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Pyddoke, R., Swärdh, J., Algers, S. et al (2021). Distributional effects from policies for reduced CO<sub>2</sub>-emissions from car use in 2030. *Transportation Research Part D: Transport and Environment*, 101. <http://dx.doi.org/10.1016/j.trd.2021.103077>

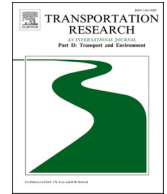
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# Transportation Research Part D

journal homepage: [www.elsevier.com/locate/trd](http://www.elsevier.com/locate/trd)

## Distributional effects from policies for reduced CO<sub>2</sub>-emissions from car use in 2030

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### ARTICLE INFO

#### JEL Codes:

D63  
H23  
R48

#### Keywords:

Distributional effects  
Equity  
Fuel tax  
Feebate  
Bonus  
Malus  
Mandated biofuel blend  
Car choice

### ABSTRACT

We analyze the distributional effects, from car use and car choice adaptation to three car-related policy instruments intended to reduce CO<sub>2</sub> emissions in Sweden to 2030: fossil-fuel taxes, a bonus-malus system for new cars, and mandated biofuel blending. The results show that even with a fast introduction of plug-in electric vehicles, many fossil cars remain, which has important distributional consequences. The fuel tax and the bonus-malus scenarios impose further burdens compared to the reference scenario. The fraction of each population group incurring substantial welfare losses is higher the lower the income. In 2030, the highest-income group can avoid some adaptation costs by their car choice. In all scenarios rural areas bear the largest burden, smaller urban areas the second largest burden, and the largest urban areas the smallest burden. Thus, individuals with high incomes and inhabitants in urban areas appear to have more opportunities to adapt and avoid welfare losses.

### 1. Introduction

Reducing CO<sub>2</sub> emissions from car traffic is central to the necessary policies for achieving international and national goals for emission reduction. Fuel taxes, bonuses and maluses payable for new cars, and mandated biofuel blending all constitute potential parts of such strategies. Although carbon taxes are attractive from an economic efficiency perspective, increases of such taxes are controversial for unfairly burdening rural inhabitants. The distributional concerns therefore emerge as an important obstacle to increased carbon taxes. As the potential burdens of climate policy become apparent, the issue of acceptability will also be a concern for policy makers (e.g. Carattini et al., 2019). Other measures to reduce carbon emissions are therefore also being considered, such as bonus-malus<sup>1</sup> systems and mandated biofuel blending. There are also suggested policies intended to compensate groups particularly burdened by such policies. This calls for more careful analysis of the short- and long-term distributional consequences of such policy instruments.

Eliasson et al. (2018) analyzed the short-term distributional effects of different fuel and car taxes in the Swedish context using a fixed car fleet, finding that these taxes are slightly regressive and affect people in rural areas more than urban residents. Important

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<sup>1</sup> A combination of rebates for low-emission cars and increased purchase taxes for high-emission cars.

<https://doi.org/10.1016/j.trd.2021.103077>

Available online 26 October 2021

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policies target future car fleets, intended to speed up the introduction of technologies such as electric cars and electric hybrids, that can reduce carbon emissions. Therefore, the issue of long-term distributional consequences will be critical for the success of initiatives to incentivize greener car fleets.

This paper analyzes distributional effects, from the car choice and car use response to three car-related policy instruments intended to decrease CO<sub>2</sub> emissions in Sweden up to year 2030. To analyze these effects on the private car fleet, we combine two previously used methods, the Swedish car fleet model (developed in 2006 and refined and updated several times, e.g. Transek, 2006; Hugosson et al., 2016; Habibi et al., 2019) and data from Swedish administrative registers on all Swedish adults and privately owned cars used by Eliasson et al. (2018). Based on the three policy scenarios, the car choices are endogenously modelled by the car fleet model on an aggregated level and the responses in terms of car use are modelled, by income and geographical residential areas, using elasticities from Eliasson et al. (2018). This is done by projecting the car fleet to 2030 in four different scenarios. A reference scenario uses the assumptions of official national forecasts made by the Swedish Transport Administration (2018) with all relevant policies in place in 2017. This reference scenario is used to compare how three policy scenarios affect the welfare of groups of individual adults in disposable income octiles and three geographical area types. The three policy scenarios involve increasing fuel prices by 50 % (though increased taxation) starting in 2020, an intensified bonus-malus system implying a higher tax on cars with emissions initially above 95 g of CO<sub>2</sub> per kilometer, also starting in 2020, and finally, a larger degree of mandated biofuel blending into gasoline and diesel. The paper is intended to indicate likely distributional effects of reasonably realistic policy instruments, but it is not intended to be a full-blown forecast for Sweden. The analysis incorporates increases and decreases in tax expenditures but does not represent them separately. No analysis is done including the use of the increased tax revenues, as Eliasson et al. (2018) clearly indicated that uniform redistribution, as well as redistribution proportional to the distribution of welfare services, made the tax policies clearly progressive.

While the speed at which new, less CO<sub>2</sub> emitting vehicles are introduced is uncertain we can see from e.g. Habibi et al. (2019), that moderate variations in the speed of introduction of such vehicles has little effect on the pattern of which groups acquire new cars. Newer cars are primarily acquired by high income earners.

This paper draws on and relates to three strands of literature. The first strand, focusing on the short-term (and sometimes longer-term) distributional effects of fuel taxes (cf. Eliasson et al., 2018), is the most extensive. Eliasson et al. (2018) find fuel taxation to be progressive over most of the income distribution but barely regressive if the highest and lowest income octiles are also included. Sterner (2012a, 2012b), reporting on fuel taxation in over two dozen countries, finds slight regressivity in high-income countries, but mostly progressive effects in low-income countries. Fewer articles study distributional effects in terms of geographic dimensions as well. Examples include Bureau (2011), who finds larger welfare losses in rural than urban areas in France, Spiller et al. (2017), also accounting for car choices, who find the same difference in the USA, and Filippini and Heimsch (2016), who find the same difference in Switzerland. A recent contribution by Chatterton et al. (2018) finds larger expenditures in rural areas and indications of strong regressivity in the UK.

In the second strand, the effects of policy on the car use and car choice of the supply and demand of new cars to various policy instruments are estimated using time series data. Examples of papers from this strand are by Huse and Lucinda (2013), Klier and Linn (2015), Bento et al. (2018b), and Grigolon et al. (2018), though these papers do not consider distributional issues. Huse and Lucinda (2013) analyze previous green car rebates in Sweden, finding that these rebates reduced the annual vehicle taxes on “green cars”. Estimations of counterfactual scenarios indicate that the rebates stimulated larger acquisitions of cars classified as green. Results also indicate that consumers would have acquired flexible-fuel cars even without the rebate. Klier and Linn (2015) estimate the effects of introducing annual carbon emission-based taxes on cars on the market shares of different car types in France, Germany, and Sweden. In France, the effects are fewer registrations of high-fuel-consuming cars; these effects are large and significant in the short term, while the long-term effects are smaller. A smaller effect is found in Germany, and the magnitude of the effect varies with estimation technique. In Sweden, the effects are indistinguishable from the effects of other trends. Grigolon et al. (2018) examine car buyer valuations of future fuel economy. They find only modest undervaluation of future fuel costs and conclude that although myopia may exist, fuel taxes are still the most effective policy for influencing car choice.

Bento et al. (2018b) review recent attempts to estimate the net social benefits of U.S. fuel efficiency standards by U.S. authorities (i.e. the Environmental Protection Agency and the National Highway Traffic Safety Administration), criticizing them for not using the best available methodologies. Their main argument is that when estimating the total effects on driving and carbon emissions, it is critical to model interactions between the new and used vehicle markets. This point is elaborated on by Jacobsen and van Benthem (2015) and Bento et al. (2018a), who find strong effects of higher new car prices, which increase the demand for used vehicles and delay scrapping. Earlier, Bento et al. (2009) studied the distributional effects of U.S. gasoline taxes, also modeling the long-term effects on car choice.

The third strand uses discrete choice modeling of car choice, so-called car fleet models, to predict behavioral responses to future policy changes (for reviews of car fleet models, see e.g. Potoglou and Kanaroglou, 2008; Anowar et al., 2014). The Swedish car fleet model system has been used in several policy evaluations, i.e. Hugosson et al. (2016), Engström et al. (2019) and Habibi et al. (2019). Habibi et al. (2019) show that the car fleet changes slowly as cars often remain in use for more than 15 years. These authors also show that this conclusion is not sensitive to moderate changes in the speed of the introduction of plug-in electric vehicles but sensitive to the choice of policy instruments. This has important implications for how fast policies directed at speeding up the turnover of the car fleet can change the whole fleet. In addition to these studies, several other papers have attempted to use discrete choice models to evaluate past policies by comparing them with counterfactual scenarios. There are several further examples of the discrete choice modeling of car fleets: Rasmussen and Strøm (2012) estimate how registration fees affect new car sales, finding that a bonus-malus scheme contributes to reduced CO<sub>2</sub> emissions per kilometer; Adamou et al. (2011), studying the German bonus-malus scheme, demonstrate the importance of having a well-defined starting point; and Brand et al. (2013) show that car purchase tax and feebate policies can be more

effective in accelerating the uptake of low-emission vehicles than can road taxes and scrappage incentives in the UK. Other such studies are by, for example, [Potoglou and Kanaroglou \(2007\)](#), [Mabit and Fosgerau \(2011\)](#), and [Mabit \(2014\)](#).

Unlike earlier analyses by, for example, [Bureau \(2011\)](#), [Filippini and Heimsch \(2016\)](#), [Spiller et al. \(2017\)](#), and [Eliasson et al. \(2018\)](#), who model distributional effects without the modelling of a dynamic car fleet, the present paper considers effects of changed car types to policy changes. The main contribution of this paper is to demonstrate the possible long-term effects of fuel taxes, bonus-malus schemes, and mandated biofuel shares on the private car fleet, carbon emissions, and welfare costs and distribution. Compared to [Eliasson et al. \(2018\)](#) this paper introduces endogenous long-term responses to policy changes in choices of new cars. The long-run behavioral changes in car choice are represented by the response to changes in car prices and fuel costs. This is combined with the use of the same short-run response elasticities as in [Eliasson et al. \(2018\)](#) to model car owner's response in terms of driven distances with respect to energy price.

The remainder of this paper is organized as follows. [Section 2](#) presents the data and methodology used. [Section 3](#) presents the three policy scenarios, while section 4 presents the results in terms of effects on the car fleet and welfare distribution. [Section 5](#) discusses the results and section 6 concludes the paper.

## 2. Data and methodology

### 2.1. Data

Data on individuals come from Statistics Sweden registers and data on cars come from the Swedish vehicle register, which covers all adults and all privately owned cars in Sweden. These data are described by [Eliasson et al. \(2018\)](#), but the available data have been expanded from 2011 to 2016. Cars are linked to their registered owners through encrypted individual codes provided by Statistics Sweden.

The main advantage of using register data, besides the fact that they cover the entire population, is that they allow us to study small population segments in detail, by geographical segments and different income levels. The main limitation is that we do not have access to household data, only data about the registered car owners. This could be a source of error if one wanted to explore variability in car use. For example, a household with two adults and one car used by both adults would appear in the register data as one individual with car use and one individual with no car use. This could be a limitation for the income analysis but will play no role in our geographical analysis.

In total, the population data cover 8.26 million adults living in Sweden in 2016, of whom 3.99 million live in large cities, 2.23 million in small cities, and 1.71 million in rural areas. In addition, the data record individual information such as disposable income, age, gender, residential location, and employment status.

The geographical residence areas are defined as follows. An "urban area" is a contiguous area where distances between houses do not exceed 200 m and the total number of inhabitants in the area exceeds 3000, including a further zone defined by a maximum car drive of 5 min to the contiguous area. Non-urban areas are defined as "rural". "Large cities" are defined as urban areas in the three major metropolitan regions (i.e. greater Stockholm, greater Gothenburg, and greater Malmö) and in municipalities where the largest city has at least 60,000 inhabitants. "Small cities" are the remaining urban areas.

Vehicle data cover 5.34 million privately owned cars distributed over 3.69 million individual car owners. We have access to yearly vehicle kilometers taken from vehicle inspection data. Other car characteristics used are age, energy type, fuel consumption, and weight. An important observation from this data, that parallels observations in Norway ([Fevang et al. 2021](#)), is that plug-in electric vehicles are initially owned mostly by high income earners.

Some exclusions from the data are necessary before the analysis. First, about 33,000 individuals could not be assigned to geographical residence areas and were excluded. Second, we excluded deregistered cars and cars weighing over 3500 kg. Third, individuals who own more than four cars were excluded because it is unlikely that these cars are used only by their registered owners. The limit of a maximum of four cars is somewhat arbitrary but excludes few car owners, so this criterion is unlikely to distort the results (especially as the individual with the most cars in fact is registered as owning 3500 cars). In total, about 50,000 individuals and 980,000 cars (over 640,000 of which are not registered for use) are excluded for the above reasons. We end up with about 4.36 million privately owned cars distributed over about 3.47 million car owners.

The car fleet model is estimated using data from a survey of new car purchases in 2014 and validated in [Hugosson et al \(2016\)](#). This model is calibrated to purchase data from 2017, further explained below.

### 2.2. Methodology

In this study, we analyze how different car policies affect distribution of welfare. This entails understanding how different policies affect car purchases as well as how income distribution is influenced by costs, including subsidies, taxes, and energy costs resulting from the car purchase and subsequent car use. Ideally, we should have a car fleet model with high resolution of socioeconomic variables, including mechanisms for reallocating used cars over time. In the absence of such a model, we use an established car fleet model recognizing three different consumer segments to predict car purchases and that propagates the car fleet over time with respect to total car ownership, scrapping and new cars purchases. The result of this model, which is sensitive to car policies, is a distribution of all personal vehicles by energy type, model year, and average fuel consumption. This result has low resolution with respect to distributional variables. We therefore use an additional method to allocate the car fleet results to groups of private car owners to subsequently estimate distributional effects. These models and methods are described in more detail below.

### 2.2.1. The Swedish car fleet model

The main structure of the Swedish car fleet model is described by [Hugosson et al. \(2016\)](#). The model calculates for a forecasting period the evolving status of a base year car fleet, defined by the number of cars classified by model year, energy type and, for this study, also weight class. To this end, the model contains three sub-models. The first sub-model is a scrapping model in the form of constant scrapping rates by car age. The second sub-model is a model of the total number of cars in the car fleet, usually given by a long-term car ownership model. The total car ownership is in our case exogenous to car type choice, implying that factors like car price do not affect total car ownership.

The number of new cars is given by the difference between the total number of cars in year  $t + 1$  minus the total number of cars in year  $t$  after scrapping. The third sub-model is a model of the choice of car type for the new cars bought in year  $t + 1$ , describing the distribution of different types of new cars added to the car fleet of year  $t$  after scrapping. This is repeated for each year in the forecasting period. The car fleet is defined by model year, energy type and (for this study) by weight class.

The car type choice sub-model is vital to the car fleet model, giving the market response to the different investigated car policies. This model has been updated in the current version of the Swedish car fleet model using data from 2014 in a survey carried out in 2015. The car choice sub-model covers three consumer segments: private buyers and company buyers with and company buyers without leasing arrangements. An important segment is cars provided by companies to employees for private use (here called benefit cars). We use the information on leasing arrangements included in the Swedish transport register as a proxy for this segment type. The estimation of models for the private and benefit car segments is described by [Engström et al. \(2019\)](#). The estimation of the car type choice sub-model for the third segment is described by [Hugosson et al. \(2018\)](#).

The estimation of the car choice sub-model resulted in a number of statistically significant parameters of car attributes, such as price, running cost (including taxes), size, range, NCAP safety class, and rust guarantee. The model is calibrated to the 2017 situation, using data from the national car register on new sales in 2017. The calibration consists of estimating new model constants for make and energy type in the new car choice sub-models for each of the three consumer segments. We then assume that the model parameters for the different explanatory variables estimated on 2014 data are valid also for 2017 (and up to 2030). This also results in consistency between the modeled and observed behavior (market shares) with respect to make and energy type for the base year 2017. We assume that the calibrated model then is valid for our purpose.

Forecasting is then conducted by inserting the scenario parameters related to the supply of cars, i.e. describing the car type alternatives in terms of future attribute values. This includes manufacturer-specific attributes such as price, energy type, size, range, and energy consumption as well as policy effects in terms of government subsidies and taxes and assumptions as to future fuel prices. This means that the scenarios must be identified in technical as well as in policy terms. A crucial issue is the expected development of new plug-in electric vehicles (i.e. plug-in hybrids and fully electric cars).

The assumption as to the technical development of supply is that each manufacturer continues to supply car types like those supplied in 2016 but with technical and price updates. One change is that each manufacturer is assumed to add one plug-in hybrid model and one fully electric car in each size class in which it currently supplies a fossil-fuel car.<sup>2</sup> Another change is that fossil-fuel cars are assumed to improve in fuel efficiency by 1.3 % per year, leading to a net improvement of 19.8 % by 2030 relative to 2016. Also, the range (in electric mode) of fully electric cars is assumed to increase by 4 % per year. The prices of fossil-fuel cars are assumed to change little, while the price difference between a fossil-fuel car and a corresponding fully electric car is assumed to be zero in 2030.

In all our scenarios, EU Regulation 2019/631 regarding the CO<sub>2</sub> emission performance standards for cars and vans is assumed to be enacted. An important goal of this policy is that the average of all new cars from one manufacturer must comply with a 37.5 % reduction of CO<sub>2</sub> emissions by 2030 relative to the realized average in 2021 based on the WLTP test cycle ([Kågeson, 2019](#)). This regulation will affect car manufacturing and the supply of new vehicles. It is difficult to judge to what extent our supply assumptions are consistent with the EU regulations. The EU regulation is not directly represented in the car fleet model, as the regulation applies to an average for the EU and not to individual cars and we have chosen not to limit the supply in any arbitrary way. The car fleet model represents the choices of Swedish car buyers. If they choose larger and less efficient cars than the EU average, the Swedish car fleet average may not comply with the intentions of the EU regulation, which is also not required of the manufacturers.

There is also no endogenous adaptation of technology, supply of new cars, or pricing of new cars in this model. Neither the prices of nor demand for used cars is affected by the supply of new cars. Also, the value of used cars is not modeled with respect to the supply of used cars. No foreign trade in used cars is represented; this may prove to reduce the value of the projected carbon emission reductions, as there is strong growth in plug-in electric vehicle exports from Sweden.

### 2.2.2. Connecting the car fleet model to individual data

There is a gap between the car fleet model, which models all cars but no individuals, and the method used in the previous analysis of distributional effects ([Eliasson et al., 2018](#)), which used the data on individuals and privately owned cars. We abstract from the demographic developments (i.e. population growth and moving) and assume the same population, with the same places of residence and the same number of cars owned in 2030 as in 2016. We therefore focus on the same distributional effects in a future population as in the current one rather than using an assumed population change. We use the following procedure to calculate the distributional effects of different car policies.

<sup>2</sup> This involves a pattern where PHEVs and EVs are introduced successively. Each car type segment that in 2017 includes a gasoline car or a diesel car will also contain one BEV and one PHEV in 2030. This addition will evolve gradually year by year from 2018 to 2030, starting with the premium segment.

Cars are sorted into 36 groups by weight, age, and energy type<sup>3</sup> and individuals are sorted into 24 population groups (i.e. income octiles and the three geographical area types of large cities, small cities, and rural areas). The distribution of the 36 car types among the 24 population groups in 2016 is determined using register data on all Swedish adults and their privately owned cars, forming a two-dimensional matrix (i.e. car type and population group) in which each cell contains the number of cars per category in 2016. We have added a second step in the modelling process to impose the car fleet model results on the distribution of cars among car groups in 2030.

Car choice is therefore involved in two steps. First the choice of new car types is modelled at an aggregate level using the car fleet model to estimate the distribution of the car fleet among car groups. This is done for each year (as described above) in the forecasting period 2016 – 2030 resulting in the car type distribution of the entire car fleet in 2030. Then, for 2030, we also want to impose this result in the choice of cars by population groups, thus also implicitly involving choice of used cars. This is modelled by using the iterative proportional fitting (IPF) process (See [Ortuzar and Willumsen \(2011\)](#) for a description and additional references) in which the 2016 distribution of car and population groups is fitted to the 2030 distribution of car group totals. In other words, we use the 2016 distribution pattern of cars as a starting point to get a 2030 distribution that matches the car fleet results for car groups in 2030. A validation exercise of this method with data from 2011 and 2016 show that forecasted and observed values match well, which indicates that the IPF process in our study only has small errors. More about this validation can be found in the appendix.

The iterative proportion fitting process relies heavily on the starting distribution. The advantage is that the initial distribution contains information on consumer choices which we assume will be relevant also in the future situation. The method also has drawbacks, such as implying strict conservation of certain relations between cells in the distribution and problems with cells with no or few cars. The first drawback is difficult to handle, while we have made some assumptions to avoid the second one. If there are no cars in a cell in 2016, there will be no cars in 2030. If there are few cars in a cell, the distribution pattern may be uncertain. This problem relates entirely to plug-in electric vehicles, as these are very rare in the 2016 car fleet. Therefore, additional assumptions regarding the distribution of plug-in electric vehicles among population groups in 2030 were made. Plug-in electric vehicles are assumed to be distributed among population groups in 2016 proportionally to how gasoline cars were distributed among population groups in 2016.<sup>4</sup> The reason for this assumption is that the distribution of plug-in electric vehicles in 2016 was highly skewed to higher incomes, and we believe that this distribution will be evened out by 2030. This method is chosen to find a reasonable association between population groups and new cars, as we do not have an individual car choice sub-model for forecasting which car type will likely be chosen by each individual in 2030. This allocation will be like the allocation of vehicles in 2016 in that low-income earners on average will own older and lighter cars and in that rural inhabitants on average will own heavier cars. The weakness of the heavy dependence on the distribution of car weights, energy type and car ages among income and geographical residence groups in the starting year may materialize more the further into the future we project and with larger changes in preferences, supply of car types, relative prices, distributions of income, and places of residence.

Our data is based on individual car ownership. Therefore, the gap between all cars in the car fleet model and the data on privately owned cars is twofold and not completely closed. The first part is the company cars not intended for private use, which numbered about 220,000 in 2016. The second part is the benefit cars owned by companies but also used privately, which numbered about 280,000 in 2016. Both these categories are needed for a complete calculation of total effects on CO<sub>2</sub> emissions, implying that this limitation must be borne in mind throughout the analysis. The second category would be needed for a complete calculation of distributional effects including benefit cars, which will not be done in this paper as we lack good data on the type of benefit car each individual has and on his/her yearly vehicle kilometers. We therefore do not include company cars in our distributional analysis, though we briefly discuss this, including a calculation example of the importance of this limitation, in the results section. As most of the benefit cars are sold to private buyers after three years and then appear as private cars, we assume that most benefit cars are included in the privately owned car fleet after the age of three years.

### 2.2.3. Calculating distributional effects

The distributional effects are evaluated as the total welfare cost for a policy, which we define as *the difference in yearly welfare between a policy scenario and the reference scenario for the individuals*, where the individuals are assumed to be homogeneous in each population group. The total welfare cost is also compared across population groups in relative terms, meaning that we divide the total welfare cost by disposable income of the particular population group.

Furthermore, we measure welfare effects on the consumers' side of the market. The welfare loss of a tax increase (before the recycling of tax revenues) is measured as the change in consumer surplus and the change in the fixed cost of owning another type of car. In the fixed cost we include the yearly fixed vehicle tax (circulation tax), depreciation cost, and cost of capital for the car value. This

<sup>3</sup> We have used 36 groups to categorize the cars, namely cross categories of 3 wt classes (car size), 4 age classes, and 3 energy-type classes. The weight classes are set so that each class consist of approximately-one third of the car fleet in our 2016 data. This means in our analysis that the smallest-car group consists of cars up to a kerb weight of 1360 kg, while the largest-car group consists of car with a kerb weight of more than 1576 kg. The cars in between are categorized in the middle-size car group. Furthermore, the age classes consist of cars with register year 2003 and older, 2004–2008, 2009–2012, and 2013 and newer, respectively. The energy-type classes is exclusively discriminating with respect to plug-in electric cars, petrol cars, and diesel cars, that is we have one class with petrol cars that are not plug-in electric, one class with diesel cars that are not plug-in electric, and one class with all types of plug-in electric cars (PHEV and BEV, but not HEV).

<sup>4</sup> The distribution of electric cars in 2030 is generated by imputing a more even distribution among population groups (by income and area type) of electric cars in 2016 (by age and weight), using a distribution proportional to the distribution of gasoline cars (by age and weight) among population groups.

means that other car costs, such as inspection, repair, parking, and tire costs, are not considered. Thus, these costs are assumed to be relatively similar across car types.

To calculate the distributional impacts of different policy scenarios, we have associated each population group with their estimated car ownership in 2030. We use additional information to calculate the policy impact on the different population groups. Driving distances in the scenarios for 2030 are calculated for each population group differentiated by car type using the average driving distance for each population group differentiated by car type in 2016 as the starting point. Note therefore that although we have data on individuals, we compare averages over groups defined by income octiles and residential areas. Then the new prices for energy (i.e. gasoline, diesel, and electricity) are used together with the elasticities of driving distance with respect to energy cost (also for plug in electric vehicles) to estimate the driving distance in 2030. Note, also, that the welfare calculations assume no other market distortions, e.g. in the labor market or public transport, caused by the tax policies.

The different mathematical formulas used to calculate the total welfare costs are presented in the Appendix.

The elasticities used here as a behavioral response to changes in energy price are the same as those used in the analysis of [Eliasson et al. \(2018\)](#). These are in turn based on estimates using the same register data on all Swedish adults as used here, but instead for the 1998–2009 period. This period enabled us to use dynamic panel-data models to estimate separate elasticities for income groups and geographical residence areas. The car-use elasticities with respect to energy price are used to predict vehicle kilometers for each car type and population group in all scenarios, using the actual vehicle kilometers in 2016 as the starting point. Note also that these elasticities vary across the 24 population groups. The “lowest” elasticity is  $-0.18$  for the highest income octiles in rural areas, while the “highest” elasticity is  $-0.58$  for the lowest income octiles in cities. Using this procedure and these elasticities is one way to represent these behavioral adaptations. Other elasticities may represent earlier and future behavior better. This paper represents one set of such assumptions.

Note that for the energy-type category consisting of both battery electric cars and plug-in hybrid cars, the energy consumption is based on the average declared energy consumption, which assumes a share of the vehicle kilometers driven on electricity. A recent study ([Plötz et al. 2021](#)) indicates that PHEVs drive significantly less on electricity and on average emit two to four times more tailpipe CO<sub>2</sub> than expected from test cycles. As the exact figures for the fleet of Swedish PHEVs is unknown, we cannot compare this magnitude, so we limit ourselves to the observation that our emission reduction figures are likely to be similarly overestimated for this category of cars.

The energy consumption of the car fleet in 2016 is adjusted to be more accurate based on [Mock et al. \(2013\)](#); see discussion of this by [Eliasson et al., 2018](#)). These adjustment factors are presented in [Table A4](#) in the Appendix. For the predicted car fleet in 2030, the new cars from 2020 onwards are based on the new WLTP test cycle. For cars from 2019 and before, the declared energy consumption is adjusted using similar but not the same adjustment factors as for the car fleet of 2016.

CO<sub>2</sub> emissions are calculated as “end-of-pipe” emissions, the standard for measuring CO<sub>2</sub> emissions for the Swedish policy goals of emission abatement. The total emissions for each scenario are calculated by multiplying for each car, driven distance, fuel consumption, and emission factors and summing. In this calculation, gasoline is assumed to emit 2.36 and diesel 2.54 kg of CO<sub>2</sub> per liter. Under the current biofuel regime blending ethanol, FAME, and HVO (assumed to have zero end-of-pipe CO<sub>2</sub> emissions), we assume that, used as car fuel in Sweden, gasoline emits 2.24 and diesel emits 2.01 kg of CO<sub>2</sub> per liter.

A rebound effect for car use or fuel consumption can be defined as an increase in aggregate fuel consumption caused by the introduction of more fuel-efficient technology. Several studies have studied different kinds of rebound effects associated with improved fuel efficiency (an early example is [Greene, 1992](#)). Similarly, the Jevons paradox is defined in this context as an improved, more fuel-efficient technology leading to higher demand for driving and fuel. In our modeling, increased fuel taxes or a bonus-malus scheme prompts car buyers to buy more fuel-efficient car models than they would have otherwise. These more fuel-efficient cars will in turn tend to be used more, as the costs of driving these cars *ceteris paribus* will be lower. The changes in driving costs due to improved energy efficiency are accounted for to the extent that the elasticities are estimated with respect to energy price and thus also capture effects of improved energy efficiency. In this study, we have not attempted to isolate and quantify the rebound effect. It is included in the change of average driven distances from 2016 to 2030 presented in [Table 7](#). In the reference scenario presented below, the assumed fuel efficiency increase for fossil-fuel cars is about 20 % in this period. This certainly has rebound effects, but these are partly cancelled out by the increase in fuel prices of about 42 %.

### 3. Policy scenarios

We study three separate scenarios of different car tax policies and their effects on the car fleet up to year 2030. The choice of policy will depend on the goals of the political decision makers. The overarching goal of Swedish national transport policy is “to ensure an economically efficient and long-term sustainable supply of transport for citizens and businesses throughout the country” (Prop. 2008/09:93). This entails aiming for both short- and long-term economic efficiency. For the total domestic transport sector (excluding air transport), the Swedish national goal is to reduce CO<sub>2</sub> emissions by 70 % between 2010 and 2030. In addition, the government has found it necessary (Prop. 2017/18:1) to incentivize the introduction of less CO<sub>2</sub> emitting vehicles by adopting a bonus-malus system.

If evaluations of policy costs are restricted to the short term, then the policy maker risks missing opportunities for lower dynamic costs by incentivizing new technologies (cf. [Gillingham and Stock, 2018](#)). For the future pursuit of the above goals, the present results contribute observations on likely long-term effects.

### 3.1. The reference scenario

The reference scenario is based on a national base scenario formulated by the [Swedish Transport Administration \(2018\)](#) using parameters given in the Appendix. This scenario is defined by the assumptions as to the trajectories of the following exogenous variables and growth parameters from 2016 to 2030: private per capita income grows by 23 %; consumer prices for gasoline and diesel increase by about 39 % and 45 %, respectively; and the price of electricity increases by about 17 %. The adaptations in the reference scenario and the policy scenarios are all modeled using the car fleet model, and the demand responses in 2030 are modeled using the elasticities of driving distance with respect to energy prices from [Eliasson et al. \(2018\)](#). The choices of new cars are modelled to be sensitive to car price conditional on income.

The current yearly vehicle tax is assumed to remain unchanged.<sup>5</sup> In the reference scenario there is already a current bonus-malus system, meaning that all buyers of new cars pay a base charge of EUR 36 per car independently of emission properties (Swedish crowns are converted to EUROS at the rate of EUR 1 = SEK 10). For cars that emit under 60 g of CO<sub>2</sub> per kilometer, the buyer can receive a bonus of up to EUR 6000. This bonus diminishes by EUR 83.3 with each gram of extra CO<sub>2</sub> emission per kilometer ([Kågeson, 2019](#)). In the 60–95-gram interval there is no bonus or malus. For vehicles emitting over 95 g of CO<sub>2</sub> per kilometer, a malus of EUR 8.2 is charged for each extra gram per year the three first years after the car is purchased. Over 140 g of CO<sub>2</sub> per kilometer, the charge increases to EUR 10.7. In addition, diesel cars pay a further base charge of EUR 25 and a further charge per gram of CO<sub>2</sub> emission of EUR 1.35.

There is also a current mandated biofuel blending policy requiring the blending of ethanol in gasoline and biodiesel in diesel. The current levels of mandated reduction of CO<sub>2</sub> emissions are 2.6 % for gasoline and 19.3 % for diesel, increasing to 4.2 % and 21 %, respectively, in 2020.

### 3.2. The fuel tax scenario

In this scenario, in addition to all current policies in the reference scenario, the taxation on fossil fuels (i.e. gasoline and diesel) is assumed to increase the consumer price by 50 % from 2020 onwards. This means that the price increases by the same pace as in the reference scenario but at a level 50 % higher from 2020 onwards. In the reference scenario, the fuel prices in 2020 are calculated to be EUR 1.59 and EUR 1.60 per liter for gasoline and diesel, respectively, whereas in the fuel tax scenario, the corresponding prices in 2020 are EUR 2.38 and EUR 2.41. This implies a CO<sub>2</sub>-tax increase of about 170 % and 114 %, respectively, for gasoline and diesel relative to 2019. The new levels of CO<sub>2</sub> taxes per liter are EUR 0.87 for gasoline and EUR 0.94 for diesel (corresponding to EUR 1.95 and EUR 1.89 per kilogram of CO<sub>2</sub>). This can be compared with the estimates of the [Swedish National Institute of Economic Research \(2017\)](#) of the CO<sub>2</sub> taxes for road transport of EUR 2.4 per kilogram needed to reach the national goal of a 70 % emission reduction by 2030. These tax increases of course imply a huge discrepancy on marginal spending for different policy instruments to reach the national goals.

### 3.3. An intensified bonus-malus scenario

The intensified bonus-malus scenario is dynamic, and its assumptions are as follows. All new cars are charged a base tax of EUR 36. In the intensified bonus-malus system, the limits for bonuses and maluses are successively lowered and the maluses successively increased. In 2030 a new car emitting less than 30 g of CO<sub>2</sub> per kilometer can receive a bonus. If it emits no CO<sub>2</sub>, the bonus is still EUR 6000. The bonus decreases by EUR 41.6 per each further gram of CO<sub>2</sub> emission per kilometer. In 2030 the malus, i.e. the tax, is charged above 30 g of CO<sub>2</sub> emission per kilometer. In the 30–75-gram interval, the malus is EUR 16.4 per gram of CO<sub>2</sub> emission for gasoline per year the three first years after the car is purchased. Above 75 g, the malus is EUR 21.4 for each extra gram of CO<sub>2</sub> emission per kilometer. Diesel cars are charged a further EUR 1.35 per gram of CO<sub>2</sub> and an environmental charge of EUR 25 per vehicle. The running cost variable in the car fleet model is calculated as an average yearly cost for the first 5 years for private buyers and a three-year average for company cars (these are typically leased for a three-year period). The effects are represented in two graphs in the appendix.

### 3.4. A mandated biofuel blend scenario

We initially intended to calculate the effects of an intensified biofuel blending mandate. When we realized the huge uncertainties concerning price forecasts for biofuels and what a reasonable policy scenario (and therefore loss of tax revenue) could be, given these uncertainties, we decided not to incorporate assumptions of a stronger mandated biofuel blending into the estimation of the CO<sub>2</sub> emission decrease by 2030 based on the car fleet of the other two scenarios.

This scenario has been the hardest to construct. On one hand, there is currently a strong desire to use biofuel blending to reduce CO<sub>2</sub> emissions, manifested in high current biofuel shares and visions of continued increases in these shares. On the other hand, international trade in biofuels such as HVO has led to accelerated deforestation to grow oil palms. The latter argument has led politicians to question the ambition to increase biofuel imports from certain sources, and the EU has imposed limits on the import of such biofuels. A further implication is that this uncertainty concerning the levels of mandate and imports makes it very difficult to forecast biofuel prices.

<sup>5</sup> In fact, the future bonus–malus system has already changed. Starting from 1 January 2020, the upper limit for receiving the bonus will rise from 60 to 70 g (see <https://www.regeringen.se/artiklar/2019/09/mer-pengar-till-klimatbonusbilar-och-for-utbyggnad-av-snabbladdning-langs-storrevagar/>).

**Table 1**

Production cost increase for replacing one liter of fossil fuel with one liter of biofuel and the current total tax for fossil fuel.

	Production cost increase for a one-liter swap	Current price	The current total tax
Gasoline	EUR 0.59	EUR 1.58	EUR 1.07
Diesel	EUR 0.62	EUR 1.56	EUR 0.94

Source: Data from SPBI – Swedish Petroleum and Biofuel institute.

**Table 2**

Descriptive statistics for individual data, 2016.

Variable	All	Large cities	Small cities	Rural areas
Car owners (at least one car)	44.69 %	36.69 %	48.86 %	58.68 %
Owns one car	34.92 %	30.50 %	38.30 %	41.19 %
Owns two cars	7.26 %	4.89 %	7.96 %	12.10 %
Owns three cars	1.63 %	0.90 %	1.74 %	3.27 %
Owns four cars	0.89 %	0.40 %	0.86 %	2.12 %
Vehicle kilometers per year	6855	5290	7149	10,263
	(10,702)	(9505)	(9505)	(12,710)
Disposable income, SEK per year	259,974	280,439	232,958	242,585
	(952,159)	(1,251,846)	(541,611)	(447,250)
Age, years	48.7	46.9	50.2	51.8
	(19.5)	(19.1)	(20.1)	(19.0)
Percentage employed	60.17 %	61.51 %	56.63 %	60.96 %
Distance to work in kilometers (given employment)	21.6	19.7	21.5	26.1
	(65.3)	(63.9)	(68.2)	(63.5)
Has company car	3.54 %	4.15 %	2.53 %	3.19 %
No. of observations	7,758,289	3,835,120	2,136,363	1,529,734

**Table 3**

Descriptive statistics for car data, 2016.

Variable	All	Large cities	Small cities	Rural areas
Vehicle kilometers per year	12,218	11,864	11,700	13,155
	(8220)	(8031)	(7930)	(8652)
Share of weight class, lightest	31.2 %	33.6 %	31.8 %	27.6 %
Share of weight class, medium	33.7 %	32.9 %	34.2 %	34.3 %
Share of weight class, heaviest	35.1 %	33.6 %	34.1 %	38.1 %
Age, years	10.8	9.7	11.1	12.0
	(8.8)	(7.8)	(8.9)	(9.8)
Fuel consumption, liter per 10 km	0.760	0.760	0.759	0.761
	(0.197)	(0.198)	(0.194)	(0.200)
Share of gasoline cars	65.94 %	66.41 %	67.53 %	64.29 %
Share of diesel cars	27.58 %	25.77 %	26.34 %	30.67 %
Share of ethanol cars	4.86 %	5.37 %	5.05 %	4.01 %
Share of battery electric cars	0.06 %	0.07 %	0.03 %	0.08 %
Share of all hybrid cars	0.99 %	1.54 %	0.66 %	0.57 %
No. of observations	4,358,429	1,681,648	1,309,884	1,216,948

So far, policy has proceeded on the assumption that biofuels were exempted from CO<sub>2</sub> taxation. Current proposals from the EU commission (<https://www.svt.se/nyheter/inrikes/biodrivmedel-kan-bli-av-med-skattebefrielsen>) indicate that these exemptions will be abolished. If this happens then biofuels are to be subject to CO<sub>2</sub> taxes.

We have therefore opted for a very simplified scenario. We do not assume that the biofuel blending share will change from the levels to be enacted starting in 2020 (requiring sellers to reduce CO<sub>2</sub> emissions from gasoline by 4.2 % and from diesel by 21 %). We assume that these blending requirements can and will be met at the same fuel prices as in the reference scenario. Instead, we assume that the increasing costs will be carried as lower tax revenues, not affecting consumer welfare in the fuel market. We assume that the production costs will be unaffected by the blending mandate and that the cost of biofuels will grow by the same rate until 2030.

To illustrate the magnitude of the costs of increasing the biofuel content of fuels, we calculated the increase in the cost of replacing one liter of fossil fuel with one liter of biofuel at prices current as of October 2019.

**Table 4**  
Weight distribution of the total fleet of privately owned cars.

Weight class	2016	Reference scenario, 2030	Fuel tax scenario, 2030	Intensified bonus-malus scenario, 2030	Mandated fuel blend, 2030
Lightest	31.2 %	21.5 %	21.2 %	21.1 %	21.5 %
Medium	33.7 %	32.3 %	32.2 %	31.9 %	32.3 %
Heaviest	35.1 %	46.2 %	46.6 %	47.0 %	46.2 %
<i>Fossil-fuel-only cars</i>					
Lightest	31.3 %	25.2 %	25.7 %	25.9 %	25.2 %
Medium	33.7 %	34.9 %	35.1 %	34.8 %	34.9 %
Heaviest	35.0 %	39.9 %	39.2 %	39.3 %	39.9 %

**Table 5**  
Energy types as shares of the total fleet of privately owned cars.

Energy type	2016	Reference scenario, 2030	Fuel tax scenario, 2030	Intensified bonus-malus scenario, 2030	Mandated fuel blend, 2030
Gasoline	72.6 %	42.1 %	40.3 %	39.5 %	42.1 %
Diesel	27.3 %	42.8 %	41.9 %	41.4 %	42.8 %
Plug-in electric	0.1 %	15.1 %	17.8 %	19.1 %	15.1 %

Table 1 shows the costs of increasing the share of biofuels. Replacing a liter of gasoline with ethanol will reduce CO<sub>2</sub> emissions by 2.36 kg per liter at a cost of EUR 0.25 per kilogram of CO<sub>2</sub>. The corresponding cost for reducing CO<sub>2</sub> emissions by substituting HVO for diesel is EUR 0.24 per kilogram of CO<sub>2</sub>. This would be affordable if the supply of biofuels were abundant.

## 4. Results

In this section we present descriptive statistics for 2016, the effects on the car fleet in the reference scenario for 2030 compared with the actual car fleet in 2016 and in the policy scenarios, and distributional effects on the consumer side of the market from the 2030 scenarios. All effects on weight and energy type are presented in the shares of each vehicle type in 2030. Note that we also compare the results with the actual car fleet in 2016 to see the effect of the current policy but bear in mind that most uncertainties of our analysis are unpredictable exogenous changes in income, population and supply of new cars from during 2016 to 2030. Still, the comparisons across our scenarios in 2030 including the distributional effects are likely to be less uncertain. The results for the fuel tax scenario in 2030 are also compared with the short-term results for 2011 in [Eliasson et al. \(2018\)](#).

### 4.1. Descriptive statistics

The data on all individual adults and privately owned cars in 2016 are summarized with their means and standard deviations (not, however, for dummy variables as the standard deviations are then a function of the mean only) in [Table 2](#) and [Table 3](#). The descriptive statistics are classified into the three geographical residence areas, i.e. large cities, small cities, and rural areas. Note also that [Table 2](#) presents data about individuals, while [Table 3](#) presents data about cars.

We can see from the descriptive statistics that there are substantial differences across the geographical residence areas. The share of car owners is the largest in rural areas and smallest in large cities. The same pattern holds for those individuals who own more than one car. Furthermore, this pattern implies that total vehicle kilometers per individual are highest in rural areas and lowest in large cities. This relatively large difference is almost exclusively a result of different car-owning shares, as we can see that the vehicle kilometers *per car* ([Table 3](#)) are not that different across the geographical residence areas. Disposable income is the highest in large cities and lowest in small cities; so too is the employment status, while the distance to work, as expected, is the longest in rural areas.

In addition, car-level data show that the cars are heaviest in rural areas. Also, rural areas have the oldest cars and the highest share of diesel cars. The fuel consumption is strikingly similar across the geographical residence areas. Here, different forces move in opposite directions: more diesel cars in rural areas leads to lower fuel consumption, but this effect is offset by the heavier as well as older cars in rural areas.

### 4.2. Effects on car weights, driving distance, and emissions

#### 4.2.1. Change in car weight and energy type

The following effects on the weight distribution of the car fleet are estimated using only the car fleet model.

[Table 4](#) shows the distribution of car weight by energy type and scenario. Note that in the mandated biofuel blend scenario in which the prices of fuel and electricity develop in the same way as in the reference scenario, the car fleet will be the same as in the reference scenario. An important observation here is that the intensified bonus-malus scenario appears to slightly increase the tendency toward

**Table 6**  
Reduction of CO<sub>2</sub> emissions in the scenarios.

Time period	Reference scenario, 2030	Fuel tax scenario, 2030	Intensified bonus-malus scenario, 2030	Mandated fuel blend, 2030
2010–2016	16.0 %	16.0 %	16.0 %	16.0 %
2016–2030	24.2 %	51.9 %	28.0 %	24.2 %
2030–2030 (scenario difference)	–	36.4 %	5.0 %	0
2010–2030	36.4 %	59.6 %	39.5 %	36.4 %

heavier cars. This in itself increases energy consumption.

There are two main reasons for this increase in weight. The first is that for equally sized cars, a plug-in electric version is heavier. The second is the preference for larger cars (e.g. improved own safety and comfort), which is easier to satisfy when income increases. Table 4 also shows that the tendency toward heavier cars from 2016 to 2030 also holds for fossil-fuel-only cars, although this increase is lower than the increase in the entire car fleet.

Table 5 presents the distribution of cars in different energy source classes by scenarios. The ensuing effects on the distribution of the energy types in the car fleet are also estimated using only the car fleet model.

The speed of introduction of plug-in electric vehicles is similar in magnitude in the fuel tax and bonus-malus scenarios. As several predictions state that plug-in electric vehicles will dominate fossil-fuel cars from a lifecycle-cost perspective, the introduction of those cars may be considered slow. There are, however, reasons why the benefits of a fossil-fuel car could exceed those of a plug-in electric vehicle. Among those reasons are relatively quick refueling, nonexistent home charging infrastructure in apartment buildings, and difficulties driving with a trailer. In the mandated fuel blend scenario in which fuel or electricity prices do not develop differently from in the reference scenario, the car fleet will be the same as in the reference scenario.

#### 4.2.2. Reduction of CO<sub>2</sub> emissions

In Table 6 the effects on the CO<sub>2</sub> emissions in the scenarios are derived using the car fleet model, the car allocations to the population groups, and the elasticities of car use in the respective groups.

It can be noted that the relative reduction in the reference scenario in the six years from 2010 to 2016 is larger with an average per year of 2.9 % than in the 14 years from 2016 to 2030 when it is 2.0 %. We have no complete explanation for this somewhat surprising finding. The large shift from gasoline to diesel cars in this period is estimated to have contributed about 6 percentage units of reduction. The reduction of CO<sub>2</sub> emissions in the intensified bonus-malus scenario compared with the reference scenario is relatively small at around 5 %. In the fuel tax scenario, on the other hand, the reduction is about 36 %. This difference depends on the behavioral response in kilometers driven with respect to the price change of fuel in the fuel tax scenario. The intensified bonus-malus scenario has no fuel-price changes compared with the reference scenario and thus no decrease in car driving.

The reduction of CO<sub>2</sub> emissions from 2016 to 2030 in the reference scenario is estimated to be 24.2 %, while the reduction in the entire Swedish transport sector between 2010 and 2016 was 16.0 % (Swedish Environmental Protection Agency, 2019). We have only calculated the aggregate reduction of CO<sub>2</sub> emissions from 2016 to 2030 in the reference scenario (24.2 %). However, we have not explicitly analyzed the separate component effects of changes in income growth, energy prices, efficiency of new fossil-fuel cars, and replacement of fossil-fuel cars with electric cars due to energy-price changes, car prices, and the bonus-malus system. However, we can say something about these separate effects. First, fuel-price increases alone lead to a car-driving effect that is almost exactly offset by income growth. In addition, the share of electric cars is estimated to increase from 0.1 % to 15 % from 2016 to 2030. This contributes to a 12 % reduction of CO<sub>2</sub> emissions if we consider that some of these electric cars are plug-in hybrids that are partly powered by fossil fuels. The increased efficiency of fossil-fuel cars in the simulated car fleet during this period is predicted to be about 17 %, but note that this efficiency gain also implies a rebound effect of more driving as the price of driving decreases which is accounted for using the elasticity.

The total reduction of CO<sub>2</sub> emissions from 2010 to 2030 in the fuel tax scenario is about 60 %, while the reduction is about 40 % in the intensified bonus-malus scenario. The goal for the total domestic transport sector (excluding air transport) is to reduce CO<sub>2</sub> emissions by 70 % from 2010 to 2030, implying that the private car segment in Sweden is far from the goal in the intensified bonus-malus scenario taken in isolation but comes relatively close to the goal in the fuel tax scenario.

Note that benefit cars (used partly for private trips; see discussion in section 2.2) and cars owned and used by organizations are not included in the analysis. If such cars, on average, adapts faster to non-fossil-fuel cars than do the cars in the overall fleet, the reduction might be larger than shown in Table 6. On the other hand, these cars are not included in any of the analyzed car fleets, i.e. the 2016 data, reference scenario, and policy scenarios in 2030. Such cars might be, in relative terms, similar to the cars in the analyzed fleets in all of the scenarios.

Note that we have not modeled any population growth during the 2016–2030 period. Incorporating such effects may counteract part of the CO<sub>2</sub>-emission reductions estimated in the analysis. If we would underestimate the CO<sub>2</sub> reduction by not including benefit cars, this underestimation might be offset by the population increase.

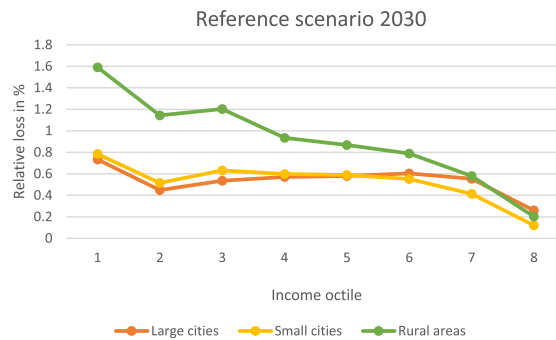
#### 4.2.3. Change in average vehicle kilometers

Table 7 presents the average vehicle kilometers per car for different energy types and scenarios. Here we can see that the behavioral

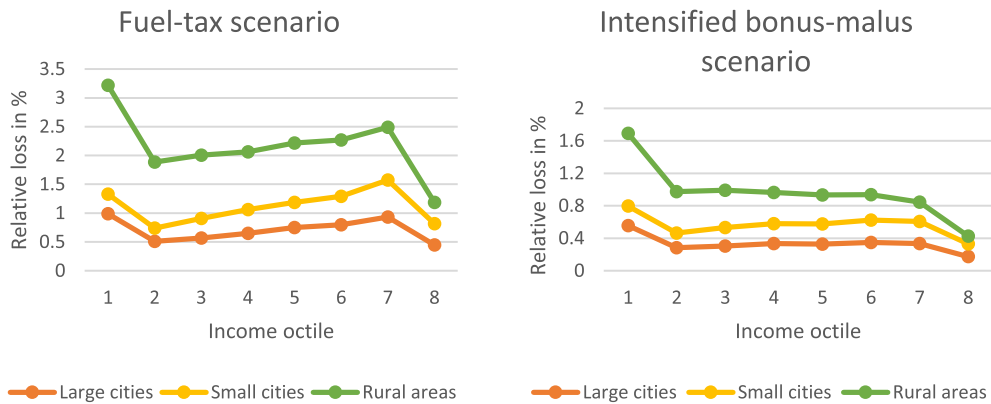
**Table 7**

Average driven distance per year for each car-energy type in each scenario, given in kilometers.

Driven distance	2016	Reference scenario, 2030	Fuel tax scenario, 2030	Intensified bonus-malus scenario, 2030	Mandated fuel blend, 2030
Gasoline	11,109	11,310	7106	11,310	11,310
Diesel	14,971	14,752	8760	14,752	14,752
Plug-in electric	12,313	13,838	13,317	13,838	13,838



**Fig. 1.** Loss of consumer surplus, given in percent of disposable income.



**Fig. 2.** Loss of consumer surplus, given in percent of disposable income.

effects are small in the reference and the intensified bonus-malus scenarios. Regarding the fuel tax scenario, on the other hand, the decrease for fossil-fueled cars is substantial. Note that there is also a small decrease in the electric and plug-in hybrid category in the fuel tax scenario compared with the reference scenario, because plug-in hybrids partly use fossil fuel.

4.3. Estimates of welfare distributional effects

The following calculations of consumer surplus losses relative to disposable income are given for each population group. First, we present a comparison of the reference scenario of 2030 with the state as of 2016, then a comparison of distributional effects across the two car tax policies compared with the reference scenario. In all comparisons for all income groups and geographical residence areas, we present the *difference between the average welfare cost per individual in a policy scenario and the average welfare cost in the reference scenario given in percent of disposable income per individual*. Note that the y-axis scale is not the same in all the figures.

In Fig. 1, we can see the distributional effects for the reference scenario of 2030 compared with 2016. The effects therefore reflect current policy, including a yearly tax increase on fuel and the implemented bonus-malus system. Note that these estimated distributional effects hinge on further assumptions that are not needed when we make comparisons across the 2030 scenarios. First, we have no access to car prices for the 2016 car fleet. As the price changes for new fossil-fueled cars between 2016 and 2030 are assumed to be relatively small, we use the price of the oldest cars in 2030 as the price for all age classes in 2016. The procedure for plug-in electric cars in 2016 is the same, but this will not be important for the analysis as the share of these cars is only 0.1 % of the fleet in 2016. In addition, we have no access to the fixed circulation tax in our 2016 car data. Here we simply assume the same tax as in the reference scenario of 2030.

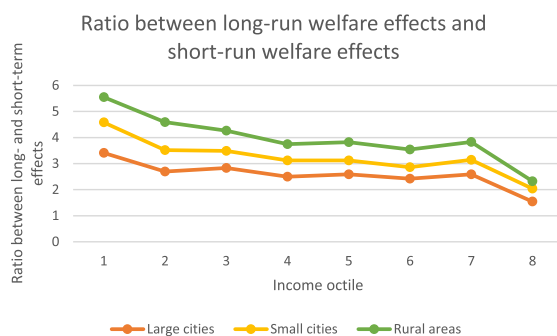


Fig. 3. Comparison of long- and short-term distributional effects.

Table 8

Suits index for both policies and all geographical areas.

	Fuel tax scenario, 2030			Intensified bonus-malus scenario, 2030		
	Large cities	Small cities	Rural areas	Large cities	Small cities	Rural areas
Income octiles 2–8	-0.056	-0.019	-0.096	-0.117	-0.090	-0.161
Income octiles 2–7	0.105	0.121	0.049	0.023	0.036	-0.029

The Fig. 1 results could be summarized in two statements: the loss in relative consumer surplus decreases with income, and the loss in consumer surplus is higher for rural than urban residents, especially in the lower part of the income distribution. These results indicate that the adjustment to a less fossil-fuel-dependent car fleet is easier for high-income earners than for low-income earners, and, except for the two highest income groups, easier for residents of cities than rural areas. The differences across the population groups are relatively large, showing that the 15 % share of plug-in cars in 2030 is distributed mainly among the highest income octiles. The burden of the path toward a less CO<sub>2</sub> emitting car fleet is thus carried mainly by low-income earners, especially in rural areas.

In Fig. 2, the welfare losses of the two *tax policies* are compared with those of the reference scenario. The consumer welfare losses in the fuel tax scenario are generally higher than those in the intensified bonus-malus scenario. Still, we also need to consider the larger decrease in CO<sub>2</sub> emissions in the fuel tax scenario (see Table 6). If we calculate the total *consumer* welfare loss in each scenario and divide this by the reduction of CO<sub>2</sub> emissions, the result per kg of CO<sub>2</sub> is about EUR 0.90 for the fuel tax scenario and about EUR 2.80 for the intensified bonus-malus scenario. This indicates that the welfare loss for consumers per unit decrease in CO<sub>2</sub> emission is larger in the intensified bonus-malus system.

We can also observe several important findings from the pattern of the figures, which largely parallel the short-term results of car-tax policies examined by Eliasson et al. (2018):

- The welfare loss is highest for people living in rural areas, followed by people living in small cities. Inhabitants in large cities suffer the lowest welfare loss.
- Over the whole income distribution, the effects of both policies are regressive. In most of the geographical areas in both scenarios, the policies are progressive in the octile 2–7 income interval. The exception is rural areas in the intensified bonus-malus scenario, in which the relative welfare costs decrease slightly with income. In general, the fuel tax scenario seems to be less regressive than the intensified bonus-malus scenario. See more about this in the discussion of the Suits index (Suits, 1977) below.
- The results for income octile 1 should be interpreted with caution. The consumption level of these individuals frequently lies well above reported income, where possible explanations among others are that they might be young adults living with their parents or that they do not declare their full income to the tax authorities.
- Individuals in income octile 8 have the lowest relative welfare loss, defined as the ratio of welfare loss to disposable income (except for small cities in the fuel tax scenario, in which octile 2 has a slightly lower welfare loss). Also, this result is similar to that of Eliasson et al. (2018), but the effect in the present long-term analysis is larger. The distribution within this octile warrants a further description. In contrast to all other octiles the distribution in this octile is highly skewed, with many individuals lying in the lower part of this octiles income interval and few with very high incomes, making the average much higher than the median. When car type and car use change over time, high-income individuals will adapt more easily as they can afford to pay for a car that costs more to buy but costs less to drive. Besides that, they may also benefit from the subsidies of such cars in a bonus-malus system.

To this end, Fig. 3 presents a comparison of the distributional effects of the fuel price scenario of this study and of the 10 % fuel tax increase of Eliasson et al. (2018). This is done by calculating the welfare loss ratios. Here we can see that the ratio clearly tends to decrease both with income and with the degree of urbanization of the geographical residence area. This implies that, in the long term, individuals with higher incomes and inhabitants in urban areas appear to have more opportunities to adapt and avoid welfare costs from car tax policies.

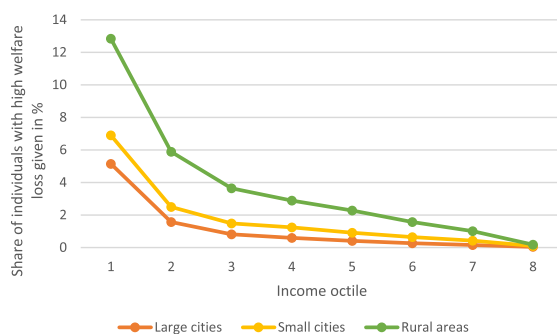


Fig. 4. Share in percent of individuals with a relative welfare loss exceeding 8% in the fuel tax scenario.

In addition, we measure the progressivity of the policies using the Suits index (Suits, 1977), which is related to both the Gini and the Kakwani indexes. This index has been used in several studies of fuel taxes (e.g. Sterner 2012b, Eliasson et al. 2018, Tirkaso & Gren 2020). A flat-rate policy has a Suits index value of 0, a regressive policy has a negative Suits index, and a progressive policy a positive index; the index ranges between  $-1$  and  $1$ . Table 8 shows the results of two Suits index calculations for two octile selections from the population. We have excluded income octile 1 and present the index both including and excluding income octile 8. In general, the policies are regressive when income octile 8 is included, but most of them are progressive in the octile 2–7 interval. Importantly, the intensified bonus-malus scenario is clearly more regressive than the fuel tax scenario. In fact, the intensified bonus-malus scenario is regressive in rural areas even in the octile 2–7 interval. Our conclusion is that for most individuals welfare burdens from the two tax instruments increase with income. The overall distributional effects is however regressive as very high income earners are little affected.

Compared with the short-term analysis of the distributional effects of a 10 % fuel tax increase by Eliasson et al. (2018), our analysis shows a more regressive outcome of the policies. This follows from the fact that subsidies of new cars (the bonus in the bonus-malus system) and adaptation to higher gasoline and diesel prices by buying a more efficient and/or electric car are both more accessible for individuals with high disposable income.

As noted above, employer-provided benefit cars that are partly used for private trips are not included in the analysis. This type of benefit is highly skewed toward the highest income octiles, as the tax deduction depends on the marginal rate of income tax, which is higher for higher incomes. As a relatively simple calculation example of how large this effect might be, we start by noting that about 5 % of individuals in the 7th octile and about 20 % in the 8th octile have access to a benefit car. Assuming that 60 % of these cars (which are nearly always under three years old) are fossil-fuel cars and that these are driven relatively long distances, the increased relative welfare loss in the fuel tax scenario for the highest income octile is calculated to change by 0.08–0.21 percentage points (depending on the geographical residence area). In the 7th octile, the effect is a lower increase by 0.02–0.05 percentage points. In reality, these effects are likely to be lower, as these company cars will even more likely be electric cars and plug-in hybrid cars than will privately owned cars. In the intensified bonus-malus system, the effect is assumed to be even lower, as most of these cars are expected to be cars receiving bonuses. The effect of not including company cars used for private trips in our analysis is therefore assessed to be small.

Moving away from average analysis only, we calculate the share of each population group that has a welfare loss exceeding 8 % of disposable income in the fuel tax scenario. Here again we use the group-specific average fuel consumption and elasticity of driving distance with respect to fuel price. The fuel price used is a weighted average of the gasoline price and diesel price with respect to the distribution of gasoline and diesel cars in the total car fleet in this policy scenario. To find differences on the population-group level, we use the population group driving distance in 2016 to estimate the driving distance in the fuel tax scenario of 2030. Note also that we do not include fixed car costs, as we do not have an individual car choice sub-model.

The result of this analysis is presented in Fig. 4. We can see that the share of the population group with large relative welfare losses is higher the lower the income is. Furthermore, the share decreases rapidly with income and approaches zero in income octile 6 in urban areas and in the highest income octile in rural areas. In addition, the share is the largest in rural rather than urban areas, where the difference between small and large cities is relatively small.

#### 4.4. Sensitivity analyses

We have done two sensitivity analyses. Changes in the assumed depreciation rate of cars only leads to very small changes in the welfare losses. In addition, we have assumed a much lower elasticity of car use with respect to energy price. The conclusion is that the results are very sensitive to the assumption of elasticity and it is not the levels per se but the direction of the effects that matter. Lower elasticity implies more regressive effects, while higher elasticity implies less regressive effects. Another important result from assuming a smaller behavioral response to fuel-price increases is that the reduction of CO<sub>2</sub> emissions will be dramatically lower than shown in Table 5.

**Table A1**

Official growth scenario exogenous variables from Swedish Transport Administration (2018); fuel prices are changed from the reference scenario to the fuel tax scenario.

Year	Reference and intensified bonus-malus system				Price changes in the fuel tax scenario	
	Income growth	Gasoline price	Diesel price	Electricity price	Gasoline price	Diesel price
2016	1.5	13.20	12.80	1.2	13.20	12.80
2017	1.5	15.13	15.26	1.2	15.13	15.26
2018	1.5	15.37	15.52	1.2	15.37	15.52
2019	1.5	15.62	15.78	1.2	15.62	15.78
2020	1.5	15.86	16.03	1.2	23.79	24.05
2021	1.5	16.11	16.29	1.3	24.17	24.44
2022	1.5	16.13	16.31	1.3	24.20	24.47
2023	1.5	16.17	16.35	1.3	24.26	24.53
2024	1.5	16.21	16.39	1.3	24.32	24.59
2025	1.5	16.27	16.46	1.3	24.41	24.69
2026	1.5	16.35	16.54	1.3	24.53	24.81
2027	1.5	16.47	16.67	1.3	24.71	25.01
2028	1.5	16.68	16.88	1.4	25.02	25.32
2029	1.5	17.09	17.31	1.4	25.64	25.97
2030	1.5	18.31	18.58	1.4	27.47	27.87

**Table A2**

Car-use elasticities with respect to fuel prices.

	Inc 1	Inc 2	Inc 3	Inc 4	Inc 5	Inc 6	Inc 7	Inc 8
Large cities	-0.58	-0.58	-0.57	-0.57	-0.53	-0.53	-0.34	-0.34
Small cities	-0.58	-0.58	-0.57	-0.57	-0.53	-0.53	-0.34	-0.34
Rural areas	-0.42	-0.41	-0.41	-0.41	-0.37	-0.37	-0.18	-0.18

**Table A3**

Car-use elasticities with respect to fuel prices: assumption with lower behavioral response.

	Inc 1	Inc 2	Inc 3	Inc 4	Inc 5	Inc 6	Inc 7	Inc 8
Large cities	-0.10	-0.09	-0.08	-0.07	-0.06	-0.05	-0.04	-0.03
Small cities	-0.09	-0.08	-0.07	-0.06	-0.05	-0.04	-0.03	-0.02
Rural areas	-0.08	-0.07	-0.06	-0.05	-0.04	-0.03	-0.02	-0.01

**Table A4**

Adjustments of declared fuel consumption in the car fleet of 2016.

Age class	Car construction year	Adjustment factor
1	1998	1.07
2	2005	1.14
3	2009	1.19
4	2013	1.26

## 5. Discussion

This analysis has both important strengths and some limitations. One important strength is that the analysis is based on models of actual choices of car attributes, allowing for a model-based representation of future car-type choices. The analysis also uses detailed data on incomes, geographical residence areas, car ownership, and car use for *all* adult Swedes in 2016. This allows for a highly differentiated and geographically resolved representation of policy effects. In the analysis, however, we abstract from the development of the population, residence, individual car ownership, and differentiated income growth. This can be justified, as we can distinguish how groups of individuals with different income levels and different residential area types, are affected differently by the policy instruments.

There are eight limitations of our modelling approach worth mentioning. First, there is considerable uncertainty about the development of the technology of new cars arriving at the market. Second, the car choice and use of cars owned by companies and organizations are not considered in the analysis. Third, the car supply is not endogenous, and there could be substantial adaptations in terms of what cars are and are not supplied and the prices at which they are sold in response to policy and demand change. Fourth, recent studies (Jacobsen and Benthem, 2015; Bento et al., 2018a) have shown that policies have a significant impact on used car prices

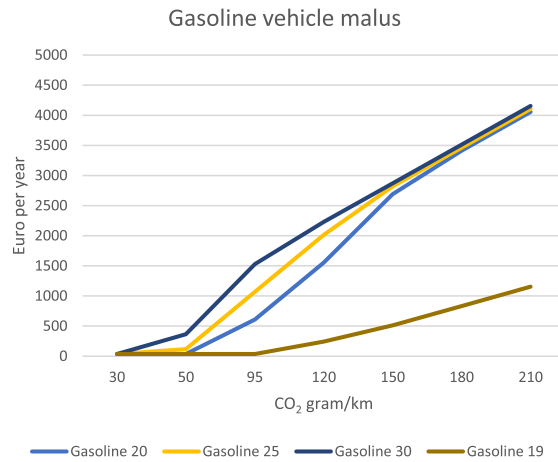


Fig. A1. Gasoline vehicle malus, Euro per year the three first years depending on CO<sub>2</sub> emission.

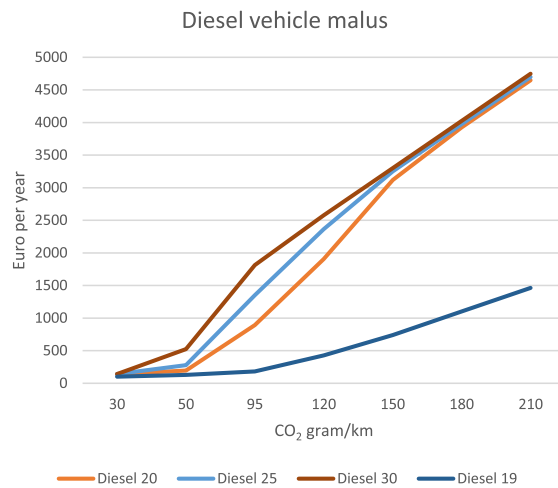


Fig. A2. Diesel vehicle malus, Euro per year the three first years depending on CO<sub>2</sub> emission.

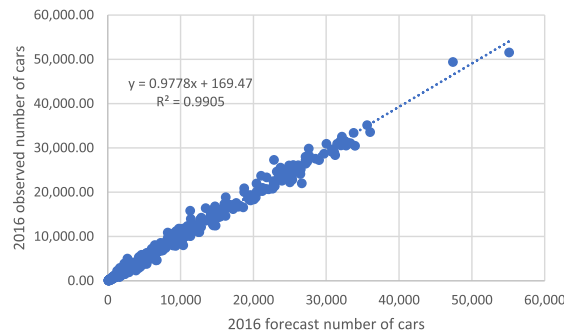
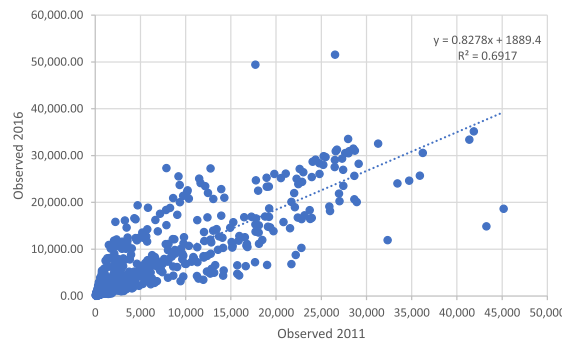
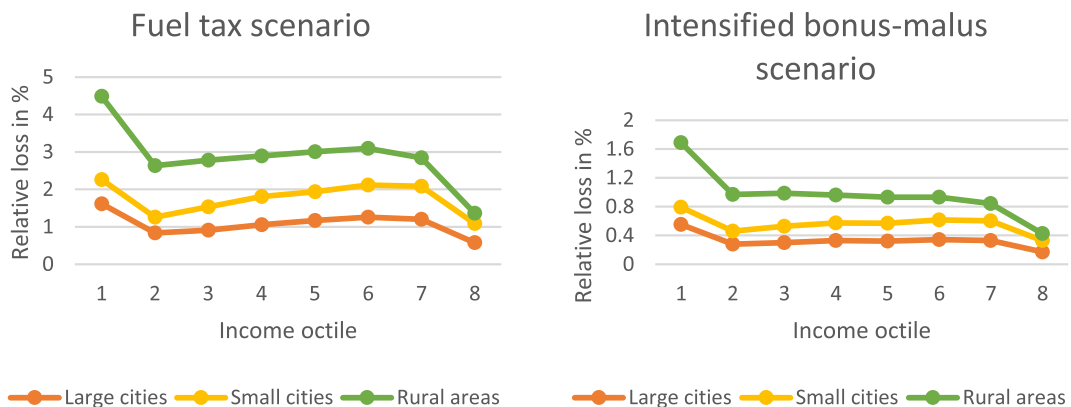


Fig. A3. Scatter plot for relative number of cars in 2016 normed to the total number in 2011 by car type and population group and the forecasted distribution using the 2011 distribution.

and scrapping, and these effects are not considered in this analysis. Fifth, neither imports nor exports of used cars are considered. Our assessment is that the current fast-growing export of electric cars could have a significant but uncertain effect on both the CO<sub>2</sub> emissions and welfare effects calculated here. Sixth, driven distance could have been added in a simultaneous analysis together with income and residential area type. Seventh, the covariation of car use fixed costs with car type and its influence on welfare distribution has not been analyzed. Eighth, it is conceivable that the life span of a car is affected by engine type and driven distance.



**Fig. A4.** Comparison of observed number of cars by category and population group 2011 and 2016, The comparison shows that the IPF forecast does much better than just assuming the same distribution.



**Fig. A5.** Distributional effects with the assumption of lower elasticity of car use with respect to fuel price.

Further policy instruments also affect the choice of car and car use, for example, the tax deductions granted for benefit cars provided by employers and tax deductions for commuting. These instruments are likely to substantially influence the mode choice and vehicle type for commuting.

As far as we know, there are no modeling results for the markets for new and used cars in Sweden. Therefore, there are no endogenous prices for cars and the effects of policies on, for example, used car prices and decisions to scrap cars are not considered.

Independently of whether or not the markets for new and used cars are modeled, important uncertainties are associated with the forecasted future. These concern the implementation and outcome of current policies and the introduction of new policies. The prices of energy and the future production costs of, for example, batteries are also uncertain. The elasticities of driving distance with respect to energy price is assumed to be constant and is applied well outside the intervals in which they were estimated.

Given these limitations our projections should not be interpreted as forecasts for what could be the actual outcome. The limitations suggest some possible unexpected or unmodelled effects. The development of competitive fossil free technologies may be both faster and slower. Concerns for the regressive distributional effects of policies may lead reluctance to implement and therefore slower introduction of plug-in electric cars. A faster introduction to lower costs for low-emission cars can reduce demand and prices for used cars and lead to faster scrapping of inefficient cars.

Although these results are for Sweden we would like to point to the generalizability of the results. First, we would remind the reader of the parallel results presented in the short literature review. Among these observations we find fuel taxes to be the most effective (e.g. Grigolon et al. 2018), that annual car taxes, if not carefully designed, may have small or even adverse effects (eg. Klier and Linn, 2015). So even if there may be further causal channels than we have modelled we believe we have both presented new and confirmed known effects.

Low-income earners in rural areas bear the largest burden imposed by the analyzed policies. One way to compensate low-income earners in rural areas would be to give subsidies to low-income car owners in rural areas. A hypothetical policy would be to compensate the car owners in octiles 1–4 in rural areas. The adult inhabitants in rural areas with disposable incomes in octiles 1–4 represent about 10 % of the total population; of these, 44 % are car owners. This means that the target group for compensation in this case would be about 4.4 % of the total population. Now, consider such compensation in the fuel tax scenario. The average total welfare loss from the tax increase in the group of car owners in rural areas with disposable incomes below the national median is about EUR 770 per individual and year. If we compensate this group for the difference from the average welfare loss of corresponding individuals in small cities, the subsidy would be EUR 270 per car owner, which would cost EUR 96 million. Compared with the increased tax revenue due to

the tax increase, which is about EUR 300 million, this compensation could be afforded by Swedish citizens if they want to decrease CO<sub>2</sub> emissions. This calculation does not consider the redistributive benefits or the administrative costs for the government.

## 6. Conclusions

The acceptability of policies to reduce CO<sub>2</sub> emissions is an increasingly important issue, and distributional effects are central to assessing the acceptability of such policies. There are widespread concerns that policies may have unwanted distributional consequences, such as unfairly burdening rural residents more than urban residents. We analyze the modelled distributional effects, from the change in car type and car use to three car-related policy instruments intended to reduce CO<sub>2</sub> emissions: increased fossil-fuel taxes, an intensified bonus-malus system for new cars, and increased mandated biofuel blending. This analysis is based on both the previously developed car fleet model and on methods for analyzing the distributional effects of car taxes using data from Swedish administrative registers covering all adults and all private cars.

There are five important observations on the distributional effects of the policies. First, the reference scenario in 2030 poses increasing burdens on all groups compared to 2016 and mostly for low-income groups residing in rural areas. Second, the fuel tax and the intensified bonus-malus scenarios impose further burdens compared to the reference scenario. The fraction of each population group incurring substantial welfare losses is higher the lower the income. Third, compared with the short-term effects, the highest-income group can mitigate more of the welfare costs by adapting their car choice, as most of the new cars are acquired by high-income earners. Fourth, in the geographical dimension, in all scenarios, rural areas bear the largest burden, smaller urban areas the second largest burden, and the largest urban areas the smallest burden. Thus, individuals with high incomes and inhabitants in urban areas appear to have more opportunities to adapt and avoid welfare losses. An important conclusion is therefore that even with a fast introduction of plug-in electric vehicles many fossil cars will remain, and this will have important distributional consequences. This conclusion is not sensitive to moderate changes in the speed of the introduction of plug-in electric cars but sensitive to the choice of policy instrument (Habibi et al. 2019). Fifth, the bonus-malus system is even slightly more regressive than the fuel tax, implying that the bonus-malus system performs worse than the fuel tax regarding both decreased CO<sub>2</sub> emissions - as it does not affect car use - and the distributional consequences as it subsidizes high-income individuals buying new cars. We expect all these patterns to be generalizable over income and similar area types in developed countries.

The burden of the path toward a less CO<sub>2</sub> emitting car fleet is carried mostly by low-income earners, especially in rural areas, which opens for more important research in this field with the following possible directions for such research. Available data in Sweden now allows for extensive update of the analysis of the elasticity of driving with respect to several important factors. Differences in current consumption of driving distance is likely to have effects on car choice and car use. Tax rebates for the acquisition of cars to be used in conjunction with work have important effects on secondhand markets. Engine type and driving distance are also likely to influence the life length of a vehicle. Postponing scrapping has been shown to have large effects on car ownership.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgements

The comments of Björn Carlén who reviewed the paper at a seminar at VTI and the reference group members as well as funding from Trafikverket (the Swedish Transport Administration) are gratefully acknowledged. We are also grateful for the comments from anonymous reviewers for many good suggestions.

## Appendix

See [Table A1-A4](#).

### Graphs for bonus-malus effects

The bonus-malus effects can be illustrated in the following graphs. [Fig. A1](#) shows the malus for gasoline cars for the current situation (Gasoline 19) and for the intensified stages of 2020, 2025, and 2030; [Fig. A2](#) shows the same for diesel cars. As is obvious from the figures, the intensified malus becomes quite large for big emitters. One should keep in mind that the maluses will to some extent be offset by the increase in fuel efficiency that is assumed to occur over time.

### Validation of the iterative proportion fitting method

The iterative proportion fitting process may be considered as a very simple method to distribute car types to different population groups. Thus, we conducted the following procedure to validate this method. We used the distribution of cars by car types (age, weight and energy type) in 2016 and distributed them to different population groups according to the distribution in 2011 by car type and population group, using IPF algorithm. This distribution is compared to the true distribution in 2016, in relative terms by ignoring the growth in total number of cars. This allows us to create a scatter diagram with pairs of numbers for each combination of car type and population group for true value and forecasted value.

As can be seen in [Fig. A3](#), forecasted and observed values match well, which indicates that the iterative proportion fitting of cars to different population groups only has small errors. However, we have only used fossil-fuel cars and in the 2030 forecast we use the

process to also include BEV and PHEV cars, which are relatively rare in 2016 (and certainly in 2011, which is why we did not include such cars in the validation test described here). How well such an inclusion performs is however difficult to validate because of lack of observations.

Another reason for a good match would be that the distribution changes very little. To investigate this possibility, we also compared the 2011 observed data to the 2016 observed data. Fig. A4 depicts a scattergram based on these two datasets.

#### Sensitivity analysis with respect to depreciation rate

We have assumed a fixed yearly depreciation rate of 15 % of current value for cars. Here, this assumption is changed both to a lower depreciation rate of 10 % and a higher depreciation rate of 20 %. The assumed changes in depreciation rate lead to very small changes in the estimated welfare losses, and even more importantly, the pattern in the figures is almost completely the same (figures not shown). The latter suggests that the assumed (constant) depreciation rate is relatively unimportant for the outcome of the analysis. However, if we had been able to model different depreciation rates for different car types and/or policy scenarios, this might have influenced the results of our analysis (cf. Jacobsen and Benthem, 2015; Bento et al., 2018a).

#### Sensitivity analysis with respect to elasticity of demand for driving distance

When the assumed elasticity of car use with respect to energy price is lower, namely, in the range of  $-0.01$  to  $-0.10$  (see Table A3 above), we can see in Fig. A5 that the intensified bonus-malus scenario remains more or less unchanged, which is completely as expected. In the fuel tax scenario, this lower elasticity assumption seems to make the policy slightly more regressive, especially in the rural areas. This is also confirmed by the Suits index (not shown). Furthermore, the consumer welfare losses increase substantially when we assume a smaller reduction in car use when fossil fuel prices increase.

However, the most important result from assuming a smaller behavioral response to fuel-price increases is that the reduction of CO<sub>2</sub> emissions will be dramatically lower than shown in Table 5. Here, the CO<sub>2</sub> emissions are estimated to be reduced by only 6.6 % in the scenario with increased fuel prices. This highlights the importance of the assumed behavioral response in terms of car use to policies for reaching ambitious CO<sub>2</sub>-emission goals. Finally, note also that the predicted reduction of CO<sub>2</sub> emissions between 2016 and 2030 in the reference scenario is strongly dependent on behavioral changes, as the real prices of gasoline and diesel also increase during this period. The decrease in CO<sub>2</sub> emissions with the assumption of low elasticity is only about 11 % compared with 24 % with the baseline-assumption elasticities. With the assumption of lower elasticity of car driving with respect to fuel price, the reduction of CO<sub>2</sub> emissions in the fuel tax scenario is estimated to be about 30 % from 2010 to 2030 instead of about 60 % with the baseline assumption of elasticities.

#### Formulae for calculating welfare costs

The description in sub section 2.2.3 is leading us to the formula for calculating the total welfare cost, *TWC*, for population group *j* in a policy scenario, *pol*:

$$TWC_j = \sum_{i=1}^{36} n_{i,j} * ((FC_{pol,i} - FC_{ref,i}) + (KMC_{pol,i} - KMC_{ref,i}) * DD_{pol,ij} + (KMC_{pol,i} - KMC_{ref,i}) * (DD_{ref,ij} - DD_{pol,ij}) * 0.5) \quad (1)$$

where *n* denotes the number of cars, *FC* the fixed cost, *i* each car type, *KMC* the cost per kilometer of driving a given car type based on the declared energy consumption and predicted real energy price, and *DD* the yearly driving distance per car. As noted by Eq. (1), the welfare cost in our model is dependent on differences in car types through fixed costs and driving cost per kilometer, and the driving distance which is specific for each combination of population group and car type.

*FC* is given by:

$$FC_i = CT_i + P_i * DF_i + 0.035 * CV_i \quad (2)$$

where *CT* denotes the yearly fixed circulation tax (including the malus when appropriate), *P* the price of the car as new (including the bonus when appropriate), *DF* the depreciation factor, and *CV* the current value of the car. The capital cost is the product of the assumed interest rate of 3.5 % and the current value. The current value of the car is calculated by multiplying the price by the depreciation factor, *P\*DF*. The depreciation factor is dependent solely on the car age, *age*, according to the formula:

$$DF_i = 0.85^{(age_i - 0.5)} - 0.85^{(age_i + 0.5)} \quad (3)$$

This means that we assume that the depreciation cost is always 15 % of the current value of the car.

The driving distance is specific for each population group (*j*) and car type (*i*), with 2016 as the basis given by the actual average for each population group and car type. For the reference scenario and the policy scenarios in 2030 (here denoted *pol*), the driving distance is given by:

$$DD_{pol,ij} = \left( DD_{2016,ij} + \left( \frac{EP_{pol}}{EP_{2016}} - 1 \right) * \epsilon_j * DD_{2016,ij} \right) * 1.232 \quad (4)$$

where  $\epsilon$  denotes the elasticity (see Table A2 in the Appendix) and *EP* the energy price. The number 1.232 represents the income growth in all scenarios.

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