

Contents lists available at [ScienceDirect](https://www.sciencedirect.com)

# Transportation Research Part D

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

## Vehicle choices and urban transport externalities. Are Norwegian policy makers getting it right?

Paal Brevik Wangsness<sup>a,c,\*</sup>, Stef Proost<sup>b</sup>, Kenneth Løvold Rødseth<sup>a</sup><sup>a</sup> Institute of Transport Economics – Norwegian Centre for Transport Research, Gaustadalleen 21, 0349 Oslo, Norway<sup>b</sup> Department of Economics-KULeuven, Naamse Straat 69, 3000 Leuven, Belgium<sup>c</sup> School of Economics and Business, Norwegian University of Life Sciences, Ås, Norway

### ARTICLE INFO

#### Keywords:

Electric vehicles  
Climate policy  
Urban transport policy  
Transport modeling

### ABSTRACT

Norway has the world's highest share of battery electric vehicles (BEVs) in its passenger car fleet, thanks to a set of policies that has included high purchase taxes for fossil fueled cars, and no tolls, no VAT, and free parking for BEVs. This paper uses a very stylized transport model for the greater Oslo area to give insights into the effects of different transport policies. With this model we go beyond the market penetration studies for EVs, as it brings together both car choice and transport patterns with mode choice for a set of heterogeneous representative model agents. We illustrate the possible effects of current policies on congestion, CO<sub>2</sub> emissions and other urban transport externalities, public transport use and crowding, tax revenues and welfare. On this basis, we explore other road toll, public transport fare and tax policies that can lead to better outcomes for the Oslo transport market while still respecting the CO<sub>2</sub>-cap that reflects the goals of Norwegian policy makers.

### 1. Introduction

Enforced in 2016, the Paris agreement responds to the pressing threat of climate change, aiming to limit the global temperature increase this century to well below 2 °C above pre-industrial levels. Being one of the top polluters, with about a quarter of global energy-related greenhouse gas emissions attributed to it ([International Energy Agency, 2017](#)), the transport sector is required to deliver major emissions reductions to achieve this target, and electrification could play an important role ([International Energy Agency, 2017](#)). In June 2017, the Clean Energy Ministerial launched its EV30@30 campaign that aims for a 30% sales share for Electric Vehicles (EVs) by 2030. Both the UK and France have announced plans that by 2040, there will be no more sales of new conventional diesel and petrol cars (Internal combustion engine vehicles – ICEVs).

Norway has the highest penetration of EVs worldwide, making it much like a social experiment to examine the results of EV-friendly policies. By the end of 2018, this country with 5.3 million inhabitants had about 190,000 battery electric vehicles (BEVs) and 90,000 plug-in hybrids (PHEVs) driving on its roads. In 2018, the market share of all new private cars were 31% and 17% for BEVs and PHEVs, respectively ([Norwegian Electric Vehicle Association, 2019](#)). The highest market share is found in and around the big cities. In Oslo, the capital, BEVs share of the car fleet was 12.8% in 2018, and about 40% of new personal cars were BEVs (*ibid*).

The rising market share for EVs in Norway is largely a result of policy,<sup>1</sup> and is in accordance with the government's National

\* Corresponding author at: Institute of Transport Economics – Norwegian Centre for Transport Research, Gaustadalleen 21, 0349 Oslo, Norway.  
E-mail address: [pbw@toi.no](mailto:pbw@toi.no) (P.B. Wangsness).

<sup>1</sup> It also helps that electricity prices in Norway are among the cheapest in Europe ([Figenbaum et al., 2019](#)), largely as a result of abundant hydropower resources, which generated about 96% of the country's electricity in 2015 ([IEA, 2017](#)).

<https://doi.org/10.1016/j.trd.2020.102384>

Transport Plan (NTP<sup>2</sup>). The overall goal of the NTP is to develop “a transport system that is safe, promotes economic growth, and contributes to the transition into a low-emission society”.

The NTP proposes a climate strategy to halve the transport sector’s greenhouse gas emissions. The NTP recommends that all new passenger cars, light commercial vans and city buses are zero emissions vehicles by 2025. The NTP also includes the government’s zero-growth objective, which states that the growth in passenger transport in urban areas should be facilitated by means of walking, cycling, and PT, and subsequently zero growth in car transport.

Several BEV-friendly policies have been implemented since the 1990s. The most notable ones are 1) exemption from VAT, 2) exemption from registration tax (since the registration tax is largely a function of type-approved carbon dioxide (CO<sub>2</sub>) emissions, the registration tax would be zero for most BEVs even without the exemption), 3) exemption from road tolls, 4) access to bus lanes, and 5) free municipal parking. Some of these policies have been moderated in recent years, as the BEV share of the car fleet has grown relatively large. For a more comprehensive review of Norwegian BEV-friendly policies, see [Figenbaum et al. \(2015\)](#).

In addition to the national ambitions for reducing CO<sub>2</sub> emissions, there are local ambitions. The city of Oslo and the county of Akershus, who together broadly make up the Oslo metropolitan area, have ambitions that surpass the national target. Oslo has a goal of bringing down CO<sub>2</sub> emissions by 50% by 2020 ([Oslo Municipality, 2016](#)). Similarly, Akershus has a target of a 50% emissions reduction by 2030 ([Akershus County Council, 2016](#)).

In this paper we take a broader look at the EV question by considering multiple market failures in urban transport and their policy implications. The key research questions we address are the following: Which policies will be the most welfare-enhancing in the urban transport system with multiple market failures (e.g., congestion, accidents, local air pollution and CO<sub>2</sub> emissions), and what role can BEVs play in achieving these policies? What characterizes the potential conflicts between welfare maximization and reaching the targets for reducing CO<sub>2</sub> emissions (where the promotion of BEVs is a key instrument) and car transport volumes in the greater Oslo area? Furthermore, what trade-offs do we see between efficiency and acceptability? To answer these questions, we develop a stylized transport model that covers passenger transport in the Oslo metropolitan area, an urban area with approximately 1.2 million inhabitants.

While the modeling approach draws on [Börjesson et al. \(2017\)](#), our paper provides three key extensions to the framework, most notably multiple heterogeneous representative agents, a car choice module, and a more comprehensive set of transport patterns as occasional long car trips are included in addition to short daily trips by car and public transport (PT). Also, instead of being based on the length of a standardized trip, the agents in this model are calibrated on large sample travel survey data from the inhabitants of the Oslo metropolitan area. The prime purpose of this model is to look into the interactions between combinations of policies and inhabitants’ car purchase, car use, public transport use and urban externalities. As far as we know this is the first paper putting all these elements together in a fully transparent model where all effects can be checked and policies can be optimized in terms of welfare and/or reaching climate goals. Our model gives a very simplified but complete description of the urban transport market equilibrium, both with regard to transport patterns and car ownership. The main simplifications are the small number of representative agents and the car choices they can make. Despite these simplifications, the model allows us to analyze how different types of agents may respond to different transport policies. This approach also allows us to study how costs and benefits of policies are distributed among agents. This distribution is key to understanding political feasibility.

Among other things, our simplified model shows that the welfare-maximizing urban transport policies in the greater Oslo area, at the recommended national reference value of CO<sub>2</sub>,<sup>3</sup> lead to very small emissions reductions. Policies for achieving the ambitious goals of halving the emissions from personal transport may bring about substantial welfare costs. These costs accrue mainly through the higher resource costs of BEVs and PHEVs, which play a crucial role in reaching ambitious emissions reductions.

As this paper is very policy-oriented, we have sought feedback from stakeholders in government agencies who advise policy makers. Earlier versions of the model and preliminary results have been presented and discussed at seminars at the Norwegian Public Roads Administration and the Ministry of Transport. The stakeholders mentioned in the Acknowledgements have also been presented an earlier version of this paper.

[Section 2](#) presents a schematic analysis of how the promotion of BEVs affect congestion and other urban transport externalities. [Section 3](#) discusses briefly the literature on EVs and reviews their potential role in policies for curbing CO<sub>2</sub> emissions and externalities from urban transport. [Section 4](#) presents the model. [Section 5](#) analyzes the model results, while [Section 6](#) provides discussion, caveats and conclusions.

## 2. How does the promotion of BEVs affect congestion and other urban transport externalities?

The various BEV-friendly policies described in the previous section, can give rise to policy goal conflicts. Before we introduce the urban transport model in [Section 4](#), we illustrate some of these conflicts that arise from different policy instruments using a highly stylized textbook case. Consider [Fig. 1](#), where a fixed number of commuting trips are made to the city center and the population has the choice between using a car or public transport (PT). The average generalized cost of car use is upward sloping as the time cost

<sup>2</sup> <https://www.regjeringen.no/no/tema/transport-og-kommunikasjon/nasjonal-transportplan/id2475111/>.

<sup>3</sup> The Green Tax Commission recommended a reference value of 420 NOK (about €50) for one tCO<sub>2</sub>e (NOU 2015:15, 2016). This represents their judgement of the appropriate shadow price of reaching the short-term emission targets in Norway. There is large uncertainty regarding the “correct” CO<sub>2</sub> price (see e.g., [Nordhaus, 2019](#); [Tol, 2005](#)). A recent example is the [IPCC \(2018\)](#) special report, where they show that the estimated CO<sub>2</sub> prices consistent with reaching the 1.5 °C target with high probability had an inter-quartile range of 179–658 USD<sub>2010</sub> in 2030 ([Huppmann et al., 2018](#)).

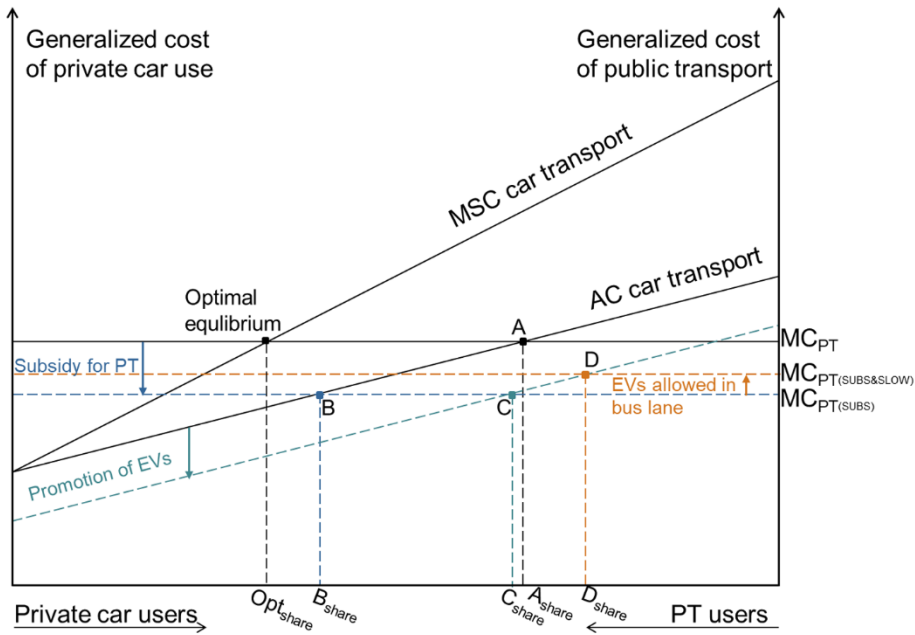


Fig. 1. Promotion of BEVs and urban transport equilibria.

increases with the number of cars on the road. The figure shows that the *average* social costs are lower than the *marginal* social costs, as the individual driver does not take into account the time cost he imposes on other drivers. We model the cost of PT by a constant marginal cost (i.e. marginal cost equals average cost) per passenger.<sup>4</sup> This is depicted by the flat line  $MC_{PT}$ .

In the optimum, the marginal social costs of private transport will equal the marginal social cost of PT (illustrated in the figure by “Optimal equilibrium”). In the absence of any policy measures we end up in user equilibrium A. In the absence of specific congestion tolls, the government often resorts to subsidies for PT. Subsidizing PT lowers the user cost of PT and leads to equilibrium B where congestion is mitigated and PT ridership has increased.

Now introduce a BEV promotion policy. This reduces the composite cost of car use. Indeed, the population will only opt for BEVs in so far as they are a lower cost option than a conventional fossil car, so the composite cost can only decrease. This results in a new equilibrium C where car use has increased again and where part of the effects of second best PT pricing have been destroyed. Finally, we allow BEVs to drive in the bus lanes. This causes higher congestion levels in the bus lanes which increase the PT user costs. This leads to an equilibrium of type D, where the market share of BEVs has increased, but at the expense of PT users, and where the urban congestion levels have gotten worse.

There is another subtle way in which the present BEV promotion leads to more congestion: the progressive CO<sub>2</sub> taxation of fossil cars. Confronted with the introduction of a progressive CO<sub>2</sub> tax on fossil cars, car drivers can react in four ways. They can abandon car use, opt for BEVs, choose a very fuel-efficient ICEV, or postpone buying a new car.

The second and the third choice reduce the variable cost of car use, which then stimulates demand for travel by private car, and consequently congestion. The conflict between fuel efficiency promotion and urban road congestion is well known (Parry et al., 2014).

The fourth option, postponing buying a new car, does not lead to more BEVs and less CO<sub>2</sub> emissions. However, it does not lead to more congestion either, as long as fuel prices remain high.

In conclusion, if policy makers want to promote BEVs and address the urban road congestion issue, there is a need for other policies that complement the promotion of BEVs. We ask: What is a better mix of policies?

### 3. Literature review

#### 3.1. Electric vehicles and policy

The rapid in-phasing of EVs to the transport system and the current policies intended to promote EVs raise many interesting transport and energy economic issues. We like to organize them in terms of the supply side for EVs, the demand side for EVs, and EVs in the urban transport market.

<sup>4</sup> We assume that the crowding externalities in PT are addressed using increases in frequency so that the average generalized cost of PT is more or less constant.

### 3.1.1. The supply side for EVs

With regards to the choice of low carbon technology for cars, BEVs are one of the options, next to PHEVs as well as biofuels and hydrogen. This raises questions on the cost development of different competing technologies and their future market shares. This question is best addressed in technology models like the IEA-developed TIMES model (see [Diaz Rincon, 2015](#)), the Canadian-developed CIMS model ([Jaccard et al., 2003](#)) or the US-developed NEMS model ([US Energy Information Association, 2019](#)). There are also important R&D policy implications, where the effects of learning by doing and pure R&D development should be included in the model ([Fischer and Newell, 2008](#); [Jaccard et al., 2003](#)).

### 3.1.2. The demand side for EVs

With regards to car purchase decisions, as EVs offer a different combination of car characteristics (e.g., range, refueling issues, and prices), one needs to study the consumer preferences with respect to these characteristics. For an early study one can consult [Brownstone et al. \(2000\)](#) which uses both stated preference and revealed preference data, and uncover large heterogeneity in consumers' preferences for alternative fuel vehicles. The EV adoption model in [Langbroek et al. \(2016\)](#) finds that some of the consumer heterogeneity can be explained by the differences in respondents' stages-of-change towards EV adoption, from pre-contemplation to action. [Axsen et al. \(2015\)](#) investigate heterogeneity in consumer preferences with regards to EV purchasing using a latent-class discrete choice model, where classes differ significantly in vehicle preferences. Using cluster-analysis and a discrete choice model, they also find that environmental and technology-interested motivations has strongest association with an interest in EVs. [Hidrue et al. \(2011\)](#) also used a latent class choice model to analyze heterogeneous preferences for EVs and different EV attributes. Other recent examples of EV adoption models include [Javid and Nejat \(2017\)](#) who estimate their model on Californian travel survey data, and [Østli et al. \(2017\)](#) who estimate a generic discrete choice model for automobile purchase on Norwegian disaggregate sales data from 1996 to 2011.

There is a growing literature on consumer adaptation of EVs (both PHEVs and BEVs) and the effects of government policy on promoting EVs. Both [Li et al. \(2017\)](#) and [Coffman et al. \(2017\)](#) provide literature reviews on factors that affect the consumers' intentions or decisions to adopt EVs. The former review includes 40 papers, while the latter includes 50. They both conclude that multiple factors are at play in affecting EV adoption. Although their taxonomies of factors differ, they both cover EV-specific (e.g., technical features and cost of the EV) and external factors (e.g., demographic and psychological factors of EV buyers or would-be buyers and government policy). An earlier review by [Rezvani et al. \(2015\)](#) includes 16 papers and covers many of the same factors, but focuses more narrowly on consumer intentions and behaviors regarding EV adoption. [Hardman et al. \(2017\)](#) review 35 papers on the effectiveness of government policy in the form of financial incentives to purchase BEVs. They state that almost all these studies, using different methodologies, point in the direction that financial purchase incentives for BEVs and PHEVs have had a positive effect on sales.

In the Norwegian context, [Bjerkan et al. \(2016\)](#) analyze the importance of 7 different incentives to promote BEVs using a membership survey by the Norwegian Electric Vehicle Association. They find that purchase tax exemption is the strongest incentive to purchase a BEV, while VAT exemption is the second strongest. Previous findings by [Figenbaum and Kolbenstvedt \(2013\)](#) indicated that the strongest incentives were VAT exemption, toll exemption and access to the bus lanes. However, [Bjerkan et al. \(2016\)](#) find that to some BEV owners, access to bus lanes or toll road exemptions are the only decisive variables. [Mersky et al. \(2016\)](#) also find that closeness to the larger Norwegian cities, where toll exemption and access to bus lanes are strong advantages, have a strong correlation with EV sales per capita. While the incentives for choosing EVs in these areas are strong, there could be some element of a "neighbor effect" ([Axsen et al., 2009](#); [Mau et al., 2008](#)), where the preferences for EVs in this area are endogenously strengthened over time as a function of the growing market share, feeding back to an even faster-growing market share. [Mersky et al. \(2016\)](#) also find that charging station availability is strongly indicative of EV sales per capita, although this relationship may not be entirely causal.

### 3.1.3. Modeling the role of EVs in the urban transport market

This market is characterized by many externalities. EVs may alleviate some of them, like CO<sub>2</sub> and local pollution, but as we discuss in [Section 2](#), they may exacerbate others. Perhaps the most costly externality in the urban setting is road congestion during peak hours ([Small and Verhoef, 2007, pp. 97-105](#); [Thune-Larsen et al., 2014](#)). In addition to these externalities, we can also mention accidents, noise and crowding on public transport (PT). Urban transport policy should look for the optimal balance of social costs and benefits. This balancing requires a model that represents explicitly the functioning of the urban transport market ([Proost and Van Dender, 2001](#)). As finding this balance is our main research question, transport externalities and the urban transport market will be the main emphasis of this paper.

This means that we in our modeling (which we will describe in [Section 4](#)) simplify some other dimensions. This includes the supply side for EVs, where we model a fixed selection of car types, and only address projected cost developments for BEVs in sensitivity analysis. This also includes parts of the demand side for EVs, where consumer tastes regarding attributes of different cars are largely ignored, there is no consumer learning, and the main driver of vehicle choice is the generalized cost of transport and total cost of ownership.

### 3.1.4. Placing our model in the Norwegian family of transport models

It is worth noting that in the existing family of transport models in Norway, none of them bring together all the elements of car choice, choice of transport pattern by mode and time of day, congestion and crowding feedback and occasional long trips into the same model (examples documented in [Flügel and Hulleberg, 2016](#); [Flügel and Jordbakke, 2017](#); [Fridstrøm et al., 2016](#); [Rekdal et al.,](#)

2014; Rekdal and Larsen, 2008; Østli et al., 2017). Our model does bring these elements together, though in a simplified way.

These members from the family of Norwegian transport models can model either travel mode choice, transport flows or the vehicle fleet far more sophisticated than ours, and on those areas they provide a valuable service for policy makers. Our model has the advantage of bringing more elements together in a transparent, relatively noncomplex model, that serves purpose of analyzing the implications that policy has for car fleet composition, and the implications car fleet composition has for striking the optimal balance of urban transport policies. As pointed out in Rødseth (2017), citing among others Frisch (1964), there is a trade-off between a model's physical realism, and its tractability and data requirements.

### 3.2. Instruments for addressing CO<sub>2</sub> emissions

A standard “textbook” approach to addressing CO<sub>2</sub> emissions is to prescribe implementing a CO<sub>2</sub> tax (Perman et al., 2003). Taxes on gasoline and diesel are, in effect, taxes on CO<sub>2</sub> as there is a fixed relationship between liters of fuel and kilos of CO<sub>2</sub>. It is also worth emphasizing that the *entire tax per liter* can be viewed as a tax on CO<sub>2</sub>, even if only a sub-component of the tax is explicitly called CO<sub>2</sub> tax (which is the case in Norway). What matters is not what the tax is meant for but how consumers react to this tax. In many European countries, gasoline and diesel for car use is taxed at 200–300 Euro/ton of CO<sub>2</sub> (OECD, 2016). This could be complemented by a CO<sub>2</sub> tax on alternative fuels (i.e., natural gas, biofuels, fossil generated electricity and hydrogen) in function of their CO<sub>2</sub> emissions. In theory, this instrument will make sure that we have the right mix of the four levers of reducing CO<sub>2</sub> emissions in transportation: more fuel-efficient driving, reduced car use, more fuel-efficient vehicles, and alternative technologies. The CO<sub>2</sub> tax can be complemented by an instrument to correct knowledge spillovers of new technologies that take the form of subsidies for learning by doing and pure R&D knowledge spillovers (Fischer and Newell, 2008).

The EU and Norway pursue this option: there are high excise taxes in place on automotive fuels and there are tax exemptions/subsidies for the purchase and use of BEVs and for R&D.

When we consider this first-best set of instruments focusing on CO<sub>2</sub> emissions, we see that the potential use of these instruments is handicapped by several constraints. First, if one region or nation has more ambitious climate targets than its neighbors, its scope for varying gasoline taxes regionally or nationally is limited as this would induce tankering and tax competition (Mandell and Proost, 2016). The choice set is therefore largely limited to (given climate goals, too low) fuel taxes, complemented by discriminating taxes on car ownership and purchases according to emission standards, and specific R&D subsidies. Second, the use of instruments to correct knowledge spillovers has only limited effects as the market for new engine technologies is a world market. Third, very fuel-efficient vehicles lead to more congestion. This could be considered a rebound effect that arises because improved energy efficiency reduces the generalized transport costs.

Climate change is a *global* problem, where *total* global emissions of greenhouse gases are expected to bring about large social costs (unevenly distributed) globally. This is probably why in many countries there is a much larger emphasis on the promotion of EVs, mainly as a means to reduce CO<sub>2</sub> emissions, than on the road congestion issue. The global total cost of greenhouse gas emissions are probably orders of magnitude larger than the global total costs of congestion, but we could still have the case that the marginal external cost of an extra conventional car contributing to congestion is higher than the marginal external cost of CO<sub>2</sub> from the same car on the same distance. The marginal price of CO<sub>2</sub> that a car user faces is reflected by the taxes on fossil fuels. In Norway, the current taxes on fossil fuels<sup>5</sup> (excluding VAT) would imply a cost of about €240<sup>6</sup> per ton of CO<sub>2</sub>. By contrast, the recommended reference value of CO<sub>2</sub> in Norway (NOU 2015:15, 2016) is 420 NOK (about €50). However, even with a much higher value on CO<sub>2</sub>, the external CO<sub>2</sub> cost may still be dwarfed by the external congestion or local air pollution cost of a km driven in a dense city during peak hours. In order for marginal cost of CO<sub>2</sub> per km for a large diesel passenger car to match the marginal cost of peak congestion in Norwegian cities, the implicit price of CO<sub>2</sub> would have to be more than 21 000 NOK per ton (more than €2300/ton) (Thune-Larsen et al., 2014). It is common in the transport economic literature to find that the per vehicle-km external costs of congestion are substantially larger than those of CO<sub>2</sub> at city-level (Anas and Lindsey, 2011; Small and Verhoef, 2007, pp. 97-105; Tscharktschiew, 2014). Our first research question addresses the problem of finding the right balance in a transport system with multiple market failures, including both CO<sub>2</sub> and congestion.

### 3.3. How to address urban congestion and continue to promote the use of BEVs

To address urban congestion, the number of vehicle-kms travelled by road during peak hours needs to be reduced and/or managed better, or the road capacity needs to increase. Additional road building is not really considered as an alternative in a country where one wants to limit overall car use in urban areas. After all, there is a large literature on how increasing road capacity over time will induce more demand for car travel and thus bring us back to a long-term equilibrium with high congestion. This is also known as “the fundamental law of road congestion” that has been verified empirically for the US, Europe and Japan (Downs, 1962; Duranton and Turner, 2011; Garcia-Lopez et al., 2017; Hsu and Zhang, 2014).

The current peak hour traffic volume could be managed better through various ITS (Intelligent Transport Systems) solutions that could e.g. provide better utilization of the existing road network (de Souza et al., 2016). But in the end, this works like a capacity

<sup>5</sup> Weighted average for gasoline and diesel, where the former counts for 59% of the car fleet's fuel use, and the latter 41%.

<sup>6</sup> The sub-component of the tax explicitly labeled CO<sub>2</sub>-tax reflects about 50 Euro per ton of CO<sub>2</sub>, but as we argue above, the *entire tax per liter* of fuel can be viewed as a tax on CO<sub>2</sub>.

extension, generating its own new traffic flow and is therefore not really solving the congestion problem.

Policy makers can pursue policies that “push” vehicle-kilometers travelled away from peak hours (e.g., through pricing), or “pull” them away (e.g., through improved PT pricing and quality). When applying “push”-policies, some drivers may adapt by rescheduling their trips to off-peak hours, some may choose to carpool/rideshare with others to split the increased toll cost, and some may choose PT, walking or biking. Pricing of all car use in the peak period is the most obvious instrument to be used. In 2017 Oslo began differentiating (slightly) between peak and off-peak car use.<sup>7</sup> BEVs started paying a peak toll in 2019.

Car traffic volumes may be “pulled” away from peak hours by promoting the use of PT. This policy has already been pursued and current PT users pay some 50% of operation costs (Ruter, 2016). The effectiveness of this policy depends on the diversion ratio, i.e. the proportion of the new PT users incentivized by reduced generalized prices of PT, that are former car users. When the diversion ratio is close to 50%, this measure can still be effective (Parry and Small, 2009). If it is closer to 20%, the measure becomes very costly. The reason is that a price reduction for PT induces many additional riders that are not paying the true supply cost (i.e. the fare is subsidized), but still need to be accommodated by providing costly extra PT capacity. Flügel, Fearnley, and Toner (2018) find that the average diversion ratio for the Oslo area from car to PT varies from 29% to 44%, depending on the mode of PT.

#### 4. Model set-up

The model is a stylized representation of the behavior of different groups of agents in the greater Oslo area, that is combined with different transport cost functions. We use it to study how agents demand daily short trips by car and public transport (PT), either during peak or off-peak hours, and how some agents demand a number of long trips by car throughout the year.

This is a very aggregated model that considers the transport of all inhabitants in the greater Oslo-area over the age of 18, where the overall population is represented by three representative agents. These three agents differ with respect to whether they are employed, and whether they go on occasional long car trips. The former criterion addresses important differences in transport patterns and income, while the latter addresses differences in range needs. These differences are relevant for policy makers in the transport sector.

##### 4.1. Model components

The main components of this stylized model are; the gross utility derived from transport, the user costs of transport, PT supply costs, and external costs of transport. These components are used to compute alternative urban transport equilibria and their welfare effects. The model is inspired by Börjesson et al. (2017), but adds a vehicle selection stage in addition to having three representative agents instead of one in the numerical application. The agents also consume a larger set of “transport products”, as occasional long car trips are included in the agents’ transport patterns, in addition to short daily trips by car and PT. The distinction between long trips and short trips is important as BEV’s still have a range handicap for longer distances.

##### 4.1.1. Gross utility derived from transport

The preferences of the agents in the model are represented by a quasi-linear utility function  $U$ . Here utility is derived from consumption of “other (non-transport) goods and services” (normalized to money  $m$ ), and from consumption of kilometers travelled for short daily trips (by car, by PT, at peak, at off-peak) and the number of long car trips per year. The utility from transport is represented by a sub-utility function  $B$ , which is assumed to be quadratic. This quasi-linear form implies that there is no income effect, which can be justified since Norwegian household income shares on transport are relatively small (Boug and Dyvi, 2008) and because we use a different utility function for each representative population group. While the quadratic sub-utility function can be considered a simplified local approximation to agents’ behavior, it has some advantages. First, it can be calibrated easily with limited data (observed prices and quantities and direct and cross-price elasticities), and second, as it enables linear demand functions it allows for clear interpretation and visualization. The following equations represents functions  $U$  and  $B$  for a given representative agent:

$$U(m, q_c^p, q_c^o, q_b^p, q_b^o, q_{lc}) = m + B(q_c^p, q_c^o, q_b^p, q_b^o, q_{lc}) \quad (1)$$

where

$$\begin{aligned} B(q_c^p, q_c^o, q_b^p, q_b^o, q_{lc}) = & [\alpha_c^p q_c^p - 0.5\beta_c^p (q_c^p)^2] + [\alpha_c^o q_c^o - 0.5\beta_c^o (q_c^o)^2] \\ & + [\alpha_b^p q_b^p - 0.5\beta_b^p (q_b^p)^2] + [\alpha_b^o q_b^o - 0.5\beta_b^o (q_b^o)^2] + [\alpha_{lc} q_{lc} - 0.5\beta_{lc} (q_{lc})^2] \\ & - i_c^{po} q_c^p q_c^o - i_b^{po} q_b^p q_b^o - i_{cb}^p q_c^p q_b^p - i_{cb}^o q_c^o q_b^o - i_{cb}^{po} q_c^p q_b^o - i_{bc}^{po} q_b^p q_c^o \end{aligned} \quad (2)$$

$q_j^t$  stands for the number of daily kilometers travelled in period  $t$  using mode  $j$ . Peak and off-peak periods are represented by the superscripts  $p$  and  $o$ , respectively. The subscripts  $c$  and  $b$  represent the modes car and PT, respectively, while the subscript  $lc$  represent long car trip. Similarly,  $\alpha_j^t$  and  $\beta_j^t$  are parameters of the sub-utility function for period  $t$  and mode  $j$ . The terms  $i_{ij}^{st}$  represents the interactions between periods and/or modes, for instance  $i_{cb}^{po}$  represents the interaction between car mode in peak hours and the PT mode in off-peak hours. These terms are symmetric, in accordance with consumer theory, i.e. the symmetry of the Slutsky matrix.

<sup>7</sup> <https://www.fjellinjen.no/private/prices/> [Last accessed April 9th 2018].

This representation of the utility function allows the derivation of inverse demand functions (willingness to pay – WTP), for the five types of transport.

$$\begin{aligned}
\frac{\partial U}{\partial q_c^p} &= \alpha_c^p - \beta_c^p q_c^p - i_c^{p0} q_c^o - i_{cb}^p q_b^p - i_{cb}^{p0} q_b^o \\
\frac{\partial U}{\partial q_c^o} &= \alpha_c^o - \beta_c^o q_c^o - i_c^{p0} q_c^p - i_{cb}^o q_b^o - i_{bc}^{p0} q_b^p \\
\frac{\partial U}{\partial q_b^p} &= \alpha_b^p - \beta_b^p q_b^p - i_b^{p0} q_b^o - i_{cb}^p q_c^p - i_{bc}^{p0} q_c^o \\
\frac{\partial U}{\partial q_b^o} &= \alpha_b^o - \beta_b^o q_b^o - i_b^{p0} q_b^p - i_{cb}^o q_c^o - i_{cb}^{p0} q_c^p \\
\frac{\partial U}{\partial q_{lc}} &= \alpha_{lc} - \beta_{lc} q_{lc}
\end{aligned} \tag{3}$$

#### 4.1.2. User costs of transport

We have standardized the consumer good *daily short-trip transport* to one kilometer, so the user costs are also on a per km basis. The user costs for daily car travel are given by:

$$uc_c^i = dc_c^i + \rho c_c + \tau_c^i + [\delta_c + \gamma(Nq_c^i)]VOT_c^{in} \tag{4}$$

The user costs comprise of the monetary distance-related costs  $dc_c^i$  (fuel, repairs, lubricants etc.), toll costs  $\tau_c^i$ , parking costs  $\rho c_c$  and time costs  $[\delta_c + \gamma(Nq_c^i)]VOT_c^{in}$ , where  $\delta_c$  is travel time during free-flow conditions and  $\gamma(Nq_c^i)$  is the added time due to congestion caused by all ( $N$ ) other road users.

The user costs for daily PT travel is given by:

$$uc_b^i = ac_b^i + \tau_b^i + \delta_b VOT_b^{in} [\varphi(Nq_b^i)] + VOT_b^w \frac{60}{2f_b^i} \tag{5}$$

The user costs comprise access time costs  $ac_b^i$ , fare costs  $\tau_b^i$  and time costs  $\delta_b VOT_b^{in} [\varphi(Nq_b^i)]$ , where  $\delta_b$  is PT travel time and  $\varphi(Nq_b^i)$  is a crowding factor that works as a weight on the agents' value of in-vehicle travel time. The crowding factor is increasing in the number of other agents riding in the PT system.<sup>8</sup>  $VOT_b^w \frac{60}{2f_b^i}$  represents the PT users' waiting time cost, as a function of frequency.

The user costs for the occasional long car trip is given by:

$$uc_{lc} = dc_{lc}^i + \tau_{lc}^i + \delta_{lc} VOT_{lc}^{in} \tag{6}$$

If the long car trip is done by a BEV, and the trip back and forth is longer than the BEV's range, we assume the agent will charge just enough to cover the remainder of the round trip. We assume that charging time gives the following disutility cost:

$$disU_{ch} = \omega_{ch} VOT_{lc} [(2lcL - r_{EV})eff_{EV}/chCap] \tag{7}$$

The charging time is thus determined by the range of the BEV and the length of the trip ( $2lcL - r_{EV}$ ), the energy efficiency of the BEV  $eff_{EV}$ , and the charging capacity  $chCap$ .<sup>9</sup> The disutility cost of charging time is assumed to be the value of travel time times a disutility weight for waiting  $\omega_{ch} VOT_{lc}$ .

#### 4.1.3. Cost of public transport supply

In the greater Oslo area PT is currently provided by metro, tram, city buses, commuter buses, and ferries. While it would have been nice to model these different PT modes separately, we have, in the numerical model, for the sake of tractability and transparency constructed a cost function for the aggregate PT system. We assume that this is a linear function of annual frequency  $f_b$  with  $FI_b$  as a fixed cost component and  $\kappa$  as the marginal unit operating cost. This is a simplification, but this function does seem to fit the aggregate data from the annual report of the PT company in the greater Oslo area quite well (Ruter, 2016).

$$C_b = FI_b + \kappa f_b \tag{8}$$

Any change in the annual frequency of PT can then be interpreted as a change in a “composite” PT-mode with shares of bus, metro, tram, and ferry.

<sup>8</sup> The crowding factor has a lower bound of 1. The crowding factor does not start to increase before all seats on the PT ride are occupied. This is a simplified way of modeling crowding costs. The literature shows that there are many ways to model crowding costs (Li and Hensher, 2011). De Palma et al. (2015) argue that the most natural way to model discomfort from crowding is through a step-function, with a jump in costs when the last seat is taken, then flat for all standing passengers, until the cost rises almost vertically as crowding reaches the legal limit of the vehicle. This opens up a trade-off between seat availability, fares and frequencies around the desired arrival times. Another recent example includes Hörcher et al. (2017), where crowding costs are modeled as a function of both crowding density and standing probability. Crowding assumptions in our numerical model are discussed in Appendix A.

<sup>9</sup> For example, with a semi-fast charger with a capacity of 22 kW, and the EV has a battery utilization rate of 0.2 kWh/km, it would take 1 h to get 110 km of driving distance charged.

#### 4.1.4. External costs of transport

Section 4.1.2 has already covered the external cost of congestion. The other important external costs are local pollution, greenhouse gas (GHG) emissions, noise, and accident risk. With regard to GHG emissions, our analysis will only focus on tank-to-wheel. Including all life-cycle emissions would require going through all the major components.<sup>10</sup> It is therefore considered out of scope for a paper focusing on urban transport policies in a world with electric vehicles. An example of a comparison of the life-cycle external costs between ICEVs and BEVs can be found in Jochem et al. (2016).

As for the valuation of GHG emissions, our analysis applies the Norwegian reference value recommended by The Green Tax Commission (NOU 2015:15, 2016). Whether the recommended reference value is the “correct” price is debatable, but it has been influential in the updating of Norwegian fuel taxes and guidelines for Cost-Benefit Analysis (CBA). It therefore gives a good approximation for how much welfare to forego in order to reduce emissions by one tCO<sub>2e</sub> in Norway.

With regard to the rest of the external costs, we assume they are constant per km per vehicle, depending on where the agents drive. This is of course a simplification. There are non-linearities in damages from local emissions and noise, but assuming constant marginal damages is a usable approximation as long as changes in traffic volumes are not too large (Thune-Larsen et al., 2014). Since the focus of this paper is urban transport policy where both PT and electric vehicles are included, we consider the simplified damage functions for local pollution and noise to be appropriate. Previous papers on urban transport policy, including Parry and Small (2009) and Börjesson et al. (2017), have made similar assumptions.

All the short daily trips are assumed to be in the city area, where population is relatively dense, thus having relatively high per-km external costs. The long car trips are assumed to be mostly on highways far from densely populated areas, thus having a fairly low per-km external cost (in addition to that we assume no congestion problems on the long trips). The external costs will also differ by the type of car. How the marginal external costs vary by car type and area can be seen in Table 3. The simple relationship for total external costs  $E$  is modeled in the following way:

$$E = \sum_{j=1}^n e_j q_j \quad (9)$$

The marginal external cost per km driven is given by  $e_j$  for mode  $j$ .

#### 4.2. Finding welfare optimum

The aggregate welfare function consists of several components, as described by Eq. (10). The first component is net consumption of other goods and the gross user surplus. The net consumption of other goods can be described as generalized disposable income after fixed and variable transport costs, the latter being the user costs described above. The second component is the net transport related deficit for the public sector (assuming the PT provider belongs to the public sector), i.e. the total revenue from the agents’ transport consumption (tolls, fares, gasoline and diesel tax, and purchasing tax and VAT on vehicles (annuity)) minus the total cost of providing PT. The third component consists of the parking company’s revenue  $P_{price}$  (agent transferring money to parking company), while the fourth component represents the opportunity cost of occupying parking space  $P_{cost}$ . The fifth component consists of external non-congestion costs. This way we account for all costs and transfers for the involved agents.

$$\begin{aligned} \Omega = & \sum_{k=1}^n [m_k + B_k(q_{ck}^p, q_{ck}^o, q_{bk}^p, q_{bk}^o, q_{lck}) \\ & - uc_{ck}^p q_{ck}^p - uc_{ck}^o q_{ck}^o - uc_{bk}^p q_{bk}^p - uc_{bk}^o q_{bk}^o - uc_{lck} q_{lck}] \\ & - \left( C_b - \tau_c^p q_c^p - \tau_c^o q_c^o - \tau_b^p q_b^p - \tau_b^o q_b^o - \tau_g g_c q_c - \sum_k \tau_c^{ann} k \right) + P_{price} - P_{cost} - E \end{aligned} \quad (10)$$

Here,  $\tau_g g_c q_c$  is the fuel tax revenue, where  $\tau_g$  is the tax rate, and  $g_c$  is the average fuel efficiency. We also have  $\sum_k \tau_c^{ann} k$ , which is the annuity of the purchase and VAT tax revenues, summed for all agents that own cars.

For simplicity, we ignore labor market distortions and assume that any public-sector deficits are financed by lump-sum taxes, implying that the marginal cost of public funds (MCF) equals 1.

We assume that, in user equilibrium, each agent adjusts her behavior so that her WTP (marginal benefit)  $\frac{\partial B}{\partial q_j^i}$  equals the generalized cost (marginal cost)  $uc_j^i + \tau_j^i$  for the use of a given mode in a given period. To derive optimal tolls and fares, we maximize the social welfare function w.r.t. the quantities of the different goods, subject to the constraints of user equilibrium for each period and transport mode.

<sup>10</sup> Even well-to-tank emissions would not be straightforward to include, as it would require knowledge about where the fuel is coming from, know the corresponding emission factors and whether and to what extent the oil production and refining is covered by the European Emission Trading scheme. The tank to wheel approach is less complete but is consistent and this is important for a comparison of policy scenarios. Besides, since the focus of Norwegian policy makers, both national and local, is on tailpipe emissions, that would be the natural focus for this paper as well.



$$\begin{aligned}
\Omega = & \sum_{k=1}^n [m_k + B_k(q_{ck}^p, q_{ck}^o, q_{bk}^p, q_{bk}^o, q_{lck}) \\
& - uc_{ck}^p q_{ck}^p - uc_{ck}^o q_{ck}^o - uc_{bk}^p q_{bk}^p - uc_{bk}^o q_{bk}^o - uc_{lck} q_{lck}] \\
& - \left( C_b - \tau_c^p q_c^p - \tau_c^o q_c^o - \tau_b^p q_b^p - \tau_b^o q_b^o - \tau_g g_c q_c - \sum_k \tau_c^{ann} k \right) + P_{price} - P_{cost} - E \\
& + \sum_{k=1}^n \left[ \lambda_{ck}^p \left( uc_{ck}^p + \tau_{ck}^p - \frac{\partial B}{\partial q_{ck}^p} \right) + \lambda_{ck}^o \left( uc_{ck}^o + \tau_{ck}^o - \frac{\partial B}{\partial q_{ck}^o} \right) + \lambda_{bk}^p \left( uc_{bk}^p + \tau_{bk}^p - \frac{\partial B}{\partial q_{bk}^p} \right) \right. \\
& \left. + \lambda_{bk}^o \left( uc_{bk}^o + \tau_{bk}^o - \frac{\partial B}{\partial q_{bk}^o} \right) + \lambda_{lck} \left( uc_{lck} + \tau_{lck} - \frac{\partial B}{\partial q_{lck}} \right) \right]
\end{aligned} \tag{11}$$

We differentiate  $\Omega$  w.r.t. the transport quantities and equal the expressions to zero and rearrange. This gives us the expressions for optimal tolls and fares:

$$\begin{aligned}
\tau_c^p &= q_c^p \frac{\partial uc_c^p}{\partial q_c^p} + e_c \\
\tau_c^o &= q_c^o \frac{\partial uc_c^o}{\partial q_c^o} + e_c \\
\tau_{lc} &= q_{lc} \frac{\partial uc_{lc}}{\partial q_{lc}} + e_{lc} \\
\tau_b^p &= q_b^p \frac{\partial uc_b^p}{\partial q_b^p} \\
\tau_b^o &= q_b^o \frac{\partial uc_b^o}{\partial q_b^o}
\end{aligned} \tag{12}$$

These equations express that the optimal tolls for cars equal the marginal external cost of congestion that they impose on other road users, plus the marginal external costs of road use not related to congestion. The optimal PT-fares for are set equal to the marginal external cost of crowding (which is affected by frequency).

#### 4.3. Constructing and calibrating the numerical model

To calibrate the numerical model we need three elements. First, we need a representation of the population by a limited number of representative user groups. For each of these user groups we observe their choices: type of car, use of different modes on different types of trips, and the associated user costs. This generates one observation for calibrating the utility function of each user group. Second, we need price and cross-price elasticities for each representative user. The first two elements complete the description of the utility function of each user. Third, we need the supply functions for road space (speed-flow relations) and PT.

The Norwegian travel survey from 2013/2014, documented in [Hjorthol et al. \(2014\)](#), is important for the calibration. The survey had approximately 60 000 respondents, and about 10 400 (18 years or older) of them lived in the Oslo metropolitan area. These respondents represent about 1.2 million inhabitants in the greater Oslo area (0.95 million over 18). The Institute of Transport Economics has constructed frequency weights for each respondent based on geography, sex, season, and time of week. Applying these weights gives us a synthetic adult population of the Oslo metropolitan area represented by the travel survey respondents. Among this population, 85% respond that they own or have a car at their disposition, and 30% have two cars at their disposition.

Using this synthetic population, we develop and calibrate a numerical model in MATLAB<sup>11</sup> following the steps described in [Table 1](#).

In this model, we have created the 3 representative agents X, Y, and Z. The agents are classified according to whether they have taken any long car trips (+100 km) in the past month (whether the travel pattern includes occasional long trips may be important for the choice of car type) and whether they are employed or not. The key agent characteristics are shown in [Table 2](#).

Other important parameters for the calibration include generalized prices for car and PT travel, and own-price and cross-price elasticities. Description of and sources for these parameters are given in [Appendix A](#), along with further details on the calibration procedure.

In addition to the user costs of travel, we include the costs of ownership.<sup>12</sup> We have found the average purchase prices (including VAT and purchase taxes) of new cars sold in Norway in 2015–2016 for the broad categories “conventional car” (diesel and gasoline), “hybrid”, “EV short-range” (range of 190 km) and “EV long-range” (range of 528 km). The prices have been transformed to annuities over cars’ average lifetime with a real interest rate of 2%<sup>13</sup> to make annual comparisons. We summarize the key car-specific parameters for technology, user costs, and externalities in [Table 3](#).

<sup>11</sup> The applied MATLAB-scripts can be obtained on request by contacting the corresponding author.

<sup>12</sup> We have used data from The Norwegian Road Federation (OVF).

<sup>13</sup> This corresponds to the recommended risk-free component in the real discount rate to be used in cost-benefit analysis in Norway ([NOU 2012:16, 2012](#)). Furthermore, car loans in Norway usually have a nominal interest rate of 4–5% and the Norwegian inflation target is 2%.

**Table 1**  
Model calibration, step by step.

Step	Description
1	Aggregate the National Travel Survey data for the counties Oslo and Akershus (that approximate “the greater Oslo area”) into 3 aggregate agents <sup>a</sup> in terms of <ul style="list-style-type: none"> <li>• Baseline travel pattern (PT and car).</li> <li>• Employment and incomes (which determine value of time).</li> <li>• Car ownership, access to parking at home, etc.</li> </ul>
2	Compute generalized transport costs of each agent for each mode and for each car type, for short and long trips
3	Select own-price and cross-price elasticities for each type of agent for the “travel products” person-km per day by car and by PT, peak and off-peak, and long car trips per year (see <a href="#">Appendix A</a> for more information).
4	Calibrate the utility function using the data from steps 1, 2, and 3.
5	Check the calibration of the utility function by simulating the choice of each agent (number of trips per mode) and cross-checking them with observed choices. This step completes the calibration of the agents’ utility functions.
6	Construct the speed-flow function for peak car trips based on a piecewise linear approximation of peak and off-peak speeds (see <a href="#">Appendix A</a> for more information).
7	Construct the cost functions for PT in peak and off peak using a linear function with intercept (fixed costs), and an automatic frequency “rule-of-thumb” optimization rule for peak and off-peak. A similar approach was used by <a href="#">Parry and Small (2009)</a> and <a href="#">Kilani, Proost, and van der Loo (2014)</a> .
8	Construct the crowding cost functions of PT (see <a href="#">Appendix A</a> for more information).
9	Construct linear cost functions for the non-congestion external costs; air pollution, noise and accidents. Values are given in <a href="#">Table 3</a> , based on <a href="#">Thune-Larsen et al. (2014)</a> .
10	Construct a welfare function to represent Eq. (11), that consists of the sum of utility for each agent – user costs for agents (including taxes, tolls, fares and parking charges) – transfers to government and parking company – external costs other than congestion – the operational costs of PT – the opportunity cost of parking spaces.

<sup>a</sup> Earlier versions of the model had a larger number of agents, but this made the model far less tractable and gave large difficulties in finding transport market equilibria. Having three agents allows for a tractable model, and allows for more insights than a single representative agent

**Table 2**  
Key agent characteristics.

Source: Norwegian travel survey from 2013/2014, survey documented in [Hjorthol et al. \(2014\)](#).

Characteristic	Agent X	Agent Y	Agent Z
Estimated number of people	267 955	468 187	210 187
Working/ Not working	Working	Working	Not working
Annual gross income (NOK)	591 183	500 972	320 821
Any long trips by car per month	Yes	No	Yes
Number of short car trips per day	1.9	1.38	1.0
Short car trip km per day	20.9	15.6	9.8
Average length of long car trip (km)	191	N/A	175
Number of long car trips per year	19.5	N/A	11.8
Number of PT trips per day	0.4	0.7	0.4
PT km per day	7.6	10.8	6.9
Number of peak car trips per day	0.9	0.7	0.3
Peak car km per day	10.5	7.7	2.8
Number of off peak car trips per day	1.0	0.7	0.7
Off peak car km per day	10.4	7.8	7.0
Number of peak PT trips per day	0.29	0.43	0.14
Peak PT km per day	4.5	6.9	2.3
Number of off peak PT trips per day	0.15	0.32	0.26
Off peak PT km per day	3.1	4.0	4.6
Disutility markup from owning a small car, relative to price difference between small and large ICEV, cf. <a href="#">Table 3</a> (own assumption)	10%	N/A	N/A

#### 4.4. The model procedure for analyzing policies

The model is ready for running policy scenarios when the utility functions of the representative agents are calibrated to fit the data, as explained in [Section 4.3](#). Solving the model for an alternative policy requires to find a new user equilibrium *first* for a given type of car ownership and *second* when all agents have chosen their preferred type of car. As the type of car determines car user costs, this requires an iterative process. The exact steps in the solution process are given in [Table 4](#).

We run the full model procedure for the most important scenarios, and a simplified version of step 2 in the procedure for a number of other scenarios. In the simplified version, the car choices are kept fixed for the different agents. This has at least two advantages: The first is that when discrete car choices have been fixed, the optimization procedure becomes simpler. In this case, it is easier to adjust the other policy variables in order to maximize welfare subject to behavioral constraints, and in some scenarios a CO<sub>2</sub> constraint consistent with the policy target and ensure convergence to a unique transport market equilibrium. The nature of the full procedure with discrete choices by multiple agents implies a problem with non-convexities and does not guarantee a unique equilibrium. The second advantage is that there are important insights to be gained from studying optimal policies under different fixed

**Table 3**  
Car specific parameters for technology, user costs, and externalities, baseline.

Parameter	ICEV small	ICEV large	PHEV	EV short	EV long	Source:
Purchase price	273 058	503 614	456 036	263 049	720 468	Norwegian sales data compiled by the Norwegian Road Federation
VPT cost	59 977	158 219	44 143			
VAT cost	42 616	69 079	82 379			
Producer price	170 464	276 316	329 514			
Annual tax	2 820	2 820	2 820	455	455	
Range (km on full battery)			47.8	190	528	
Fuel usage (liters per 100 km)	7.99	9.50	6.15			
Share of city trips in e-mode <sup>a</sup>	0	0	73%	100%	100%	Figenbaum and Weber (2017) Figenbaum (2018)
kWh-usage per km, summer				0.15	0.17	
kWh-usage per km, winter				0.20	0.22	
kWh-usage per km, average			0.28	0.17	0.20	
Non-fuel costs per km (including taxes, not tolls)	2.05	2.05	2.05	1.98	1.98	Cowi (2014)
Non-congestion external cost per km in city (NOK)	0.70	0.70	0.36	0.36	0.36	Thune-Larsen et al. (2014)
Non-congestion external cost per km far from densely populated areas (NOK)	0.16	0.16	0.16	0.15	0.15	

<sup>a</sup> It is assumed that PHEVs run on electricity 73% of the distance on short daily trips, but long trips we assume that they run entirely on fossil fuels.

**Table 4**  
Steps in the model procedure for analyzing transport policies.

Step	Description
1	Change one or more exogenous policy variable (tolls, fares, parking charges)
2	Simulate a new equilibrium by <ol style="list-style-type: none"> <li>Solving for new individual utility optimum for agent X Generating new utility-maximizing quantities for agent X (for each possible car option) Agent makes discrete car choice (large ICEV, small ICEV, PHEV, short-range EV, long-range EV, or no car) – the choice that gives the highest net utility for the user, i.e. utility from transport and net consumption of other goods (net income minus fixed costs, e.g. annuity for car purchase) Inserting the new quantities into the congestion and PT cost functions</li> <li>Solve for new individual utility optimum generating new quantities (and possible car choice) for agent Y, using the new congestion and crowding levels that are generated in step a</li> <li>Solve for new individual utility optimum generating new quantities (and possible car choice) for agent Z, using the new congestion and crowding levels that are generated in step b</li> <li>Iterate: Redo step a using the updated congestion and crowding functions of step c</li> <li>Iterate: Redo step b and c using the updated congestion and crowding functions of the previous step</li> <li>Stop updating congestion levels and car choice after 3 iterations to avoid convergence problems<sup>a</sup></li> </ol>
3	Based on quantities in new equilibrium, calculate the total new social welfare levels and its components associated with the changed policy variable values

<sup>a</sup> We tested the need for more iterations and found that in cases where there was convergence, it did not make much difference to have 3, 5 or 10 iterations. In order to save computing time, we settled for 3 iterations.

car combinations. The optimized policies are later run through the three steps described above to check for incentive compatibility, i.e. whether the agents will make the choice of vehicle combination the optimal policies are designed for. The robustness of the equilibrium found is then tested by redoing the simulations with a varying number of starting points. The model equilibrium can be considered a medium-run/long-run equilibrium for given land-use, where the time horizon corresponds to the average life-span of a car. This is about 17 years in the Norwegian case (Fridstrøm et al., 2016).

## 5. Policy analysis and results

This section presents the results from the modeling exercises, designed to answer the three stated research questions.

We first investigate what medium-term effects the current policies might have. What is the welfare status of the current situation for the greater Oslo area? To what equilibrium are we heading if 2014 policies are continued, i.e., the business-as-usual (BAU) scenario? What equilibrium would we end up in if BEVs were treated the same as ICEVs with regard to tolls, parking, and VAT (EV-SAME-scenario)?

In a second step we explicitly optimize policies to maximize welfare under constraints. We do this again in two rounds. First, we calculate welfare-maximizing policies (adjusting tolls and fares) for all the possible car combinations. The best combination is then checked for incentive compatibility, here meaning that agents choose the optimal car combinations under optimal policies (i.e., tolls

**Table 5**

Policy combinations under different scenarios. ICl = Large conventional car, ICs = Small conventional car, Hy = Plug-in Hybrid, EVl = Long-range EV, EVs = Short-range EV, N/A = Not applicable to this scenario. X, Y and Z denotes the model agents.

Policy variables	Scenarios						
	Exogenous policies		Maximizing welfare, no CO <sub>2</sub> -constraint		Maximizing welfare, with CO <sub>2</sub> -constraint		
	Reference/BAU	EV-SAME	Best: X: ICl Y: ICs Z: ICs	Worst: X: EVs Y: EVs Z: EVs	Best: X: Hy Y: ICs Z: EVs	2nd Best, but simpler: X: Hy Y: EVs Z: ICs	Worst: X: ICl Y: ICs Z: ICs
Peak toll ICEV, NOK per km	0.31	0.31	1.47	N/A	2.23	1.44	23.02
Off-peak toll ICEV, NOK per km	0.31	0.31	0.68	N/A	1.52	0.63	22.46
Toll on long trips ICEV, NOK per km	0.16	0.16	0	N/A	1.05	0	14.83
Peak toll EV, NOK per km	0	0.31	0.48	1.72	3.37	1.8	N/A
Off-peak toll EV, NOK per km	0	0.31	0.48	0.92	1.73	1.02	N/A
Toll on long trips EV, NOK per km	0	0.16	0.09	0.09	0	0.09	N/A
Peak fare, NOK per average trip	33	33	52.36	51.84	51.69	52.08	77.47
Off-peak fare, NOK per average trip	33	33	22.98	23.5	21.35	23.76	18.41
Average parking cost ICEV, NOK per average roundtrip	17.5	17.5	17.5	17.5	17.5	17.5	17.5
Average parking cost EV, NOK per average roundtrip	0	17.5	17.5	17.5	17.5	17.5	N/A
EV VAT, %	0%	25%	0%	N/A	25%	-21%	N/A
Change in PHEV purchase tax for incentive compatibility			Add 150%	N/A	Un-changed	Un-changed	N/A
Change in ICEV purchase tax for incentive compatibility			Un-changed	N/A	Add 210%	Un-changed	N/A

and fares) when given the full car choice set. If they are not incentive compatible, vehicle taxes<sup>14</sup> are adjusted to make each user group choose its optimal car combination. This leads to the welfare-maximizing, incentive compatible policy mix.

Finally, we check whether the optimal car purchase and car use policies achieve the goals in terms of CO<sub>2</sub> emissions reductions; cf. [Section 1](#). If necessary, we adjust the set of policies to reach the CO<sub>2</sub>-reduction target with the lowest social cost.

### 5.1. What is the welfare status of the current situation for the greater Oslo area?

The reference situation for the greater Oslo area is 2014, where “everybody” (98%) is driving an ICEV. Public transport (PT) fares and tolls are uniform across peak and off-peak. Only ICEVs pay for tolls and parking. The policies for the reference scenario, the BAU scenario (where car owners have had the option to adapt fully to the current policies), and for other key scenarios are given in [Table 5](#). The main results for all these scenarios are given in [Table 6](#). Results include total welfare, calculated at 644 bn NOK per year in the reference scenario. The main results further include total tank-to-wheel CO<sub>2</sub> emissions from personal transport and kilometers driven in the city, which in the reference scenario is calculated to be 1.2 mill tons and 3.7 bn km, respectively. As explained in [Section 4](#), CO<sub>2</sub> emissions are valued in the welfare calculations via a reference value of CO<sub>2</sub>. This is common practice in CBA in the Norwegian transport sector ([Norwegian Public Roads Administration, 2018](#)). The Norwegian reference value of CO<sub>2</sub> represents the opportunity cost of not reducing emissions in the transport sector. If emissions are not cut in the transport sector in the greater Oslo area, then welfare needs to be foregone somewhere else in order to reduce emissions, up to the recommended shadow price of 420 NOK per tCO<sub>2e</sub>.

### 5.2. To what equilibrium are we heading if 2014-policies are continued, i.e., the BAU-scenario?

In our stylized model, we view the reference scenario as a result of historical choices *before* BEVs and PHEVs were widely available. In our BAU-scenario, we assess the choices of the agents when all five car types are widely available at current prices, and current policies remain constant.

When all agents have adapted to the policies and found a new equilibrium, we have that Agent X (employed and makes occasional long trips) has switched to a PHEV, Agent Y (employed, but does not go on long car trips) has switched to a short-range BEV, and Agent Z (not employed, but makes occasional long trips) has remained a user of a small ICEV. The result is a 64% drop in CO<sub>2</sub> emissions, exceeding the goal of a 50% reduction. However, due to lower user costs of both PHEVs and BEVs, the Oslo area becomes

<sup>14</sup> For the general case, vehicle taxes are adjusted to ensure incentive compatibility, as these taxes are only considered transfers between agents and government. For difficult cases, policies are re-optimized subject to incentive compatibility constraints where tolls, fares, parking charges and purchase taxes are instruments in the welfare maximization.

**Table 6**

Transport, environmental and welfare related results under different scenarios. Absolute levels shown in reference situation, and absolute differences relative to reference situation shown in the other scenarios. ICl = Large conventional car, ICs = Small conventional car, EVI = Long-range EV, EVs = Short-range EV. X, Y and Z denotes the model agents.

Policy outcomes	Scenarios							
	Exogenous policies			Maximizing welfare, no CO <sub>2</sub> -constraint		Maximizing welfare, with CO <sub>2</sub> -constraint		
	Reference (level)	BAU	EV-SAME	Best:	Worst:	Best:	2nd Best, but simpler:	Worst:
			X: ICl Y: ICs Z: ICs	X: EVs Y: EVs Z: EVs		X: Hy Y: ICs Z: EVs	X: Hy Y: EVs Z: ICs	X: ICl Y: ICs Z: ICs
City road use (mill vkm)	3 729	78.9	14.9	-24.7	19.5	-52.7	-35.9	-1 206.7
PT use (mill pkm)	2 147	-113.3	-16.9	-1.1	-59.7	48.5	-23.5	1 487.0
CO <sub>2</sub> emissions (1000 tons)	1 198	-765.6	-378.1	-2	-1 198.50	-599.4	-764.3	-599.2
Transport utility + general disposable income, Agent X (bn NOK)	223	1.1	1.2	-1	-3.6	-2	0.2	-35.4
Transport utility + general disposable income, Agent Y (bn NOK)	324	2	0	-1.6	-2	-7.1	-0.4	-34.2
Transport utility + general disposable income, Agent Z (bn NOK)	88	0	0	-0.2	-0.9	-2.3	-0.2	-12.3
Transport externality costs (bn NOK)	3.3	-1.4	-0.6	0	-1.8	-0.9	-1.4	-1.3
Net government surplus (bn NOK)	12.8	-8.9	-2.9	3	-10.7	6.6	-6.6	57.2
Welfare (bn NOK)	644	-5.9	-1.1	0.2	-15.4	-3.8	-5.6	-23.5

more congested with a 2.1% increase in transport volume (for a constant population), thus failing to reach the zero-growth goals. Welfare is also reduced because of higher resource costs per car and higher congestion levels.

### 5.3. What equilibrium would we end up in if BEVs were treated the same as ICEVs with regard to tolls, parking and VAT (EV-SAME-scenario)?

Compared to the reference situation, Agent X switches to PHEV, while the two other agents stick to their small ICEVs. Agent X's shift leads to CO<sub>2</sub>-emission reductions of about 30%, as most of the city driving is assumed to be done in electric mode. While a large reduction, it is still not large enough to meet the stated policy goals. In addition, the lower user costs also lead to increases in total distance driven with 0.4% in the city. Compared to the reference situation, welfare levels drop because of higher resource costs per car and higher congestion levels, though not as much as in the BAU-scenario.

### 5.4. What is the scope for welfare improvements?

For the three agents in this stylized model, there are 20 relevant combinations of vehicle ownership. This gives us 20 scenarios, for which the model maximizes welfare (see description above) by eliciting optimal tolls, fares, and parking charges under fixed vehicle combinations.

Welfare maximizing policies imply drastic changes from the reference situation. In all scenarios, welfare is enhanced with higher tolls, especially during peak hours. This goes for BEVs and ICEVs alike. In addition, we find that higher fares during peak hours and lower fares during off-peak hours increase welfare. Finally, welfare-maximizing policies involve all cars paying the opportunity cost of parking space, so BEVs and ICEVs would pay the same price.

The changes in welfare levels relative to the reference situation for all these scenarios (20 optimized scenarios plus the BAU- and EV-SAME-scenario) are given in Table 8 in Appendix B. The vehicle combination that achieves the highest welfare level when tolls, fares, and parking charges are optimized is the same as in the reference situation, with Agent X driving the large ICEV and the other agents driving small ICEVs. The changes in tolls and fares lead to a 0.7% decrease in city driving, a 1% increase in rural driving and a 0.2% decrease in CO<sub>2</sub>-emissions. The results indicate a 218 mill NOK increase in annual welfare from the reference situation, achievement of the zero-growth goal, but failure to reach the CO<sub>2</sub> emission reduction target. The goal of reducing CO<sub>2</sub> emissions by 50% implies a shadow price of CO<sub>2</sub> that is far higher than the nationally recommended reference value.

With the optimal transport user policies in place, and the agents given the free choice of cars, some additional adjustments are needed to make the optimal car combination incentive compatible. These adjustments make sure that Agent X does not choose the PHEV and Agent Y does not choose the short-range EV. To avoid PHEVs, the purchase tax for PHEVs needs to be increased by at least 150% (which still implies a 50 000 NOK lower purchase tax than the large ICEV). To avoid any short range EVs, tolls for EVs need to be imposed, at least amounting to 33% of the toll for ICEVs at peak, and EVs and ICEVs need to pay the same parking charge.

We stress that this is a very stylized model where we optimize car choices for only 3 representative agents. This is an important limitation, but the small number of representative agents has allowed us to optimize toll, fare, and car taxation policies. This joint

optimization of private and public transport parameters is rather rare in the literature, mainly because of the complexity that increases strongly with the number of representative agents. Given the limits of our modelling approach, we conduct sensitivity tests for optimal policies in all the 20 scenarios with fixed vehicle combinations. We test the following assumptions that may affect the welfare-ranking of vehicle combinations:

- What if PHEVs could drive in e-mode for *all* of their city driving? (relevant for 4 scenarios)
- What if Agent X's disutility markup (see Section 4.3) on driving small cars was only 1% and not 10%? (relevant for 8 scenarios)
- What if the resource costs of BEVs were reduced by 25%?<sup>15</sup> (relevant for 17 scenarios)
- What are the implications of assuming a higher discount rate? (relevant for all scenarios)

In the four scenarios where Agent X drives a PHEV, allowing for 100% driving in e-mode on short trips, adds 154–155 mill NOK extra in welfare. The emissions reductions also become larger as more than 62 000 additional tons of CO<sub>2</sub> is abated. We see from Table 8 (cf. Appendix B) that one of the tested scenarios climbs in the welfare ranking, from 9th to 8th place.

In the eight scenarios where Agent X drives a small car but his disutility markup from driving a small car is a lot smaller than initially assumed, welfare becomes about 389 mill NOK higher per year. We see from Table 8 that six of the tested scenarios climb in the welfare ranking. The highest ranked scenario of the affected ones climbs from 5th to 4th place.

The change in assumptions that causes the largest changes in welfare is the 25% reduction in resource costs of BEVs. This change increases welfare by between 967 mill NOK and 6 498 mill NOK per year in the affected scenarios. This causes several changes to the internal welfare ranking of scenarios. The highest ranked scenario with BEVs climbs from 7th to 5th place.

As a final sensitivity analysis, we also tested the implications of higher discount rates, set at 7.5%. This is the implicit discount rate of European car buyers with a 15-year time horizon estimated in Grigolon et al. (2018). As Table 8 in Appendix B shows, the same car combination as in the reference case maintains the highest welfare rank. We also see that car combinations with smaller, cheaper car variants climb ranks compared to the original optimization.

It is worth noting that the scenario where policies are optimized under the same car combination as in the reference situation, still generates the highest welfare in all of the sensitivity tests. Within our stylized modeling framework; we see that the welfare-maximizing vehicle combination finding is robust.

### 5.5. How do we reach the CO<sub>2</sub>-reduction targets at least cost?

In 9 of the 20 scenarios with fixed vehicle combinations, the 50% CO<sub>2</sub> emissions reductions target is not reached, and the welfare-maximizing scenario does not even come close to the target. We next impose the CO<sub>2</sub> target as a constraint in the welfare maximization in these scenarios. As noted in Section 3.2, the probably most efficient instrument for reducing tank-to-wheel CO<sub>2</sub> emissions would be the fuel tax, but the use of this tax is limited due to fuel tax competition from neighboring regions/countries. Our approach then is to set the CO<sub>2</sub> emissions reduction target as a constraint, and let the tolls, fares and parking charges be the instruments for maximizing welfare under this constraint. The CO<sub>2</sub>-cap is binding in all of the 9 scenarios that in the original optimization did not reach the target, and welfare is consequently reduced in all of these scenarios. The scenarios that were furthest away from achieving the emissions reductions target incur the greatest cost. The vehicle combination from the reference situation, which yielded the highest welfare level in both the original optimization and the sensitivity tests, results in the lowest welfare levels under the CO<sub>2</sub> constraint. This is because the policies necessary to achieve the target drastically decrease mobility, since the agents are stuck with their ICEVs. For instance, the necessary peak tolls would be 16 times their optimal levels, and off-peak tolls would be 33 times larger.

The highest achievable welfare levels under the binding CO<sub>2</sub>-cap is with the combination of Agent X driving a PHEV, Agent Y driving a small ICEV and Agent Z driving a short-range BEV. Compared to the highest-ranking scenario in the initial optimization, the welfare reduction is of about 4 bn NOK per year. The average welfare cost per ton of CO<sub>2</sub> for achieving the emissions reductions target is 6 671 NOK (€682/ton). This comes in addition to the recommended reference cost of CO<sub>2</sub> of 420 NOK/ton, that was already internalized in the initial optimization. While this shows that achieving the ambitious climate goals requires a shadow price of CO<sub>2</sub> far higher than the reference price, the shadow price we find is well within what IPCC (2018) displays as the interquartile range for the global price of CO<sub>2</sub> needed by 2035 in order to stay on a path where global warming is limited to 1.5 °C by 2100 with low probability of overshooting (Huppmann et al., 2018).

The tolls, fares, and parking charges that bring us to target emission levels at least cost when car combinations are fixed, are not incentive compatible. Without further interventions, Agent Y would choose the short-range BEV and not the small ICEV and Agent Z would choose the small ICEV and not the short-range BEV. Policies need to be adjusted so that one car becomes more attractive for one type of agent, but less attractive for the other, which of course is a bit tricky. This requires another model run with an incentive compatibility constraint. To ensure incentive compatibility at least cost, both tolls and purchase taxes need to be adjusted. The purchase tax for small ICEVs needs to increase by 210%, and the BEV would get a full VAT of 25%. At the same time, city tolls for ICEVs are reduced, but tolls for driving in rural areas are increased. Toll for BEVs driving in the city are increased, but tolls for BEVs driving in rural areas are eliminated. Agent Y and Z then end up choosing the welfare maximizing car combination. The annual cost addition of these policies is about 7 mill NOK, which implies that the average welfare cost for achieving the CO<sub>2</sub> target increases up to

<sup>15</sup> This is roughly in line with assumptions by The Norwegian Environment Agency (2016), where they assume a 4% annual decrease in costs of EVs, and a 2% annual cost decrease for ICEVs, giving the EV a 25% cost decrease relative to ICEVs by 2030.

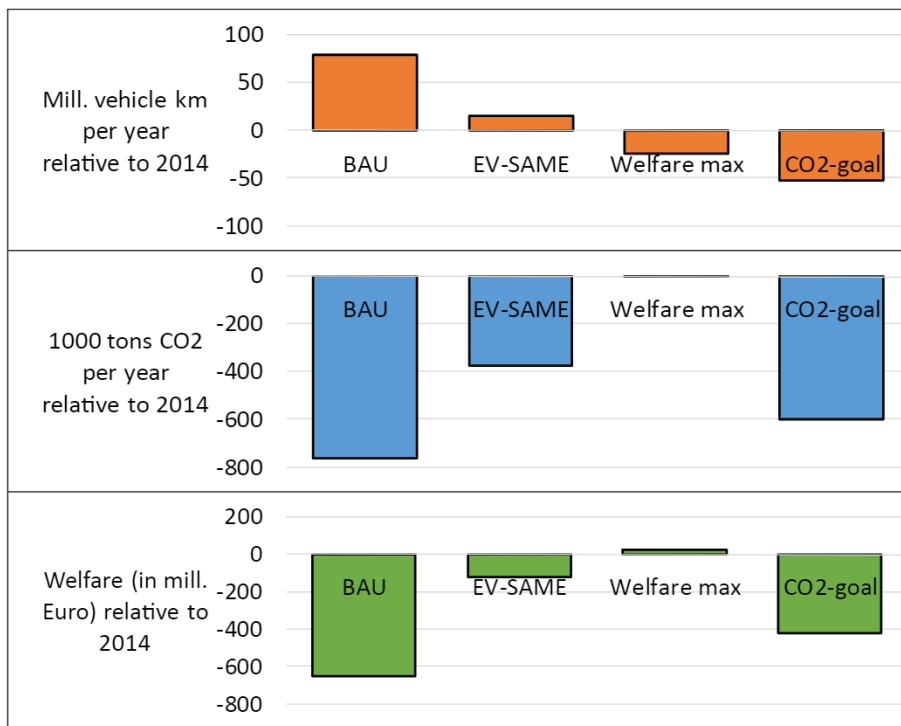


Fig. 2. Vehicle kms, CO<sub>2</sub> emissions and welfare in four main scenarios compared to the reference situation.

6 690 NOK per ton of CO<sub>2</sub> (€684/ton). Hence, we see that incentive compatible policies adds new complexity to the policy regime for achieving the emissions reduction goal at least cost. However, these adjustments to ensure incentive compatibility do not change the ranking of car combinations.

The second-ranking car combination has a more intuitive policy package. It achieves the CO<sub>2</sub>-goal when Agent X drives a PHEV, Agent Y drives a short-range BEV, and Agent Z drives a small ICEV under optimized policies. Ensuring incentive compatibility is more intuitive here. Before adjusting any purchase taxes, optimal policies would make both Agent Y and Agent Z choose the small ICEV. Getting Agent Y to switch to a short-range BEV under optimal transport user policies would require increasing the price difference between the small ICEV and the short-range BEV. This increase in price difference has to be at least as large as a 21% subsidy of the short-range BEV. This achieves a welfare level that is 5.9 bn NOK lower than in the highest ranked scenario in the initial optimization (see Table 8 in Appendix B), resulting in an average welfare cost of 7 661 NOK per ton of CO<sub>2</sub> reduced.

In Tables 5 and 6 we show the optimized policies and the transport- and welfare-related results from the following scenarios: The reference situation, the business-as-usual scenario, the EV-SAME-scenario, and the best and the worst scenario from the initial optimization and the optimization under the CO<sub>2</sub>-constraint.

We see that our stylized model finds substantial welfare differences between car combinations, even when policies are set to maximize welfare within each combination. Under the initial optimization, the difference between the lowest- and highest-achieving combination is an annual welfare difference of almost 16 bn NOK. The discrepancy gets even larger under optimization with the CO<sub>2</sub>-cap, where it is almost 20 bn NOK.

The key results can be summarized in Fig. 2. Here we summarize the main outcomes city driving, CO<sub>2</sub> emissions and welfare for the main scenarios compared to the reference situation:

## 6. Discussion, caveats and conclusions

Our stylized model shows that highest welfare is found when policies induce *optimal travel demand* and *optimal choice of car*. Optimal travel demand is achieved by setting fares and tolls to strike an optimal balance between public transport (PT) and car travel during peak and off-peak hours. For cars this means pricing of congestion and other external costs. For PT, this implies peak load pricing. These tolls and fares will vary with the car combination in any given scenario because PT and car transport volumes will be different, as indicated by Tables 5 and 6.

We learn from the BAU-scenario that if BEVs do not face any tolls or parking charges, along with a favorable purchase tax system, we end up in an equilibrium with high BEV-penetration. This substantially reduces CO<sub>2</sub> emissions, but leads to more city driving and congestion, which *on the margin* has a higher social cost. If BEV-driving remains unregulated, there is a clear goal conflict between reducing CO<sub>2</sub> emissions and stopping the growth of passenger car transport in the city.

The highest welfare levels are found when policies are optimized in the scenario where the agents use the same car types as in the

reference situation; agent X drives a large ICEV and agents Y and Z drive small ICEVs. This means that utility-maximizing agents would not choose BEVs, and there are no welfare gains from policies supporting BEVs under the current Norwegian reference value of CO<sub>2</sub>. In our stylized modeling framework, this implies that the agents have made the socially optimal car choice already. This scenario also implies non-significant CO<sub>2</sub> emissions reductions. It is clear that an ambitious target of reducing transport emissions in the greater Oslo area is in conflict with welfare maximization at the recommended reference value of CO<sub>2</sub>. This also illustrates the mismatch between CO<sub>2</sub> prices used in CBA, typically in the range €20-€60 in 2020, and the CO<sub>2</sub> prices needed in order to reach ambitious climate goals, including the “well below 2 °C” target from the Paris agreement (IPCC, 2018).

We set the CO<sub>2</sub> target as a constraint, and let the tolls, fares, and parking charges be instruments for maximizing welfare under this constraint. Once the CO<sub>2</sub>-cap becomes binding, the best car combination from the initial optimization becomes the worst. The best vehicle combination is a PHEV to Agent X, a small ICEV to agent Y and a short-range BEV to agent Z. It is clear here that BEVs (or other low- or zero emissions vehicles) play a role in reaching ambitious CO<sub>2</sub> targets at least cost. With this vehicle combination and optimized policies, we also see a decline in car traffic volumes in the city, implying achievement of the zero-growth goals as well.

However, there is a conflict between ambitious climate goals and welfare maximization. The policies that achieve the emissions reductions target at least cost still cause large reductions in welfare. Our stylized model finds an average cost per ton of CO<sub>2</sub> reduced, compared to the welfare maximizing policies, that is about 16 times higher than the recommended reference value of CO<sub>2</sub>.

It is likely that the optimized policies (CO<sub>2</sub>-cap or not) are going to be unpopular as all agents get decreased transport utility because they have to pay higher peak fares and tolls. However, in the best scenario without a CO<sub>2</sub>-cap, the net increase in government revenue allows for redistribution to make all agents better off, without a need to raise taxes elsewhere. In the best scenario under the CO<sub>2</sub>-cap however, there is no such opportunity. Compensating agents would require more than the net increase in government revenue, thus requiring raising taxes elsewhere. Hence, reaching ambitious CO<sub>2</sub> targets will require fairly large sacrifices from transport users and/or taxpayers. Politicians that are serious about reaching these targets would need a strong mandate from voters. Because it is not going to be painless.

### 6.1. Putting findings in context

Although the numerical results must be interpreted with caution, our stylized model gives some indication of areas where policy may strike a better balance between costs and benefits in the transport system.

First, efficiency can be gained through more toll differentiation between peak and off-peak hours. Oslo added a peak charge to its cordon toll system in October 2017, and BEVs have had to pay a modest toll in peak-hours since June 2019. The differentiation is an important step, but widening the gap between peak and off-peak would probably be beneficial. We can look to Sweden for comparison, where both the cities of Gothenburg and Stockholm have implemented congestion taxes with larger differences between peak and off-peak hours, and differences *within* the times of day with high traffic levels (Transportstyrelsen, 2019).

Second, widening the gap between peak and off-peak fares in PT would also probably produce efficiency gains. The model finds that large increases in peak fares would be welfare enhancing, but reducing the consumer price for riding off-peak seems like a promising first step. It could perhaps be framed as an “off-peak-discount” to give positive connotations. Oslo’s PT company Ruter proposed increasing fares in peak hours back in 2012. The proposal was hit by a wave of unpopularity in the media,<sup>16</sup> and the debate died. Framing the proposal in a different way could perhaps avoid this problem. To find that optimal policies entail increasing peak tolls and fares, and reducing off-peak tolls and fares, is fairly common in the transport economics literature (see e.g., Börjesson et al., 2017).

Third, our model results illustrate how purchase taxes can be powerful instruments for achieving policy goals. As noted in Section 3.2, it is not the most efficient instrument to correct transport market failures, but it can serve a valuable purpose in a second-best world where the potential for fuel taxes is limited by tax competition. This confirms the finding from Fridstrøm and Østli (2017) that there is a lot of potential for CO<sub>2</sub> emission reductions by inducing the uptake of BEVs and PHEVs through vehicle purchase taxes and feebates. A useful way of viewing the problem is in terms of market correction and incentive compatibility. Tolls, fares, and parking charges can incentivize optimal transport use, and thereby provide corrections in the transport market. Purchase taxes (and possibly their exemptions) on the other hand, can ensure incentive compatibility in the corrected transport market. It can ensure that agents actually select the car combination the optimal policies are designed for. This can serve as an argument for maintaining a purchase tax structure that discriminates according to CO<sub>2</sub> emissions, if ambitious emission targets are to be achieved. The merits of the CO<sub>2</sub>-differentiated purchase tax are further strengthened when other countries, such as Sweden, Germany and South Korea provide subsidies to BEVs. The BEV price in Norway, though competitive with ICEVs, is higher than the subsidized BEV prices in these countries, leading to a sizeable export of slightly used BEVs to Norway (Fridstrøm, 2019).

### 6.2. Caveats

As the results of our analysis depend on our model assumptions, it is important to discuss some of the important caveats. First of all, the model we use is very stylized. Although it adds some layers of complexity to comparable models found in the literature, it contains many simplifying assumptions. An important simplification is that we only have five stylized car types. We thus ignore the range of car options and prices and thus the possibilities of even cheaper options. We also ignore that features like e.g., range and

<sup>16</sup> <https://www.nrk.no/ostlandssendingen/kan-bli-rushtidsavgift-pa-bussen-1.8079403> [last accessed April 9th 2018].



energy efficiency will change during the period from the reference situation to the new equilibrium, although we do a sensitivity test where the cost of BEVs is dramatically lowered relative to ICEVs, in line with expected cost reductions in BEV manufacturing in general and battery manufacturing in particular.

We also underline the simplification that agents only care about the quantity and mode of transport, and thus care only about the generalized cost of transport for a given mode. We have a small exception, with high-income Agent X who has a disutility cost of driving a small car. The other attributes of the car, e.g., comfort or brand, or whether their neighbors drive a certain type of car, do not enter the agents' utility function. We also limit the agents to owning only one car each.

And finally, having three representative agents add more insights than only one, but the model still overlooks many relevant issues of heterogeneity. This could be issues related to income, travel patterns, age, employment, family situation, etc. Differences in environmental preferences, which our modeling cannot account for, could also be a driver of behavior. Stronger environmental preferences could drive agents towards choosing BEVs over conventional cars and/or having a higher share of their transport covered by PT (or walking and biking for that matter).

It is worth noting that we assume no government budget constraint, and that the MCF equals 1. Optimizing policies under budget constraints and/or MCF higher than 1 would most likely entail less government spending on PT (Parry and Small, 2009), and the setting of tolls, fares, and purchase taxes would be influenced by their respective price elasticities. Later analysis using this model could test the implications of a MCF higher than 1, which could also serve as a "moral sensitivity analysis" (Mouter, 2016).

Another caveat is that our stylized transport model does not consider the interactions between transport markets, housing markets and labor markets. Long run changes in generalized costs of travel for the different modes and different periods are small in our main scenarios, but can be expected to have second-order effects. There may be effects on the relative attractiveness of different work and residential locations that could potentially lead to both demand and supply shifts in these markets as well as to agglomeration effects (Proost and Thisse, 2019). Such interactions are better captured in a Land Use and Transport Integrated (LUTI) model. However, our model has the advantage of being less complex, more transparent and able to incorporate the car choice dimension (which is not common for LUTI models) and therefore serves our purpose better.

A final category of caveats concerns behavioral parameters. For example, some price elasticity values have been obtained from different Norwegian transport models, and others have been obtained from Börjesson et al. (2017), which cover transport users in Stockholm. The elasticity values have also been assumed to be the same for all of the agents.

Acknowledging the uncertainty in the model parameters, we have addressed some of the parameter uncertainty through sensitivity testing of the e-mode share of PHEV city driving, the disutility parameter for agent X related to driving small cars, the cost of BEVs and the discount rate. The scenarios with the binding CO<sub>2</sub>-cap can also be seen as sensitivity tests to how the model results change under a higher CO<sub>2</sub> price.

The exact numerical results should therefore be interpreted with caution. Still, we argue that our enhancement of the model from Börjesson et al. (2017) and the results provide insights into the different mechanisms at play, and what balances policies need to strike in order to be welfare improving. Future developments of this model will enable firmer numerical results, as some of the caveats of the current model can be addressed. Most notably, the model would benefit from a richer set of cars and a richer set of heterogeneous agents, as long as the reduction in tractability does not become too large. Further, the cars could differ in a larger number of attributes and the car choice module could be made more sophisticated. With the goal of having a model that can give insights useful for policy making, future extensions of the model will be discussed with stakeholders in the National Public Roads Administration.

### 6.3. Conclusions

Extending the model of Börjesson et al. (2017) with car choice, heterogeneous agents, and occasional long trips has proven to be valuable, as understanding both car ownership choices and transport patterns for different population groups is important in the search for welfare enhancing transport policies. The agents' combination of cars matters for what the optimal policies are, and for the welfare levels achieved in any scenario. Optimal policies means providing the right incentives for both transport demand and for car choice. We find that optimal car choice often will differ for agents with different travel patterns. In particular, agents that demand occasional long trips, e.g., to their cabins, would often be better off with a different car than agents who do not have long trips in their transport consumption basket.

The key question policy makers must ask themselves in this context is: what balance do they want to strike between welfare maximization and CO<sub>2</sub>-reductions; or in other words, how much welfare are they willing to sacrifice in order to reduce CO<sub>2</sub> emissions? Welfare-maximizing policies at the recommended Norwegian reference value of CO<sub>2</sub> (about €50/ton) lead to very small emissions reductions. Policies for achieving the ambitious goals of halving the emissions from personal transport will inevitably bring about substantial welfare costs. These costs accrue mainly through the higher resource costs of BEVs and PHEVs, which play a crucial role in reaching ambitious emissions reductions. On the bright side, the cost of batteries for BEVs, one of the main cost disadvantages, have been falling markedly over the last years and is expected to continue to fall (Norwegian Environment Agency, 2016). If the world will look more like the sensitivity test with cheaper BEVs, then the cost of reaching ambitious climate goals will be reduced.

### CRedit authorship contribution statement

**Paal Brevik Wangsness:** Conceptualization, Methodology, Software, Validation, Formal analysis, Writing - original draft, Writing - review & editing. **Stef Proost:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing.

**Kenneth Løvold Rødseth:** Conceptualization, Writing - original draft, Writing - review & editing.

## Acknowledgements

We thank for valuable comments and insights given from Knut Einar Rosendahl, Chau Man Fung, participants at the presentation at the 40th Annual Meeting of the Norwegian Association of Economists and participants at the presentations at the Norwegian Public Roads Administration. We also thank four anonymous referees for detailed and insightful comments.

## Funding

This work was supported by the Research Council of Norway (RCN), Norway, and the Industry Partners Co-Financing RCN project 255077 (Energy Norway, Norwegian Water Resources and Energy Directorate, Ringeriks-Kraft AS, Norwegian Public Roads Administration and Statkraft Energi AS).

## Appendix A. Details for calibration of the model

For calibration we need quantities for each agent, generalized prices, and elasticities. The quantities used are kilometers travelled on short trips per day, in peak and off-peak, by car and PT, and long trips (100 km + ) by car per year. For short trips agents can substitute between PT and car, and peak and off-peak. For long trips, the agents can only choose the number of long trips per year.

A way to visualize this stylized world is a greater Oslo area where agents travel by car and PT every day, and a couple of times a month/year, some of them take a longer drive to their cabin, relatives etc.

Generalized prices are described in [Section 4.3](#). The own-price elasticities for short car trips are taken from the newest version of the regional transport model RTM23, documented in [Rekdal and Larsen \(2008\)](#). Own-price elasticities for PT and the cross-price elasticities between car transport and PT are taken from the transport model for the greater Oslo area MPM23, documented in [Flügel and Jordbakke \(2017\)](#). The cross-price elasticities for shifting between peak and off-peak, and cross-price elasticities for shifting between both modes and travel time, are the same as those applied in [Börjesson et al. \(2017\)](#). We apply the aggregate elasticity from the National Transport Model, documented in [Rekdal et al. \(2014\)](#) for long car trips. The elasticity values are given in [Table 7](#).

With all these values, MATLAB solves a system of 16 equations with 16 unknowns to complete the calibration of the utility function for each agent. This means we obtain the various parameter values of  $\alpha$ ,  $\beta$  and  $i$  (cf. Eq. (2)) for the various agents.

The generalized prices for short car trips are the distance-based costs (fuel, repair, lubricants etc.), toll and time costs. Distance-based costs are the same as those applied in the National Public Road Administration's (NPRA) tool for CBA, documented in [Cowi \(2014\)](#). Toll costs are based on reporting from the toll companies to NPRA. The value of time is based on the Norwegian valuation study, documented in [Samstad et al. \(2010\)](#). For long car trips, the generalized prices are distance and time costs for the average long car trip, for a given agent. For BEVs there is an added cost to the trip related to charging the car to fill the gap between the range and the length of the average trip times two (assuming back and forth). The time cost of charging is assumed to be VOT for long leisure trips, weighted by the same disutility weights as applied for waiting time for PT on long trips (0.6).

The generalized prices for PT is given by ticket costs and time costs (on board time, access time and waiting time). [Samstad et al. \(2010\)](#) also provide the basis for VOT for PT trips, waiting time and access time. In the presence of a large share of PT users having either 30-day tickets or 12-month tickets, and different price zones, we apply the method for calculating average ridership payment used in [Dovre Group and Institute of Transport Economics \(2016\)](#).

Additional costs: If agents were to buy EVs, a fixed cost is also added for charging equipment, and for renting parking close to home for the share of agents who do not have easy access to parking at or close to their home. Charging cost equipment is assumed to have an up-front cost 10 000 NOK ([Norwegian Environment Agency, 2016](#)). Parking rental is assumed to cost 1 400 NOK per month (median rent for parking space in Oslo in October 2017 on website finn.no).

With regard to the rest of the transport system, we have cost functions for PT and speed-flow functions for car transport. The cost function for PT is simply the annual aggregated operating costs for Ruter, the PT company for Oslo and Akershus, as a linear function

**Table 7**  
Elasticity values.

Elasticity Parameter	Value
Own money price elasticity, peak car trips	-0.152
Own money price elasticity, off-peak car trips	-0.152
Own money price elasticity, peak PT trips	-0.255
Own money price elasticity, off-peak PT trips	-0.284
Cross money price elasticity between peak and off-peak car trips	0.100
Cross money price elasticity between peak car trips and peak PT trips	0.100
Cross money price elasticity between off-peak car trips and off-peak PT trips	0.086
Cross money price elasticity between off-peak car trips and peak PT trips	0.096
Cross money price elasticity between off-peak car trips and off-peak PT trips	0.050
Cross money price elasticity between peak and off-peak PT trips	0.050
Own money price elasticity, long car trips	-0.172

of annual frequency. In addition, there is a crowding cost function, where the travel time cost is weighted by a crowding factor. The crowding factor has been calibrated to be a piecewise linear function where the current peak ridership per hour gives a crowding factor of 1.3, same as in Minken (2017), and current average off-peak ridership gives a crowding factor of 1. The crowding factor will not get smaller if ridership falls below this level, so 1 serves as a lower bound for the crowding factor.

The speed-flow functions are based on model simulations from RTM23 on aggregate car travel and travel speed in Oslo and Akershus for a range of scenarios, but with constant road capacity. The result is an aggregate piecewise linear speed-flow function. The linearity simplifies the model calculation, but as shown in Arnott, De Palma, and Lindsey (1993), it also serves as a good approximation for a traffic bottleneck model. The aggregation of the speed-flow functions over a whole area is useful as we analyze policies that are not spatially differentiated, so we assume implicitly that the city is homogeneous in terms of response to the general policies we study here.

## Appendix B. Sensitivity analysis table

See Table 8.

**Table 8**

Difference in welfare relative to reference situation for all car combinations for agents X, Y and Z under different scenarios. ICL = Large conventional car, ICs = Small conventional car, Hy = Plug-in Hybrid, EVI = Long-range EV, EVs = Short-range EV. X, Y and Z denotes the model agents.

Welfare rank under original optimization and BAU and EV-SAME scenario	Scenarios: Fixed car combinations and BAU and EV-SAME scenario	Welfare difference under original optimization	Welfare difference under sensitivity test: PHEV e-share	Welfare difference under sensitivity test: Agent X less disutility of small cars	Welfare difference under sensitivity test: Cost of EVs	Welfare difference under sensitivity test: Higher discount rate	Welfare difference under CO2-cap
1	X: ICL Y: ICs Z: ICs	218	218	218	218	-6 616	-23 494
2	X: Hy Y: ICs Z: ICs	-894	-739	-894	-894	-8 338	-6 561
3	EV-SAME	-1 108	-954	-1 108	-1 108	-8 833	N/A
4	X: ICL Y: ICs Z: EVs	-2 588	-2 588	-2 588	-1 620	-10 199	-15 223
5	X: ICs Y: ICs Z: ICs	-2 802	-2 802	-2 413	-2 802	-8 614	-22 212
6	X: Hy Y: ICs Z: EVs	-3 700	-3 545	-3 700	-2 732	-11 921	-3 766
7	X: ICL Y: EVs Z: ICs	-4 524	-4 524	-4 524	-2 370	-13 089	-8 168
8	X: ICs Y: ICs Z: EVs	-5 608	-5 608	-5 219	-4 641	-12 197	-14 905
9	X: Hy Y: EVs Z: ICs	-5 637	-5 482	-5 637	-3 483	-14 811	-5 637
10	BAU	-5 880	-5 726	-5 880	-8 929	-15 334	N/A
11	X: ICL Y: EVs Z: EVs	-7 330	-7 330	-7 330	-4 209	-16 672	-7 355
12	X: ICs Y: EVs Z: ICs	-7 545	-7 545	-7 156	-5 391	-15 088	-8 972
13	X: EVI Y: ICs Z: ICs	-7 606	-7 606	-7 606	-4 229	-18 825	-7 606
14	X: EVs Y: ICs Z: ICs	-7 811	-7 811	-7 422	-6 578	-14 614	-7 811
15	X: Hy Y: EVs Z: EVs	-8 443	-8 289	-8 443	-5 322	-18 395	-8 443
16	X: ICs Y: EVs Z: EVs	-10 351	-10 351	-9 962	-7 230	-18 671	-10 351
17	X: EVI Y: ICs Z: EVs	-10 412	-10 412	-10 412	-6 068	-22 408	-10 412
18	X: EVs Y: ICs Z: EVs	-10 617	-10 617	-10 228	-8 417	-18 196	-10 617
19	X: EVI Y: EVs Z: ICs	-12 350	-12 350	-12 350	-6 818	-25 299	-12 350
20	X: EVs Y: EVs Z: ICs	-12 554	-12 554	-12 165	-9 167	-21 087	-12 554
21	X: EVI Y: EVs Z: EVs	-15 156	-15 156	-15 156	-8 658	-28 882	-15 156
22	X: EVs Y: EVs Z: EVs	-15 361	-15 361	-14 972	-11 006	-24 671	-15 361

## References

- Akershus County Council, 2016. På vei mot et fossilfritt Akershus i 2050 - Planprogram for Regional plan for klima og energi i Akershus 2018-2030. Akershus: Vedtatt av fylkesutvalget 6. juni 2016.
- Anas, A., Lindsey, R., 2011. Reducing urban road transportation externalities: road pricing in theory and in practice. *Rev. Environ. Econ. Policy* 5 (1), 66–88.
- Arnott, R., De Palma, A., Lindsey, R., 1993. A structural model of peak-period congestion: a traffic bottleneck with elastic demand. *Am. Econ. Rev.* 161–179.
- Axsen, J., Bailey, J., Castro, M.A., 2015. Preference and lifestyle heterogeneity among potential plug-in electric vehicle buyers. *Energy Econ.* 50, 190–201.
- Axsen, J., Mountain, D.C., Jaccard, M., 2009. Combining stated and revealed choice research to simulate the neighbor effect: the case of hybrid-electric vehicles. *Resour. Energy Econ.* 31 (3), 221–238.
- Bjerkkan, K.Y., Nørbech, T.E., Nordtømme, M.E., 2016. Incentives for promoting battery electric vehicle (BEV) adoption in Norway. *Transp. Res. Part D: Transp. Environ.* 43, 169–180.
- Boug, P., Dyvi, Y., 2008. MODAG-en makroøkonomisk modell for norsk økonomi. Statistisk sentralbyrå.
- Brownstone, D., Bunch, D.S., Train, K., 2000. Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. *Transp. Res. Part B: Methodol.* 34 (5), 315–338.
- Börjesson, M., Fung, C.M., Proost, S., 2017. Optimal prices and frequencies for buses in Stockholm. *Econ. Transp.* 9, 20–36.
- Coffman, M., Bernstein, P., Wee, S., 2017. Electric vehicles revisited: a review of factors that affect adoption. *Transp. Res.* 37 (1), 79–93.
- Cowi, 2014. Oppdatering av enhetskostnader i nytte-kostnadsanalyser i Statens vegvesen. Retrieved from Oslo: [www.cowi.no](http://www.cowi.no).
- De Palma, A., Kilani, M., Proost, S., 2015. Discomfort in mass transit and its implication for scheduling and pricing. *Transp. Res. Part B: Methodol.* 71, 1–18.
- de Souza, A.M., Yokoyama, R.S., Maia, G., Loureiro, A., Villas, L., 2016. Real-time path planning to prevent traffic jam through an intelligent transportation system. In:

- Paper presented at the 2016 IEEE Symposium on Computers and Communication (ISCC).
- Diaz Rincon, A., 2015. Essays on transport policy and technology. (PhD), KU Leuven, Leuven, Belgium.
- Dovre Group, Institute of Transport Economics, 2016. Oslo-Navet: Kvalitetssikring av beslutningsunderlag for konseptvalg (KS1). Statens prosjektmodell, Rapport nummer D035a.
- Downs, A., 1962. The law of peak-hour expressway congestion. *Traffic Quart.* 16 (3).
- Duranton, G., Turner, M.A., 2011. The fundamental law of road congestion: evidence from US cities. *Am. Econ. Rev.* 101 (6), 2616–2652.
- Figenbaum, E., 2018. Electromobility Status in Norway: Mastering Long Distances—the Last Hurdle to Mass Adoption. TØI Report(1627/2018).
- Figenbaum, E., Assum, T., Kolbenstvedt, M., 2015. Electromobility in Norway: experiences and opportunities. *Res. Transp. Econ.* 50, 29–38.
- Figenbaum, E., Kolbenstvedt, M., 2013. Electromobility in Norway-experiences and opportunities with Electric Vehicles.
- Figenbaum, E., Weber, C., 2017. Experimental Testing of Plug-in Hybrid Vehicles: CO<sub>2</sub>-Emission, Energy Consumption and Local Pollution. TØI Report(1539/2016).
- Figenbaum, E., Ydersbond, I.M., Amundsen, A.H., Pinchasik, D.R., Thorne, R.J., Fridstrøm, L., Kolbenstvedt, M., 2019. 360 degree analysis of the potential for zero-emission vehicles (TØI Report 1744/2019). Retrieved from <https://www.toi.no/publikasjoner/360-graders-analyse-av-potensialet-for-nullutslippkjoretøy-article35999-8.html>.
- Fischer, C., Newell, R.G., 2008. Environmental and technology policies for climate mitigation. *J. Environ. Econ. Manage.* 55 (2), 142–162.
- Flügel, S., Fearnley, N., Toner, J., 2018. What factors affect cross-modal substitution?—Evidences from the Oslo Area. *Int. J. Transp. Develop. Integrat.* 2 (1), 11–29.
- Flügel, S., Hulleberg, N., 2016. Trenklin 2: Review of the Model and Discussion about Fields of Application. TØI Report(1534/2016).
- Flügel, S., Jordbakke, G.N., 2017. Videreutvikling av markedspotensiellmodell for Oslo and Akershus (MPM23 v2.0) [Further development of the market potential model for Oslo and Akershus (MPM23 V2.0)]. Retrieved from <https://www.toi.no/publikasjoner/videreutvikling-av-markedspotensiellmodell-for-oslo-and-akershus-mpm23-v2-0-article34628-8.html>.
- Fridstrøm, L., 2019. Dagens og morgendagens bilavgifter [Current and future taxation of cars]. TØI rapport 1708/2019.
- Fridstrøm, L., Østli, V., 2017. The vehicle purchase tax as a climate policy instrument. *Transp. Res. Part A: Policy Practice* 96, 168–189.
- Fridstrøm, L., Østli, V., Johansen, K.W., 2016. A stock-flow cohort model of the national car fleet. *Eur. Transp. Res. Rev.* 8 (3), 22.
- Frisch, R., 1964. *Theory of Production*. Springer Science & Business Media.
- Garcia-Lopez, M.-A., Pasidis, I., Viladecans-Marsal, E., 2017. Highway congestion and air pollution in Europe's cities. (From PhD in Economics Thesis), Universitat de Barcelona, Working paper.
- Grigolon, L., Reynaert, M., Verboven, F., 2018. Consumer valuation of fuel costs and tax policy: evidence from the European car market. *Am. Econ. J.: Econ. Policy* 10 (3), 193–225.
- Hardman, S., Chandan, A., Tal, G., Turrentine, T., 2017. The effectiveness of financial purchase incentives for battery electric vehicles—a review of the evidence. *Renew. Sustain. Energy Rev.* 80, 1100–1111.
- Hidru, M.K., Parsons, G.R., Kempton, W., Gardner, M.P., 2011. Willingness to pay for electric vehicles and their attributes. *Resour. Energy Econ.* 33 (3), 686–705.
- Hjorthol, R., Engebretsen, Ø., Uteng, T.P., 2014. Den nasjonale reisevaneundersøkelsen 2013/14: nøkkelrapport. Transportøkonomisk institutt.
- Hsu, W.-T., Zhang, H., 2014. The fundamental law of highway congestion revisited: evidence from national expressways in Japan. *J. Urban Econ.* 81, 65–76.
- Huppmann, D., Kriegler, E., Krey, V., Riahi, K., Rogelj, J., Rose, S.K., et al., 2018. IAMC 1.5°C Scenario Explorer and Data hosted by IIASA (Publication no. 10.22022/SR15/08-2018.15429). from Integrated Assessment Modeling Consortium & International Institute for Applied Systems Analysis <https://data.ene.iiasa.ac.at/iamec-sr15-explorer>.
- Hörcher, D., Graham, D.J., Anderson, R.J., 2017. Crowding cost estimation with large scale smart card and vehicle location data. *Transp. Res. Part B: Methodol.* 95, 105–125.
- IEA, 2017. Energy Policies of IEA Countries - Norway 2017 Review. Retrieved from <http://www.iea.org/publications/freepublications/publication/EnergyPoliciesofIEACountriesNorway2017.pdf>.
- IPCC, 2018. Global Warming of 1.5 °C. Retrieved from <http://www.ipcc.ch/report/sr15/>.
- Jaccard, M., Nyboer, J., Bataille, C., Sadownik, B., 2003. Modeling the cost of climate policy: distinguishing between alternative cost definitions and long-run cost dynamics. *Energy J.* 49–73.
- Javid, R.J., Nejat, A., 2017. A comprehensive model of regional electric vehicle adoption and penetration. *Transp. Policy* 54, 30–42.
- Jochem, P., Doll, C., Fichtner, W., 2016. External costs of electric vehicles. *Transp. Res. Part D: Transp. Environ.* 42, 60–76.
- Kilani, M., Proost, S., van der Loo, S., 2014. Road pricing and public transport pricing reform in Paris: complements or substitutes? *Econ. Transp.* 3 (2), 175–187.
- Langbroek, J.H., Franklin, J.P., Susilo, Y.O., 2016. The effect of policy incentives on electric vehicle adoption. *Energy Policy* 94, 94–103.
- Li, W., Long, R., Chen, H., Geng, J., 2017. A review of factors influencing consumer intentions to adopt battery electric vehicles. *Renew. Sustain. Energy Rev.* 78, 318–328.
- Li, Z., Hensher, D.A., 2011. Crowding and public transport: a review of willingness to pay evidence and its relevance in project appraisal. *Transp. Policy* 18 (6), 880–887.
- Mandell, S., Proost, S., 2016. Why truck distance taxes are contagious and drive fuel taxes to the bottom. *J. Urban Econ.* 93, 1–17.
- Mau, P., Eyzaguirre, J., Jaccard, M., Collins-Dodd, C., Tiedemann, K., 2008. The 'neighbor effect': simulating dynamics in consumer preferences for new vehicle technologies. *Ecol. Econ.* 68 (1–2), 504–516.
- Mersky, A.C., Sprei, F., Samaras, C., Qian, Z.S., 2016. Effectiveness of incentives on electric vehicle adoption in Norway. *Transp. Res. Part D: Transp. Environ.* 46, 56–68.
- Minken, H., 2017. In-vehicle crowding: An overview with suggestions for future work. TØI Report(1551/2017).
- Mouter, N., 2016. Dutch politicians' use of cost–benefit analysis. *Transportation* 1–19.
- Nordhaus, W., 2019. Climate change: the ultimate challenge for economics. *Am. Econ. Rev.* 109 (6), 1991–2014.
- Norwegian Electric Vehicle Association, 2019. Statistikk elbil. Retrieved from <https://elbil.no/elbilstatistikk/>.
- Norwegian Environment Agency, 2016. Tiltakskostnader for elbil - Samfunnsøkonomiske kostnader ved innføring av elbiler i personbilparken. (M-620). Miljødirektoratet, Oslo [Norwegian Environment Agency] Retrieved from <http://www.miljodirektoratet.no/no/Publikasjoner/2016/Oktober-2016/Tiltakskostnader-for-elbil/>.
- Norwegian Public Roads Administration, 2018. Handbook V712 - Impact assessment [Håndbok V712 - Konsekvensanalyser]. Oslo Retrieved from <https://www.vegvesen.no/attachment/704540/>.
- NOU 2012:16, 2012. Samfunnsøkonomiske analyser. Departementenes servicesenter, Oslo.
- NOU 2015:15, 2016. Sett pris på miljøet - Rapport fra grønn skattekomisjon [Put a price on the environment - Report from the green tax commission]. Departementenes sikkerhets- og serviceorganisasjon, Oslo.
- OECD, 2016. Effective Carbon Rates: Pricing CO<sub>2</sub> Through Taxes and Emissions Trading Systems: OECD.
- Oslo Municipality, 2016. Klima- og energistrategi for Oslo [Climate and energy strategy for Oslo]. Oslo: Behandlet av Oslo bystyre 22.06.2016 (sak 195/16).
- Parry, I.W., Evans, D., Oates, W.E., 2014. Are energy efficiency standards justified? *J. Environ. Econ. Manage.* 67 (2), 104–125.
- Parry, I.W., Small, K.A., 2009. Should urban transit subsidies be reduced? *Am. Econ. Rev.* 99 (3), 700–724.
- Perman, R., Ma, Y., McGlivray, J., Common, M., 2003. *Natural Resource and Environmental Economics*. Pearson Education.
- Proost, S., Thisse, J.-F., 2019. What can be learned from spatial economics? *J. Econ. Literat.* 57 (3), 575–643.
- Proost, S., Van Dender, K., 2001. The welfare impacts of alternative policies to address atmospheric pollution in urban road transport. *Regional Sci. Urban Econ.* 31 (4), 383–411.
- Rekdal, J., Hamre, T.N., Flügel, S., Steinsland, C., Madslie, A., Grue, B., et al., 2014. NTM6 – Transportmodeller for reiser lengre enn 70 km. Møreforskning Rapport, 1414.
- Rekdal, J., Larsen, O.I., 2008. RTM23 +, Regional modell for Oslo-området. Dokumentasjon av utviklingsarbeid og teknisk innføring i anvendelse. MFM rapport, 806, 2008.

- Rezvani, Z., Jansson, J., Bodin, J., 2015. Advances in consumer electric vehicle adoption research: a review and research agenda. *Transp. Res. Part D: Transp. Environ.* 34, 122–136.
- Ruter, 2016. Årsrapport 2016 [Annual report 2016]. Retrieved from <https://ruter.no/globalassets/dokumenter/aarsrapporter/ruter-arsrapport-20161.pdf>.
- Rødseth, K.L., 2017. Axioms of a polluting technology: a materials balance approach. *Environ. Resour. Econ.* 67 (1), 1–22. <https://doi.org/10.1007/s10640-015-9974-1>.
- Samstad, H., Ramjerdi, F., Veisten, K., Navrud, S., Magnussen, K., Flügel, S., Martin, O., 2010. Den norske verdsettingsstudien. Sammendragsrapport. TOI Rapport 1053, 2010.
- Small, K.A., Verhoef, E.T., 2007. *The Economics of Urban Transportation*. Routledge.
- Thune-Larsen, H., Veisten, K., Rødseth, K.L., Klæboe, R., 2014. Marginale eksterne kostnader ved vegtrafikk med korrigerte ulykkeskostnader (1307/2014). Retrieved from Oslo: <https://www.toi.no/getfile.php?mmfileid=38978>.
- Tol, R.S., 2005. The marginal damage costs of carbon dioxide emissions: an assessment of the uncertainties. *Energy Policy* 33 (16), 2064–2074.
- Transportstyrelsen, 2019. Congestion taxes in Stockholm and Gothenburg. Retrieved from <https://www.transportstyrelsen.se/en/road/Congestion-taxes-in-Stockholm-and-Goteborg/> (last accessed 25.11.2019).
- Tscharaktschiew, S., 2014. Shedding light on the appropriateness of the (high) gasoline tax level in Germany. *Econ. Transp.* 3 (3), 189–210.
- US Energy Information Association, 2019. The National Energy Modeling System: An Overview 2018. Retrieved from [https://www.eia.gov/outlooks/aeo/nems/overview/pdf/0581\(2018\).pdf](https://www.eia.gov/outlooks/aeo/nems/overview/pdf/0581(2018).pdf).
- Østli, V., Fridstrøm, L., Johansen, K.W., Tseng, Y.-Y., 2017. A generic discrete choice model of automobile purchase. *Eur. Transp. Res. Rev.* 9 (2), 16.