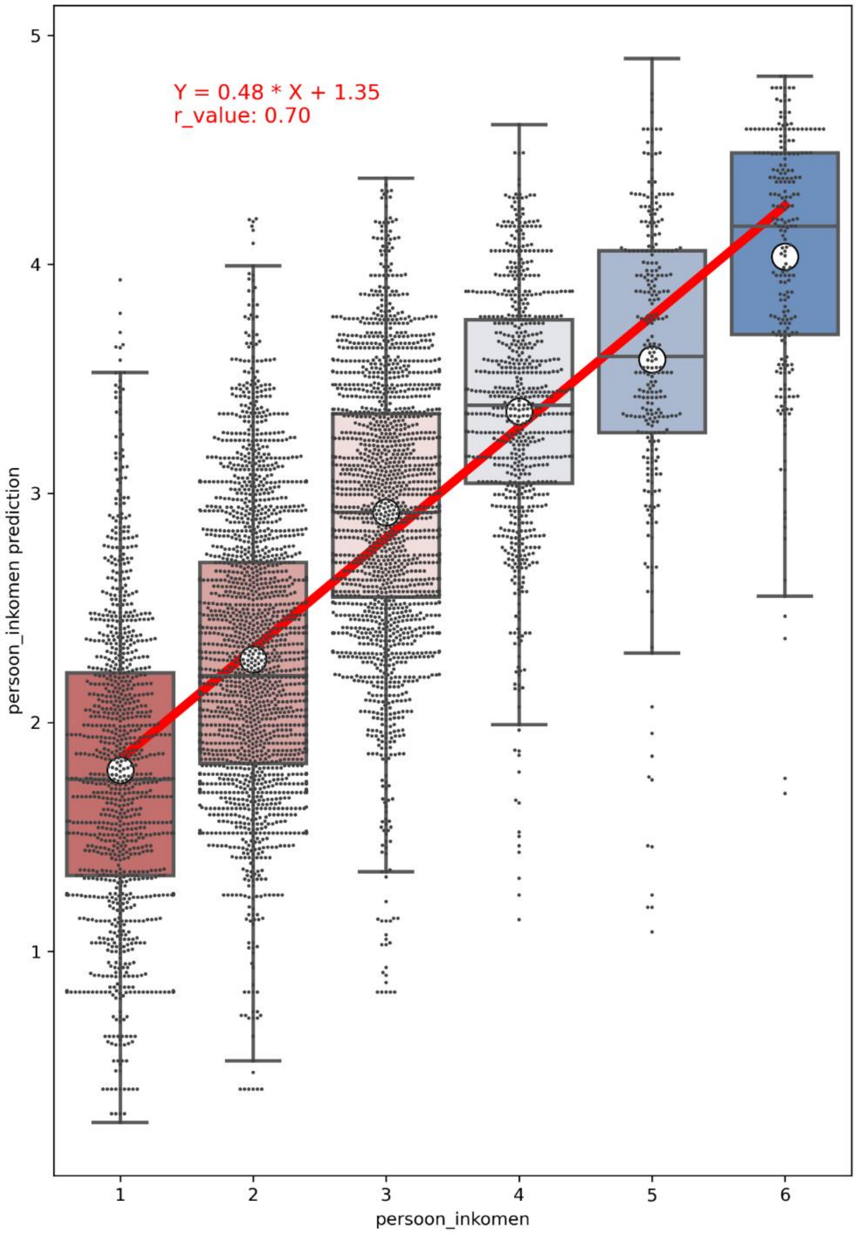
Figure A 10 Observations by income class – corrected by using proxies for income parameters



Source: Own calculations based on OVG 5

The regression model and its evaluation on the training data is shown below.

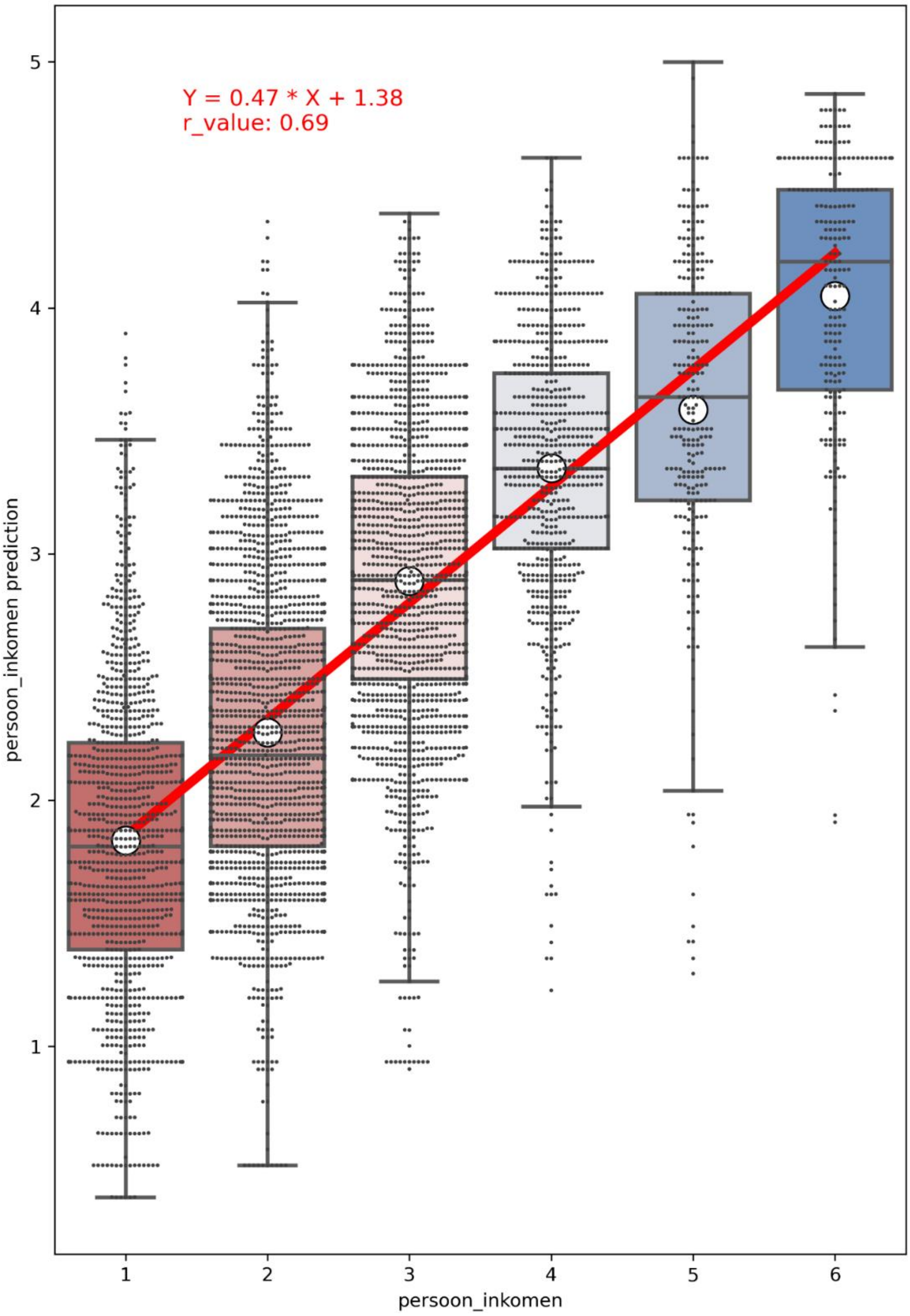
Figure A 11 Personal income versus predicted personal income using person characteristics



Source: Own calculations based on OVG 5

This is a quite good model, but unfortunately we cannot use it as in quite a significant number of cases where personal income is not reported, some of these model parameters/variables are also not reported. In particular, company car usage is for some reason extremely underreported along the subset of people who did not report their income category. Suspicions or not, we are not going to comment on that, but we need a solution. We could go a level deeper and build a multivariate model trying to infer company car use for these people from another set of parameters, but this seems to be beyond the potential of this data set, therefore we decided to simply skip parameters that have a large number of gaps in the sample of people that did not report their income, and as such, create a b version (naming convention includes an extra tag _b in file names) of the multivariate model with parameters 'geslacht', 'diploma', 'gezinshoofd', 'gebruik_vliegtuig', 'n_auto+bestelwagen_prive+bedrijf', 'gezin_inkomen_rep&pred'/ This actually results in an extremely similar model, so we do not miss too much information by omitting the variable about company car use. The resulting model is again shown below.

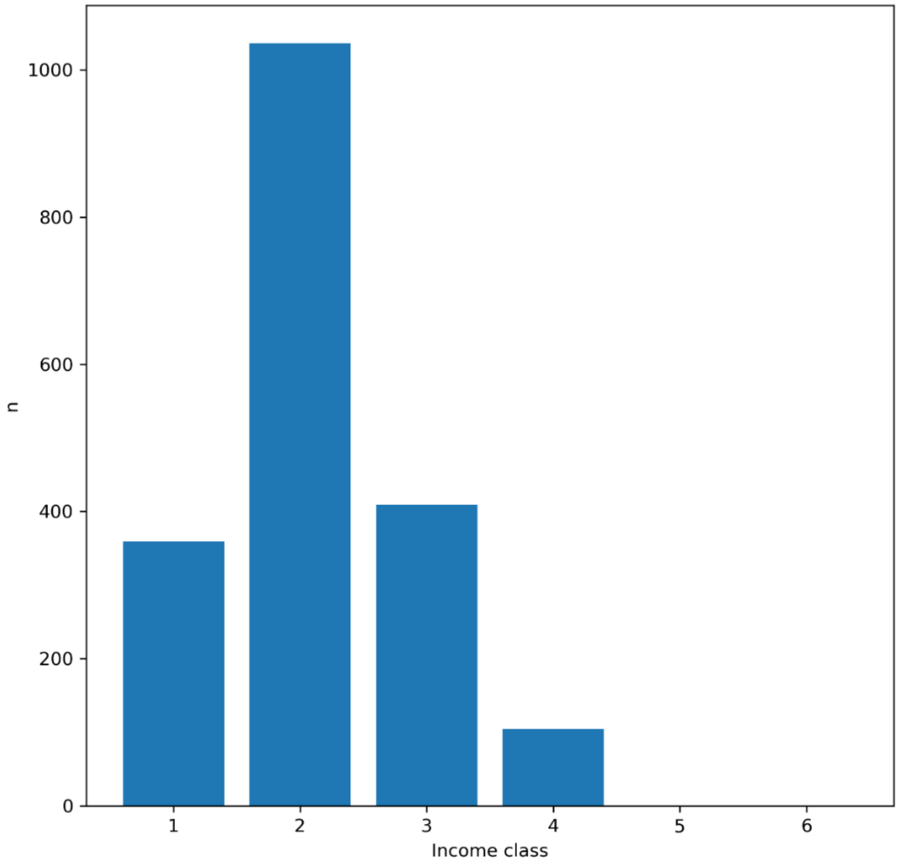
Figure A 12 Personal income versus predicted personal income using person characteristics and use of company cars



Source: Own calculations based on OVG 5

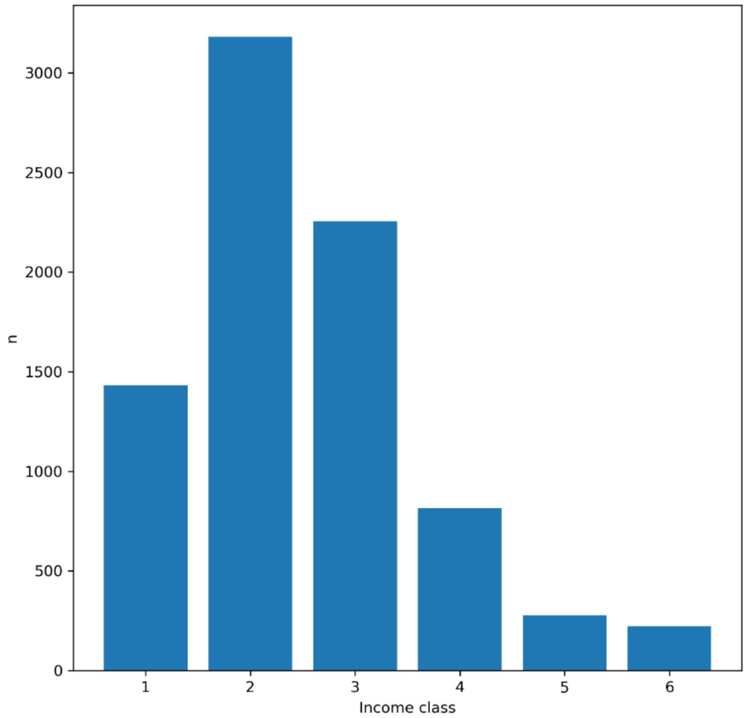
We follow the technique described in the household income modelling to evaluate the model on the subset of people who did not report their income and accept the modelled income value for these people (while keeping the reported values for people who reported them), and store the now complete income category. The distribution of modelled incomes and the complete set of reported and modelled incomes is shown below.

Figure A 13 Population (persons) according to income class missing values – using prediction model



Source: Own calculations based on OVG 5

Figure A 14 Final data – persons according to income class – using prediction model



Source: Own calculations based on OVG 5

These resulting two files containing the household and person level incomes can be used to create statistics with the disaggregate or aggregate trip data, since now we can add income as a third category in the statistics from earlier.

Here we do the same as we did before, but we include other statistics in the calculation from the last step, to create a 3rd and 4th dimension in our mileage/trip calculations over urban/rural regions. Most important is the newly calculated income classes, so we make those calculations first, and then generalise so any available 3rd (and 4th) parameter can be chosen later on.

In the version with population data one also gets added statistics on the total weights of the individual people, and also their households that fall into the individual parameter combination categories. So while in some categories there might be no trips reported, there might still be people and households that fall into that category, they simply did not make trips so their mileage or trip numbers are zero.

The results from 'company car access' may be biased as from 8190 people only 7584 have actually answered this question. Many of the people who answered the question additionally report 'not to have a company car'. This is not in line with overall statistics on company cars.

We were also curious about statistics based on the **home location of the respondents**, so we derived locations (by matching the already localised trips with the respondents) and added them to the joint personal-household data. When reconstructing the postcode (and urbanisation level) for every respondent, we end up with 5925 people where this is successful, and 2265 where it is not successful. The success rate of doing this for the trip data was much higher (22666 trip sections out of a total 23238 trip sections were successfully given destination postcodes), which comes from the fact that we needed trip data to do this reconstruction, so for respondents who did not make any trips, we were not able to reproduce their home location due to lack of data.