Norwegian University of Life Sciences
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# Economics and policies for the electrification of transport

## Elbilpolitikk fra et samfunnsøkonomisk perspektiv

Paal Brevik Wangsness

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## Summary

This thesis focuses on the **economics and polices for the electrification of transport**. Over the last few years we have observed a rapid rise in the number of battery electric vehicles (BEVs) in Norway. This growth is the combined result of rapid technological change and a targeted national climate policy. The rising share of BEVs relative to the share of conventional vehicles could lead to socio-economic benefits such as reduced greenhouse gas emissions and local pollution, but it could also pose new challenges such as pressure on the capacity of the electricity distribution network. In addition, BEVs have similar negative externalities as fossil-fueled vehicles with regards to congestion, road wear and accidents. BEVs can mitigate some market failures and exacerbate others, creating a messy optimization problem for the social planner. This illustrates the need for new knowledge on mechanisms and welfare enhancing policies in the transport and electricity markets as they become more integrated. This thesis seeks to contribute to the body of knowledge on the subject, in the following introductory chapter and four independent chapters. The latter chapters are written as scientific papers that are either published or in the process of getting published in peer-reviewed journals.

The first chapter takes a national perspective. An increasing market share of BEVs relative to ICEVs leads to, *ceteris paribus*, reduced government revenue. BEVs also have many of the same externalities as ICEVs, but they cannot be captured by a fuel tax, and it seems implausible to tax EVs explicitly through their electricity charging. I find that a distance-based road pricing scheme, differentiated by vehicle type and when and by where the driving takes place, can be a good response to this issue.

The second chapter takes the analysis down to the city level, where the growth in BEVs has been most pronounced. The area of study is the Oslo metropolitan areas, where they have very ambitious short-term emission targets. Reaching these targets implies extremely high social costs, *even if costs are kept to a minimum.* A least-cost strategy will require a relatively large shift to BEVs, but where appropriate balances are stricken between road prices, public transport fares and vehicle purchase taxes.

At the time of writing, there is no ability for the local grid operators, the DSOs (Distribution System Operators), to differentiate their grid tariffs over the day. There is therefore no incentive for the individual BEV owner to reschedule charging times, and if charging during peak hours leads to extra cost for the DSO, the cost is borne by all of their customers. This would be a case of a pecuniary externality in an incomplete market. In the third chapter we investigate the feedback between the transport market and electricity market and how policies in one market can affect the equilibrium in the other.

Can the local grid costs stemming from BEVs be estimated empirically? We answer this question in the fourth chapter. If any country would have any usable data to test this, it would be Norway. Norway has had many years with high growth in BEVs, where the absolute number of BEVs in certain places could have had an impact on DSO costs. We do find statistically and economically significant effects from BEVs on DSO costs, but there is a lot of heterogeneity in the results.

**The main overarching contribution is new and improved understanding of how the emergence of BEVs, as a technology in the transport sector, changes the calculus of social costs and benefits and how policies optimally should respond to these changes.** This is done by extending well-established modeling frameworks to include BEVs and charging issues, and econometric analysis of a new and highly relevant dataset on BEV density and DSO costs. With this we can better understand the mechanisms at play, and what balances need to be struck to form welfare-enhancing policies.

## Sammendrag

Denne avhandlingen tar for seg **elbilpolitikk i et samfunnsøkonomisk perspektiv**. De siste årene har vi opplevd en rask økning i antall elbiler i Norge. Denne veksten er et resultat av både rask teknologisk utvikling og en målrettet nasjonal klimapolitikk. Den økende andelen av elbiler i forhold til andelen konvensjonelle biler kan føre til samfunnsøkonomiske fordeler som reduserte klimagassutslipp og lokal forurensning, men det kan også gi nye utfordringer som press på kapasiteten til strømdistribusjonsnettet. I tillegg har elbiler tilsvarende eksterne kostnader som konvensjonelle biler med tanke på kø, veislitasje og ulykker. Elbiler kan dempe noen markedssvikt og forverre andre, og skape et rotete optimaliseringsproblem for samfunnsplanleggeren. Dette understreker behovet for ny kunnskap om den gjensidige påvirkningen mellom transport- og elektrisitetsmarkedet, og hva som kan være samfunnsmessig effektiv politikk. Denne avhandlingen bidrar til kunnskapen om emnet, i det følgende kappen og fire uavhengige kapitler. De siste kapitlene er skrevet som vitenskapelige artikler som enten er publisert eller i ferd med å bli publisert i fagfellevurderte tidsskrifter.

Det første kapittelet tar et nasjonalt perspektiv. En økende markedsandel av elbiler i forhold til konvensjonelle biler fører til, *ceteris paribus*, reduserte offentlige inntekter. Elbiler har også mange av de samme eksternalitetene som konvensjonelle biler, men de kan ikke fanges opp av en drivstoffavgift, og det virker usannsynlig å kunne skattlegge elbiler eksplisitt gjennom ladingen av bilene. Jeg finner at et distanse-basert veiprisingssystem, differensiert etter kjøretøytype og når og hvor kjøringen foregår, kan være en god måte å møte dette problemet.

Det andre kapittelet tar analysen ned til bynivå, der veksten i elbiler har vært mest markant. Fokuset er på Oslo-området, der de har svært ambisiøse utslippsmål på kort sikt. Å nå disse målene innebærer ekstremt høye samfunnskostnader, selv om kostnadene holdes på et minimum. En minstekostnadsstrategi vil kreve et relativt stort skifte til elbiler, men fordrer en effektiv balansering mellom veipriser, kollektivpriser og engangsavgifter for bil.

I skrivende stund er det ingen muligheter for de lokale nettselskapene til å differensiere nettleien time for time. Det er derfor ikke noe insentiv for den enkelte elbileier å tilpasse når hen lader, for hvis lading i topplasttimer fører til ekstra kostnader for nettselskapet, blir kostnadene spredd på alle kundene deres. Det blir et tilfelle av en pekuniær eksternalitet i et ufullstendig marked. I det tredje kapittelet undersøker vi samspillet mellom transport- og strømmarkedet og hvordan politikk i det ene markedet kan påvirke likevekten i det andre.

Kan de kostnader i distribusjonsnettet som stammer fra elbiler estimeres empirisk? Dette gjør vi i fjerde kapittel. Hvis noe land ville ha brukbare data for å teste dette, vil det være Norge. Norge har hatt mange år med høy vekst i elbiler, men med mye lokal variasjon, så det er mulig å identifisere hvordan elbiler påvirker nettkostnader. Vi finner statistisk og økonomisk signifikante effekter fra elbiler på nettkostnader, men det er mye heterogenitet i resultatene.

**Det viktigste overordnede bidraget er ny og forbedret forståelse av hvordan fremveksten av elbiler, som en teknologiendring i transportsektoren, endrer regnestykket av samfunnsmessig nytte og kostnader, og hvordan politikk optimalt skal svare på disse endringene.** Ved å bygge videre på veletablerte modellrammeverk til å omfatte elbiler og aspekter knyttet til elbillading, og en økonometrisk analyse av et nytt og relevant datasett, kan vi bedre forstå mekanismene og hvordan ulike politiske virkemidler kan brukes til å styrke det samfunnsøkonomiske overskuddet.

# Acknowledgements

One morning back in 2015 the Textbook Social Planner knocked on my office door. He offered me an assignment.

"Paal, I got 99 problems, and I want to know if electrification of transport also is one. We got projections for strong growth in battery electric vehicle (BEV) sales driven by policy measures, and I am not convinced that this is a symptom of something good. As you know, what I really want is marginal damages to be equal marginal abatement costs. Could you do some digging for me? I am swamped with economic issues all over the place so I am trying to delegate as much as I can. People are super-busy these days, but I saw your schedule was open over the next few years".

"Sure", I said hesitantly, as I felt that the assignment delegation had a strong element of convenience and not just a consequence of my personal merits, "seems like a respectable problem to solve". I made grand title gestures with my hands and said "Economics & Policies for the electrification of transport – A PhD-thesis by Paal Brevik Wangsness".

"Sounds good", mumbled the Social Planner and started back towards the door. "You got 3 man-years over a 4-year period", he said and hurried out. Probably to delegate more assignments to other economists.

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OK, it didn't exactly happen that way. Back in 2015 I was a part of a team of researchers putting together a proposal for the Norwegian Research Council with the title ELECTRANS (Electrification of Transport – Challenges, Mechanisms and Solutions). The project included financing of my PhD. We put together a solid proposal, along with the support of partners from both government and industry. So from the very get-go, I have received help from people around me.

Thank you, Knut Einar Rosendahl, for being a great supervisor. I have appreciated your guidance, our serious discussions when going through plans and article drafts, and your encouraging feedback.

I want to thank my co-supervisor and co-author Kenneth Løvold Rødseth, for valuable input to the articles and many good discussions. I also appreciated all the quick sanity checks over the years, as they have been very helpful.

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I want to thank my wonderful colleagues at TØI, in particular at the Department of Economics. I have knocked on many doors and asked a lot of questions, and I am very grateful for your time and patience. I hope you know that I want to return the favor. And thank you to TØI, the institution, for providing such favorable conditions for researchers to get a PhD.

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I also want to thank my loving family; both the ones I have around me now, and those who are not around anymore. You give me love and strength. And finally, a great thanks to my loving wife, Cecilia, who has provided great moral support in times of need. I thank you for all the love, and for putting up with me during this prolonged period of focused nerdery.

It has been 4 very rewarding years, and I feel extremely fortunate to get the time and freedom to dig deep into important and interesting topics in transport economics, build skills, build a network, get feedback and inspirations at conferences, workshops and seminars (a great thanks for all the feedback and discussions I have had with opponents and participants over the years), and to grow as an economist. I count my blessings, and this PhD period is one of them.

# Contents

# Introductory chapter to PhD thesis Economics and policies for the electrification of transport

# 1 Introduction and motivation

I recall my professor in an undergraduate microeconomics course saying "Without any market failures, there wouldn't be any need for economists!". While such a statement was probably meant more as motivation for the class rather than being an undisputable fact, it contributed to form and reinforce my thought process whenever I discuss our analyze a policy issue. Some of the early questions I ask early in the thought process are "What exactly are the market failures here?", "Or is it a government failure?" or "Could it be a tricky trade-off between market failures and government failures?".

Perman, Ma, McGlivray, and Common (2003) provide the following set of necessary conditions for markets to produce efficient allocations:

1. Markets exist for all goods produced and consumed.
2. All markets are perfectly competitive.
3. All transactors have perfect information.
4. Private property rights are fully assigned in all resources and commodities.
5. No externalities exist.
6. All goods and services are private goods, i.e. there are no public goods.
7. All utility and production functions are "well-behaved".
8. All agents are maximizers.

Throughout this dissertation I will be covering issues where several of these conditions do not hold, more specifically conditions 1 (missing markets), 2 (imperfect competition), 5 (externalities) and 6 (public goods). **The transport and energy sector, the overarching research area for this thesis, are more or less embedded with textbook market failures.** These sectors are also subject to a lot of policy. There is a magnitude of regulations and taxes (with more or less targeted exemptions), subsidies and infrastructure financed by distortionary taxes elsewhere in the economy. It can be argued that some of this policy is targeted towards correcting market failures, but a lot of it is not. And the policies that are targeted towards correcting market failures are likely to be sub-optimally assigned. In other words, we might be pretty far away from any theoretical perfectly competitive Pareto-efficient market. So there is room for improvement.

The topics of the thesis are the **economics and polices for the electrification of transport**. Over the last few years we have observed a rapid rise in the number of battery electric vehicles (BEVs) in Norway. This growth is the combined result of rapid technological change and a targeted national climate policy. So what are the issues here? The rising share of BEVs relative to the share of internal combustion engine vehicles (ICEV) could lead to socio-economic benefits such as reduced greenhouse gas emissions and local pollution, but it could also pose new challenges such as pressure on the capacity of the electricity distribution network. In addition, BEVs have similar negative externalities as fossil-fueled vehicles with regards to congestion, road wear and accidents (Thune-Larsen, Veisten, Rødseth, & Klæboe, 2014). On top of that, the low cost of driving a BEV will also affect the relative competitiveness of public transportation (and walking and cycling), which may prevent the exploitation of scale economies for scheduled urban transport, see Mohring (1972). In other words, BEVs can mitigate some market failures and exacerbate others, creating a messy optimization problem for the social planner. This illustrates the need for new knowledge on mechanisms and welfare enhancing policies in the transport and electricity markets as they become more integrated.

These issues need to be boiled down to some applicable research questions, and the scope must be limited to what can be done during the time of the project. The first scope limitation is that the research will be focusing on the case of Norway. With electrification of transport as a problem area, it makes sense to focus on Norway. It is the country in the world with the highest share of BEVs among new car sales, and with the subsequent fastest growth in the BEV share of the car fleet. Challenges and benefits related to the electrification of transport will be visible here first.

It is useful to start with the big picture. The externalities stemming from car transport, and the strain on government budgets due to declining tax revenue from the purchase, ownership and use of cars, are *national* issues. With regards to the latter, an increasing market share of BEVs relative to ICEVs leads to, *ceteris paribus*, reduced government revenue (Ministry of Finance, 2017). BEVs also have many of the same externalities as ICEVs, but they cannot be captured by a fuel tax, and it seems implausible to tax EVs explicitly through their electricity charging. And even if all types of cars could be taxed through fueling, such a system would still be unable to internalize externalities that depend on when and where the driving takes place. In summary, what we are seeing is that the current system for vehicle taxation is unable to get BEVs to internalize the externalities from their driving, and there is a large government revenue loss.

Most transport economists would suggest a road pricing scheme as a potential candidate to counter this emerging problem. A promising variant could be distance-based road pricing, differentiated across vehicle types and pre-defined areas and time periods according to their external costs, also factoring in revenue recycling through reduced labor taxation. Such price differentiation can be made possible by using satellite technology. This seems like a good topic for the first analysis, on national level.

The rapid growth in the BEV stock is a national issue, but it is clear that fastest uptake is happening in and around the largest cities (Figenbaum, 2018). That means that in addition to the issues of externalities and government revenue, we also have the interaction with the cities' public transport (PT) system. This seems like a good topic for the second analysis, where we take it down to city level.

In addition to adding new complexity to both the transport systems and government finances, BEVs add new complexity to the electricity system. Continued growth in BEV sales in accordance with the National Transport Plan will lead to about 1.5 million BEVs by 2030 (about half of the passenger car stock), which will increase national electricity consumption by less than 3% according to Skotland, Eggum, and Spilde (2016). However, they point out that the charging of BEVs, especially if many do so simultaneously and at high capacity, could challenge the capacity of the electricity grid. As pointed out in the literature, BEV charging can lead to a peak capacity problem in the local grid (Azadfar, Sreeram, & Harries, 2015; Masoum, Deilami, Moses, Masoum, & Abu-Siada, 2011). And at the time of writing, there is no ability for the local grid operators, the DSOs (Distribution System Operators), to differentiate their grid tariffs over the day. There is therefore no incentive for the individual BEV owner to reschedule charging times, and if charging during peak hours leads to extra cost for the DSO, the cost is borne by all of their customers. This would be a case of a pecuniary externality in an incomplete market. Hence, for a third analysis, we want to investigate the feedback between the transport market and electricity market and how policies in one market can affect the equilibrium in the other. We will assess how polices can be optimized to reach policy goals at least cost. It will be a question of optimizing the car fleet, the transport equilibrium and the charging equilibrium.

Can the local grid costs stemming from BEVs be estimated empirically? If any country would have any usable data to test this, it would be Norway. By the end of the project, Norway will have had many years with high growth in BEVs, where the absolute number of BEVs in certain places could have had an impact on DSO costs. This seems like a good venue for the fourth analysis.

These four analyses contribute to the common goal of **building knowledge on how to deal with the challenges and opportunities that arise from transport electrification**. The scope of this work is centered on the Norwegian perspective, so more global issues such as the production of BEVs and the challenges arising from the BEV supply chain is out of scope. However, while the research is mainly focusing on the Norwegian case, the findings will provide useful knowledge far beyond Norwegian borders. As other nations are aiming to increase the BEV share of the car fleet, learning from Norwegian successes and mistakes will be useful.

The remainder of the introductory chapter goes as follows: Section 2 provides some background to the thesis problem area. Section 3 gives and overview of the theory, methods and data applied in the thesis. In section 4 I provide a synthesis of the thesis. Here I first give an overview, discuss the main findings and an how the papers contribute to the literature, before providing a brief summary of each paper. Section 5 provides conclusions and implications. A snapshot of all papers, with research questions, theory, methods, data and findings can be found in a summary table in the Appendix.

# 2 Background

I will briefly put the market failures this thesis will investigate in context with the Norwegian economy. An overall estimate of total external costs from road transport given in van Essen et al. (2019). They estimate that these external costs totaled up to €7.4 bn in 2016, which corresponded to about 3.4% of Norwegian GDP. Although such figures are subject to large uncertainty, it gives an idea of the welfare cost of some of the market failures in transport.

The $CO_2$ emissions from road transport have generally been growing since the 1990s, along with the growth in the number of passenger cars and kilometers driven. However, emissions per vehicle kilometer has fallen over the same period, with the sharpest declines after 2015. These accelerations in emission efficiency have largely been helped by the rapid growth in hybrids, plug-in hybrids and in particular, BEVs (see Figure 1).

The growth in BEVs has been largely policy-driven. Over the years, the policies affecting the relative competitiveness of BEVs have included exemption from VAT, exemption from the purchasing tax (although only the weight component would generate a positive tax for BEVs), exemption from tolls and ferry fares, free municipal parking and access to bus lanes (Figenbaum, 2018). However, probably the most powerful policy measure is the $CO_2$-component of the purchase tax (see Figure 1). This tax component is piecewise linear function of measured $gCO_2$/km per vehicle, where the marginal cost per $gCO_2$/km increases after thresholds 70, 95, 125 and 150 g/km. Passenger cars with very high emissions per km may experience a tax burden that may be double the pre-tax purchase price. Many of these policy measures will be discussed in the articles of this thesis.

Finally, an increase in the BEV fleet leads to an increase in electricity consumed, as the cars need to be charged. In 2018, electricity consumed for road transport reached 475 GWh[1]. This still only corresponds to 0.4% of Norway's electricity use in 2018, but the growth will continue. With continued growth in BEV sales, Skotland et al. (2016) projects that Norway will have about 1.5 million passenger BEVs on the road by 2030, more than half of the passenger car fleet. This would entail a 3% increase in national electricity usage compared to 2015. In other words, a dramatic shift in the car fleet will not result in dramatic shifts in electricity usage. However, as we discuss above, we are more concerned about the capacity of the components i the local grid. The annual revenue cap, which is a function of annual costs for DSOs have grown from NOK 10.1 bn in 2007 to NOK 13.9 bn (about €1.4 bn) in 2019[2]. This is about 0.4% of Norwegian GDP.

**The market failures in the transport and electricity sector matter to the Norwegian economy**. Effectively reducing the external costs of transport, and avoiding cost escalations in the local grid sector, would be welfare enhancing. This provides good motivation for finding policy improvements, which again provides good motivation for analysis in this thesis.

[1] https://www.ssb.no/energi-og-industri/artikler-og-publikasjoner/stadig-mer-alternativt-drivstoff-i-transport

[2] https://www.nve.no/reguleringsmyndigheten/okonomisk-regulering-av-nettselskap/nokkeltall-for-nettselskapene/

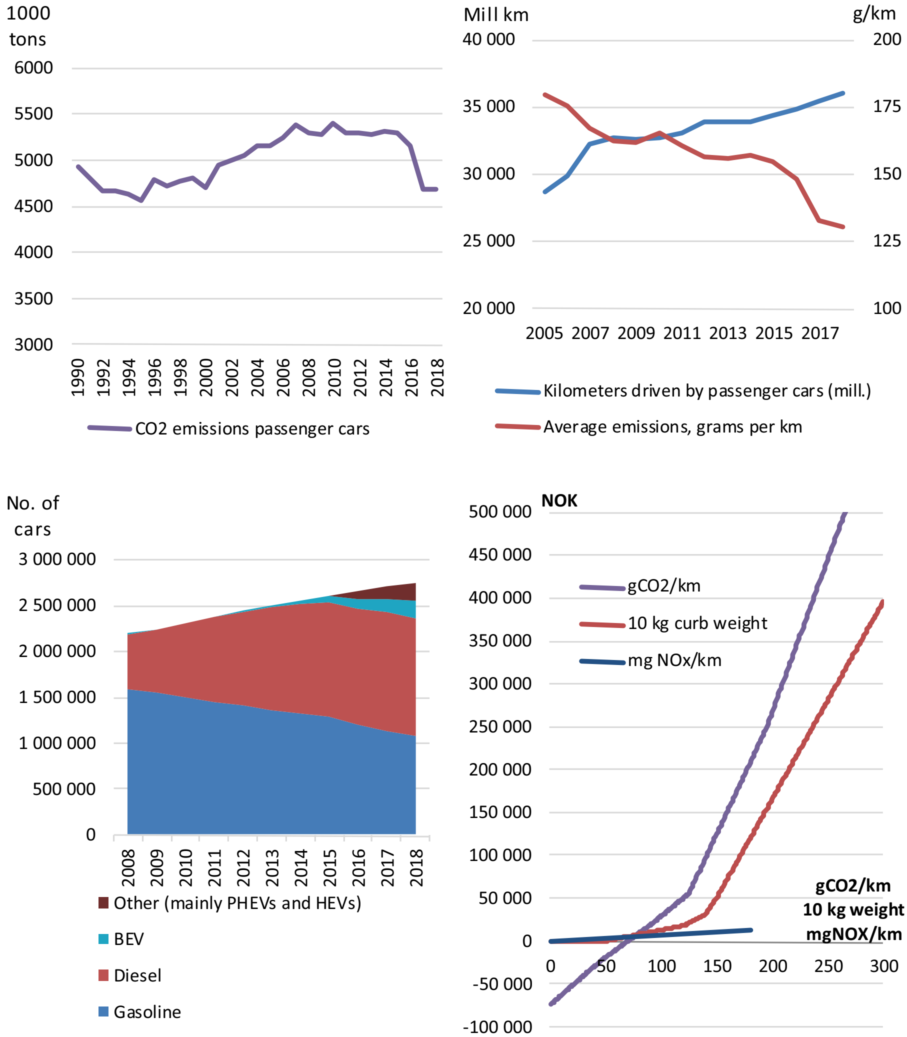


*Figure 1: Upper left: Trends in $CO_2$ emissions from passenger cars (Source: Statistics Norway). Upper right: Trends in kilometers traveled and $CO_2$ emissions per km from passenger cars (Source: Statistics Norway). Lower left: Developments in the Norwegian passenger car fleet (Source: Statistics Norway). Lower right: Rates for different components of the purchasing tax for passenger cars in Norway in 2019 (Source: Fridstrøm (2019)).*

# 3 Theories, methods and data

In this section I present the strands of economic theory, the methodological traditions and the type of data central to my thesis, and how the articles relate and contribute to the scientific literature. A more compact presentation of theories, methods and data used in the articles can be found in the summary table in the Appendix.

## 3.1 Theories

The main branch of economic theory that underpins this thesis is welfare economics. Welfare economics *attempts to provide a framework in which normative judgements can be made about alternative configurations of economic activity* (Perman et al., 2003, p. 7). In order to rank different resource allocations in the economy, the analyst has to accept some ethical criterion. In mainstream economics it is common to apply ethical criteria derived from utilitarian moral philosophy, developed by thinkers such as David Hume, Jeremy Bentham and John Stuart Mill. In this structured form of utilitarianism, social welfare consists of some weighted average of the total utility levels of all society's individuals (ibid).

Under the strict conditions for a perfectly efficient market listed in the opening section, the market will bring about a resource allocation that maximizes social welfare. When one or many of these conditions do not hold, we have a market failure. These market failures are obstacles to reaching the goal of maximized social welfare. As economists, we want to assess the mechanisms and magnitudes of the concrete market failures, as part of a welfare analysis. The next step of the analysis is to identify policies that can bring about the maximal welfare improvement in the presence of these market failures.

We now move our focus to the specific sectors where we find the market failures of interest in this thesis. One of the main categories is externalities, notably environmental externalities. This is where we move into the branch of economic theory called environmental economics. According to Perman et al. (2003) and Pearce (2002), the first systematic treatment of pollution as an externality was done in Pigou (1920). However, it was in the 1960s that environmental economics truly came of age (Pearce, 2002), with seminal works such as Coase (1960), Boulding (1966) and Ayres and Kneese (1969). Going back to Pigou (1920) again, this contains also one of the earliest discussions of road pricing as a means to efficiently respond to externalities from transport. With this we move into the economics branch of transportation economics.

*Market failures in the transport sector*

It is hard to imagine a transport sector that could qualify as a perfectly competitive market. Let us start with the road itself. Where roads fit on the spectrum from private to public goods depend on their institutional arrangement with respect to excludability, and traffic flow (congestion) with respect to rivalry (Benson, 2017). The financing of building and maintenance of roads can be done by user payments (e.g., by a private road operator with a natural monopoly) and/or by government budgets, often financed by distortionary taxes. Both of these ways of funding can hamper market efficiency.

Even if the infrastructure market failure is "solved" there would still be the issues of the multiple external costs that are generated by the use of the infrastructure. In the case of road transport, these negative externalities include global emissions ($CO_2$), local emissions (e.g., $NO_X$ and particulate matter), noise, accident risk, road wear and congestion (Rødseth et al., 2020; van Essen et al., 2019). $CO_2$ emissions stem from the burning of fossil fuels, and the marginal damage cost is independent of where the burning (i.e., driving) takes place. However, the marginal cost stemming from the other externalities depend on where and when the driving takes place, and what kind of car is driven (Thune-Larsen et al., 2014). A kilometer driven by a BEV on a highway with free-flow volumes far from any towns or cities, imposes a much lower cost on society than an old diesel car driving during congested peak hours in the middle of a dense city on a cold, windless day.

Public transport (PT) ridership has its own externalities. It can contribute to many of the same externalities as car driving does, but the average per-passenger kilometer external cost is generally lower. If a portion of the car drivers shift to PT, the amount of external costs can be expected to go down (Parry & Small, 2009). However, PT in many cities experience crowding during peak hours, which implies an external cost that the individual rider imposes on the other riders (De Palma, Kilani, & Proost, 2015; Hörcher, Graham, & Anderson, 2017; Li & Hensher, 2011). It may also be efficient to subsidize PT in order to exploit the "Mohring effect" (Mohring, 1972), as increasing route density and frequency will reduce PT users' waiting costs and access cost (Parry & Small, 2009).

The ideal policy prescribed from a transport economics textbook would be road pricing, where drivers would pay a tax per kilometer equal to the marginal external costs of driving that kilometer. Economists have been making the case for the policy of road pricing ever since Pigou (1920) and Knight (1924) in order to manage the externality of congestion. Hundreds of papers have been written on road pricing since then, with examples of seminal contributions to the theory from Walters (1961), who translated the backwards -bending speed-flow functions to a cost function and derived optimal gasoline taxes and optimal congestion tolls, and Vickrey (1969), who developed a bottleneck model and analyzed congestion pricing not only as a means to secure efficient utilization of current infrastructure, but also vitally informing the planning for future infrastructure expansions. Another important example is Mohring and Harwitz (1962), who established that under certain conditions, an optimal congestion pricing scheme will exactly cover the cost of the optimal supply of road capacity.

It has long been acknowledged that the world in which economists recommend road pricing is more complex than what is shown in the simplest models, moving the analysis to second-best solutions (Lindsey & Verhoef, 2000). Such cases include the issues of pricing both public transport (an imperfect substitute to car driving) and road use (Button, 2004; Small, 2004), constraints on the price and/or how much of the network that can be priced (Marchand, 1968; Small & Yan, 2001; Verhoef, Nijkamp, & Rietveld, 1996), complexities in linking the road price to financing road infrastructure (Verhoef & Rouwendal, 2004), issues in the political economy (Evans, 1992), issues of implementation and acceptance (Rouwendal & Verhoef, 2006), and revenue recycling of road prices in the presence of distortionary labor taxes (Munk, 2008; Parry & Bento, 2001; Parry & Small, 2005). The latter subject is related to the double dividend hypothesis, a widely debated area of environmental economics (Bovenberg, 1999; Jacobs & de Mooij, 2015).

A hundred years after Pigou, the case for road pricing is particularly strong. One reason is that the technology that enables road pricing, e.g., satellite and sensor technology, has vastly improved over the last decades (de Palma & Lindsey, 2011; Small & Verhoef, 2007). Another reason is related to changes in the vehicle fleet. Fuel taxes have worked as an instrument to imprecisely correct market failures from transport, but increased fuel efficiency and the growth in BEVs reduces the relevance of this instrument. These developments reduce the tax cost per vehicle km, potentially increasing the discrepancy between the tax and distance-based external costs, and also stimulating more driving, often referred to as a rebound effect

(Parry, Evans, & Oates, 2014; Proost, Delhaye, Nijs, & Van Regemorter, 2009). BEVs also strengthen the case for road pricing, as government revenue from fuel taxes will decline, and covering this shortfall with distortionary taxes elsewhere would exacerbate other inefficiencies in the economy (Fridstrøm, 2019). BEVs also bring us into a sub-field of energy economics, as they bring in new challenges for the market of electricity distribution, which has its own market failures.

*Market failures in electricity distribution*

There are interesting aspects of market failure in many parts of the electricity supply chain, from generation to transmission, to distribution and finally to retailers. In generation, there is a large focus on the environmental externalities, most notably greenhouse gas emissions from fossil fueled plants (Decker, 2014). Electricity transmission, where the generated electricity is transported over long distances in high-voltage power lines in order to minimize energy losses, is a classic case of increasing returns to scale and natural monopoly in addition to network externalities stemming from the physical laws that govern power flows in an interconnected network (Hsu, 1997). In my research I focus on the distribution side, i.e. the local grid.

DSOs (Distribution System Operators) manage the transport of electricity after it has been transformed to lower voltage so that it is safe to use for end consumers. These companies need to invest in a lot of physical infrastructure, such as transformers, sub-stations, overhead and underground cables and monitoring and signaling equipment. Many of these investments are sunk, long-lived and immobile. It is a typical case of high fixed costs and low marginal costs, giving rise to natural monopoly conditions (Decker, 2014, p. 229).

There are many ways to regulate a DSO. Examples include rate of return regulation, various form of price cap regulation, and as they do in Norway; yardstick competition. Under yardstick competition, a theory with early works from Shleifer (1985), the regulated firms are benchmarked against each other, and receive a revenue cap as a function of the most efficient firms among its peers. In Norway, the regulator does the benchmarking through a series of Data Envelopment Analyses (see e.g., Coelli, Rao, O'Donnell, & Battese, 2005). This form of regulation mimics the workings of a competitive market, as it gives a firm incentives to reduce costs in order to stay ahead or not fall behind its peers in order to maximize profits or limit losses (Agrell, Bogetoft, & Tind, 2005). The firms will be driven by the pressure of benchmarking to reduce costs while delivering required services. This cost-saving potential would largely be the firms' private information under other forms of regulation. From the regulator's point of view, benchmarking reduces the firms' informational advantage (Fehr, Hagen, & Hope, 2002). However, the regulator still has to ensure that the firms do not collude or find other ways to game the system, and has to calculate the industry efficient level correctly, and to factor in aspects regarding both demand conditions and production opportunities that are out of the firms' control (Decker, 2014, pp. 135-137).

With more than a hundred DSOs in Norway regulated under benchmark competition, the natural monopoly issues are at least addressed. But there is another market failure that may be causing problems. The missing incomplete market of distribution grid capacity. Here, the monthly grid tariffs that consumers pay are a function of a fixed component and a per kWh component that is uniform throughout the day. Without the ability for prices to signal scarcity, there will be instances where enough consumers simultaneously drawing electricity from the same sub-station will cause a need for the capacity of the existing sub-station to be upgraded before the end of its technical life (Haidar, Muttaqi, & Sutanto, 2014; Masoum et al., 2011). This means that DSOs need to undertake investments, meaning higher capital costs. In the short run there also may be higher operating costs due to maintenance and inspections. In Norway, higher DSO costs translates into higher revenue caps. 40% of the revenue cap is based on cost recovery and the rest is based on the cost norm from the yardstick competition. Hence, unless the DSO affected by the higher cost due to higher capacity demand is at the efficiency frontier and therefore sets the cost norm, the DSOs cost increase will not be matched by a revenue increase, leading to lower profits. In addition , the increased revenue cap leads to higher tariffs for *all* consumers, not just the consumers who's consumption pushed the DSO to undertake new costs. Due to the incomplete market for capacity in the distribution grid, these customers can impose costs on others, and pay only a fraction of the cost they caused. This can be considered a pecuniary externality in a missing market (Greenwald & Stiglitz, 1986).

There are reasons to expect that many BEV owners could be such consumers. Without any tariff differentiation across the day, there is no incentive for BEV owners to do anything but what is most convenient. For many that would entail plugging in the car to charge directly after coming home from work (Barton et al., 2013; De Hoog, Alpcan, Brazil, Thomas, & Mareels, 2015). This coincides with peak hours electricity demand. The Norwegian regulator of the electricity distribution sector, NVE (The Norwegian Water Resources and Energy Directorate) developed a stress-test for neighborhoods with high BEV density. They simulated a case where 70% of the residents charge their BEVs simultaneously during peak hours, they find that power demand can increase by up to 5 kW per household. This results in overload for more than 30% of the transformer stations currently servicing the distribution network (Skotland et al., 2016).

*The theoretical intersection for the thesis*

This thesis can be placed in the intersection of welfare economics, environmental economics, transport economics and energy economics. It seeks to model optimal second-best policies in the presence of both environmental externalities and other externalities in the transport market in light of the growth in BEVs in Norway, and value the potentially exacerbated pecuniary externalities stemming from peak grid capacity usage. This modeling will then be used to discuss potentially welfare-enhancing policies.

## 3.2 Methods and data

### 3.2.1 Numerical modelling in transport economics

The first three papers have theoretical sections where I derive analytical expressions for optimal policies. The analytical results are then solved numerically. This provides illustrations of the magnitudes of welfare changes from the polices, and provide insights into the various mechanisms at play in the optimization problem. The numerical models can in essence be considered very stylized transport models.

Flügel, Flötteröd, Kwong, and Steinsland (2014) provides a useful typology of transport models, where the models can be classified according to how they represent time (static/dynamic/quasi-dynamic), their resolution (micro-/meso-/macroscopic) and how they deal with uncertainty (deterministic/stochastic). Within this typology, the transport models in this thesis can be classified as a static, macroscopic and deterministic model.

I would like to contrast this with the more elaborate transport modeling systems applied in Norwegian transport planning and project appraisal. The transport model that forms the basis for paper 2 and paper 3 has a small set of heterogeneous representative agents, a limited number of car types and they drive on aggregate, representative road links. Furthermore, 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. The regional transport models (RTMs), with the Oslo-region version documented in Rekdal and Larsen (2008), and the national transport model (NTM), documented in Rekdal et al. (2014), are classic 4-step transport demand models (Ortúzar & Willumsen, 2011) that find their equilibrium in a complete transport network. However, there is only one representative car type, the car stock is exogenous, and there is no crowding feedback in public transport. Keeping car type choice exogenous and omitting crowding feedback is also the case for the urban transport models for Oslo (MPM23 (Flügel & Jordbakke, 2017)) and Trondheim (using MATSim (Horni, Nagel, & Axhausen, 2016)), along with the model EFFEKT (Vegdirektoratet, 2015) that the Norwegian Public Roads Authority uses for cost-benefit analysis. The Railway directorate's model TRENKLIN (Flügel & Hulleberg, 2016) includes crowding feedback on trains, but has no modeling of car transport. As for the main model for car choice and predicting market shares for cars, the BIG[3]-model (Fridstrøm, Østli, & Johansen, 2016; Østli, Fridstrøm, Johansen, & Tseng, 2017), it has no modeling of how the cars are used. While all of 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, our model has the advantage of bringing more elements together in a transparent, relatively noncomplex model.

The established transport models used for transport planning and project appraisal in the Norwegian setting are not suited to work with the research questions in Paper 1 either. This model is even more stylized than the model in Paper 2 and Paper 3, as it has an even narrower set of model agents and car types, and excludes aspects like public transport. However, I wanted to add some (stylized) representation of labor market responses and the trade-off that policy-makers face when they have a binding budget constraint and distortionary labor taxes. With this goal in mind, there is not much to build from the current family of Norwegian transport models.

I also would like to contrast the stylized transport models in this thesis with the models that inspired them. The numerical modeling exercise in Paper 1 largely builds on the modeling done in Parry and Small (2005) and Tscharaktschiew (2014), but extends the analysis with road pricing in multiple areas with multiple car types, which provides new nuance and insight to this framework used to derive optimal gasoline (or diesel) taxes. In this model the goal is to find the set of road prices that optimizes the balance between the external costs from passenger car driving with the costs of financing a binding government budget constraint with distortionary labor taxes.

In Paper 2 the numerical modeling builds on the modeling from Börjesson, Fung, and Proost (2017) and extends it to include a car choice module, multiple heterogeneous agents, occasional long car trips. As this model gives insight into the mechanisms driving both car choice and transport patterns, it opens up to a rich and transparent analysis of trade-offs for urban transport policy, in particular in light of ambitious climate targets and the availability of EVs in consumers choice set. The model in Paper 3 is an extension of the model in Paper 2, where we add a distribution grid cost module. Here we model the feedback between the transport sector and the grid sector, where model agents that choose to own an EV affect the cost of the local grid, that again affect grid tariffs for all electricity consuming agents.

The model parameters build on numerous data sources, many of them publicly available, such as car ownership and travel data from Statistics Norway. The transport model in Paper 2 and Paper 3 also heavily uses the data from the National Travel Survey from 2014, documented in Hjorthol, Engebretsen, and Uteng (2014) to calibrate the model agents. The

[3] BIG is a Norwegian-language acronym meaning "vehicle cohort model"

travel survey is also an important data source for many of the aforementioned members of the Norwegian family of transport models. All the numerical modeling also relies on parameters, such as elasticities, from Norwegian transport models and the transport model literature. I emphasize in the papers that these parameters are subject to uncertainty, and therefore provide sensitivity analysis in all of these papers to illustrate how the results should be evaluated in light of this uncertainty.

### 3.2.2 Econometric models for grid costs & BEV density

Because Norway has built up a relatively high density of BEVs over a number of years, there is a possibility of analyzing if and how much local growth in BEVs affect DSO costs. By merging together data from NVE on annual costs of DSOs applied for regulation, their operational area, and data on registered cars at municipal level, we get a unique panel dataset (repeated observations on individual units – in our case DSOs) for such analysis. This dataset allows us to investigate how BEVs affect DSO costs by exploiting local differences in the growth of BEVs over time.

We apply linear regression models with fixed effects to this dataset, in order to address problems such as unobservable variables which can cause bias. Fixed effects models are a common part of many econometrics textbooks (Cameron & Trivedi, 2005; Hill, Griffiths, & Lim, 2008; Wooldridge, 2002). The fixed effects will control for all time-constant variation, both time-invariant explanatory variables and unmeasured time-invariant variables. Algebraically, it works as estimating based on the deviations from means for the individual unit. A variable that does not vary over time for an individual unit, will by definition not deviate from its mean. Hence, deviations from the mean kills all time-invariant individual effects. And most importantly, it kills off *unobserved* individual effects (Angrist & Pischke, 2008), that can cause omitted variable bias. Using the explanation from Cameron and Trivedi (2005), given the key assumption that all unobserved variables are time-invariant, the causative effect of BEVs on DSO costs is then measured by the relationship between individual changes in costs and individual growth rates in the BEV stock.

Some of the time-invariant variables may have a relatively strong correlation with our variable of interest, the number of BEVs. An example of an unmeasured time-invariant variables could be the distances within and between the populated areas in DSOs operational areas, which drives up DSO costs per customer and drives down the attractiveness of BEVs due to longer driving distances. An example of the measured time-invariant explanatory variables could be *Average temperature*, as colder winters could affect both DSO costs positively and the attractiveness of BEVs negatively as it reduces their range (Figenbaum & Weber, 2017). By using fixed effects, we reduce the problem of omitted variable bias when we analyze the relationship between BEVs and DSO costs. However, fixed-effects estimation has the drawback of not being able to estimate effects of time-invariant measurable variables, even though this may be of some interest.

Another drawback with the fixed effects model is that prediction of the conditional mean is not possible (Cameron & Trivedi, 2005). We can only predict the *changes* in the conditional mean, in our case, DSO costs, caused by the *changes* in the time-varying regressors. However, the first and most important step forward is estimating the marginal impact of BEVs on DSO cost, for which fixed effects estimation is very suitable.

# 4 Synthesis of papers

## 4.1 Overview, main findings and how the papers contribute to the literature

The four articles written for this thesis are briefly summarized in the upcoming subsections. All the papers feed in to the overarching theme of the thesis, namely **how to best respond to a transport sector that is becoming increasingly electrified**, although their approaches differ. In one end I approach the theme through broad policy analysis in complex settings of BEVs and multiple market failures that need to be simulated in numerical models in order to be able to analyze all the various mechanisms at play. In the other end, I approach through a narrow empirical analysis of what are the marginal costs of inflicted on DSOs when the number of BEVs increases. Figure 2 gives an overview of how the papers relate to each other and the overarching theme.

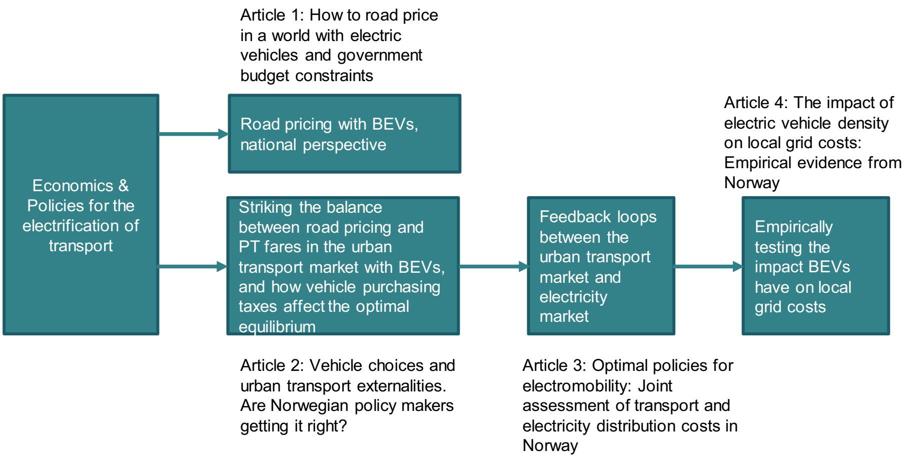


*Figure 2: A schematic overview of papers in the thesis, and their main topics*

*Main findings*

All three papers that use numerical modeling to analyze policy aspects relating to BEVs fall into the strand of the economics literature that addresses the search for optimal policy instruments when dealing with multiple externalities. But in all of the papers, market failures outside of road transport are included, which brings in some of the complexities and trade-offs in a second-best world where the traditional Pigovian solution may not be the optimal. Such complicating factors are: government budget constraints and distortionary taxes (Paper 1), the presence of public transport that gets crowded during peak hours and shifting equilibria with different car ownership shares in an urban transport setting (Paper 2), and the presence of pecuniary externalities in the incomplete grid capacity market (Paper 3). The findings from the model results in all three papers point to that Norwegian transport policies are quite misspecified compared to the policies that maximize social welfare (in the model). ICEVs are found to be undertaxed for their city driving, and overtaxed for their driving in rural areas. But then again, the driving of BEVs is undertaxed in general. Many of the findings are in line with what is found in the road pricing literature (e.g., De Borger & Mayeres, 2007;

Munk, 2008; Parry & Bento, 2001). When the question changes from how to use policy to optimize welfare, to how to use policy to reach stated emission targets at least cost, we find that the role of BEVs and optimal policies change. The resulting policies will make owning and driving ICEVs far more expensive, making a switch to BEVs a cost-minimizing response for many agents. However, we find that the social cost of achieving these emission targets come in the order of several thousand NOK per ton abated, in line with what is found in other papers analyzing where the transport sector is narrowly targeted for emission cuts (Mayeres & Proost, 2013; Proost et al., 2009).

In Paper 3 our model finds that higher BEV density leads to higher costs to users of the electricity grid, as they increase the need for distribution transformers to be replaced before their technical life runs out. This leads to higher grid tariffs, although not very large, and it does add extra to the cost of $CO_2$ abatement. This is of course sensitive to how prematurely the transformer has to be replaced. In paper 4 we approach the question of cost additions to the local grid due to BEV charging from another angle. We try to investigate empirically how large the local grid costs imposed from BEV charging have been over the last decade. Here we use annual data at the DSO level, with regards to DSO outputs, costs and registered BEVs, which can be considered a more top-down approach to the question. We find statistically and economically significant cost elasticities, in line with conclusions from simulation exercises on the subject (see e.g., De Hoog et al., 2015; Masoum et al., 2011). The findings imply a cost per BEV far higher than what is found in Paper 3 for the median DSO. However, for the DSO in the Oslo area (the largest in the country), the estimated marginal cost per BEV is lot lower and thus closer to what is implied in Paper 3. We also find that the heterogeneity among DSOs, especially along the dimensions of size and average cost-per-customer, matters a lot.

*Contribution to the literature*

While the contribution of each paper is summarized more in detail in each article summary[4] in the upcoming subsection, I want to spend a few paragraphs on the overarching contribution of this thesis to the literature. **In short, the main overarching contribution is new and improved understanding of how the emergence of BEVs, as a technology in the transport sector, changes the calculus of social costs and benefits and how policies optimally should respond to these changes.** This is done by extending well-established modeling frameworks to include BEVs and issues related to their charging, and econometric analysis of a new and highly relevant dataset on BEV density and local grid costs. With this we can better understand the mechanisms at play, and what balances need to be struck to form welfare-enhancing policies.

Paper 1 provides new insights into how to optimally design a road pricing scheme in a world with electric vehicles and government budget constraints and distortionary labor taxes. The modeling framework, which in previous literature has mainly been used to analyze fuel taxes on an aggregate, national level (see e.g., Parry & Small, 2005; Tscharaktschiew, 2015), is extended to incorporate how the external costs of driving varies by time, place and type of vehicle, and how this scheme fits in with ambitious policy goals for reducing $CO_2$-emissions.

Paper 2 contributes to the literature with improved understanding of how the mix of policy instruments tolls, fares, parking charges and car purchase taxes interact with each other in the transport market equilibrium, especially with the availability of EVs, and how to use these instruments to strike the balance between costs and benefits in the urban setting. It also illustrates a way of seeing the division of labor between different policy instruments. While

[4] A condensed synthesis of the papers can also be found in Table 1 in Appendix to the introductory chapter.

tolls, fares and parking charges can be used to optimize the transport equilibrium, car purchasing taxes can be used to optimize the car fleet of agents participating in the optimized transport market. The insights from this model continue in Paper 3, where it is extended to include the impacts that higher EV density can have on local grid costs, and how that changes the optimal policy mix. All the extensions from the modeling framework of Börjesson et al. (2017) contributes with a useful tool for analysis in the transport economics literature.

The thesis also contributes to the literature on the impacts EV charging may have on the distribution grid with an econometric analysis on real data on the relationship between BEVs and DSO costs. As far as we know, no such analysis has been done with real nation-wide data before, as the literature until now has analyzed the problem through simulation exercises. Uncovering the social costs stemming from BEV charging improves the understanding of social costs and benefits in the transport and electricity sector when BEVs are available.

The thesis provides a clarifying perspective to the social costs and benefits of an increasing BEV share. It is clear that the usage of BEVs, at least the way they are driven and charged under current policies, have social costs. Policies can contribute to improve the cost-benefit-ratio, but it is clear that as long as policy makers are committed to the high ambitions of the Paris agreement, a large shift from conventional cars to BEVs is a part of a cost-minimizing response.

*Limitations and future research*

There are some caveats worth mentioning. The numerical models used in papers 1-3 are quite stylized, so the exact numerical results should be interpreted with caution. There are some major model simplifications. An important one is the use of a small number of representative agents, which means that there is a lot of heterogeneity in how people behave in the transport market, how they respond to policies and how they are affected by policies, that are not captured. These agents have simplified utility functions, where important aspects like consumer tastes and quality differences for cars are ignored, and their valuation of a vehicle is largely a function of generalized travel cost. The models also rely on parameters that can be considered fairly uncertain. We address some of this uncertainty by conducting sensitivity analysis in order to show how the uncertainty in the underlying parameters affect the results. We do this for some of the most uncertain parameters in all three papers with numerical models.

I would also like to mention some important caveats with regards to estimating grid costs. The data we have only allows us to observe the BEVs *registered* in the DSOs operational area. We do not observe the owners' actual charging behavior and their power usage from other appliances, i.e., the very usage of grid capacity we expect to drive up DSO costs. In addition, some of the charging from BEVs may even occur in other areas than where the car is not registered, e.g., on cabin trips. So even though we have identified a statistically significant and relatively robust relationship between BEV density and DSO costs, there are still some unanswered questions regarding what happens in this relationship.

There are many promising ways to expand the research in this thesis. The numerical models could be expanded with a wider range of vehicles for a wider range of heterogeneous agents to choose from. Aspects of agents' tastes and quality differences of the cars would also be promising model extensions. If data permitting, the empirical analysis of the effect BEVs have on grid costs can be expanded to include the BEV ownership of cabin owners, and the composition of different household types and different types of BEVs, as they may have different charging patterns. The empirical framework can also be used to analyze the effect of peak grid tariffs, if regulation eventually will allow for this.

## 4.2 Article 1: How to road price in a world with electric vehicles and government budget constraints

Published in Transportation Research Part D: Transport & Environment

In this paper we examine what characterizes second-best road prices targeting external costs from driving BEVs and internal combustion engine vehicles (ICEV) when there are distortionary labor taxes and binding government budget constraints. Further, we examine how this second-best pricing fits with government $CO_2$ emissions reduction targets.

Our paper makes the following contributions: First, it extends an established modeling framework (see e.g., Lin & Prince, 2009; Parry & Small, 2005; Tscharaktschiew, 2015) for optimal taxation in transport with revenue recycling of distortionary labor taxes to include a) different areas and time periods where external costs vary, and b) both ICEVs and EVs and their associated taxes. This allows us to take a broad view how a national road pricing scheme optimally would look like. As road prices per combination of vehicle type, area and time period, and the labor tax rate are determined simultaneously, this model also allows us to see the endogeneity of how changes in one road price affects the levels of the others. This can result in road prices that differ from traditional Pigovian solutions, and we can see how costs and benefits of the scheme are distributed geographically. Second, it provides numerical results for the case of Norway, a country where the Ministry of Transport has started investigating the possibilities for distance-based road pricing applying satellite technology. It is also the country with the highest BEV share of the car fleet in the world, strengthening both fiscal and externality arguments for moving from fuel tax to a more sophisticated way of road pricing.

We find that optimal road pricing scheme is characterized by large price differentials between when and where the driving takes place. This demonstrates how analyzing a road pricing scheme that differs over different spatiotemporal states and car types adds more nuance and insight than, for example, analyzing a single gasoline tax. In the optimal scheme ICEVs face a higher cost in large cities but lower costs in most parts of the country compared to the initial situation, even if it leads to a slightly higher labor tax rate. We also find that BEVs should be taxed, and in rural areas they should be taxed higher than ICEVs due to large fiscal interaction effects. We find that interaction with the rest of the fiscal system generally leads to a tax markup on the external costs. In sum, the road pricing scheme leads to higher welfare.

We also find that as long as the optimal road pricing scheme applies the recommended reference price for $CO_2$ in Norway, it will not contribute much to reaching the short-term government emission target. In order to reach this target at least cost, a shadow price 16 times the recommended reference price is needed, indicating a large mismatch between the recommended reference price for $CO_2$ and the target, a finding similar to that in Mayeres and Proost (2013) and De Borger and Proost (2015). This $CO_2$ constrained optimization leads to substantially higher road prices for ICEVs and somewhat lower for EVs compared to the second-best optimum.

## 4.3 Article 2: Vehicle choices and urban transport externalities. Are Norwegian policy makers getting it right?

Co-authored with Stef Proost and Kenneth Løvold Rødseth

Accepted in Transportation Research Part D: Transport & Environment

This paper uses a stylized numerical transport model for the greater Oslo area to analyze transport policies. The modeling approach draws on Börjesson et al. (2017), but 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 PT. The prime purpose of this model is to look into the interactions between combinations of policies and inhabitants' car purchase, car use, PT use and urban transport 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 simplified but complete description of the urban transport market equilibrium, both with regard to transport patterns and car ownership. It allows us to analyze how different types of agents respond to different transport policies, and how they are affected.

First, we explore the medium-term effects of the current BEV friendly policies. Second, the model is used to explore the potential for more efficient pricing of car and PT use, and more efficient purchase taxes. We find that the current policies lead to massive penetration of BEVs and therefore to a strong reduction of $CO_2$ emissions. However, they also lead to much more congestion and decreased use of PT. More welfare-enhancing policies require efficient pricing of road congestion and PT, and provide incentives for consumers to choose the most efficient combinations of cars. Such policies lead to a less extreme penetration of BEVs than the current transport policies. However, they do achieve a more efficient transport equilibrium and substantial resource cost savings, leading to higher welfare levels. We also use the model to identify policies that leads to the achievement of the emission reduction targets in the greater Oslo area at least cost. Reaching these targets in a cost-effective way will require a large switch to BEVs. However, the welfare cost per ton of $CO_2$ abated that will far exceed the recommended reference value of $CO_2$.

Although the exact numbers from the reported results must be interpreted with caution, they can provide some important policy lessons. First, efficiency can be gained through more toll differentiation between peak and off-peak hours. Second, widening the gap between peak and off-peak fares in PT would also probably produce efficiency gains. A third policy lesson from our findings is that purchase taxes are powerful instruments for achieving policy goals, confirming findings from Fridstrøm and Østli (2017). It is not the most efficient instrument to correct transport market failures, but it can serve a valuable purpose in a second-best world. Such second-best considerations include cases where the potential for fuel taxes is limited by fuel tax competition (Mandell & Proost, 2016). A useful way of viewing the problem in this paper 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.

## 4.4 Article 3: Optimal policies for electromobility: Joint assessment of transport and electricity distribution costs in Norway

Co-authored with Stef Proost and Kenneth Løvold Rødseth

The electrification of transport will make the transport and energy systems more intertwined: EV-friendly transport policies increase the demand for power, thus challenging the distribution grid's capacity, while electricity policies impact the generalized costs of driving EVs. There exists some literature that looks at how the electrified transport will affect the need for grid investments and/or demand management in order have sufficient power capacity (De Hoog et al., 2015; Neaimeh et al., 2015). Most of these studies assume that transport demand, and therefore EV users' demand for electricity, is exogenous (Daina, Sivakumar, & Polak, 2017a, 2017b). This paper contributes to the literature by looking at the mechanisms and outcomes in both the transport and energy market, and the feedback in-between them.

This paper builds on the stylized numerical transport model for the greater Oslo area from Paper 2 of this thesis. Here, we add a module for using the distribution grid to charge EVs, so we can study costs and benefits in both the electricity market and transport market jointly. The model allows the agents to choose type of car (or no car), their transport pattern and (if they own an EV) how much to home charge during power peak and off-peak hours. If enough EV-owning agents charge during power peak hours, costly grid expansions may be needed. With this, we can examine how the distribution grid company can respond in order to mitigate these costs with different pricing schemes and how this in turn affects the transport equilibrium.

To our knowledge, it is the first time these features have been applied in the same model. The analysis will give insight into the feedback between the transport market and electricity market and how policies in one market can affect the equilibrium in the other. With this we can assess how polices can be optimized to reach policy goals at least cost.

We find that as today's EV-policies drive up the EV-share of the car fleet, they also drive up investment costs in the local distribution grid as old transformers need to be replaced prematurely with transformers with higher capacity. Our model finds an equilibrium where the increased cost of transformers leads to between NOK 12 and 18 (approx. € 1.3 - € 2) in added annual non-car electricity costs per agent, depending on the DSO's pricing scheme. We find that a pricing scheme that applies peak tariffs for the grid will help strike a better balance between investment costs and EV-owners' disutility of charging during off-peak hours.

We argue that the resulting increase in electricity expenses is small, and would probably go unnoticed by most households as it represents less than a 0.1% increase in annual electricity costs (including tariffs and taxes) for households with normal consumption between 10 000 and 20 000 kWh per year. However, our sensitivity analysis shows that the cost can get substantially higher if the old transformers have to be replaced sooner than in the baseline.

The shift to BEVs and PHEVs is an integral part of reaching the ambitious goals of reducing $CO_2$-emissions by 50% in the greater Oslo area at least cost. We find that adding the charging issues leads to NOK 17-27 in additional costs per $tCO_2e$ under baseline assumptions. If the policy makers have committed to the $CO_2$-target and are willing to pay the cost of reaching it, adding the grid costs is not going to be very discouraging.

## 4.5 Article 4: The impact of electric vehicle density on local grid costs: Empirical evidence from Norway

Co-authored with Askill Harkjerr Halse

We observe a rapid rise in the number of BEVs in Norway, and there exists a literature (see e.g., De Hoog et al., 2015; Masoum et al., 2011) that warns that BEV charging will cause substantial future costs to the local grid, unless measures are put in place. If indeed the aggregate uncoordinated charging by BEV owners does induce higher costs to DSOs, then Norwegian data would be the first place to investigate. Detailed data of all Norwegian DSOs and all registered BEVs during the last ten years give a unique opportunity to analyze this relationship. To our knowledge, such an empirical analysis has not been done before on real data in a country-wide analysis. It will therefore push the knowledge frontier on a debated, but relatively unexplored topic empirically. Findings may have implications for how to regulate DSOs, how to price household power usage and how to assess the net social cost of achieving emission reduction targets through promoting BEVs.

By merging together data from NVE on annual costs of DSOs applied for regulation, their operational area, and data on registered cars at municipal level, we get a unique panel dataset for such analysis. The two first data sets were also merged together in Orea, Álvarez, and Jamasb (2018) for the purpose of efficiency analysis using a spatial econometric approach. Our data set of 107 Norwegian DSOs outputs, costs and registered BEVs in their operational area between 2008 and 2017 allows us to investigate how BEVs affect DSO costs. Exploiting local differences in the growth of the BEV fleet over time, we investigate how an increase in the number of BEVs affects the costs of the local DSO, using fixed-effects estimation that account for time-invariant characteristics of the DSO (see e.g., Mehmetoglu & Jakobsen, 2016). We also control for growth in output indicators that could be correlated with growth in the BEV fleet. We look at both total costs and individual cost components.

We find that increases in the BEV fleet are associated with positive and statistically significant increases in costs when controlling for other DSO outputs and year dummies. The point estimates also imply that the effect is economically significant, with a preferred model giving a cost elasticity of 0.018 from increases in the local BEV stock. This finding is robust to the addition of several controls and removal of outliers. We also find the strongest impact through operational costs, and not capital costs. Although we find significant effects in the national sample, there is a lot of heterogeneity in these results, with the marginal cost estimates being a lot higher for small DSOs in rural areas, and a lot lower for larger DSOs. This heterogeneity also indicates that the BEV-induced costs is not a major problem that has affected a large number of consumers. The half of the sample with the largest DSOs, where the estimated cost elasticity from BEVs was close to zero, serve over 93 % of the customers in the entire sample.

Finding that increased BEV ownership is associated with higher DSO costs, implies that the case for a well-specified peak-pricing system for grid tariffs is strengthened, so that efficient load-shifting is properly incentivized. Many BEV owners would probably respond by installing smart charging systems, which would ease the household cost minimization and ensure more efficient grid capacity utilization, even with small hour-to-hour price differences.

# 5 Conclusions and implications

The fundamental question is whether society actually accepts our politicians pledge to limit global average temperature rise to well below 2 degrees. Reaching that goal is going to imply an extremely high shadow price for greenhouse gas emissions, *even if costs are kept to a minimum.* Implementing policies that actually lead to fulfillment of the Paris agreement will require a strong mandate from voters. It is clear that a shift to BEVs is part of a best response to the policies that lead to fulfillment of the Paris agreement, a part of a cost minimizing strategy. But just because we observe a rapid rise in the number of BEVs, it does not mean that we are fulfilling the agreement at minimized cost, nor does it mean that we are fulfilling it at all. Policymakers can fail at both. This research shows that there are substantial welfare gains from optimizing incentives in both transport and electricity markets, and that these incentives will make this promising technology actually promising. The main policy implications from the thesis can be summarized as follows:

Distance-based **road pricing** differentiated according to where, when and what type of car can be welfare enhancing compared to today's system of fuel taxes and tolls. Compared to today's situation in Norway, it would be more efficient with a lower tax burden for driving in rural areas, and a higher burden for driving in congested times and areas of dense cities. The growth in BEVs strengthen the argument for such a road price. BEVs are a lot harder to tax than conventional cars, so a road price will be the best tool to do that, both for transport optimizing purposes, and for fiscal purposes. However, should it become reality, it is imperative that the system is designed for privacy protection from the get-go. We want a more efficient transport market, not Big Brother!

In the urban transport setting the policy makers need to **strike the right balance between road prices and public transport fares** in order to optimize the transport system. In particular, this means a larger differentiation between peak and off-peak prices. Perhaps labeling this price differential as an "off-peak discount" could be more palatable way of framing it. The **composition of vehicle purchase taxes** can also be optimized so that agents will choose the car fleet that maximizes social welfare under optimized policies. Purchase taxes have in any case proven to be very powerful instruments.

In order to incentivize efficient use of local grid capacity, **peak hour grid tariffs** can be an efficient instrument. When businesses and households get the right signal for economizing on their grid capacity usage, costly investments can be postponed and the system can be operated efficiently. As the BEV fleet grows, the case for peak grid tariffs grows, as shown in paper 3 and paper 4, and the tariffs will be a price signal for *all* usage of grid capacity. BEV charging, aided by smart-chargers, could be some of the easiest capacity usage to load shift away from peak hours, even with small price differentials.

There are some promising signals from some Norwegian policy-makers and regulators to try to put together more efficient policies, such as distance-based road prices and peak tariffs. Although economists may give the impression, we know that efficiency is not the only aspect that needs to be considered in constructing such policies. However, I am hopeful that sound economic arguments will be a part of the democratic debate and the rest of the policy making process. Part of the power of economics is the ability to highlight important trade-offs and providing a framework on how to systematically strike a balance between the various costs and benefits. I have done my best to harness some of that power in putting together this thesis, and I hope it can provide a meaningful contribution to the debate, and thus go beyond its contribution to the academic literature. At least with some probability.

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# 7 Appendix to introductory chapter

*Table 1: Thesis synthesis table*

| Paper | Research questions | Theory | Data | Methods | Key findings |
|---|---|---|---|---|---|
| I | What characterizes the set of second-best road prices targeting external costs from driving EVs and ICEVs when there are distortionary labor taxes and binding government budget constraints?<br>How are these prices affected by tax distortions in the labor, electricity and car ownership market?<br>How does this second-best pricing fit with government set goals of reducing $CO_2$ emissions? | Theory of optimal taxation of multiple externalities in the presence of distortionary taxes | National car ownership and travel data, parameters from transport models and literature | Numerical modeling, solving for optimal road prices | 1) Optimal road prices imply large price differentials between when and where the driving takes place.<br>2) In the optimal scheme ICEVs face a higher cost in large cities but lower costs in most parts of the country compared to the initial situation, even if it leads to higher labor taxes.<br>3) EVs should be taxed, and in rural areas they should be taxed higher than ICEVs due to large fiscal interaction effects.<br>4) In sum, the road pricing scheme leads to higher welfare. |
| II | Which policies will be the most welfare-enhancing in the urban transport system with multiple market failures (i.e., congestion, accidents, local air pollution and $CO_2$ emissions), and what role can BEVs play in achieving these policies?<br>What characterizes the potential conflicts between welfare maximization and the greater Oslo area targets for reducing $CO_2$ emissions (where the promotion of BEVs is a key instrument) and car transport in cities?<br>Furthermore, what trade-offs do we see between efficiency and acceptability? | Theory of optimal taxation of multiple externalities in multiple, interlinked sectors | National travel survey data, parameters from transport models and literature | Numerical modeling, solving for optimal road tolls, parking fees, fares and purchase taxes | 1) Current policies lead to massive penetration of BEVs and therefore to a strong reduction of $CO_2$ emissions. However, they also lead to much more congestion and decreased use of public transport.<br>2) More welfare-enhancing policies require efficient pricing of road congestion and public transport (in particular a large price differential between peak and off-peak driving) and provide incentives for consumers to choose the most efficient combinations of cars.<br>3) Reaching $CO_2$-targets in a cost-effective way will require a large switch to BEVs. However, the welfare cost per ton of $CO_2$ abated that will far exceed the recommended reference value of $CO_2$. |

| Paper | Research questions | Theory | Data | Methods | Key findings |
|---|---|---|---|---|---|
| III | When we factor in the current uniform grid tariff system, what are the welfare impacts of today's EV policies and polices for reaching $CO_2$-targets at least cost?<br>How can these welfare costs be affected by a better pricing of electricity distribution? | Theory of optimal taxation of multiple externalities in multiple, interlinked sectors | National travel survey data, parameters from transport models and literature | Numerical modeling, solving for optimal road tolls, parking fees, fares purchase taxes and grid tariffs | 1) Our model finds an equilibrium where the increased cost of transformers due to EV charging leads to between NOK 12 and 18 in added non-car electricity costs per agent, depending on the DSO's pricing scheme.<br>2) A pricing scheme that applies peak tariffs for the grid will help strike a better balance between investment costs and EV-owners' disutility of charging during off-peak hours.<br>3) The shift to EVs and PHEVs is an integral part of reaching the ambitious goals of reducing $CO_2$-emissions by 50% in the greater Oslo area at least cost. We find that adding the charging issues leads to NOK 17-27 in additional costs per $tCO_2e$. |
| IV | What are the *marginal costs* inflicted on DSOs when the number of BEVs increases?<br>Through which *mechanisms*, i.e. which of the DSOs cost components, do we find the cost associated with a larger BEV stock? | Cost function framework | Dataset of Norwegian DSOs outputs, costs and registered BEVs in their operational area over the time period 2008-2017 | Fixed effects regression models | 1) Increases in the BEV fleet are associated with positive and statistically significant increases in costs. The point estimates also imply that the effect is economically significant, with a preferred model giving a cost elasticity of 0.018 from increases in the local BEV stock.<br>2) The strongest cost impact associated with BEV growth happening through operational costs, and not capital costs.<br>3) There is a lot of heterogeneity in these results, with the marginal cost estimates being a lot higher for small DSOs in rural areas, and a lot lower for larger DSOs. |

# Chapter 1:
# How to road price in a world with electric vehicles and government budget constraints

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# How to road price in a world with electric vehicles and government budget constraints

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ABSTRACT

In this paper we examine what characterizes second-best road prices targeting external costs from driving electric (EV) and conventional (ICEV) vehicles when there are distortionary labor taxes and binding government budget constraints. Further, we examine how this second-best pricing fits with government set goals of reducing $CO_2$ emissions. The paper further develops an analytical framework for assessing first- and second-best road prices on vehicle kilometers, extending it to include EVs and externalities that vary geographically and by time of day. We find that optimal road prices largely vary with external cost, but are also significantly affected by the interactions with the rest of the fiscal system. Not surprisingly, the highest road prices should be for ICEVs in large cities during peak hours due to high external costs. More surprisingly, we find that the road price for ICEVs in rural areas should be lower than that for EVs due to large fiscal interaction effects. These road prices give large welfare gains, but they lead to no reduction in carbon emissions when applying the currently recommended social cost of carbon.

## 1. Introduction

The road transport market is associated with market imperfections such as local and global pollution, accidents, noise and road wear. Thune-Larsen et al. (2014) calculate external costs in Norway of up to NOK 30 billion (Norwegian kroner; 1 NOK = €0.11 = $0.13) per year from road transport – a figure that does not include $CO_2$ costs, even though road transport in 2015 accounted for 19% of Norway's greenhouse gas (GHG) emissions (Ministry of Finance, 2017). In addition to externalities from road transport, inefficiencies in the economy arise from distortionary taxes elsewhere. Externalities and inefficiencies in the tax system have recently come under renewed scrutiny with government-assigned expert committees publishing so-called Norwegian Official Reports (Norges Offentlige Utredinger – NOU), with NOU 2014:13 – *Capital Taxation in an International Economy* and NOU 2015:15 – *Green Tax Commission.* Looking for ways by which to mitigate these inefficiencies is in itself motivation for this paper.

As recommended by many transport economists before us, we propose a road pricing scheme for mitigating these inefficiencies. More specifically, we propose distance-based road pricing, differentiated across vehicle types and pre-defined areas and time periods according to their external costs, also factoring in revenue recycling through labor taxation.

We raise the following research questions: What characterizes the set of second-best road prices targeting external costs from driving EVs and ICEVs when there are distortionary labor taxes and binding government budget constraints? How are these prices affected by tax distortions in the labor, electricity and car ownership market? How does this second-best pricing fit with government set goals of reducing $CO_2$ emissions?

Our paper makes the following contributions: First, it extends an established modeling framework for optimal taxation in

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transport with revenue recycling of distortionary labor taxes to include (a) different areas and time periods where external costs vary, and (b) both ICEVs and EVs and their associated taxes. This allows us to take a broad view how a national road pricing scheme optimally would look like. As road prices per combination of vehicle type, area and time period, and the labor tax rate are determined simultaneously, this model also allows us to see the endogeneity of how changes in one road price affects the levels of the others. This can result in road prices that differ from traditional Pigovian solutions in several dimensions. We can also see how costs and benefits of the scheme are distributed geographically. Second, it provides numerical results for the case of Norway, a country where the Ministry of Transport has started investigating the possibilities for distance-based road pricing applying satellite technology. It is also the country with the highest EV share of the car fleet in the world, strengthening both fiscal and externality arguments for moving from fuel tax to a more sophisticated way of road pricing.

Our paper is constructed as follows. In Section 2 we provide some background and literature review. In Section 3 we introduce the analytical framework and derive expressions for optimal road prices. The numerical modeling with parameter values and scenarios is explained in Section 4, while the results from the modeling exercise are given in Section 5. Section 6 concludes.

## 2. Background and literature

In order to strike the appropriate balance between costs and benefits in the affected markets, the "textbook economics" solution would be to find a set of taxes that provide the incentives for economic agents to do so. The optimal gasoline (or diesel) tax is given as one solution in several papers; for instance, in the cases of the UK and USA (Parry and Small, 2005), and Germany (Tscharaktschiew, 2014, 2015).

However, there are shortcomings to correcting road transport market failures through fuel taxation. First, the external costs of driving vary depending on where and when it takes place, making a fuel tax an imprecise instrument. In addition, a fuel tax provides incentives for more energy efficiency, which could be beneficial with regard to carbon emissions and oil reliance, but lead to higher external costs because lower user costs per kilometer would induce more driving. This has been pointed out in several papers (see e.g., Parry et al., 2014a; Parry and Small, 2005; Proost et al., 2009).

Second, the possibility for fuel taxes to (imprecisely) correct for externalities and generate government revenue is reduced when EVs (electric vehicles)[1] are introduced. EVs have many of the same externalities as ICEVs (internal combustion engine vehicles), but they cannot be captured by a gas tax and it seems implausible they can be taxed explicitly from electricity use.

So, are there better ways of taxing, ways that internalize external cost more precisely and allow for the taxation of all cars? This brings us into the discussion of road pricing. A vast literature on road pricing has accumulated over the decades. Button and Verhoef (1998, p. 4) refer to Pigou (1920) and Knight (1924) as the spiritual fathers of road pricing. Since then, hundreds of theoretical and empirical papers on a wide variety of road pricing schemes have been published, making it useful to specify exactly what kind of road pricing this article will focus on. Levinson (2010) developed a typology with 90 types of road pricing, organizing it along the three dimensions; the spatial resolution, the temporal resolution and the pricing objective. Within the dimensions of this typology, this article focuses on area based,[2] time-varying, second-best road pricing.

We focus on this specific type of road pricing because we believe it has a potential to generate large efficiency improvements for a country like Norway. Support for the merits of the distance-based aspects can be found in the literature. Analysis from Parry and Small (2005) and from May and Milne (2004) shows that distance-based road pricing can generate greater social benefits than, for example, fuel taxation and cordon-tolling. Furthermore, modeling analysis from Meurs et al. (2013) suggests that distance-based road pricing using satellite technology can be beneficial for the Netherlands compared to the current tax system for car-use and car-ownership. Small and Verhoef (2007) along with André de Palma and Lindsey (2011) argue for the potential for high economic efficiency of distance-based road pricing, and note that GPS technology is suitable for a scheme like this. The latter argue that a satellite-based road-pricing system has advantages with regards to scale economies and in the potential for value-added services and revenue generation.

The technologies underlying satellite-based road pricing have matured over the last decades, meaning that the timing is good for research having this in mind. Such technology could in theory enable the theoretically best type of road pricing according to the typology from Levinson (2010); dynamic marginal cost pricing on differentiated links. However, both privacy concerns and the understandability of the system for the general public sets a limit on spatial and temporal granularity. It will probably not be permissible for the road pricing authority to monitor car users at the finest level of detail, and a large number of car users cannot be expected to understand a system with a wide variety of dynamically changing road prices. This makes distance-based prices differentiated across pre-defined areas and time periods a promising alternative. Finally, because of the new emphasis on reducing inefficiencies in the Norwegian tax system, we want to focus on second-best road prices as a part of a tax reform where revenues are recycled back into the economy through reduced distortionary labor taxes.

Many of the aspects included in this specific form of road pricing have been covered in previous literature. The term road pricing has primarily been associated with road traffic congestion (Button and Verhoef, 1998, p. 6), and this has been the study of numerous papers. Over time, several papers have included environmental and/or accident externalities along with congestion (De Borger and Mayeres, 2007; De Borger and Wouters, 1998; André De Palma et al., 2004; Munk, 2008). Several papers have considered how road

[1] In this paper, when we refer to electric vehicles (EVs) we consistently mean pure battery electric vehicles (BEVs), without any hybrid technology.

[2] More specifically, distance-based road pricing that vary by a small number of areas; large city, small city and rural.

prices should differ across areas, e.g., between the urban and the non-urban setting (Munk, 2008; Proost and Van Dender, 1998) or across the diesel and gasoline cars (De Borger and Mayeres, 2007), and an integrated transport and land-use model that can e.g., simulate the effects of distance-based road pricing differentiated by area and gasoline, diesel and electric cars is under development in the OECD (Tikoudis and Oueslati, 2017). Finally, many influential papers have considered road prices in interaction with other distortionary taxes (see e.g., De Borger, 2009; André De Palma and Lindsey, 2004; Mayeres and Proost, 1997; Munk, 2008; Parry and Bento, 2001; Parry and Small, 2005; Van Dender, 2003).

We build on an analytical framework introduced by Parry and Small (2005), who applied it in deriving the optimal First-Best Pigou-Ramsey tax for gasoline in the UK and USA. This model was also used by Lin and Prince (2009) and by Antón-Sarabia and Hernández-Trillo (2014) in calculating the optimal gasoline tax in California and Mexico, respectively. A modified version is used in Parry (2009) and Tscharaktschiew (2015). Parry (2009) uses it to calculate optimal gasoline and diesel taxes, and Tscharaktschiew (2015) uses it to calculate optimal gasoline taxes in a model with both electric and diesel cars. It is a fairly simple model that generates insight and intuition. To a large extent, we build on the Tscharaktschiew (2015) version, which contains EV considerations. In this paper, we extend these model exercises in several dimensions in order to assess the optimal second-best tax for vehicle kilometers (hereafter, road prices). First, we analyze optimal road prices for both EVs and ICEVs and not just a single policy instrument such as gasoline tax. Second, we model how externalities vary geographically and by time of day, which gives us a set of second-best road prices that differ across four different stylized spatiotemporal states, large cities during peak hours, large cities off-peak, small cities and in rural areas. Third, we apply the model to analyze the shadow price for reaching a (sector-specific) GHG emissions reduction target at least cost.

The Pigovian solution of setting the corrective tax equal to marginal external cost (MEC) is well known (see e.g., Perman, Ma et al., 2003). In this paper, we place ourselves in a second-best world with binding budget constraints and distortionary labor taxes, so we want to find second-best road prices. This is related to the debate on how to correctly assess optimal environmental taxation in the presence of distortionary taxation elsewhere in the economy (see e.g., Bovenberg, 1999; Jacobs and de Mooij, 2015) and the marginal cost of public funds (MCF) (for a recent review, see Holtsmark and Bjertnæs, 2015). This literature shows that the debates on these topics are far from settled. We construct a model for analyzing optimal road prices in an economy with distortionary taxes, and any analyst using it may choose to disallow MCF above 1, perhaps as part of a "moral sensitivity analysis" (see e.g., Mouter, 2016). The model can thus serve as a practical tool for analyzing the costs and benefits of road prices under varying assumptions.

## 3. Analytical framework

As explained above, we emphasize the importance of differentiating between spatiotemporal states, because the estimated value of the externalities varies between them. In order to avoid cumbersome notation, we attempt to solve the model for a single state containing all of the externalities, a state that can be thought of as a large city during peak hours. The numerical model calculates solutions for all of the states under consideration.

We make the simplifying assumption that agents and their cars are constrained to remain within one state only. Although this constraint is fairly strict, it should still cover the main purpose each agent has with her car.

We consider a static, closed economy model with a representative household with the following utility function:

$$U = u(m_F, v_F, m_P, v_P, X, l, T, E) \tag{1}$$

The utility function $u(.)$ considers goods in per household terms. It is quasi-concave and increasing in arguments $m_F$ and $m_P$, kilometers driven per car of type ICEV ($F$) and EV ($P$). It is also increasing in $v_F$ and $v_P$; the number of cars per type.[3] This also applies for general consumption $X$, and leisure $l$. In contrast, utility is decreasing in arguments $T$, total in-vehicle travel time that, in addition to being an activity with some disutility (possibly), also reduces household utility through taking away time potentially used for working (and earning for consumption) and leisure. Utility is also decreasing in $E$, representing an index of environmental externalities.

Total travel time for a household depends on aggregate vehicle kilometrage $\bar{M}$ in a particular area. We use bar notation to denote economy-wide variables perceived as exogenous by travelers. The total per-period travel time for a household is given by:

$$T_i = t(\bar{M})M \tag{2}$$

The average travel time per kilometer $t(\bar{M})$ is increasing in the aggregate vehicle kilometers travelled ($t' > 0$) as higher economy-wide kilometrage leads to time delays due to congestion (in our stylized model we assume that such large traffic volumes in one area only occur in large cities during rush hours) and

$$M = M_P + M_F = m_P v_P + m_F v_F \tag{3}$$

is the per-household distance traveled by car per period.

Environmental externalities $E_i = \{E_F(\bar{F}), E_P(\bar{P}), E_{M_F}(\bar{M}_F), E_{M_P}(\bar{M}_P)\}$ cover traffic externalities stemming from energy consumption $E_F$ and $E_P$ (increasing in the use of fossil fuels and electricity, $F$ and $P$) and from vehicle kilometrage $E_{M_i}$ (increasing in $\bar{M}_i$ for each vehicle type $i$). The partial derivatives of E translate into marginal external damage (in units) from energy usage and kilometers traveled by car. We assume in this paper that there are no externalities associated with producing and consuming electricity for EVs,

[3] We look at average ownership rates of vehicle types per household, treating it as a continuous variable.

i.e., $E_P(\bar{P}) = 0$. In regard to GHGs, this assumption may hold for Norway, whose electricity generation consists overwhelmingly of hydro (95.8% hydro in 2015) (IEA, 2017). The argument is further strengthened by the fact that Norway is a part of the EU ETS market, as discussed in Bjertnæs (2016).

In the household monetary budget constraint, expenditures related to car transport and other consumption are set equal to after-tax income in the following way:

$$[(R_F\widetilde{f} + c_F^d)m_F + \tau_{mF}\, m_F + c(\widetilde{f}\,) + \Gamma_F]v_F + [(R_P\widetilde{p} + c_P^d)m_P + \tau_{mp}\, m_P + c(\widetilde{p}\,) + \Gamma_P]v_P + P_X X = (1-\tau_L)wL \tag{4}$$

Here, $R_i = (r_i + \tau_i)$ denotes the consumer price per unit of energy type $i$. All consumer prices contain the pure fixed producer energy supply price $r_i$ and the energy tax $\tau_i$. Energy intensity for cars, expressed in units per kilometer, is denoted $\widetilde{f}$ for ICEVs and $\widetilde{p}$ for EVs – lower energy intensity means higher energy efficiency. The terms $c_F^d$ and $c_P^d$ denote the other distance-dependent costs (repairs, service, etc.). We assume away any costs related to range anxiety or waiting time at charging stations for EVs.[4] Tolls are averaged to per-kilometer road prices ($\tau_{mF}$ and $\tau_{mp}$). The terms $c(\widetilde{f}\,)$ and $c(\widetilde{p}\,)$ denote the other costs of owning a car, independently of distance. This would mainly be an annuity of the pre-tax purchase cost – costs assumed to depend on energy efficiency. These capture how increasing energy efficiency comes at a cost (otherwise every-one would choose the highest level of energy efficiency). As we will see later, the model agent has an elasticity of fuel efficiency and can thus respond to changes in consumer fuel costs by choosing higher or lower fuel intensity. $\Gamma_i$ represents the sum of the annual ownership tax and the annuity of the purchase tax for vehicle type. The cost of the general consumption goods basket is given by $P_X X$.

Net labor income per household is given by $(1-\tau_L)wL$, where $\tau_L$ is the tax rate on labor. Finally, $w$ represents hourly gross wage, while $L$ represents labor supply (total per-year working hours). Total pre-tax labor income is denoted as $W$.

The relationship between fuel use, energy intensity and kilometers driven is given by:

$$F = \widetilde{f}\, M_F = \widetilde{f}\, m_F v_F \tag{5}$$

$$P = \widetilde{p}\, M_P = \widetilde{p}\, m_P v_P \tag{6}$$

Households also have a time constraint that can be written as follows:

$$L + l + t(\bar{M})M = \bar{L} \tag{7}$$

Available time $\bar{L}$ is distributed between the activities labor, leisure and car travel.

The government is subject to the following budget constraint, where fixed public spending $GOV$ is set equal to net revenue from all taxes:

$$GOV = \tau_F F + \tau_P P + \tau_{mF}\, m_F v_F + \tau_{mp}\, m_P v_P + \tau_L wL + \Gamma_P v_P + \Gamma_F v_F, \tag{8}$$

We make the simplifying assumptions that general consumption goods are produced by firms under perfect competition and with constant returns to scale technology, where labor is the only production input. This means that the firms generate no pure economic profits and all producer prices are fixed. The gross wage for workers, $w$, equates the value of the marginal product of labor, which is assumed to be constant.

### 3.1. Maximizing utility

Households are assumed to maximize their utility function given in Eq. (1) with respect to the choice variables $m_F, v_F, \widetilde{f}\,, m_P, v_P, \widetilde{p}\,, X$ and $l$. The optimization is subject to Eqs. (4) and (7), representing the monetary budget constraint and time constraint, respectively. Households treat travel times (affected by aggregate kilometrage), external environmental damages and all tax levels as given. We form the Lagrangian – where $\mu$ is the Lagrange multiplier for the complete economic household budget constraint and can be interpreted as the marginal utility of income. We get first-order conditions from the optimization and use these to obtain the household's indirect utility function, which yields maximized utility given prices, taxes and income, but also travel time and externalities determined by the *aggregate* level of driving.

The households' indirect utility function can be expressed by the following set of parameters $\Omega \equiv \{\tau_{mF}, \tau_{mp}, \tau_P, \Gamma_F, \Gamma_P, \tau_L, t, E\}$. These parameters (policy variables and time and environmental externalities) are, as previously mentioned, treated as given by the households. The government's aim is to maximize the indirect utility function using the road pricing scheme policy variables.

$$\begin{aligned} V(\Omega) \equiv \max_{m_F, v_F, \widetilde{f}, m_P, v_P, \widetilde{p}, X, l} & u(m_F, v_F, m_P, v_P, X, l, T, E) - \mu([(R_F\widetilde{f} + c_F^d)m_F + \tau_{mF}\, m_F + c(\widetilde{f}\,) + \Gamma_F]v_F \\ & + [(R_P\widetilde{p} + c_P^d)m_P + \tau_{mp}\, m_P + c(\widetilde{p}\,) + \Gamma_P]v_P + P_X X - (1-\tau_L)w(\bar{L} - l + t(\bar{M})M)) \end{aligned} \tag{9}$$

We show the analytical exercise of deriving the optimal tax on EV-km, $\tau_{mp}$. Government revenues from $\tau_{mp}$ are recycled through reducing labor taxes, and all other transport and energy taxes are kept constant. All the steps of the analytical derivations are given in

[4] A standard range of 190 km would be sufficient for most daily commuters that charge the car at home. According to Figenbaum (2018), there are about 1000 fast-chargers in Norway, amounting to one fast-charger per 140 BEV owners. The fast-chargers are mainly located in and around the cities, and along the highways between cities. In addition, there are about 7500 slow or semi-fast chargers that are public (and/or work place), making coverage adequate for most trip purposes in most parts of the country, but not all.

Appendix A. Here, in the main part of the paper, only the most central equations are noted before we get to the analytical results. The analytical exercise starts with total differentiation of the household's indirect utility function with respect to $\tau_{mp}$. After some algebra and redefining of the externality terms we get the following expression for the marginal welfare effect of the kilometer tax:

$$\frac{1}{\mu}\frac{\partial V}{\partial \tau_{mp}} = \underbrace{e_F\left\{-\frac{dF}{d\tau_{mp}}\right\}}_{\text{energy related externalities}} + \underbrace{e_m^c(M)\left\{-\frac{dM}{d\tau_{mp}}\right\}}_{\text{congestion externalities}} + \underbrace{e_{mF}^{nc}\left\{-\frac{dM_F}{d\tau_{mp}}\right\} + e_{mp}^{nc}\left\{-\frac{dM_P}{d\tau_{mp}}\right\}}_{\text{kilometrage related non-congestion externalities}} - \underbrace{\left[\tau_{mp}\left\{-\frac{dM_P}{d\tau_{mp}}\right\} + \tau_{mF}\left\{-\frac{dM_F}{d\tau_{mp}}\right\}\right]}_{\text{km-tax revenue}}$$
$$-\underbrace{\left[\tau_F\left\{-\frac{dF}{d\tau_{mp}}\right\} + \tau_P\left\{-\frac{dP}{d\tau_{mp}}\right\}\right]}_{\text{energy tax revenue}} \underbrace{+D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}}}_{\text{direct/indirect tax revenue/cost from vehicle stock}} + \underbrace{\tau_L\frac{dW}{d\tau_{mp}}}_{\text{labor tax revenue}} \tag{10}$$

Parameter $e_F$ represents the MEC stemming from the consumption of fossil fuel. We also have MEC of driving 1 km when contributing to congestion $e_m^c(M)$, which is increasing in traffic volumes. Similarly, parameters $e_{mF}^{nc}$, and $e_{mp}^{nc}$ represent the environmental MEC from driving 1 km from ICEVs and EVs, respectively (assumed to be constant within a given state). Parameters $D_F$ and $D_P$ represent the per vehicle annual tax revenue $\tau_{mF}m_F + \tau_F\widetilde{f}\,m_F + \Gamma_F$ and $\tau_{mp}m_P + \tau_P\widetilde{f}\,m_P + \Gamma_P$. As we can see, the EV-km tax brings about a number of different changes in Eq. (10), which shows that the kilometer tax affects overall welfare through several channels.

### 3.2. Deriving second-best road prices

We set the marginal welfare change (given by Eq. (10)) equal to zero and solve for $\tau_{mp}$. This gives us the following expression:

$$\tau_{mp}^* = e_F\left\{\frac{dF/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + e_m^c(M)\left\{\frac{dM/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + e_{mF}^{nc}\left\{\frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + e_{mp}^{nc}$$
$$+\left[\tau_{mF}\frac{dM_F}{d\tau_{mp}} + \tau_F\frac{dF}{d\tau_{mp}} + \tau_P\frac{dP}{d\tau_{mp}} + D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}}\right]\frac{1}{-dM_P/d\tau_{mp}} \tag{11}$$

After more algebra, which is shown in Appendix A, we get the final expression for the optimal kilometer tax:

$$\tau_{mp}^* = \tau_{mp}^C + \tau_{mp}^I = \tau_{mp}^C + \tau_{mp}^{RR} + \tau_{mp}^{TI} = \tau_{mp}^C + \tau_{mp}^{RR} + \tau_{mp}^{(TI)} + \tau_{mp}^{CF} \tag{12}$$

The first term is the corrective component:

$$\tau_{mp}^C = e_{mp}^{nc} + e_m^c(M) + \eta_F\left(e_m^c(M) + e_{mF}^{nc}\right) + \chi_F e_F \tag{13}$$

Parameters $\eta_F$ and $\chi_F$ are for how consumption of ICEV-kms and fossil fuel react to the EV-km tax. Note that in our second-best world we have to look at the total effect of the road price, and not simply equate the corrective tax to MEC.

The second term in (12) is the revenue recycling component:

$$\tau_{mp}^{RR} = \Omega_{\tau_L}\left(\frac{(R_P\widetilde{p} + c_P + \tau_{mp})}{-\varepsilon_{M_P}} - \tau_{mp}\right) \tag{14}$$

The term consists of the marginal cost of public funds, $\Omega_{\tau_L}$, times the net tax revenue from marginally increasing the EV-km tax. The parameter $\varepsilon_{M_P}$ is the own-price elasticity of EV-kms.

The third term in (12) is the tax interaction component (excluding the congestion feedback component):

$$\tau_{mp}^{(TI)} = -(1+\Omega_{\tau_L})\left[\left(\frac{\tau_L(R_P\widetilde{p} + c_P^d + \tau_{mp})(\varepsilon_{MI}^c + \varepsilon_{LI})}{(-\varepsilon_{M_P})(1-\tau_L)}\right) + \eta_F\tau_{mF} + \chi_F\tau_F + \widetilde{p}\,\tau_P + \kappa_P D_P + \varphi_F D_F\right] \tag{15}$$

The fourth term is the congestion feedback component:

$$\tau_{mp}^{CF} = (1+\Omega_{\tau_L})\frac{\tau_L}{(1-\tau_L)}(\varepsilon_{LI}(1-\varepsilon_{MI})\varepsilon_{LL}^c)e_m^c(M)[\eta_F + 1] \tag{16}$$

The previously unmentioned parameters in these expressions are $\varepsilon_{MI}^c$ and $\varepsilon_{MI}$, the compensated and uncompensated income elasticities for vehicle kilometers, $\varepsilon_{LI}$, the income elasticity of labor supply, and $\varepsilon_{LL}^c$, the compensated elasticity of labor supply. $\Omega_{\tau_L}$ is the marginal cost of public funds (MCF), which has the following formula:

$$\Omega_{\tau_L} \equiv \frac{-\tau_L w\frac{\partial L}{\partial \tau_L}}{W + \tau_L w\frac{\partial L}{\partial \tau_L}} = \frac{\frac{\tau_L}{(1-\tau_L)}\varepsilon_{LL}}{1-\frac{\tau_L}{(1-\tau_L)}\varepsilon_{LL}} \tag{17}$$

This term reflects the marginal efficiency cost of raising public funds through taxing labor. On the flip side, it also reflects the marginal efficiency gain from cutting tax on labor, which could be done by, e.g., raising funds from road pricing. The numerator in this expression represents the efficiency cost from an incremental increase in labor taxation, while the denominator gives us the marginal change in public revenue. $\varepsilon_{LL} > 0$ represents the elasticity of labor supply (uncompensated). We have $\Omega_{\tau_L} > 0$ as a consequence of $\varepsilon_{LL} > 0$ and $1 > \frac{\tau_L}{(1-\tau_L)}\varepsilon_{LL}$. The latter implies that $\tau_L$ is not so large that we find ourselves on the right side of the Laffer curve's peak, meaning that government revenue from increasing labor taxation will, on the margin, be positive.

Components of the optimal tax have been described thoroughly in Tscharaktschiew (2014, 2015), but here is a brief explanation.

The corrective tax component addresses the external environmental damages from driving an EV-km. It includes the kilometer-related externalities in relation to congestion (same for all vehicles), and externalities such as pollution, noise and accident risk (differs between EVs and ICEVs). Note that the tax on EV-kms may induce more driving of ICEVs, which contributes to a reduction in the level of the corrective component.

The revenue recycling component is the efficiency gain from using additional EV-km tax revenue to cut the distortionary labor tax and increase the efficiency of the tax system. The effect is equal to the marginal cost of public funds times the marginal net EV-km tax revenue gains due to the increase in EV-km taxation.

The tax interaction component accounts for the efficiency loss in the labor market from the higher tax on kilometers. On the one hand, higher taxes reduce the real household wage and have a discouraging effect on labor supply. On the other, they include the income effect on labor supply from a higher km-tax. The other terms cover how the EV-km tax interacts with secondary markets, e.g., the electricity market, and the tax distortions there.

The congestion feedback component accounts for how raising the cost of travel through road prices may reduce vehicle kilometers and congestion, and in that way affect labor supply through reductions in travel time. Workers may then allocate less of their time on travel, and more of their time on either working or enjoying leisure activities. Since labor is subject to taxation, such a feedback effect would improve welfare and *ceteris paribus* cause upward adjustments to the second-best kilometer tax. When we present our numerical results, this is included in the tax interaction component where relevant, i.e. in the state large cities during peak hours.

### 3.3. Functional relationships

Parameters such as $\eta_F = \frac{dM_F / d\tau_{mp}}{dM_P / d\tau_{mp}}$ quantify our assumptions on how households respond to changes in tax parameters. These parameters can be expressed in terms of elasticities, e.g., $\eta_F = \frac{M_F \varepsilon_{M_F}^{M_P}}{M_P \varepsilon_{M_P}}$, where $\varepsilon_{M_F}^{M_P}$ is the cross-price elasticity for ICEV-km, with respect to price change for EV-km. Furthermore, the *direct* response in per-vehicle demand for vehicle-kms when the EV-km tax changes can be expressed through $m_F = m_F^0 \left( \frac{R_P \widetilde{p} + c_P^d + \tau_{mp}^*}{R_P \widetilde{p} + c_P^d + \tau_{mF}^0} \right)^{\varepsilon_{M_F}^{M_P}}$ and $m_P = m_P^0 \left( \frac{R_P \widetilde{p} + c_P^d + \tau_{mp}^*}{R_P \widetilde{p} + c_P^d + \tau_{mp}^0} \right)^{\varepsilon_{mp}}$, where we assume constant elasticity of demand. This is common in these kinds of analysis of optimal pricing in the transport sector, as can be seen in for example Parry and Small (2005), Parry (2009) and Tscharaktschiew (2014, 2015). We have similar expressions for responses in vehicle stock. The parameters $m_F^0$ and $m_P^0$ are the per-vehicle kilometrage in the initial equilibrium. The levels in the new equilibrium depend on the road prices in the new equilibrium. If, for example, $\tau_{mp}^*$ does not differ from $\tau_{mp}^0$, then there will be no change in the new equilibrium, as $m_P$ would equal $m_P^0$.

As we can see from the equations that comprise the optimal taxes, the tax levels are on both the left-hand and right-hand sides of the equation, so they must be solved numerically. In addition, we solve the model for road prices for both ICEVs and EVs, and for all the stylized states simultaneously. The next step involves inserting parameter values into the model and calculating the optimal tax rates.

## 4. Numerical model description and parameter values

In this section, we explain the scenario for calculating optimal tax levels for EV- and ICEV-kms. The thought experiment for the calculation can be summarized as: (1) an assumption that the optimal kilometer taxes were implemented at the time of writing in 2017; (2) there is a medium-run adjustment from agents towards 2020[5]; and (3) based on these medium-run adjustments, we get values for the optimal taxes in 2020.

Our calculations ignore dynamics in the adjustments. We simply calculate the tax rates for 2020 with 2020 values on externalities (i.e. values applied today are real-price adjusted for future years, as is recommended practice for CBA conducted in Norway; see, e.g., NOU 2012:16 (2012)). All monetary values are given in 2015 prices. Applied values for vehicle kilometers and levels of labor and electricity taxes are also based on 2015 values.

Ideally, one would want to have individual tax levels for hundreds of car types based on the car's individual characteristics. In our model, we work with two types of car, an ICEV and an EV. The numerical values applied to the ICEVs are based on a weighted average of diesel and gasoline-powered vehicles, weighted by their estimated aggregate vehicle kilometers in 2015,[6] based on the BIG model[7] at the Institute of Transport Economics.

In the theoretical framework we have taxes on labor, fossil fuel, electricity, vehicle purchase and vehicle ownership, ICEV-km and

[5] This is reflected in the choice of elasticities in the model. A way to think of the changes in a medium -run equilibrium in e.g., the transport market, households are able to adjust their driving style, choices of destinations and frequencies, and a small fraction of them have had time to change vehicle ownership. We would expect e.g., little change in the choice of residential and work place location.

[6] Gasoline had 59% of the ICEV kms travelled in 2015, while diesel had 41%. To use the weighted average of gasoline and diesel as "fossil fuel" is a simplification that allows us to focus on the differences between EVs and ICEVs. While there are large differences between diesel and gasoline both with regards to external costs and current tax policy (Harding, 2014), the differences between electricity and any of the fossil fuels are even larger.

[7] The acronym is derived from "bilgenerasjonsmodell", meaning "car cohort model".

EV-km. In the numerical model, the current tax on fossil fuels, along with average tolls in the various states, is converted to a corresponding tax on ICEV-kms. When we optimize road prices, drivers will face a price that strikes a balance between costs and benefits from mitigating transport externalities and distortions in the labor market. That price will give drivers the incentive to economize their kilometers appropriately. However, in the corrective component of the road prices we find both the distance-dependent external costs (e.g., accident risk, local pollution, noise, etc.) and the external cost from fuel usage, which in this analysis derives from the social cost of $CO_2$. This cost component gives not only incentives for economizing on kilometers but also on fuel use. Changes in the external cost of fuel use would induce changes to both kilometers driven and fuel efficiency. It can be thought of as if taxes on fuel have been removed from the pump, but incorporated within the road price. Parts of the road price for a particular car would then differ according to its fuel intensity and be an implicit fuel tax. This model technicality is useful when we calculate the shadow price of reaching a GHG emissions reduction target at least cost using this road pricing scheme.

The government budget constraint must hold in equilibrium. The sum of changes from optimized km-tax revenue (that in the initial condition contains current fuel taxes and tolls), and subsequent changes in electricity, vehicle purchase and ownership tax revenue,[8] must be offset by changes in the labor tax. This makes the equilibrium labor tax rate endogenous.

The scenario mimics a reform where fuel taxes and tolls are shifted over to distance-based road prices, differentiated across area, time of day and vehicle type (almost exactly the reform recommended for Europe in De Borger and Proost (2015)), which are then optimized, taking into account that labor tax rates change to maintain revenue neutrality. A situation where optimal road prices lead to a reduction in labor tax rates corresponds to a net shift in tax burden from labor income to transport.

For the transport variables, the representative household in the model is considered as a weighted average of values for the different geographical areas we consider. The areas are large cities (more than 100 000 inhabitants), small cities (between 15 000 and 100 000 inhabitants), and rural areas (fewer than 15 000 inhabitants), which contain 28%, 32%, and 40% of Norwegian households, respectively. This is the same classification as in Thune-Larsen et al. (2014).

The applied parameter values for the model are given in Table 1.

Values for the external costs from road transport are all taken from Thune-Larsen et al. (2014), a report made for the Ministry of Finance, Ministry of Transport and Communications and The Ministry of Climate and Environment, that now serves as official guideline parameters for conducting CBA in Norway.[9] The congestion costs in this report are estimated for both freight and passenger car transport. We only apply the estimates for passenger car transport, implicitly assuming a constant level of freight transport. The external non-congestion costs consist of (with each component's share of the national average estimate in parenthesis) external cost estimates for local pollution (25%), noise (3%), accident risk (55%), road wear (< 1%) and winter management (16%). The component that causes the largest differences between large cities, small cities and rural areas is the local pollution component. This component is set to zero for EVs, and is the only difference between EVS and ICEVs with regards to non-congestion costs per km.[10] More information about the parameter values is given in Appendix C.

## 5. Model results

Here we present the calculations of the second-best distance-based road prices differentiated by vehicle and spatiotemporal state. Main results are given in Table 2.

### 5.1. Baseline second-best road pricing

The model calculates road prices that vary significantly between states and car types, largely reflecting the variation in external costs. This can be seen in Table 2. The highest price is on driving an ICEV in a large city during peak hours, mainly because of the external congestion costs. However, the marginal external congestion costs are lower in the new equilibrium than in the initial situation, as the transport volumes during peak hours have been reduced significantly for both EVs and ICEVs. It is still worth noting that the tax per kilometer is more than five times higher than the current sum of average toll and fuel tax per kilometer during peak hours.

The lowest price is on driving an ICEV in rural areas. The tax per kilometer is actually 60% lower in the new equilibrium than the sum of average toll and fuel tax per kilometer was initially. It is also worth noting that the optimal road price for ICEVs in rural areas is actually lower than for EVs in these areas. This is also the case for driving in small cities. Hence, the current preferential treatment of EV use, essentially facing zero taxation (except for general electricity taxation), is way below optimal road pricing.

In all cases there is a markup from the revenue recycling component, showing the efficiency gain from replacing revenue from

[8] The purchase and ownership taxes per ICEV is assumed to remain constant in this model. This is a caveat, as the purchase tax is progressive in both type approved $CO_2$-emissions and $NO_X$-emissions per km. Any increase in fuel efficiency in the car fleet will result in a decrease in purchase tax revenue, *ceteris paribus*. On the other hand, with a higher pre-tax cost of more fuel efficient cars, the VAT revenue will increase.

[9] Other possible external cost estimates could include estimates from the IMF (Parry et al., 2014b), but they only provide a national average for external costs, and we make a point of using estimates that vary across areas and times of day. Applying the parameters specifically estimated for the Norwegian context and recommended by official guidelines, also makes this exercise more relevant for a Norwegian policy discussion. This is also discussed in the sensitivity analysis.

[10] Note that EVs are assumed to have the same noise cost per km as ICEVs in spite of the higher engine noise from the latter. This is because noise from tires on asphalt dominates at speeds over 30 km/h according to Thune-Larsen et al. (2014). In any case, noise makes up a relatively small portion of the external costs, even in large cities.

**Table 1**
Parameter values for baseline calculations.

| Model parameters | Symbol | Value | Denomination | Sources used and additional information |
|---|---|---|---|---|
| *Vehicle technology, usage and ownership* | | | | |
| Initial "fossil" fuel intensity | $\tilde{f}^0$ | 0.079 | l/km | Institute of Transport Economics, BIG model |
| EV electricity intensity (average of winter and summer) | $\tilde{p}^0$ | 0.25 | kWh/km | Institute of Transport Economics, BIG model |
| Initial vehicle kilometrage per car (EV & ICEV), large cities, peak (lp) | $m_{ilp}^0$ | 940 | km | Institute of Transport Economics, Thune-Larsen et al. (2014) and Statistics Norway StatBank (2018c) |
| Initial vehicle kilometrage per car (EV & ICEV), large cities, off-peak (lo) | $m_{ilo}^0$ | 10,806 | km | [These kms per car per area numbers are weighted according to area's share of households. In sum, this results in a national average of 12 230 km per car] |
| Initial vehicle kilometrage per car (EV & ICEV), small cities (s) | $m_{is}^0$ | 12,004 | km | |
| Initial vehicle kilometrage per car (EV & ICEV), rural (r) | $m_{ir}^0$ | 12,761 | km | |
| ICEVs per household, large cities (Fl) | $v_{Fl}^0$ | 0.960 | cars | Statistics Norway StatBank (2018f), Statistics Norway StatBank (2018a), Statistics Norway StatBank (2018b) |
| ICEVs per household, small cities (Fs) | $v_{Fs}^0$ | 1.128 | cars | [These cars per household per area numbers are weighted according to area's share of households. In sum, this results in on average 1.112 ICEVs per household and 0.029 EVs per household, implying on average 1.141 cars in total per Norwegian household] |
| ICEVs per household, rural (Fr) | $v_{Fr}^0$ | 1.123 | cars | |
| EVs per household, large cities (Pl) | $v_{Pl}^0$ | 0.046 | cars | |
| EVs per household, small cities (Ps) | $v_{Ps}^0$ | 0.033 | cars | |
| EVs per household, rural (Pr) | $v_{Pr}^0$ | 0.015 | cars | |
| Car life-span | | 16.5 | years | Fridstrøm, Østli, and Johansen (2016) |
| *Prices and taxes* | | | | |
| "Fossil fuel" producer price | $r_F$ | 6.82 | NOK/l | Statistics Norway (2015) |
| Corresponding initial fossil-km producer price | | 0.54 | NOK/km | |
| Other private km costs for ICEVs | $c_F^d$ | 1.32 | NOK/km | Vegdirektoratet (2015) |
| Electricity consumer price (includes VAT and electricity tax) | $R_P$ | 0.81 | NOK/kWh | Statistics Norway StatBank (2018e) |
| Corresponding EV-km price (includes VAT and electricity tax) | | 0.20 | NOK/km | |
| Other private km costs for EVs | $c_P^d$ | 1.13 | NOK/km | Vegdirektoratet (2015) |
| Initial fossil fuel tax | $\tau_F^0$ | 6.58 | NOK/l | Finansdepartementet (2016) |
| Corresponding initial fossil-km tax | $\tau_{mF}^0$ | 0.52 | NOK/km | |
| Electricity tax per kWh | $\tau_P$ | 0.18 | NOK/kWh | Finansdepartementet (2016) |
| Corresponding electricity tax EVs pay per km | | 0.045 | NOK/km | |
| Average toll, large cities | | 0.47 | NOK/km | Calculated from National Public Road Administration's toll statistics and Statistics Norway's passenger car transport statistics. Users pay per passing of tolling station, but the numbers have been normalized to per km |
| Average toll, small cities | | 0.25 | NOK/km | |
| Average toll, rural | | 0.11 | NOK/km | |
| Purchase tax + VAT for ICEV | | 164,892 | NOK | Based on disaggregate car sales data provided by Norwegian Road Federation (OVF) |
| Purchase tax + VAT for EV | | 0 | NOK | |
| Annual ownership tax for ICEV | | 3565 | NOK | Finansdepartementet (2016) |
| Annual ownership tax for EV | | 435 | NOK | |
| Real discount rate for purchase tax annuity | | 2% | | Risk-free component in real discount rate applied in CBA (NOU 2012:16, 2012). In addition, car loans are usually given at 4–5% and the Norwegian inflation target is 2.5% |
| Average marginal labor tax rate (benchmark) | $\tau_L$ | 40% | | Bjertnæs (2015) |
| *Household behavior parameters* | | | | |
| Own-price elasticity of fossil fuel intensity (i.e. the isolated elasticity component for fuel efficiency w.r.t. consumer fuel price) | $\varepsilon_{\tilde{f}}$ | −0.092 | | Norsk Petroleumsinstitutt (2011) |
| Own-price elasticity of ICEV kilometers | $\varepsilon_{MF}$ | −0.152 | | Rekdal and Larsen (2008) |
| Own-price elasticity of EV kilometers | $\varepsilon_{MP}$ | −0.152 | | Rekdal and Larsen (2008) |
| Own-price elasticity of ICEV ownership w.r.t. costs per km | $\varepsilon_{MF}^{vF}$ | −0.121 | | Boug, Dyvi, Johansen, and Naug (2002) |
| Own-price elasticity of EV ownership w.r.t. costs per km | $\varepsilon_{MP}^{vP}$ | −0.121 | | |
| Cross-price elasticity of EV kilometers i.e. how ICEV ownership increases when the cost of EV-km increases | $\varepsilon_{MP}^{vF}$ | 0.0015 | | Institute of Transport Economics, BIG-model |
| Cross-price elasticity of ICEV kilometers, i.e. how EV ownership increases when the cost of ICEV-km increases | $\varepsilon_{MF}^{vP}$ | 0.486 | | Institute of Transport Economics, BIG-model |
| Income elasticity of vehicle kilometers | $\varepsilon_{MI}$ | 0.185 | | Steinsland and Madslien (2007) |
| Compensated income elasticity of vehicle kilometers | $\varepsilon_{MI}^c$ | 0.151 | | Weighting estimates from West and Williams III (2007) on average Norwegian household demographics |
| Income elasticity of labor supply | $\varepsilon_{LI}$ | −0.03 | | Correspondence with Thor-Olav Thoresen on LOTTE-model at Statistics Norway, documented in Dagsvik, Jia, Kornstad, and Thoresen (2007) |
| Labor supply elasticity (uncompensated) | $\varepsilon_{LL}$ | 0.178 | | Dagsvik et al. (2007) |

(continued on next page)

**Table 1** (*continued*)

| Model parameters | Symbol | Value | Denomination | Sources used and additional information |
|---|---|---|---|---|
| Labor supply elasticity (compensated) | $\varepsilon_{LL}^{c}$ | 0.208 | | $\varepsilon_{LL}^{c} = \varepsilon_{LL} - \varepsilon_{LI}$ |
| *Externalities from car transport* | | | | |
| External congestion costs per kilometer, initially, large cities, peak | $e_m^c(M^0)$ | 6.339 | NOK/veh-km | Thune-Larsen et al. (2014) |
| Calibrated congestion function parameter – marginal congestion cost per km as a linear function of total vehicle km driving in peak hours. This can be considered a sub-component of $e_m^c$ | | 0.0237 | | |
| External non-congestion costs per km ICEV, large cities, peak (lp) | $e_{mFlp}^{nc}$ | 0.958 | NOK/veh-km | |
| External non-congestion costs per km EV, large cities, peak (lp) | $e_{mplp}^{nc}$ | 0.423 | NOK/ veh-km | |
| External non-congestion costs per km ICEV, large cities, off-peak (lo) | $e_{mFlo}^{nc}$ | 0.823 | NOK/ veh-km | |
| External non-congestion costs per km EV, large cities, off-peak (lo) | $e_{mplo}^{nc}$ | 0.423 | NOK/ veh-km | |
| External non-congestion costs per km ICEV, small cities (s) | $e_{mFs}^{nc}$ | 0.492 | NOK/ veh-km | |
| External non-congestion costs per km EV, small cities (s) | $e_{mps}^{nc}$ | 0.419 | NOK/ veh-km | |
| External non-congestion costs per km ICEV, rural (r) | $e_{mFr}^{nc}$ | 0.171 | NOK/ veh-km | |
| External non-congestion costs per km EV, rural (r) | $e_{mpr}^{nc}$ | 0.161 | NOK/ veh-km | |
| Fossil fuel related external costs | $e_F$ | 1.034 | NOK/l | Based on recommended social cost of carbon (420 NOK/ton) from NOU 2015:15 (2016) |

labor taxation with revenue from road pricing. We can also see that the tax interaction component lowers the final road prices. This is because of the negative impact that the total changes in road prices and labor taxes have on labor supply. The impact on other tax revenue leads to higher total road price levels. The exception is for ICEV driving in rural areas, small cities and cities off peak, as the negative impact on other tax revenue becomes greater. Incentivizing EV driving over ICEV driving in these states will result in lower tax revenues from, for example, purchase taxes, with inadequate substitution from EV road prices. This is why the impact on other tax revenue drives the EV road price upwards. This shows some of the endogeneity between road prices, and how they affect the size of each other's tax interaction component, which again will affect the revenue recycling component and the total road price level. In all cases the final road price is greater than the corrective component that targets the internalization of externalities, with the exception of driving ICEV in rural areas, where the final road price is even lower than its direct external cost. For this case, the tax interaction component has a larger impact on the final price than the revenue recycling component.

In all states, the optimal km-taxes are higher than their current levels for EVs. For ICEVs, however, the optimal km-taxes are lower than current levels of fuel taxes and tolls with the exception of large cities. It seems that ICEVs are taxed higher than optimal in most parts of the country. Hence, the optimal car travel volumes are higher than current volumes in these areas. This results in total 0.2% more vehicle kilometers travelled per household, from 14 129 to 14 150 km per year, despite a large reduction in city driving. The model also finds 0.5% lower rates of average vehicle ownership, from 1.152 to 1.146 cars per household. The impacts differ greatly between states. In large cities, EV ownership rates increase by 36% as the cross-price effect from the road price on ICEVs dominates the own-price effect for EVs. At the same time, ownership rates of ICEVs drop by 8% in large cities. For the rest of the country, the effects are in the opposite direction. On average, ownership rates for EVs increase by about 11%, while the rates for ICEVs fall by 0.8%.

Because the model results indicate over-taxation of ICEVs in most parts of the country in the initial situation, the net revenue from the road-pricing scheme is lower than the initial revenue. This indicates that in optimum it is better with a slightly higher labor tax burden than a higher tax burden from road pricing, given the same government budget constraint. The total increase in labor taxes corresponds to an increase in the average marginal tax rate from 40% to 40.1%. This could be an effect of Norway currently having among the world's highest taxes on gasoline and diesel, but it is worth noting that there are several European countries with similar or higher fuel taxes (U.S. Department of Energy, 2018).

In order to calculate the welfare effect of this road pricing scheme, we numerically integrate the marginal welfare impact (shown in Eq. (10) and rewritten in Eq. (B.7)). When numerically integrating the marginal welfare effect for all road prices, we end up with an annual welfare gain of NOK 255 (about €28 or $33) per household. By comparison, Tscharaktschiew (2014) finds a welfare gain of €13 per household when optimizing gasoline taxation. It is worth noting that the welfare gain is the *national* per capita average. The gain will be higher in large cities where congestion would be curbed (making it comparable to welfare gains found in urban road pricing case studies such as André De Palma et al. (2006)), and somewhat lower in rural areas.

What are the GHG emission implications when values such as these are applied in the model and second-best road prices are calculated? The applied social cost of carbon (SCC) of NOK 420 per ton (about €47 or $53) is the parameter $e_F$ in the corrective component in the ICEV road price that gives a direct incentive to economize fuel, while the road price as a whole gives an incentive to economize kilometers. It is equivalent to moving fuel tax from the pump, but incorporating it in road pricing that would differ with the vehicle's fuel intensity. The SCC is lower than the current tax on fuel, so fuel efficiency incentives become weaker in the new

**Table 2**

Results from model calculations of second-best road prices in 2020. Road prices are given in 2015 NOK per km for a given state.

| Vehicle type and state | Corrective component – own vehicle | Corrective component – indirect impact | Revenue recycling component | Tax interaction component – labor market and congestion[a] | Tax interaction component – other taxes | Total | Initial (tolls and fuel tax per km) |
|---|---|---|---|---|---|---|---|
| EV cities peak hours | 5.33 | −0.89 | 6.66 | −5.17 | 1.30 | 7.24 | 0.00 |
| ICEV cities peak hours | 6.01 | −1.10 | 7.68 | −5.93 | 1.33 | 7.97 | 0.99 |
| EV cities off-peak | 0.42 | −0.13 | 1.93 | −1.40 | 0.16 | 0.97 | 0.00 |
| ICEV cities off-peak | 0.96 | −0.09 | 2.65 | −1.92 | −0.28 | 1.31 | 0.99 |
| EV small cities | 0.42 | −0.22 | 1.85 | −1.34 | 0.16 | 0.88 | 0.00 |
| ICEV small cities | 0.63 | −0.03 | 2.17 | −1.54 | −0.53 | 0.68 | 0.77 |
| EV rural areas | 0.16 | −0.25 | 1.64 | −1.17 | 0.22 | 0.59 | 0.00 |
| ICEV rural areas | 0.31 | −0.01 | 1.83 | −1.27 | −0.61 | 0.23 | 0.63 |

[a] Including congestion feedback where relevant, i.e. in cities peak hours.

optimized equilibrium. This leads to agents choosing ca 5% lower average fuel efficiency. With almost unchanged travel demand in the nation as a whole, the annual GHG emissions from transport increase by 5.1% in optimum. It is clear that reducing GHG emissions through an optimal road-pricing scheme implies that the carbon price would have to be higher than the recommended values.

### 5.2. Optimal road prices and a shadow price on $CO_2$

The Norwegian government's goal by 2030 is to reduce GHG emissions from 1990 levels by 40%. In 2016, annual emissions were about 3% higher than in 1990. For the road transport sector, emissions were about 28% higher.[11] We consider now a binding emission reduction requirement for passenger car transport from 2015 levels (the initial situation in the model) to about 2020, when the new equilibrium following the policy change would be reached. We consider a 15% reduction to be roughly in line with the necessary trajectory for the emission reduction requirement to be met.

For this exercise, we set a constraint on equilibrium emissions. We allow the carbon price component in the road price (in effect, the fuel tax) to not be set equal to the recommended SCC, but to vary freely. The model will solve given constraints for the optimal road pricing scheme where the carbon price component will serve as a shadow price for the emission constraint. We then have the case of achieving the emission reductions in the most efficient pricing scheme available, i.e. reducing emissions at least cost. The results are given in Table 3.

The most notable difference in Table 3 compared to Table 2 is that the road price for ICEVs increases for driving in all states. The increase is between 20% (driving in large cities during peak hours) and 550% (driving in rural areas). The same comparison for EVs results in reductions for all states. The reduction is between 7% (driving in large cities in off-peak hours) and 24% (driving in small cities). These road price changes working against the ICEV arise from a substantial increase in the carbon price component, now the shadow price of the emission constraint. This shadow price is given in Table 4 alongside the social cost of carbon (SCC) and the initial fuel tax (59% gasoline, 41% diesel) measured in NOK per liter.

It can be seen from Table 4 that the shadow price of the emission constraint is about 16 times the SCC, which corresponds to a carbon price of NOK 7057/ton (about €784 or $882). We can also see that the carbon cost component exceeds the initial fuel tax by about 150%. This means that to achieve the emissions reduction target at least cost alongside an optimized road pricing scheme would not just be a question of "shifting from fuel tax and tolls to road price", it would require increasing the tax burden on *both* fossil fuel and kilometers.

So *how* do agents reduce their emissions at least cost? They could drive ICEVs less and/or more efficiently (or replace them with more efficient ICEVs). The results show an approximate 10.3% drop in total household driving with ICEVs and average fuel intensity drops by about 5.3%. Some of the reduction in ICEV kilometers materializes in a shift from ICEV to EV ownership. The results show about 9.6% fewer kilometers driven in total when EVs are included. EV ownership has increased by about 33% nationwide (even higher in cities). On the ICEV side, ownership rates have dropped by about 5.5% nationwide.

The increase in road pricing in this scenario means larger cuts in labor taxation. The total reduction in labor taxes corresponds to a drop in the average marginal tax rate from 40% to 37%. However, this is not enough to save the scenario from substantially less welfare compared to the initial situation. In this scenario, each household gets a welfare decrease of NOK 219 per year. The calculation assumes that the actual welfare cost of a ton of GHG is NOK 420, the SCC, even though a higher shadow price has been forced on the transport sector. The high shadow price for the emission constraint reflects high welfare costs from large-scale $CO_2$ abatement within the transport sector. For the Norwegian economy as a whole, the shadow price of a $CO_2$ constraint like this would probably be lower, because the existing emissions taxation is generally lower than in the transport sector (see e.g., NOU 2015:15, 2016), so cheaper abatement opportunities would be exploited.

### 5.3. Sensitivity analysis and alternative scenarios

The model results are reliant on the parameter values, which in some cases derive from uncertain estimates (see e.g., Thune-Larsen et al., 2014). We therefore provide sensitivity analysis to show how uncertainty in the underlying parameters creates uncertainty in the results. This applies for estimates of both external costs[12] and behavioral relationships, i.e. elasticities. We focus mainly on testing the sensitivity of the elasticity values. The implications for road price levels of higher/lower external cost values are easier to imagine; we have already shown the implications of higher carbon costs.

There are many ways to do sensitivity analysis. A common practice is varying the central parameters one-by-one to show how a change in one parameter affects the result. We often find it more rewarding to vary a set of variables simultaneously in a consistent scenario, which is useful in showing the range of outcomes, and helps the reader see the uncertainty in terms of different "stories".

Two of our scenarios focus on uncertainty about how the agents will respond in the transport market, i.e. uncertainty in transport-related elasticity parameters. In one of the scenarios, the agents turn out to be less responsive to transport policies, and vice versa for the other. The parameters we vary in the two scenarios are given in Table 5.

[11] Statistics Norway: StatBank: Table: 08940: Greenhouse gases, by source, energy product and pollutant 1990–2016 (retrieved November 2017).

[12] Many of the uncertainties underlying these estimates are discussed in Thune-Larsen et al. (2014), and the external cost estimates for Norway in this report differ somewhat from those found in Parry et al. (2014b). For example, the latter finds national average marginal accident costs per km to be about the same as the former, but finds lower local pollution costs per liter of fuel (about half) than in the former, mostly due to lower average emission factors.

**Table 3**
Results from model calculations of second-best road prices in 2020 under a GHG emission constraint of 15% reduction from 2015 levels. Road prices are given in 2015 NOK per km for a given state.

| Vehicle type and state | Corrective component – own vehicle | Corrective component – indirect impact | Revenue recycling component | Tax interaction component – labor market and congestion | Tax interaction component – other taxes | Total |
|---|---|---|---|---|---|---|
| EV cities peak hours | 5.10 | −0.82 | 5.39 | −4.18 | 1.22 | 6.72 |
| ICEV cities peak hours | 7.72 | −1.33 | 7.71 | −5.99 | 1.56 | 9.65 |
| EV cities off-peak | 0.42 | −0.24 | 1.63 | −1.18 | 0.30 | 0.94 |
| ICEV cities off-peak | 2.91 | −0.12 | 3.29 | −2.46 | −0.74 | 2.86 |
| EV small cities | 0.42 | −0.48 | 1.46 | −1.04 | 0.32 | 0.67 |
| ICEV small cities | 2.58 | −0.05 | 2.71 | −2.00 | −1.25 | 1.97 |
| EV rural areas | 0.16 | −1.05 | 1.35 | −0.96 | 1.00 | 0.50 |
| ICEV rural areas | 2.26 | −0.01 | 2.27 | −1.65 | −1.55 | 1.30 |

**Table 4**
Fuel taxes/carbon cost component in road price. 2015 NOK per liter.

| | Initial fuel tax (including VAT) | Social cost of carbon (SCC) | Shadow price of emission constraint |
|---|---|---|---|
| NOK per liter fossil fuel | 6.58 | 1.034 | 17.37 |

**Table 5**
Direction and relative change of parameter values in two scenarios for sensitivity analysis on responsiveness in transport markets.

| Elasticity parameter | More responsive transport market (MRTM) | Less responsive transport market (LRTM) |
|---|---|---|
| Own-price elasticity of fossil intensity | +30% | −30% |
| Own-price elasticity of ICEV kilometrage | +30% | −30% |
| Own-price elasticity of EV kilometrage | +30% | −30% |
| Own-price elasticity of ICEV purchase w.r.t. ICEV km cost | +30% | −30% |
| Own-price elasticity of EV purchase w.r.t. EV km cost | +30% | −30% |
| Cross-price elasticity of ICEV purchase w.r.t. EV km cost | +30% | −30% |
| Cross-price elasticity of EV purchase w.r.t. ICEV km cost | +30% | −30% |

The next two scenarios focus on the uncertainty concerning how agents will respond in the labor market. In one of them, we look at the case where agent behavior in the labor market is less responsive to changes, and vice versa in the other scenario. The parameters we vary in the two scenarios are given in Table 6.

We add two more scenarios that test the implications of different developments for EV purchases and EV purchase taxes. The first considers the case where the stock of EVs has doubled at the expense of ICEVs, i.e. a doubling of the EV share under the same car fleet size. This is particularly relevant since the growth of EV's has been fairly large since 2015, the base year of the analysis. This scenario is denoted 2X EV.

The last scenario considers the case where the government relaxes the biggest incentive for purchasing EVs, namely the exemption from VAT. A 25% VAT on the average EV sold in Norway would correspond to NOK 91 558 on top of the sales price. This is implemented in the model as an increase in the purchase tax annuity for EVs. In addition, EVs will pay the same annual ownership tax as ICEVs, which corresponds to an increase from NOK 455 to NOK 3565 NOK per year. This scenario is denoted EV VAT.

The resulting second-best road price levels in these scenarios are given in Table 7.

The four scenarios that test sensitivity to elasticity values show that relatively moderate ranges ( ± 30%) for these values lead to relatively large ranges for optimal taxes; 30% larger transport-related elasticity values leads to 45–87% lower optimal road prices compared to baseline. The direction is not surprising, as more responsiveness makes it less attractive to tax because the agents are more willing to reduce kilometrage and ownership and/or switch to another vehicle in response to prices. The absolute value of both

**Table 6**
Direction and relative change of parameter values in two scenarios for sensitivity analysis on responsiveness in labor markets.

| Elasticity parameter | More responsive labor market (MRLM) | Less responsive labor market (LRLM) |
|---|---|---|
| Labor supply elasticity (uncompensated) | +30% | −30% |
| Income elasticity of labor | +30% | −30% |

**Table 7**
Results from model calculations of second-best road prices in 2020 under various scenarios. Road prices are given in 2015 NOK per km for a given state.

| Vehicle type and state | Baseline | MR-TM | LR-TM | MR-LM | LR-LM | 2X EV | EV VAT |
|---|---|---|---|---|---|---|---|
| EV cities peak hours | 7.24 | 6.27 | 9.21 | 10.78 | 4.97 | 8.95 | 7.21 |
| ICEV cities peak hours | 7.97 | 6.89 | 10.20 | 13.64 | 5.33 | 39.90 | 8.01 |
| EV cities off-peak | 0.97 | 0.78 | 1.40 | 2.19 | 0.23 | 0.62 | 0.96 |
| ICEV cities off-peak | 1.31 | 1.08 | 1.79 | 3.04 | 0.44 | 5.50 | 1.35 |
| EV small cities | 0.88 | 0.67 | 1.32 | 2.06 | 0.16 | 0.72 | 0.88 |
| ICEV small cities | 0.68 | 0.53 | 1.00 | 1.56 | 0.10 | 1.53 | 0.70 |
| EV rural areas | 0.59 | 0.32 | 1.16 | 2.51 | −0.34 | 0.50 | 0.60 |
| ICEV rural areas | 0.23 | 0.13 | 0.45 | 0.83 | −0.20 | 0.21 | 0.24 |

the revenue recycling and tax interaction components becomes smaller, but it is the reduced revenue recycling component that is predominant. The corresponding road prices in the LRTM scenario are 27–96% higher than the baseline.

The more responsive the agents are in the labor market, the higher the road price; 30% greater elasticities for own-price and income elasticity with respect to labor supply resulted in 49–320% higher road prices compared to the baseline. This is because larger own-price elasticity of labor supply drives up the marginal cost of public funds and in turn the revenue recycling component; income elasticity drives up the value of the tax interaction component (makes it less negative). At the opposite end, road prices in the LRLM scenario are 31–184% lower than the baseline. The labor supply elasticity and income elasticity of labor are estimated to be relatively small in the Norwegian LOTTE modeling system at Statistics Norway (see e.g., Dagsvik et al., 2007), namely 0.178 and −0.03, respectively.[13] This makes the optimal prices quite sensitive to changes in these parameters.

In the 2X EV scenario it can be seen that a doubled initial stock of EVs implies higher road prices for ICEVs in large and small cities, but lower in rural areas. As for EVs, the optimal road price becomes lower, with the exception of cities during peak hours. This is mainly because for given elasticities[14] the absolute changes related to EV stock will be larger and for ICEV stock lower. This increases the absolute value of parameters for household shifting to EV km and EV ownership when ICEV road prices increase, and shifting from EV ownership when EV road prices increase (parameters $\eta_P$, $\varphi_P$ and $\kappa_P$). Conversely, the corresponding parameters for ICEVs decrease in absolute value. This will tend to lower road prices for EVs and increase for ICEVs.

In the EV VAT scenario we can see that removing the VAT exemption for EVs would imply a 1–4% higher road price for ICEVs, while for EVs there is hardly any change (1% or less). The changes are driven by the impact the annual tax revenue per vehicle has on the tax interaction component of the road price. When there is VAT on EVs, a higher road price on ICEVs is, on the margin, less of a fiscal problem, as the government revenue loss from a switch to EVs becomes smaller. This is similar to Tscharaktschiew (2015) finding that introducing EV purchase subsidies reduces the optimal gasoline tax.

We also find that removing the VAT exemption for EVs increases the welfare potential for the second-best road pricing scheme by about 1% compared to the baseline results. This welfare increase would be in addition to whatever gains made from alternative use of the revenue the government would have earned if EVs had the same VAT rate as other cars. In 2017, the VAT exempted from EV purchases added up to 3.2 bn. NOK (Ministry of Finance, 2018).

These sensitivity tests give some indication of how this model would produce different optimal road prices for different countries. Elasticity estimates in the transport market are a bit on the low side for Norway (further discussed in Appendix C) compared to other countries, leading one to expect that optimal road prices will be higher in Norway, than in most other countries. Norway also seems to put a higher value on external costs, and also has relatively high fuel taxes and tolls as a part of government revenue compared to other countries, which also leads us to expect that Norwegian road prices would be higher than in most countries. On the other hand, elasticities in the Norwegian labor market seems to be in the lower end. If other countries' labor force is more responsive to labor tax changes, it would drive road prices upwards and labor taxes downwards, compared to Norway.

## 6. Discussion and conclusion

Here we go through the research questions and how they have been answered.

### *6.1. What characterizes the set of second-best road prices targeting external costs from driving EVs and ICEVs when there are distortionary labor taxes and binding government budget constraints?*

The short answer to this question is that it is characterized by (1) large price differentials between states, (2) ICEVs face a higher

[13] These elasticity values are well within the normal range found in the meta-study by Bargain and Peichl (2016), although somewhat in the lower end in absolute value. The labor supply elasticity is a national average, and it is lower for men and higher for women in absolute value, as is common. The study mentions how the labor supply elasticity for women in Nordic countries seem to be relatively low (closer to those of men), as seems to be a pattern in countries with relatively high participation rates for women in the labor force.

[14] A large change in shares for the two car types would probably imply changes to their respective cross-price elasticities, but this was not included in the sensitivity analysis.

cost in large cities but lower costs in most parts of the country compared to the initial situation, even if it leads to a slightly higher labor tax rate, and (3) EVs should not be untaxed. In sum, the road pricing scheme leads to higher welfare.

It is common to find that driving is undertaxed and labor overtaxed in previous literature using the analytical framework developed by Parry and Small (2005) and other authors referenced in the Introduction. In our study, we found that driving in large cities is undertaxed, and in the rest of the country the opposite. This demonstrates how analyzing a road pricing scheme that differs over four spatiotemporal states and two car types adds more nuance and insight than, for example, analyzing a single gasoline tax. It also takes the big differences in external costs between spatiotemporal states seriously. The extended analytical framework can serve as a tool for calculating second-best road prices in other countries as well, but, as the calculations and the sensitivity analysis show, using parameters relevant for the national context is important.

### *6.2. How are these prices affected by tax distortions in the labor, electricity and car ownership market?*

We find that interaction with the rest of the fiscal system generally leads to a price markup on the external costs. The differences between states and car types largely reflect the differences in external costs per kilometer, the corrective component, but also an interaction component that reflects how the km-tax in a given state with a given car type interacts with the rest of the fiscal system. Within this interaction component there are two opposing forces. Revenue recycling through reducing labor taxation drives up road prices, while road price interaction with the labor market and the rest of the tax system generally drives the price down. We can also see that VAT exemption for EVs drives the optimal road price for ICEVs downwards in order to reduce the shift to EVs and the subsequent loss of government revenue. The VAT exemption also reduces the overall welfare potential from the road pricing scheme.

### *6.3. How does this second-best pricing fit with government-set goals of reducing $CO_2$ emissions?*

The second-best road pricing scheme applies the recommended social cost of carbon of NOK 420 per ton, which in turn reflects the part of the road price that directly concerns fossil fuel. Using the SCC, the direct tax on fuel becomes lower than in the initial situation, giving less incentive to strive towards fuel efficiency. So even though the road pricing scheme gives incentives to economize on travel distance (depending on the state), the net effect on GHG emissions is actually an increase. The short answer to the research question is: as long as the optimal road pricing scheme applies the recommended SCC, it will not contribute much to reaching the government emission target. This means that the goal of reducing $CO_2$ emissions from passenger car transport implies a higher carbon price than the recommended SCC.

In order to reach a 15% emission reduction requirement at least cost, a shadow price of carbon 16 times the SCC is needed. This is reflected in road prices that are between 20% and 550% higher for ICEVs and between 7% and 24% lower for EVs compared to the second-best optimum. Adaptation to these prices comes mainly through the ICEVs being driven less, but also through increased fuel efficiency. Some of the reduced driving of ICEVs is reflected in a big increase in EV driving.

The large-scale $CO_2$ abatement within the transport sector comes at a high welfare cost, which reveals a large mismatch between the SCC and the government's emission target. This can be interpreted as a goal conflict between welfare maximization and ambitious emission targets. This is in line with De Borger and Proost (2015), who claim that too much emphasis has been put on climate issues, compared to the other market imperfections related to the transport sector. It is worth noting that for the Norwegian economy as a whole the cost would lower as cheaper abatement opportunities outside the transport sector would be exploited. This was the conclusion for Belgium in Proost et al. (2009). Mayeres and Proost (2013) also find marginal abatement costs of many hundred Euros when pursuing narrow measures within the transport sector.

### *6.4. Concluding remarks*

As many great transport economists have suggested before, there are good reasons for policy makers to look closely at road pricing as a future main instrument for regulating transport. We make the case for distance-based road pricing, differentiated across vehicle types and pre-defined areas and time periods using satellite technology.

These results suggest that such a road pricing scheme is likely to be welfare enhancing. In the case of Norway, a policy implication would be to start the formal process of investigating how to design and implement such a road pricing scheme. This paper and the extended modeling framework can serve as input for analysis in such a process.

There are some caveats worth mentioning. Even though the model expressions are a bit messy and a bit tedious to derive, it is still a fairly simple static model with one representative household. Future extensions could include heterogeneous agents, public transport, freight transport, and a more comprehensive treatment of the car purchase tax system, which already provides incentives for lower emission vehicles. The opportunity to substitute driving in one state with another (in particular driving in peak and off-peak hours in large cities), and the cost of establishing and running such a road pricing scheme would also be promising extension. Distributional impacts and political feasibility could also be looked at more closely. The modeling involves moving from one static equilibrium to another, and the numerical modeling is based on 2015 being an equilibrium situation, although in many respects it could be considered transitory, at least with regard to the EV stock. We try to incorporate this within the analysis through sensitivity testing.

The numerical results also have their caveats, as they are based on estimates obtained from noisy data. Our sensitivity analysis shows us that changes in uncertain behavioral parameters could imply a wide range of different optimal road prices. This brings us to another policy implication: If a formal process of investigating satellite-based road pricing is undertaken, the process should be mindful of these uncertainties with regard to design and implementation planning.

The development of satellite-based road pricing for passenger cars in Singapore and the trials in Oregon and California are exciting developments in real-world transport economics. Theory and numerical simulations make a good case for such a scheme. As the share of EVs grow, the case will get even better.[15] However, many steps need to be taken before satellite-based road pricing can be seen widely in the real world. Citizens may be skeptical, for instance about privacy concerns (Duncan et al., 2017). However, the Data Protection Agency in Norway claims that a satellite-based road pricing scheme could be designed to respect (and maybe even enhance) privacy protection.[16] Principles such as ownership of the data belonging to the car owner, and the scheme not being useable for detailed tracking without informed consent, would to a large degree align such a scheme with privacy concerns.

Another important real-world factor is how the scheme would take form after a political process. Politics and other constraints could easily reduce the efficiency of such schemes (see e.g., Anthoff and Hahn, 2010; Evans, 1992), and could hinder them from being implemented in the first place. We saw in the case of the Dutch attempt to design a national road pricing scheme that politics was the main reason for the project being stopped in 2011 after years of progress, seemingly close to the finishing line (Geerlings et al., 2012).

Attempts to develop satellite-based road pricing schemes may finally be successful, or they could continue to fail. In any case, valuable learning experiences will be gained, and we strongly believe contributing to the body of knowledge on road pricing is a worthy pursuit.

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## Declarations of interest

None.

## Appendix A. Deriving second-best road prices

We follow many of the same analytical steps as in Tscharaktschiew (2015) when we here derive optimal road prices.

The household's optimization program is to maximize the utility function Eq. (1) with respect to the choice variables $m_F$, $v_F$, $\widetilde{f}$ , $m_P$, $v_P$, $\widetilde{p}$ , $X$ and $l$ subject to monetary budget Eq. (4) and time constraints Eq. (7). Households treat travel times (affected by aggregate kilometrage), external environmental damages and all tax levels as given. We form the Lagrangian where $\mu$ is the Lagrange multiplier for the complete economic household budget constraint and can be interpreted as the marginal utility of income. We get first-order conditions (FOCs) from the optimization and use these to obtain the household's indirect utility function, which yields maximized utility given prices, taxes and income, but also travel time and externalities determined by the *aggregate* level of driving.

The government's optimization program is then to maximize the household's indirect utility function with respect to a set of parameters $\Omega \equiv \{\tau_{mF}, \tau_{mp}, \tau_P, \Gamma_F, \Gamma_P, \tau_L, t, E\}$. These parameters, policy variables and time and environmental externalities, are treated as given by the households.

$$V(\Omega) \equiv \max_{m_F, v_F, \widetilde{f}, m_P, v_P, \widetilde{p}, X, l} u(m_F, v_F, m_P, v_P, X, l, T, E) - \mu([(R_F\widetilde{f} + c_F^d)m_F + \tau_{mF} m_F + c(\widetilde{f}) + \Gamma_F]v_F + [(R_P\widetilde{p} + c_P^d)m_P + \tau_{mp} m_P + c(\widetilde{p}) + \Gamma_P]v_P + P_X X - (1-\tau_L)w(\bar{L} - l + t(\bar{M})M)) \tag{A.1}$$

The policy instrument subject to change in its level is the km-tax for EVs. At the same time, changes in governmental tax revenue, per kilometer travel time, and external costs are considered explicitly.

The analytical exercise of deriving the optimal tax on EV-km, $\tau_{m_p}$. starts by total differentiation of the household's indirect utility function with respect to $\tau_{mp}$. For optimization of $V(\Omega)$ through $\tau_{mp}$, with revenue recycling through $\tau_L$ we can consider the policy instruments $\tau_{mF}$, $\tau_F$, $\tau_P$, $\Gamma_P$ and $\Gamma_F$ as fixed in this exercise. Assuming $d\tau_{mF}/d\tau_{mp} = d\tau_F/d\tau_{mp} = d\tau_P/d\tau_{mp} = d\Gamma_P/d\tau_{mp} = d\Gamma_F/d\tau_{mp} = 0$, we

[15] In a future with autonomous cars, where the generalized travel cost could get greatly reduced, and the average occupancy rate of cars could drop (e.g., if autonomous cars drive people to work, drive back home empty, and drive empty to the workplace at the end of the day to pick up again), regulating transport demand with distance-based road pricing using satellite technology could be essential.

[16] http://www.ofv.no/artikler-2017/dynamisk-veiprising-kan-fjerne-bomstasjonene-article515-299.html (in Norwegian, easily translated using translation software) [last accessed April 5th 2018].

get:

$$\frac{dV}{d\tau_{mp}} = \frac{\partial V}{\partial \tau_{mp}} + \frac{\partial V}{\partial \tau_L}\frac{d\tau_L}{d\tau_{mp}} + \frac{\partial V}{\partial t}\frac{dt}{d\tau_{mp}} + \frac{\partial V}{\partial E}\frac{dE}{d\tau_{mp}} \tag{A.2}$$

where

$$\frac{\partial V}{\partial E}\frac{dE}{d\tau_{mp}} = \frac{\partial V}{\partial E_F(\bar{F})}\frac{\partial E_F(\bar{F})}{\partial F}\frac{dF}{d\tau_{mp}} + \frac{\partial V}{\partial E_P(\bar{P})}\frac{\partial E_P(\bar{P})}{\partial P}\frac{dP}{d\tau_{mp}} + \frac{\partial V}{\partial E_{M_F}(\bar{M}_F)}\frac{\partial E_{M_F}(\bar{M}_F)}{\partial M_F}\frac{dM_F}{d\tau_{\tau_{mp}}} + \frac{\partial V}{\partial E_{M_P}(\bar{M}_P)}\frac{\partial E_{M_P}(\bar{M}_P)}{\partial M_P}\frac{dM_P}{d\tau_{\tau_{mp}}} \tag{A.3}$$

represents (dis-)utility stemming from a marginal change in aggregate externalities via changes in a car's energy consumption and kilometrage caused by a marginal increase in the km-tax for EVs. From here on, we assume that there are no externalities associated with producing and consuming electricity for EVs, i.e.$E_P(\bar{P}) = 0$. This is further discussed in Section 2. (A.2) can then be rewritten as:

$$\frac{\partial V}{\partial \tau_{m_p}} = \frac{\partial V}{\partial \tau_{m_p}} + \frac{\partial V}{\partial \tau_L}\frac{d\tau_L}{d\tau_{mp}} + \frac{\partial V}{\partial t}\frac{dt}{d\tau_{m_p}} + V_{E_F}E_F'\frac{dF}{d\tau_{mp}} + V_{E_{M_F}}E_{M_F}'\frac{dM_F}{d\tau_{mp}} + V_{E_{M_P}}E_{M_P}'\frac{dM_P}{d\tau_{mp}} \tag{A.4}$$

Replacing partial derivative terms $\frac{\partial V}{\partial \tau_{mp}}$, $\frac{\partial V}{\partial \tau_L}$, $\frac{\partial V}{\partial t}$ yields:

$$\frac{dV}{d\tau_{mp}} = -\mu m_P v_P - \mu wL\frac{d\tau_L}{d\tau_{mp}} + \frac{\partial V}{\partial T}M\frac{dt}{d\tau_{mp}} - \mu(1-\tau_L)wM + V_{E_F}E_F'\frac{dF}{d\tau_{mp}} + V_{E_{M_F}}E_{M_F}'\frac{dM_F}{d\tau_{mp}} + V_{E_{M_P}}E_{M_P}'\frac{dM_P}{d\tau_{mp}} \tag{A.5}$$

We divide both sides by $\mu$, the marginal utility of income, and get the welfare change in monetary terms:

$$\frac{1}{\mu}\frac{dV}{d\tau_{mp}} = -m_P v_P - wL\frac{d\tau_L}{d\tau_{mp}} + \frac{1}{\mu}\frac{\partial V}{\partial T}M\frac{dt}{d\tau_{mp}} - (1-\tau_L)wM\frac{dt}{d\tau_{mp}} + \frac{1}{\mu}V_{E_F}E_F'\frac{dF}{d\tau_{mp}} + \frac{1}{\mu}V_{E_{M_F}}E_{M_F}'\frac{dM_F}{d\tau_{mp}} + \frac{1}{\mu}V_{E_{M_P}}E_{M_P}'\frac{dM_P}{d\tau_{mp}} \tag{A.6}$$

In order to derive $d\tau_L/d\tau_{mp}$ we totally differentiate the government budget constraint (remember $W = wL$ and only electric cars receive tax benefits):

$$\frac{dGOV}{d\tau_{mp}} = \frac{\partial GOV}{\partial \tau_{mp}} + \frac{\partial GOV}{\partial M_P}\frac{dM_P}{d\tau_{mp}} + \frac{\partial GOV}{\partial M_F}\frac{dM_F}{d\tau_{mp}} + \frac{\partial GOV}{\partial F}\frac{dF}{d\tau_{mp}} + \frac{\partial GOV}{\partial P}\frac{dP}{d\tau_{mp}} + \frac{\partial GOV}{\partial v_P}\frac{dv_P}{d\tau_{mp}} + \frac{\partial GOV}{\partial v_F}\frac{dv_F}{d\tau_{mp}} + \frac{\partial GOV}{\partial \tau_L}\frac{d\tau_L}{d\tau_{mp}} + \frac{\partial GOV}{\partial W}\frac{dW}{d\tau_{mp}} \tag{A.7}$$

yielding

$$\frac{dGOV}{d\tau_{mp}} = M_P + \tau_{mp}\frac{dM_P}{d\tau_{mp}} + \tau_{m_F}\frac{dM_F}{d\tau_{mp}} + \tau_F\frac{dF}{d\tau_{mp}} + \tau_P\frac{dP}{d\tau_{mp}} + (\tau_{mp}m_P + \tau_P\widetilde{p}\,m_P + \Gamma_P)\frac{dv_P}{d\tau_{mp}} + (\tau_{m_F}m_F + \tau_F\widetilde{f}\,m_F + \Gamma_F)\frac{dv_F}{d\tau_{mp}} + W\frac{d\tau_L}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}} \tag{A.8}$$

We set the expressions $\tau_{m_i}m_i + \tau_i\widetilde{p}\,m_i + \Gamma_i$ equal to $D_i$ for notational simplicity.

Equating $dGOV/d\tau_{mp}$ to zero and solving for $d\tau_L/d\tau_{mp}$ yields:

$$\frac{d\tau_L}{d\tau_{mp}} = -\frac{M_P + \tau_{mp}\frac{dM_P}{d\tau_{mp}} + \tau_{m_F}\frac{dM_F}{d\tau_{mp}} + \tau_F\frac{dF}{d\tau_{mp}} + \tau_P\frac{dP}{d\tau_{mp}} + D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}}}{W} \tag{A.9}$$

Plugging Eq. (A.9) into Eq.(A.6), recalling $M = m_P v_P + m_F v_F$ (see Eq. (3)), gives:

$$\frac{1}{\mu}\frac{dV}{d\tau_{mp}} = \tau_{mp}\frac{dM_P}{d\tau_{mp}} + \tau_{m_F}\frac{dM_F}{d\tau_{mp}} + \tau_F\frac{dF}{d\tau_{mp}} + \tau_P\frac{dP}{d\tau_{mp}} + D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}} + \frac{1}{\mu}\frac{\partial V}{\partial T}M\frac{dt}{d\tau_{mp}} - (1-\tau_L)wM\frac{dt}{d\tau_{mp}} + \frac{1}{\mu}V_{E_F}E_F'\frac{dF}{d\tau_{mp}} + \frac{1}{\mu}V_{E_{M_F}}E_{M_F}'\frac{dM_F}{d\tau_{mp}} + \frac{1}{\mu}V_{E_{M_P}}E_{M_P}'\frac{dM_P}{d\tau_{mp}} \tag{A.10}$$

We define the value of travel time as $-\frac{1}{\mu}\frac{\partial V}{\partial T} + (1-\tau_L)w \equiv \theta$, where $\frac{\partial V}{\partial T} < 0$ is the household's disutility from aggregate travel time. It also follows from Eq. (2) that $\frac{dt}{d\tau_{mp}} = t'\frac{dM}{d\tau_{mp}}$. When we replace both of these expressions in Eq. (A.10) we get:

$$\frac{1}{\mu}\frac{dV}{d\tau_{mp}} = \tau_{mp}\frac{dM_P}{d\tau_{mp}} + \tau_{m_F}\frac{dM_F}{d\tau_{mp}} + \tau_F\frac{dF}{d\tau_{mp}} + \tau_P\frac{dP}{d\tau_{mp}} + D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}} - \theta t'M\frac{dM}{d\tau_{mp}} + \frac{1}{\mu}V_{E_F}E_F'\frac{dF}{d\tau_{mp}} + \frac{1}{\mu}V_{E_{M_F}}E_{M_F}'\frac{dM_F}{d\tau_{mp}} + \frac{1}{\mu}V_{E_{M_P}}E_{M_P}'\frac{dM_P}{d\tau_{mp}} \tag{A.11}$$

For notational simplicity we rewrite the expressions for marginal external costs (marginal external damage expressed in monetary terms) stemming from the consumption of fuel and kilometrage

$$e_F \equiv \frac{1}{\mu}V_{E_F}E_F' \tag{A.12}$$

$$e_m^c(M) \equiv \theta t' M \tag{A.13}$$

$$e_{mF}^{nc} \equiv \frac{1}{\mu} V_{E_{M_F}} E'_{M_F} \tag{A.14}$$

$$e_{mp}^{nc} \equiv \frac{1}{\mu} V_{E_{M_P}} E'_{M_P} \tag{A.15}$$

We also reorganize the expression to get a clearer view of the marginal welfare effect of the km-tax:

$$\frac{1}{\mu}\frac{\partial V}{\partial \tau_{mp}} = \underbrace{e_F\left\{-\frac{dF}{d\tau_{mp}}\right\}}_{\text{energy related externalities}} + \underbrace{e_m^c(M)\left\{-\frac{dM}{d\tau_{mp}}\right\}}_{\text{congestion externalities}} + \underbrace{e_{mF}^{nc}\left\{-\frac{dM_F}{d\tau_{mp}}\right\} + e_{mp}^{nc}\left\{-\frac{dM_P}{d\tau_{mp}}\right\}}_{\substack{\text{kilometrage related}\\ \text{non-congestion externalities}}} - \underbrace{\left[\tau_{mp}\left\{-\frac{dM_P}{d\tau_{mp}}\right\} + \tau_{mF}\left\{-\frac{dM_F}{d\tau_{mp}}\right\}\right]}_{\text{km-tax revenue}}$$
$$- \underbrace{\left[\tau_F\left\{-\frac{dF}{d\tau_{mp}}\right\} + \tau_P\left\{-\frac{dP}{d\tau_{mp}}\right\}\right]}_{\text{energy tax revenue}} \underbrace{+ D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}}}_{\text{direct/indirect tax revenue/cost from vehicle stock}} + \underbrace{\tau_L\frac{dW}{d\tau_{mp}}}_{\text{labor tax revenue}} \tag{A.16}$$

As we can see, the EV-km tax causes numerous different changes in Eq. (A.16), which shows that the km-tax affects overall welfare through various channels.

## A.1. Deriving second-best road prices

We set the marginal welfare change seen in Eq. (A.16) equal to zero and solve for $\tau_{mp}$. This gives us the following expression:

$$\begin{aligned}\tau_{mp}^* &= e_F\left\{\frac{dF/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + e_m^c(M)\left\{\frac{dM/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + e_{mF}^{nc}\left\{\frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + e_{mp}^{nc}\\ &+ \left[\tau_{mF}\frac{dM_F}{d\tau_{mp}} + \tau_F\frac{dF}{d\tau_{mp}} + \tau_P\frac{dP}{d\tau_{mp}} + D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}}\right]\frac{1}{-dM_P/d\tau_{mp}}\\ &= e_F\left\{\frac{dF/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + (e_m^c(M) + e_{mF}^{nc})\left\{\frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + e_{mp}^{nc} + e_m^c(M)\\ &+ \left[\tau_{mF}\frac{dM_F}{d\tau_{mp}} + \tau_F\frac{dF}{d\tau_{mp}} + \tau_P\frac{dP}{d\tau_{mp}} + D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}}\right]\frac{1}{-dM_P/d\tau_{mp}}\end{aligned} \tag{A.17}$$

We simplify the following expressions into reaction parameters.

$$\eta_F = \frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}} \tag{A.18}$$

$$\chi_F = \frac{dF/d\tau_{mp}}{dM_P/d\tau_{mp}} \tag{A.19}$$

$$\kappa_P = \frac{dv_P/d\tau_{mp}}{dM_P/d\tau_{mp}} \tag{A.20}$$

$$\varphi_F = \frac{dv_F/d\tau_{mp}}{dM_P/d\tau_{mp}} \tag{A.21}$$

The expression in (A.17) can be aggregated to the following expression for the optimal km-tax:

$$\tau_{mp}^* = \tau_{mp}^C + \tau_{mp}^I \tag{A.22}$$

The optimal km-tax is expressed here by both a corrective component, $\tau_{mp}^C$ and a "fiscal interaction" component $\tau_{mp}^I$. We apply the definitions in (A.18) and (A.19) to the first part of the expression in (A.17) and get the following expression for the corrective component.

$$\tau_{mp}^C = \chi_F e_F + \eta_F\left(e_m^c(M) + e_{mF}^{nc}\right) + e_{mp}^{nc} + e_m^c(M) \tag{A.23}$$

This component accounts for traffic-related externalities from EVs, but also the impact the km-tax for EVs may have on externalities (through kilometers driven) from ICEVs.

The remaining part of the expression in (A.17) is the fiscal interaction component.

$$\tau_{mp}^I = \left[\tau_{mF}\frac{dM_F}{d\tau_{mp}} + \tau_F\frac{dF}{d\tau_{mp}} + \tau_P\frac{dP}{d\tau_{mp}} + D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}}\right]\frac{1}{-dM_P/d\tau_{mp}} \tag{A.24}$$

This component represents interaction of EV-km tax with the broader fiscal system in the economy. The first, second and third terms denote how a change in $\tau_{mp}$ affects tax revenue from ICEV km-tax, fossil fuel tax and electricity tax, respectively. The fourth and fifth terms denote how a change in $\tau_{mp}$ affects revenue from annual ownership and purchase taxes. The sixth term denotes how a change in $\tau_{mp}$ affects labor tax revenue.

We proceed in this exercise by totally differentiating the terms in brackets in:

$$\frac{dM_F}{d\tau_{mp}} = \frac{\partial M_F}{\partial \tau_{mp}} + \frac{\partial M_F}{\partial \tau_L}\frac{d\tau_L}{d\tau_{mp}} \tag{A.25}$$

$$\frac{dF}{d\tau_{mp}} = \frac{\partial F}{\partial \tau_{mp}} + \frac{\partial F}{\partial \tau_L}\frac{d\tau_L}{d\tau_{mp}} \tag{A.26}$$

$$\frac{dP}{d\tau_{mp}} = \frac{\partial P}{\partial \tau_{mp}} + \frac{\partial P}{\partial \tau_L}\frac{d\tau_L}{d\tau_{mp}} \tag{A.27}$$

$$\frac{dv_P}{d\tau_{mp}} = \frac{\partial v_P}{\partial \tau_{mp}} + \frac{\partial v_P}{\partial \tau_L}\frac{d\tau_L}{d\tau_{mp}} \tag{A.28}$$

$$\frac{dv_F}{d\tau_{mp}} = \frac{\partial v_F}{\partial \tau_{mp}} + \frac{\partial v_F}{\partial \tau_L}\frac{d\tau_L}{d\tau_{mp}} \tag{A.29}$$

$$\frac{dW}{d\tau_{mp}} = \frac{\partial W}{\partial \tau_{mp}} + \frac{\partial W}{\partial \tau_L}\frac{d\tau_L}{d\tau_{mp}} + \frac{\partial W}{\partial t}\frac{dt}{d\tau_{mp}} = w\left(\frac{\partial L}{\partial \tau_{mp}} + \frac{\partial L}{\partial \tau_L}\frac{d\tau_L}{d\tau_{mp}} + \frac{\partial L}{\partial t}\frac{dt}{d\tau_{mp}}\right) \tag{A.30}$$

Concerning the demand for vehicle kilometers, fossil fuels, electricity and car ownership, it is assumed that *indirect* changes in labor taxation (through the government budget constraint) have a small impact on corresponding demands relative to the *direct* impact of the km-tax. This is a reasonable approximation since Norwegian household income shares and income elasticities for operating costs and purchase costs for own car are relatively small (Boug and Dyvi, 2008). This means that the largest part of any compensation through revenue recycling will be spent on other goods. It is therefore reasonable to use uncompensated elasticities (see Willig, 1976) in order to parameterize demand elasticities for vehicle kilometers, transport related energy and car ownership. The total differential of $W \equiv wL$ decomposes the change in labor income (labor supply) into three effects: The first component arises from the labor supply effect of raising the price of EV-kms relative to leisure which depends on the degree of substitution or complementarity between EV-kms and leisure. The second term is the effect of revenue recycling, i.e. using EV-km tax revenues to reduce $\tau_L$ will increase labor supply. The third effect is the change in labor supply due to a change in commuting travel time caused by a EV-km tax induced change in vehicle kilometrage and, thus, congestion levels.

Plugging Eq. (A.30) into $d\tau_L/d\tau_{mp}$ as displayed in Eq. (A.9) and grouping terms gives

$$\frac{d\tau_L}{d\tau_{mp}} = -\frac{B_1}{B_2} \tag{A.31}$$

where

$$B_1 = M_P + \tau_{mp}\frac{dM_P}{d\tau_{mp}} + \tau_{m_F}\frac{dM_F}{d\tau_{mp}} + \tau_F\frac{dF}{d\tau_{mp}} + \tau_P\frac{dP}{d\tau_{mp}} + D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L w\left(\frac{\partial L}{\partial \tau_{mp}} + \frac{\partial L}{\partial t}\frac{dt}{d\tau_{mp}}\right) \tag{A.32}$$

and

$$B_2 = W + \tau_L w\frac{\partial L}{\partial \tau_L} \tag{A.33}$$

The expression in (A.30) can be manipulated further by applying the following expression for the marginal cost of public funds:

$$\Omega_{\tau_L} \equiv \frac{-\tau_L w\frac{\partial L}{\partial \tau_L}}{W + \tau_L w\frac{\partial L}{\partial \tau_L}} = \frac{\frac{\tau_L}{(1-\tau_L)}\varepsilon_{LL}}{1-\frac{\tau_L}{(1-\tau_L)}\varepsilon_{LL}} \tag{A.34}$$

This term reflects the marginal efficiency cost of raising public funds through taxing labor. On the flip side, it also reflects the marginal efficiency gain from cutting tax on labor, which could be done by, e.g., raising funds from road pricing. The numerator in this expression represents the efficiency cost from an incremental increase in labor taxation, while the denominator gives us the marginal change in public revenue. $\varepsilon_{LL} > 0$ represents the elasticity of labor supply (uncompensated). We have $\Omega_{\tau_L} > 0$ as a consequence of $\varepsilon_{LL} > 0$ and $1 > \frac{\tau_L}{(1-\tau_L)}\varepsilon_{LL}$. The latter implies that $\tau_L$ is not so large that we find ourselves on the right side of the Laffer curve's peak, meaning that government revenue from increasing labor taxation will, on the margin, be positive.

We substitute $d\tau_L/d\tau_{mp} = -B_1/B_2$ into Eq. (A.30), then plug the resulting expressions into Eq. (A.24), where we regroup terms and use the definition of $\Omega_{\tau_L}$ in Eq. (A.34). We then get:

$$\tau_{mp}^I = \left[\tau_{m_F}\frac{dM_F}{d\tau_{mp}} + \tau_F\frac{dF}{d\tau_{mp}} + \tau_P\frac{dP}{d\tau_{mp}} + D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L w\left(\frac{\partial L}{\partial \tau_{mp}} + \frac{\partial L}{\partial t}\frac{dt}{d\tau_{mp}}\right) + \Omega_{\tau_L}B_1\right]\frac{1}{-dM_P/d\tau_{mp}} \tag{A.35}$$

Multiplying each term by $\frac{1}{-dM_i/d\tau_{m_i}}$, and using the definitions of $\eta_F$ (Eq. (A.18)), $\chi_F$ (Eq. (A.19)), $\kappa_P$ (Eq. (A.20))) and $\varphi_F$(Eq. (A.21)) gives

$$\tau_{mp}^{I} = -\eta_F \tau_{mF} - \chi_F \tau_F - \chi_P \tau_P - \kappa_P D_P - \varphi_F D_F + \tau_L w \left( \frac{\partial L}{\partial \tau_{mp}} + \frac{\partial L}{\partial \tau_L} \frac{d\tau_L}{d\tau_{mp}} \right) \frac{1}{-dM_P/d\tau_{mp}} + \Omega_{\tau_L} B_1 \frac{1}{-dM_P/d\tau_{mp}} \tag{A.36}$$

The fiscal interaction component can be broken down into a revenue recycling component and a tax-interaction component. To obtain a clear expression for the former, we need to manipulate Eq. (A.36). First, we obtain the following expressions from the own-price demand elasticity of EV-km:

$$\varepsilon_{M_P} = \frac{dM_P}{d\tau_{mp}} \frac{(R_P \tilde{p} + c_P^d + \tau_{mp})}{M_P} \Rightarrow \frac{M_P}{dM_P/d\tau_{mp}} = \frac{(R_P \tilde{p} + c_P^d + \tau_{mp})}{\varepsilon_{M_P}} \tag{A.37}$$

The term $R_P \tilde{p} + c_P^d + \tau_{mp}$ is the private cost of a vehicle-km by electric car.

We multiply the expression $\Omega_{\tau_L} B_1$ by $\frac{1}{-dM_P/d\tau_{mp}}$ and apply the definitions of $\eta_F$ (Eq. (A.18), $\chi_F$ (Eq. (A.19)), $\kappa_P$ (Eq. (A.20)) and $\varphi_F$(Eq. (A.21)), and we get:

$$\Omega_{\tau_L} B_1 \frac{1}{-dM_P/d\tau_{mp}} = \Omega_{\tau_L} \left( \begin{array}{c} \frac{(R_P \tilde{p} + c_P^d + \tau_{mp})}{-\varepsilon_{M_P}} - \tau_{mp} - \eta_F \tau_{mF} - \chi_F \tau_F - \tilde{p}\, \tau_P - \\ \kappa_P D_P - \varphi_F D_F - \tau_L w \left( \frac{\partial L}{\partial \tau_{mp}} + \frac{\partial L}{\partial t} \frac{dt}{d\tau_{mp}} \right) \frac{1}{-dM_P/d\tau_{mp}} \end{array} \right) \tag{A.38}$$

We can now define the following expression for the revenue recycling effect of the EV-km tax:

$$\tau_{mp}^{RR} = \Omega_{\tau_L} \left( \frac{(R_P \tilde{p} + c_P^d + \tau_{mp})}{-\varepsilon_{M_P}} - \tau_{mp} \right) \tag{A.39}$$

We thus can rearrange Eq. (A.36) to:

$$\tau_{mp}^{I} = \tau_{mp}^{RR} + (1 + \Omega_{\tau_L})[-\eta_F \tau_{mF} - \chi_F \tau_F - \tilde{p}\, \tau_P - \kappa_P D_P - \varphi_F D_F] + (1 + \Omega_{\tau_L}) \left( \tau_L w \frac{\partial L}{\partial \tau_{m_i}} + \tau_L w \frac{\partial L}{\partial t} \frac{dt}{d\tau_{m_i}} \right) \frac{1}{-dM_i/d\tau_{m_i}} \tag{A.40}$$

From the Slutsky equation it follows that:

$$\frac{\partial L}{\partial \tau_{mp}} = \frac{\partial L^c}{\partial \tau_{mp}} - \frac{\partial L}{\partial I} M_P \tag{A.41}$$

where superscript $c$ indicates the compensated elasticity and $\partial L/\partial I$ is the income effect on labor supply. From the Slutsky symmetry property and after some manipulation we get:

$$\begin{aligned} \frac{\partial L}{\partial \tau_{mp}} &= \frac{\partial L^c}{\partial \tau_{mp}} - \frac{\partial L}{\partial I} M_P = \frac{\partial M_P^c}{\partial (1-\tau_L) w} - \frac{\partial L}{\partial I} M_P \Rightarrow \\ \frac{(1-\tau_L) w}{M_P} \frac{\partial L}{\partial \tau_{mp}} &= \frac{(1-\tau_L) w}{M_P} \frac{\partial M_P^c}{\partial (1-\tau_L) w} - \frac{(1-\tau_L) w}{M_P} \frac{\partial L}{\partial I} M_P \\ &= -\varepsilon_{MI}^c - \frac{L(1-\tau_L) w}{L} \frac{\partial L}{\partial I} = -\varepsilon_{MI}^c - \varepsilon_{LI} \\ \Rightarrow \frac{\partial L}{\partial \tau_{mp}} &= -\varepsilon_{MI}^c \frac{M_P}{(1-\tau_L) w} - \varepsilon_{LI} \frac{M_P}{(1-\tau_L) w} \end{aligned} \tag{A.42}$$

$\varepsilon_{MI}^c$ represents the income elasticity for vehicle kilometers (alternatively the compensated cross-price elasticity of leisure). $\varepsilon_{LI}$ represents the income elasticity for labor.

Plugging Eq. (A.42) into Eq. (A.40) and using Eq. (A.37) gives:

$$\begin{aligned} \tau_{mp}^{I} &= \tau_{mp}^{RR} + (1 + \Omega_{\tau_L})[-\eta_F \tau_{mF} - \chi_F \tau_F - \tilde{p}\, \tau_P - \kappa_P D_P - \varphi_F D_F] + \\ &\quad (1 + \Omega_{\tau_L}) \left( \tau_L w \left( -\varepsilon_{MI}^c \frac{M_P}{(1-\tau_L) w} - \varepsilon_{LI} \frac{M_P}{(1-\tau_L) w} \right) + \tau_L w \frac{\partial L}{\partial t} \frac{dt}{d\tau_{mp}} \right) \frac{1}{-dM_P/d\tau_{mp}} \\ &= \tau_{m_i}^{RR} + (1 + \Omega_{\tau_L}) \left[ \left( \frac{\tau_L M_P (-\varepsilon_{MI}^c - \varepsilon_{LI})}{(-dM_P/d\tau_{mp})(1-\tau_L)} \right) - \eta_F \tau_{mF} - \chi_F \tau_F - \tilde{p}\, \tau_P - \kappa_P D_P - \varphi_F D_F \right] \\ &\quad + (1 + \Omega_{\tau_L}) \left( \tau_L w \frac{\partial L}{\partial t} \frac{dt}{d\tau_{mp}} \right) \frac{1}{-dM_P/d\tau_{mp}} \\ &= \tau_{mp}^{RR} - (1 + \Omega_{\tau_L}) \left[ \left( \frac{\tau_L (R_P \tilde{p} + c_P^d + \tau_{mp})(\varepsilon_{MI}^c + \varepsilon_{LI})}{(-\varepsilon_{M_P})(1-\tau_L)} \right) + \eta_F \tau_{mF} + \chi_F \tau_F + \tilde{p}\, \tau_P + \kappa_P D_P + \varphi_F D_F \right] \\ &\quad + (1 + \Omega_{\tau_L}) \left( \tau_L w \frac{\partial L}{\partial t} \frac{dt}{d\tau_{mp}} \right) \frac{1}{-dM_P/d\tau_{mp}} \\ &= \tau_{mp}^{RR} + \tau_{mp}^{(TI)} + (1 + \Omega_{\tau_L}) \tau_L w \frac{\partial L}{\partial t} \frac{dt}{d\tau_{mp}} \frac{1}{-dM_P/d\tau_{mp}} \\ &= \tau_{mp}^{RR} + \tau_{mp}^{TI} \end{aligned} \tag{A.43}$$

The terms $\tau_{mp}^{RR}$, $\tau_{mp}^{TI}$ and $\tau_{mp}^{(TI)}$ are the road price components for revenue recycling, tax interaction and pure tax interaction, respectively.

Because $\frac{dt}{d\tau_{mp}} = t'\frac{dM}{d\tau_{mp}}$ and $\frac{\partial L}{\partial t} = \frac{\partial L}{\partial R_M}\theta$ with $R_M$ as the full economic price (private cost) of vehicle kilometrage, we can write:

$$(1 + \Omega_{\tau_L})\tau_L w\frac{\partial L}{\partial t}\frac{dt}{d\tau_{mp}}\frac{1}{-dM_P/d\tau_{mp}} = -(1 + \Omega_{\tau_L})\tau_L w\frac{\partial L}{\partial R_M}\theta t'\left[\frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}} + 1\right] \tag{A.44}$$

It follows from the Slutsky equation applied to the demand function that:

$$\frac{\partial L}{\partial R_M} = \frac{\partial L^c}{\partial R_M} - \frac{\partial L}{\partial I}M \tag{A.45}$$

and from the Slutsky symmetry property for goods in the utility function:

$$\frac{\partial L^c}{\partial R_M} = \frac{\partial M^c}{\partial \tau_L} = \frac{\partial M}{\partial \tau_L}(1-\tau_L)w\frac{\partial L^c}{\partial \tau_L} \tag{A.46}$$

where $(1-\tau_L)w\partial L^c/\partial\tau_L$ is the change in disposable income following a compensated increase in the labor tax. After some manipulation, we get:

$$\begin{aligned}&\frac{(1-\tau_L)w}{M}\frac{\partial L}{\partial R_M} = \frac{(1-\tau_L)w}{M}\frac{\partial M}{\partial \tau_L}(1-\tau_L)w\frac{\partial L^c}{\partial \tau_L} - \frac{(1-\tau_L)w}{M}\frac{\partial L}{\partial I}M = -\varepsilon_{MI}\varepsilon_{LL}^c - \varepsilon_{LI}\\ &\Rightarrow \frac{\partial L}{\partial R_M} = -\varepsilon_{MI}\varepsilon_{LL}^c\frac{M}{(1-\tau_L)w} - \varepsilon_{LI}\frac{M}{(1-\tau_L)w}\end{aligned} \tag{A.47}$$

Plugging Eq. (A.47) into Eq. (A.44) gives:

$$\begin{aligned}&(1 + \Omega_{\tau_L})\tau_L w\frac{\partial L}{\partial t}\frac{dt}{d\tau_{mp}}\frac{1}{-dM_P/d\tau_{mp}}\\ &= -(1 + \Omega_{\tau_L})\tau_L w\left(-\varepsilon_{MI}\varepsilon_{LL}^c\frac{M}{(1-\tau_L)w} - \varepsilon_{LI}\frac{M}{(1-\tau_L)w}\right)\theta t'\left[\frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}} + 1\right]\\ &= -(1 + \Omega_{\tau_L})\frac{\tau_L}{(1-\tau_L)}(-\varepsilon_{MI}\varepsilon_{LL}^c - \varepsilon_{LI})\theta t' M\left[\frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}} + 1\right]\end{aligned} \tag{A.48}$$

Substituting $\varepsilon_{LI} = \varepsilon_{LL} - \varepsilon_{LL}^c$ and $e_m^c(M) \equiv \theta t' M$ and $\eta_F = \frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}}$, after regrouping terms we obtain the congestion feedback effect:

$$\tau_{mp}^{CF} = (1 + \Omega_{\tau_L})\tau_L w\frac{\partial L}{\partial t}\frac{dt}{d\tau_{mp}}\frac{1}{-dM_P/d\tau_{mp}} = (1 + \Omega_{\tau_L})\frac{\tau_L}{(1-\tau_L)}(\varepsilon_{LI}(1-\varepsilon_{MI})\varepsilon_{LL}^c)e_m^c(M)[\eta_F + 1] \tag{A.49}$$

We thus get the final expression for the optimal km-tax:

$$\begin{aligned}\tau_{mp}^* &= \tau_{mp}^C + \tau_{mp}^I = \tau_{mp}^C + \tau_{mp}^{RR} + \tau_{mp}^{TI}\\ \tau_{mp}^* &= \tau_{mp}^C + \tau_{mp}^{RR} + \tau_{mp}^{(TI)} + \tau_{mp}^{CF}\end{aligned} \tag{A.50}$$

It has the components:

$$\tau_{mp}^C = e_{mp}^{nc} + e_m^c(M) + \eta_F\left(e_m^c(M) + e_{mF}^{nc}\right) + \chi_F e_F \tag{A.51}$$

$$\tau_{mp}^{RR} = \Omega_{\tau_L}\left(\frac{(R_P\tilde{p} + c_P^d + \tau_{mp})}{-\varepsilon_{MP}} - \tau_{mp}\right) \tag{A.52}$$

$$\tau_{mp}^{(TI)} = -(1 + \Omega_{\tau_L})\left[\left(\frac{\tau_L(R_P\tilde{p} + c_P^d + \tau_{mp})(\varepsilon_{MI}^c + \varepsilon_{LI})}{(-\varepsilon_{MP})(1-\tau_L)}\right) + \eta_F\tau_{mF} + \chi_F\tau_F + \tilde{p}\tau_P + \kappa_P D_P + \varphi_F D_F\right] \tag{A.53}$$

$$\tau_{mp}^{CF} = (1 + \Omega_{\tau_L})\frac{\tau_L}{(1-\tau_L)}(\varepsilon_{LI}(1-\varepsilon_{MI})\varepsilon_{LL}^c)e_m^c(M)[\eta_F + 1] \tag{A.54}$$

We solve the model in exactly the same way for $\tau_{mF}^*$, and obtain analogous expressions that look like the following:

$$\tau_{mF}^* = \tau_{mF}^C + \tau_{mF}^I = \tau_{mF}^C + \tau_{mF}^{RR} + \tau_{mF}^{TI} = \tau_{mF}^C + \tau_{mF}^{RR} + \tau_{mF}^{(TI)} + \tau_{mF}^{CF} \tag{A.55}$$

with the corrective component

$$\tau_{mF}^C = e_{mF}^{nc} + e_m^c(M) + (\tilde{f} + \sigma_F)e_F + \eta_P\left(e_m^c(M) + e_{mp}^{nc}\right) \tag{A.56}$$

the revenue recycling component

$$\tau_{mF}^{RR} = \Omega_{\tau_L}\left(\frac{(R_F\tilde{f} + c_F^d + \tau_{mF})}{-\varepsilon_{MF}} - \tau_{mF}\right) \tag{A.57}$$

the tax interaction component (excluding the congestion feedback component).[17]

$$\tau_{mF}^{(TI)} = -(1+\Omega_{\tau_L})\left[\left(\frac{\tau_L(R_F\tilde{f} + c_F^d + \tau_{mF})(\varepsilon_{MI}^c + \varepsilon_{LI})}{(-\varepsilon_{MF})(1-\tau_L)}\right) + \eta_P\tau_{mp} + \chi_P\tau_P + (\tilde{f} + \sigma_F)\tau_F + \kappa_F D_F + \varphi_P D_P\right] \tag{A.58}$$

and, finally, the congestion feedback component,

$$\tau_{mF}^{CF} = (1+\Omega_{\tau_L})\frac{\tau_L}{(1-\tau_L)}(\varepsilon_{LI}(1-\varepsilon_{MI})\varepsilon_{LL}^c)e_m^c(M)[\eta_F + 1] \tag{A.59}$$

The expressions for $\tau_{mF}$ mirror those for $\tau_{mp}$. The parameters applied are given the same symbol, but with subscript *F,* and illustrate the mechanisms for the agents' responses to a change in the tax on ICEV-kms.

## Appendix B. Deriving the welfare measure

As can be seen in Eq. (A.16), we have the following marginal welfare effect of increasing the road price:

$$\frac{1}{\mu}\frac{\partial V}{\partial\tau_{mp}} = \underbrace{e_F\left\{-\frac{dF}{d\tau_{mp}}\right\}}_{\text{energy related externalities}} \underbrace{e_m^c(M)\left\{-\frac{dM}{d\tau_{mp}}\right\}}_{\text{congestion externalities}} + \underbrace{e_{mF}^{nc}\left\{-\frac{dM_F}{d\tau_{mp}}\right\} + e_{mp}^{nc}\left\{-\frac{dM_P}{d\tau_{mp}}\right\}}_{\text{kilometrage related non-congestion externalities}} - \underbrace{\left[\tau_{mp}\left\{-\frac{dM_P}{d\tau_{mp}}\right\} + \tau_{mF}\left\{-\frac{dM_F}{d\tau_{mp}}\right\}\right]}_{\text{km-tax revenue}}$$
$$-\underbrace{\left[\tau_F\left\{-\frac{dF}{d\tau_{mp}}\right\} + \tau_P\left\{-\frac{dP}{d\tau_{mp}}\right\}\right]}_{\text{energy tax revenue}} \underbrace{+D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}}}_{\text{direct/indirect tax revenue/cost from vehicle stock}} + \underbrace{\tau_L\frac{dW}{d\tau_{mp}}}_{\text{labor tax revenue}} \tag{B.1}$$

The next step is to factor out $-\frac{dM_P}{d\tau_{mp}}$ and rearrange. This gives us:

$$\frac{1}{\mu}\frac{\partial V}{\partial\tau_{mp}} = \left[(e_{mp}^{nc}-\tau_{mp}) + (e_F-\tau_F)\left\{\frac{dF/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} - \tau_P\left\{\frac{dP/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + (e_{mF}^{nc}-\tau_{mF})\left\{\frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + e_m^c(M)\left\{\frac{dM/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\}\right.$$
$$\left. + \left(D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}}\right)\frac{1}{-dM_P/d\tau_{mp}}\right]\left\{-\frac{dM_P}{d\tau_{mp}}\right\} \tag{B.2}$$

Further rearranging gives:

$$\frac{1}{\mu}\frac{\partial V}{\partial\tau_{mp}} = \left[e_{mp}^{nc} - \tau_{mp} + \chi_F e_F - \chi_F e_F - \tau_P\left\{\frac{dP/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + \eta_F\left(e_m^c(M) + e_{mF}^{nc}\right) + e_m^c(M) - \tau_{mF}\left\{\frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\}\right.$$
$$\left. + \left(D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}}\right)\frac{1}{-dM_P/d\tau_{mp}}\right]\left\{-\frac{dM_P}{d\tau_{mp}}\right\} \tag{B.3}$$

Parts of this expression can be converted to the corrective component:

$$\frac{1}{\mu}\frac{\partial V}{\partial\tau_{mp}} = \left[\tau_{mp}^C - \tau_{mp} - \tau_F\left\{\frac{dF/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} - \tau_P\left\{\frac{dP/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} - \tau_{mF}\left\{\frac{dM_F/d\tau_{mp}}{dM_P/d\tau_{mp}}\right\} + \left(D_P\frac{dv_P}{d\tau_{mp}} + D_F\frac{dv_F}{d\tau_{mp}} + \tau_L\frac{dW}{d\tau_{mp}}\right)\frac{1}{-dM_P/d\tau_{mp}}\right]\left\{-\frac{dM_P}{d\tau_{mp}}\right\} \tag{B.4}$$

Other parts can be converted into the interaction component (see Eq. (A.24))

$$\frac{1}{\mu}\frac{\partial V}{\partial\tau_{mp}} = [\tau_{mp}^C - \tau_{mp} + \tau_{mp}^I]\left\{-\frac{dM_P}{d\tau_{mp}}\right\} \tag{B.5}$$

This gives us:

$$\frac{1}{\mu}\frac{\partial V}{\partial\tau_{mp}} = [\tau_{mp}^* - \tau_{mp}]\left\{-\frac{dM_P}{d\tau_{mp}}\right\} \tag{B.6}$$

We can rewrite $\left\{-\frac{dM_P}{d\tau_{mp}}\right\}$ using Eq. (A.37). This gives us:

$$\frac{1}{\mu}\frac{\partial V}{\partial\tau_{mp}} = [\tau_{mp} - \tau_{mp}^*]\frac{M_P\varepsilon_{MP}}{(R_P\tilde{p} + c_P^d + \tau_{mp})} \tag{B.7}$$

We numerically integrate this expression to find the change in welfare from a non-marginal change in the km-tax.

[17] This expression has a term that is not present for determining road prices for EVs, namely $\sigma_F = M_F\frac{d\tilde{f}\,/\,d\tau_{mF}}{dM_F\,/\,d\tau_{mF}}$. This term is related to induced changes in fuel efficiency.

## Appendix C. About the parameter values

Some of the parameter values in Table 1 require further explanation.

Initial vehicle kilometrage per car (EV & ICEV): Statistics Norway provides data of average kilometers driven annually per car on a municipal level. We aggregate these to averages on the analysis area level, large cities, small cities and rural areas, according to definitions from Thune-Larsen et al. (2014). This report finds that 8% of vehicle kilometers driven in large cities are spent in congested peak traffic, which is used to divide between peak and off-peak kilometrage.

Car ownership per household: Statistics Norway provides data on car ownership on a municipal level, and separates between ICEVs and EVs. We aggregate these to average car ownership per household on the analysis area level, large cities, small cities and rural areas, according to definitions from Thune-Larsen et al. (2014). These numbers are again weighted according to each area's share of total households, so we get the weighted average car ownership per household.

Average toll: Data on toll paid by passenger cars to toll companies have been provided by the National Public Road Administration's toll statistics. Statistics on passenger car traffic volumes are given by Statistics Norway StatBank (2018d). Users pay per passing of tolling station, but the numbers have been normalized to per kilometer by dividing passenger car toll revenue by passenger car traffic volumes at county level. The national average was 0.31 NOK per km. The average tolls per kilometer for large cities, small cities and rural areas were then approximated by dividing toll revenue by traffic volumes for counties where these area types dominate.

Purchase tax and VAT: The Norwegian Roads Federation (OVF) provides disaggregated car sales data from which the average price, purchase tax and VAT for the average ICEV can be calculated for any given year.

Own-price elasticity of car kilometrage: The newest estimates of elasticity values for the National and Regional Transport Modeling system (NTM and RTM) in Norway give an own price elasticity w.r.t. all kilometer costs and tolls together of $-0.152$ (documented in Rekdal and Larsen (2008)). When putting this elasticity (adjusted for the ca. 40% fuel share of total kilometer costs and tolls) together with the own-price elasticity of fossil fuel intensity (i.e. the isolated elasticity component for fuel efficiency w.r.t. consumer fuel price), valuated at $-0.092$ (Norsk Petroleumsinstitutt, 2011) we get the relatively more familiar own price elasticity for fuel. This sums up to $-0.153$. This is lower than the elasticity for gasoline applied for the US in Parry and Small (2005) ($-0.55$) and Lin and Prince (2009) ($-0.221$) and the German case with Tscharaktschiew (2015), that totaled up to $-0.5$. Fridstrøm (2017) argues that car transport in Norway has a quite low price sensitivity on a national level because most Norwegians do not live in dense, urban areas with public transport as an alternative. In addition, Norwegians have for years gotten used to having both relatively high average incomes, and high costs of car transport.

Cross-price elasticity of kilometer costs with respect to car ownership, i.e. how ownership of one car type increases when the kilometer costs of another increases. This is obtained by simulating the effect of increasing energy costs on new car sales in the BIG-model for the simulation year 2015, which then gives us a counterfactual change in the car stock. We extend this effect over 3 years and convert the implied elasticity measure for energy into an elasticity measure for kilometer costs.

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# Chapter 2: Vehicle choices and urban transport externalities. Are Norwegian policy makers getting it right?

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

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## 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, CO2 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 CO2-cap that reflects the goals of Norwegian policy makers.

Keywords: electric vehicles; climate policy; urban transport policy; transport modeling

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# 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 (ibid). 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. And both the UK and France have both 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 personal 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[2], and is in accordance with the government's National Transport Plan (NTP[3]). 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 $CO_2$ 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 polices 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, Assum, and Kolbenstvedt (2015).

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[2] 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).

[3] https://www.regjeringen.no/no/tema/transport-og-kommunikasjon/nasjonal-transportplan/id2475111/

In addition to the national ambitions for reducing $CO_2$ 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 $CO_2$ 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 $CO_2$ 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 CO2 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, Fung, and Proost (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 polices 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 $CO_2$[4], lead to very small emissions reductions. Policies for achieving the ambitious goals of halving the emissions from personal transport may bring about

[4] The Green Tax Commission recommended a reference value of 420 NOK (about €50) for one $tCO_2e$ (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" $CO_2$ price (see e.g., Nordhaus, 2019; Tol, 2005). A recent example is the IPCC (2018) special report, where they show that the estimated $CO_2$ prices consistent with reaching the 1.5 $^oC$ target with high probability had an inter-quartile range of 179-658 $USD_{2010}$ in 2030 (Huppmann et al., 2018).

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 National Public Roads Administration (both centrally and the eastern regional branch), 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 $CO_2$ 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 polices 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 Figure 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 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[5]. 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

[5] 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.

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 increases 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.

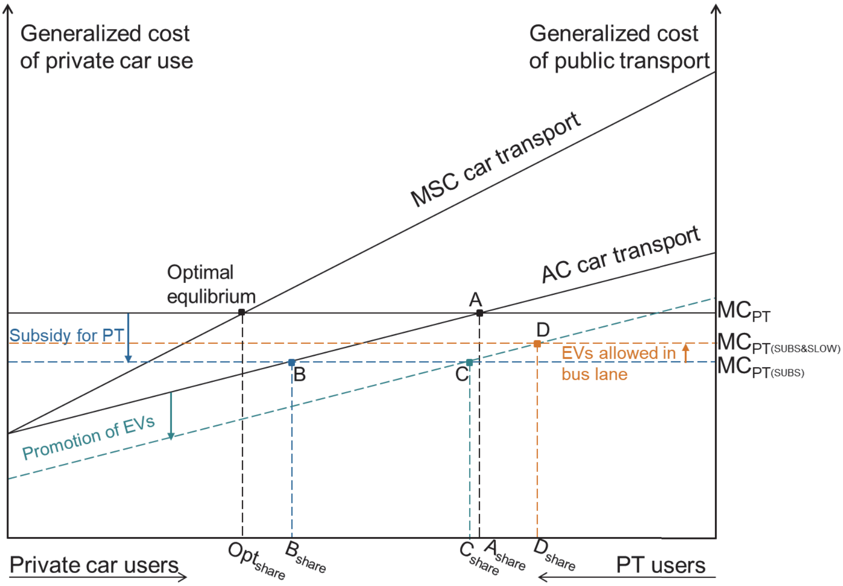


*Figure 1: Promotion of BEVs and urban transport equilibria*

There is another subtle way in which the present BEV promotion leads to more congestion: the progressive $CO_2$ taxation of fossil cars. Confronted with the introduction of a progressive $CO_2$ 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, Evans, & Oates, 2014).

The fourth option, postponing buying a new car, does not lead to more BEVs and less $CO_2$ 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.

*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, Nyboer, Bataille, & Sadownik, 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 & Newell, 2008; Jaccard et al., 2003).

*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, Bunch, and Train (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, Franklin, and Susilo (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, Bailey, and Castro (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, Parsons, Kempton, and Gardner (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, Fridstrøm, Johansen, and Tseng (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 W. Li, Long, Chen, and Geng (2017) and Coffman, Bernstein, and Wee (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, Jansson, and Bodin (2015) includes 16 papers and covers many of the same factors, but focuses more narrowly on consumer intentions and behaviors regarding EV adoption. Hardman, Chandan, Tal, and Turrentine (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, Nørbech, and Nordtømme (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, Sprei, Samaras, and Qian (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, Mountain, & Jaccard, 2009; Mau, Eyzaguirre, Jaccard, Collins-Dodd, & Tiedemann, 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.

*Modeling the role of EVs in the urban transport market*

This market is characterized by many externalities. EVs may alleviate some of them, like $CO_2$ and local pollution, but as we discuss in section 2, they may exacerbate others. Perhaps most costly externality in the urban setting is road congestion during peak hours (Small & Verhoef, 2007, pp. 97-105; Thune-Larsen, Veisten, Rødseth, & Klæboe, 2014). In addition to the mentioned 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 & 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 the 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.

*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 & Hulleberg, 2016; Flügel & Jordbakke, 2017; Fridstrøm, Østli, & Johansen, 2016; Rekdal et al., 2014; Rekdal & 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 CO2 emissions

A standard "textbook" approach to addressing $CO_2$ emissions is to prescribe implementing a $CO_2$ tax (Perman, Ma, McGlivray, & Common, 2003). Taxes on gasoline and diesel are, in effect, taxes on $CO_2$ as there is a fixed relationship between liters of fuel and kilos of $CO_2$. It is also worth emphasizing that the *entire tax per liter* can be viewed as a tax on $CO_2$, even if only a sub-component of the tax is explicitly called $CO_2$ 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 to 300 Euro/ton of $CO_2$ (OECD, 2016). This could be complemented by a $CO_2$ tax on alternative fuels (i.e., natural gas, biofuels, fossil generated electricity and hydrogen) in function of their $CO_2$ emissions. In theory, this instrument will make sure that we have the right mix of the four levers of reducing $CO_2$ emissions in transportation: more fuel-efficient driving, reduced car use, more fuel-efficient vehicles, and alternative technologies. The $CO_2$ 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 & 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 $CO_2$ 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 & 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 $CO_2$ 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 $CO_2$ from the same car on the same distance. The marginal price of $CO_2$ that a car user faces is reflected by the taxes on fossil fuels. In Norway, the current taxes on fossil fuels[6] (excluding VAT) would imply a cost of about €240[7] per ton of $CO_2$. By contrast, the recommended reference value of $CO_2$ in Norway (NOU 2015:15, 2016) is 420 NOK (about €50). However, even with a much higher value on $CO_2$, the external $CO_2$ 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 $CO_2$ per km for a large diesel passenger car to match the marginal cost of peak congestion in Norwegian cities, the implicit price of $CO_2$ 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 $CO_2$ at city-level (Anas & Lindsey, 2011; Small & Verhoef, 2007, pp. 97-105; Tscharaktschiew, 2014). Our first research question addresses the problem of finding the right balance in a transport system with multiple market failures, including both $CO_2$ 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 & Turner, 2011; Garcia-Lopez, Pasidis, & Viladecans-Marsal, 2017; Hsu & 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, Yokoyama, Maia, Loureiro, & Villas, 2016). But

[6] Weighted average for gasoline and diesel, where the former counts for 59 % of the car fleet's fuel use, and the latter 41 %.
[7] The sub-component of the tax explicitly labeled $CO_2$-tax reflects about 50 Euro per ton of $CO_2$, but as we argue above, the *entire tax per liter* of fuel can be viewed as a tax on $CO_2$.

in the end, this works like a capacity 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.[8] 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 & 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 supply costs. 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 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

[8] https://www.fjellinjen.no/private/prices/ [Last accessed April 9th 2018]

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 & 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 underpins linear demand functions it allows for clear interpretation and visualization. The following equations represents functions *U* and *B* for a given representative agent:

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

where

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

$q_j^t$ 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 $i_{jj}^{tt}$ 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. This representation of the utility function allows the derivation of inverse demand functions (willingness to pay – WTP), for the five types of transport.

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

### 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:

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

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 $\left[\delta_c + \gamma\left(Nq_c^i\right)\right] VOT_c^{in}$, where $\delta_c$ is travel time during free-flow conditions and $\gamma\left(Nq_c^i\right)$ is the added time due to congestion caused by all (*N*) other road users.

The user costs for daily PT travel is given by:

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

The user costs comprise access time costs $ac_b^i$, fare costs $\tau_b^i$ and time costs $\delta_b VOT_b^{in}\left[\varphi\left(Nq_b^i\right)\right]$, where $\delta_b$ is PT travel time and $\varphi\left(Nq_b^i\right)$ 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.[9] $VOT_b^w \tfrac{60}{2f_b^i}$ represents the PT users' waiting time cost, as a function of frequency.

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

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

---

[9] 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 (Z. Li & Hensher, 2011). De Palma, Kilani, and Proost (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, Graham, and Anderson (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.

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:

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

The charging time is thus determined by the range of the BEV and the length of the trip $\left( 2lcL - r_{EV} \right)$, the energy efficiency of the BEV $eff_{EV}$, and the charging capacity $chCap$ [10]. 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.

### 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[11]. 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, Doll, and Fichtner (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

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[10] 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 hour to get 110 km of driving distance charged.

[11] 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.

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 $tCO_2e$ 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 by area can be seen in Table 3. The simple relationship for total external costs $E$ is modelled in the following way:

$$E = \sum_{j=1}^{n} e_j q_j \tag{9}$$

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 $P_{\text{cost}}$. The fifth component consists of external non-congestion costs. This way we account for all costs and transfers for the involved agents.

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

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.

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

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:

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

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, Engebretsen, and Uteng (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[12] following the steps described in Table 1.

[12] The applied MATLAB-scripts can be obtained on request by contacting the corresponding author.

*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[13] in terms of<br>• Baseline travel pattern (PT and car).<br>• Employment and incomes (which determine value of time).<br>• Car ownership, access to parking at home, etc. |
| 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 Appendix 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 Appendix 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 Parry and Small (2009) and Kilani, Proost, and van der Loo (2014). |
| 8 | Construct the crowding cost functions of PT (see Appendix A for more information). |
| 9 | Construct linear cost functions for the non-congestion external costs; air pollution, noise and accidents. Values are given in Table 3, based on Thune-Larsen et al. (2014). |
| 10 | Construct a welfare function to represent equation (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. |

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

[13] 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.

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.

*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. Table 3 (own assumption) | N/A | N/A | 10% |

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.[14] 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 high range" (range of 528 km). The prices have been transformed to annuities over cars' average lifetime

[14] We have used data from The Norwegian Road Federation (OVF)

with a real interest rate of 2%[15] to make annual comparisons. We summarize the key car-specific parameters for technology, user costs, and externalities in Table 3.

*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[16] | 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 | |

## 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.

[15] 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 2.5%.
[16] 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<br>a. Solving for new individual utility optimum for agent X<br>Generating new utility-maximizing quantities for agent X (for each possible car option)<br>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)<br>Inserting the new quantities into the congestion and PT cost functions<br>b. 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<br>c. 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<br>d. Iterate: Redo step a using the updated congestion and crowding functions of step c<br>e. Iterate: Redo step b and c using the updated congestion and crowding functions of the previous step<br>f. Stop updating congestion levels and car choice after 3 iterations to avoid convergence problems[17] |
| 3 | Based on quantities in new equilibrium, calculate the total new social welfare levels and its components associated with the changed policy variable values |

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 $CO_2$ 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

[17] 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 and fares) when given the full car choice set. If they are not incentive compatible, vehicle taxes[18] 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 $CO_2$ emissions reductions; cf. section 1. If necessary, we adjust the set of policies to reach the $CO_2$-reduction target with the lowest social cost.

**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 $CO_2$ 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, $CO_2$ emissions are valued in the welfare calculations via a reference value of $CO_2$. This is common practice in CBA in the Norwegian transport

[18] 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.

sector (Norwegian Public Roads Administration, 2018). The Norwegian reference value of $CO_2$ 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 $tCO_2e$.

**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 polices 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 PHEVs, 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 ICEVs. The result is a 64 % drop in $CO_2$ emissions, exceeding the goal of a 50% reduction. However, due to lower user costs of both PHEVs and BEVs, the Oslo area becomes 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.

**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 $CO_2$-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.

**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 $CO_2$-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 $CO_2$ emission reduction target. The goal of reducing $CO_2$ emissions by 50% implies a shadow price of $CO_2$ 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 was reduced by 25%?[19] (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 $CO_2$ is abated. We see from Table 8 (cf. Appendix B) that one of the tested scenarios climbs in the welfare ranking, from 9$^{th}$ to 8$^{th}$ place.

[19] 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.

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 5$^{th}$ to 4$^{th}$ 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 7$^{th}$ to 5$^{th}$ 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, Reynaert, and Verboven (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.

**How do we reach the $CO_2$-reduction targets at least cost?**

In 9 of the 20 scenarios with fixed vehicle combinations, the 50% $CO_2$ emissions reductions target is not reached, and the welfare-maximizing scenario does not even come close to the target. We next impose the $CO_2$ 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 $CO_2$ 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 $CO_2$ emissions reduction target as a constraint, and let the tolls, fares and parking charges be the instruments for maximizing welfare under this constraint. The $CO_2$-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 $CO_2$ 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 $CO_2$-cap is with the combination of Agent X driving PHEVs, Agent Y driving small ICEVs 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 $CO_2$ for achieving the emissions reductions target is 6 671 NOK

(€682/ton). This comes in addition to the recommended reference cost of $CO_2$ 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 $CO_2$ 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 $CO_2$ 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. Tolls 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 $CO_2$ target increases up to 6 690 NOK per ton of $CO_2$ (€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 $CO_2$-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 $CO_2$ reduced.

In Table 5 and Table 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 $CO_2$-constraint.

*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.*

| **Scenarios** / **Policy variables** | **Exogenous policies** | | **Maximizing welfare, no CO2-constraint** | | **Maximizing welfare, with CO2-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 |

*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, EVl=Long-range EV, EVs=Short-range EV. X, Y and Z denotes the model agents.*

| Scenarios / Policy outcomes | **Exogenous policies** | | | **Maximizing welfare, no CO2-constraint** | | **Maximizing welfare, with CO2-constraint** | | |
|---|---|---|---|---|---|---|---|---|
| | Reference (level) | 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 |
| 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 |
| $CO_2$ 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 |

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 $CO_2$-cap, where it is almost 20 bn NOK.

The key results can be summarized in Figure 2. Here we summarize the main outcomes city driving, $CO_2$ emissions and welfare for the main scenarios compared to the reference situation:

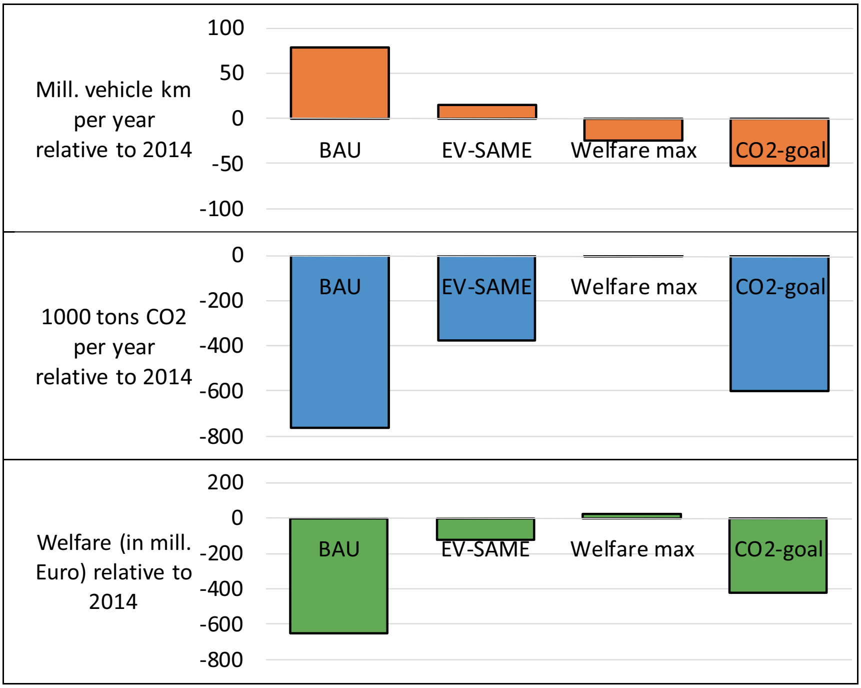


*Figure 2: Vehicle kms, CO2 emissions and welfare in four main scenarios compared to the reference situation*

# 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 Table 5 and Table 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 $CO_2$ 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 $CO_2$ 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 $CO_2$. In our stylized modeling framework, this implies that the agents have made the socially optimal car choice already. This scenario also implies non-significant $CO_2$ 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 $CO_2$. This also illustrates the mismatch between $CO_2$ prices used in CBA, typically in the range €20-€60 in 2020, and the $CO_2$ 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 $CO_2$ target as a constraint, and let the tolls, fares and parking charges be instruments for maximizing welfare under this constraint. Once the $CO_2$-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 $CO_2$ targets at least cost. With this vehicle combination and optimized policies, we also see a decline in car traffic volumes in the city, so those goals do not conflict in this scenario.

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 $CO_2$ reduced, compared to the welfare maximizing policies, that is about 16 times higher than the recommended reference value of $CO_2$.

It is likely that the optimized policies ($CO_2$-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 $CO_2$-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 $CO_2$-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 $CO_2$ 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.

*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,[20] 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 $CO_2$ 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 $CO_2$ emissions, if ambitious emission targets are to be achieved. The merits of the $CO_2$-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).

*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 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

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

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 then 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 & 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 & 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 $CO_2$-cap can also be seen as sensitivity tests to how the model results change under a higher $CO_2$ 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.

*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 polices 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 $CO_2$-reductions; or in other words, how much welfare are they willing to sacrifice in order to reduce $CO_2$ emissions? Welfare-maximizing policies at the recommended Norwegian reference value of $CO_2$ (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.

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# 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 MPMM23, 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.

*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 |

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 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

*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, EVl=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: EVl 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: EVl 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: EVl 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: EVl 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 |

# Chapter 3:
# Optimal policies for electromobility: Joint assessment of transport and electricity distribution costs in Norway

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# Optimal policies for electromobility: Joint assessment of transport and electricity distribution costs in Norway

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## Abstract

We observe a rapid increase in the share of electric vehicles (EVs) in Norway, as policy makers have reduced the costs of purchase and use of EVs relative to conventional vehicles. Electrification of transport will make the transport and energy systems more intertwined: EV friendly transport policies increase the demand for electricity, which in periods of high demand could challenge the distribution grid's capacity, while electricity policies immediately impact on the generalized costs of driving EVs. This paper develops a stylized economic model for passenger transport in the greater Oslo area, in which the agents' choices of car ownership, transport pattern, and EV home charging are jointly determined. If enough EV-owning agents charge during power peak hours, costly grid expansions may be needed. We examine how the distribution grid companies can mitigate these costs with different pricing schemes and how this in turn affects the transport market equilibrium. We find that applying power tariffs differentiated between peak and off-peak periods will help strike a better balance between grid investment costs and EV-owners' disutility of charging during off-peak hours. Most importantly, we find that imposed grid cost from EV home charging amounts to relatively small extra costs to other electricity users, and relatively small additions to the cost necessary to reach ambitious $CO_2$ targets in the greater Oslo area.

**Keywords:** electric vehicles, climate policy, urban transport policy, transport modeling, electricity distribution costs

**JEL classification:** H71, Q41, Q48, Q54, Q58, R41, R48

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# 1 Introduction

The Paris agreement was adopted in 2015 and came into force in 2016 as a response to the imminent threat of climate change. It aims to limit the global temperature increase in this century to well below 1.5°C above pre-industrial levels. The transport sector accounts for approximately one quarter of global energy-related greenhouse gas emissions (International Energy Agency, 2017) and about one third of Norway's greenhouse gas emissions[2]. It is therefore required to deliver major emissions cuts in this sector to meet the objectives of the Paris agreement.

The electrification of transport is viewed as a potent measure to reduce greenhouse gas emissions (IEA, 2017). Norway's strategy is to ensure that all new passenger vehicles are zero emission vehicles by 2025. EV-friendly transport policies – including low vehicle taxes, toll road exemptions, and access to bus lanes – have therefore been put in place, which has resulted in the highest penetration of EVs worldwide. By January 2020, there were about 260 000 battery electric vehicles (BEVs) and 115 000 plug-in hybrids (PHEVs) in Norway, a country with only 5.3 million inhabitants. In 2019, BEVs accounted for 42 percent and PHEVs for 14 percent of all new vehicles (Norwegian Electric Vehicle Association, 2020).

According to the Norwegian energy regulator, 1.5 million EVs in Norway in 2030 would only amount to a 3 percent increase in the domestic electricity consumption (Skotland, Eggum, & Spilde, 2016). Hence, the main challenge is not expected to be that of aggregate electricity generation. However, while an EV's energy consumption may be modest, its power consumption could be quite high. The current power demand per electricity consuming unit in a household is normally of the order of from 2.3 to 7.3 kW (Skotland et al., 2016). The power demand from fast-chargers (currently up to 350 kW) will come in addition to that.

Uncoordinated charging (also known as dumb charging) will increase the electricity consumption during the morning and evening peaks (Graabak, Wu, Warland, & Liu, 2016). De Hoog, Alpcan, Brazil, Thomas, and Mareels (2015) and Neaimeh et al. (2015) point out that if vehicle charging is not controlled, adverse impacts on the distribution network are expected: power demand may exceed distribution transformer ratings; line current may exceed line ratings; phase unbalance may lead to excessive current in the neutral line; and voltages at customers' points of connection may fall outside required levels.

Several studies examine the effects that low-carbon technologies such as BEVS and PHEVs (in this paper we will group them together as PEVs – Plug-in Electric Vehicles) can have on the electricity market. Hattam and Greetham (2017) look at how PEVs affect load profiles on neighborhood level in low voltage networks. Azadfar, Sreeram, and Harries (2015) asses charging behavior of PEV users in terms of time of day, duration, frequency, and electricity consumption, and its implication for electricity network management. Barton et al. (2013) study the challenges for grid balancing when PEV charging and heat pumps become more prominent. They stress the importance of demand side management with time-shifting of electricity loads from periods of peak demand to off-peak, and from periods of low renewable energy supply to periods of high supply. However, in some areas it may be difficult to shift away from periods of peak demand and at the same time avoid periods of high emission intensity in the electricity supply (Fang, Asche, & Novan, 2018). Other studies also argue for demand side management (see e.g., Haidar, Muttaqi, & Sutanto, 2014; Masoum, Deilami, Moses, Masoum, & Abu-Siada, 2011), and many argue for pricing schemes that disincentivize charging during off-peak hours (see e.g., Barton et al., 2013; Clement-Nyns, Haesen, & Driesen, 2011; Masoum et al., 2011; O'Connell et al., 2012), as an alternative to costly upgrades of distribution transformers.

[2] Statistics Norway: "Emissions to air", https://www.ssb.no/en/klimagassn.

In the future, vehicle to grid[3] (V2G) may provide also a means to mitigate capacity problems in electricity distribution (see e.g., Barton et al., 2013; Clement-Nyns et al., 2011; Green II, Wang, & Alam, 2011; Hagem, Greaker, & Proost, 2019; Mwasilu, Justo, Kim, Do, & Jung, 2014), but bidirectional PEV charging is in its infancy (Haidar et al., 2014), and seem to come at a relatively high cost due to energy losses, changes in infrastructure, and extra communication between PEVs and the grid (Habib, Kamran, & Rashid, 2015). Drivers may also see a high inconvenience cost associated with committing to a V2G contract (Parsons, Hidrue, Kempton, & Gardner, 2014) and/or have a relatively low and variable willingness-to-pay for V2G capabilities (Noel et al., 2019).

Most of the reviewed studies assume that transport demand, and therefore EV users' demand for electricity, is exogenous (see also Daina, Sivakumar, & Polak, 2017a, 2017b). This paper contributes to the literature by looking at the mechanisms and outcomes in *both* the transport and energy market, and the feedback between them. We use a stylized transport and energy model for the greater Oslo area to study costs and benefits in both the electricity market and transport market jointly. The model allows the agents to choose type of car (or no car), their transport pattern and (if they own an EV) how much to home charge during power peak and off-peak hours. To our knowledge, it is the first time these features have been applied in the same modeling framework. The analysis will give insight into the feedback between the transport market and electricity market and how policies in one market can affect the equilibrium in the other. With this we can assess how polices can be optimized to reach policy goals at least cost.

Sector-wise policy making implies that Norway's EV-policies have paid little consideration the cost of enhancing the local grid to meet the demand for PEV-charging. The electrification of transport will make the transport and energy systems more intertwined: EV-friendly transport policies increase the demand for electricity and thus impacting the grid, while electricity policies immediately impact on the generalized costs of driving PEVs. In order to respond to this concern, our paper addresses the following research questions: 1) When we factor in the current uniform grid tariff system, what are the welfare impacts of today's EV policies and polices for reaching $CO_2$-targets at least cost? 2) How can these welfare costs be affected by a better pricing of electricity distribution?

Section 2 briefly discusses policies and market distortions relevant for electromobility and power distribution. Section 3 presents the theoretical model. In section 4 and 5, we present the numerical model, and describe the scenarios we run. In section 6 we present and analyze model results. Section 7 provides discussion and conclusion.

# 2 Policies for electromobility and power distribution

## 2.1 The Norwegian power system and electrified transport

The rapid rise in the number of EVs in Norway is to a large degree a result of incentives in Norwegian transport policy (Figenbaum & Kolbenstvedt, 2016; Fridstrøm & Østli, 2018). This growth will entail an increase in power consumption. The focus of this paper is solely on the lower end of the electricity sector value-chain, with the power consumption of households, and capacity in the low-voltage distribution grid. As will be subsequently explained, owners/operators of fast charging stations usually internalize the costs of transmission capacity, while households may not.

The energy sector is preparing for the electrification of transport. The Norwegian energy regulator NVE (The Norwegian Water Resources and Energy Directorate) has produced two technical reports that assess the strain that electric cars put on electricity transmission. The first report

[3] V2G involves using EVs as storage for electricity.

(Skotland et al., 2016) pays attention to how the diffusion of electric vehicles can impact the electricity distribution network. NVE estimates that 75 percent of the charging of EVs takes place at home, 15 percent at work, and 10 percent is fast charging. NVE finds that 70-80 percent of PEV drivers seldom use fast charging. However, NVE expects the demand for fast charging to increase in the future.

NVE's review indicates that charging of electric vehicles primarily takes place at night, while some also charge their vehicle immediately after work. Figure 1 shows NVE's prediction of a power consumption profile for an average household, with and without home charging of PEVs.

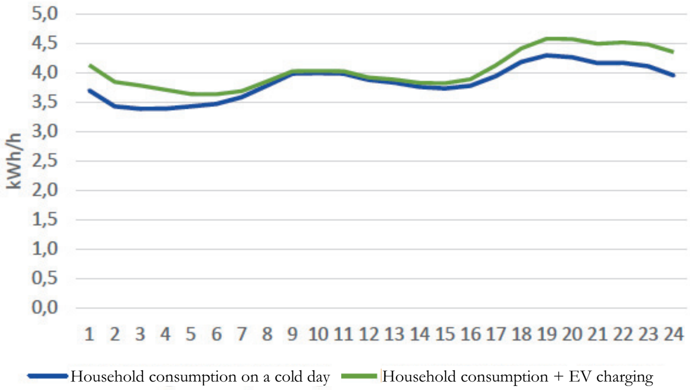


*Figure 1: Average household power consumption per hour on a cold day (blue line), and total household power consumption when the assumed pattern for home charging EV is included (green line). Source: Figure 4.3 in Skotland et al. (2016).*

NVE argues that the introduction of power-based tariffs will provide incentives to postpone charging until after peak-hours. They have recently submitted a proposal for a new electricity tariff based on the demand for power[4]. This is now technologically feasible after January 1st 2019, as smart meters are compulsory for all Norwegian households. The new meters will enable households to closely monitor their temporal electricity consumption profiles, and both distribution grid companies and electricity retailers to bill accordingly.

NVE develops stress-tests for neighborhoods with high PEV-density. Assuming periods where 70% of the residents charge their EVs simultaneously, it finds that the power demand can increase by up to 5 kW per household. This results in overload of more than 30 percent of the transformers currently servicing the Norway's distribution network. NVE's follow-up report (Skotland & Høivik, 2017) concludes that a full-scale electrification of transport (including also buses and ferries) is primarily a threat to the low-voltage grid and transformers. The upgrades of several of these components are planned today, which reduces the problem of overload in the future. Yet, NVE reports that, as of 2017, few of the electricity distribution companies account for the electrification of transport when forecasting the demand for power.

On the local grid level, the capacity may need to be expanded for the transformer, or for the cable between the transformer and the households, or both. In a metropolitan area there will be large variations in neighborhoods' ability to absorb increases in peak power demand with the current infrastructure. And given the need to invest in more capacity, the cost will also vary greatly between neighborhoods. It will depend on whether enhancements need to be done for the transformer and/or the cables between the households, the capacities that need to be installed, whether the new transformer fits in the old box that contained the old transformer, and the costs of digging

[4] It is currently (first quarter of 2019) out on a public hearing http://publikasjoner.nve.no/rme_hoeringsdokument/2020/rme_hoeringsdokument2020_01.pdf [in Norwegian].

(i.e. how many meters of cables need to be laid, and the costs per meter, which are generally higher in denser, urban areas).

Grid expansion costs may or may not accrue to the household that demands higher capacity. Let's say that some households increase their capacity demand so that total demand in the neighborhood exceeds the capacity of the local distribution transformer. The local grid company will invest in a higher capacity transformer, thus increasing its capital costs. Local grid companies (or Distribution System Operators – DSOs) are regulated under a revenue cap model, where they set their tariffs based on this revenue cap. The revenue cap is composed of 40% cost recovery and 60% cost norm based on benchmark modeling. This means that at least some of the increase in capital cost will lead to higher tariffs, and that these tariffs will have to be paid by all electricity consumers connected to the local grid company, and not just the households demanding more capacity. It can be viewed as a pecuniary external cost in an incomplete market (Greenwald & Stiglitz, 1986). That is, the households demanding more capacity do not face the full cost of the capacity expansion, and indirectly impose costs on other consumers[5].

The case becomes a little different if a household demands higher power capacity than currently installed in the household, and *this* increased capacity demand exceeds the capacity of the local distribution transformer. This household may be required to pay for some or all of the capacity expansion of the transformer through connection charges, in addition to paying for the household's capacity expansion. Practices seem to vary between Norwegian DSOs, but the DSO in the Oslo metropolitan areas, Elvia, will in such a case charge the household that induced the new investment in proportion to the added installed capacity for that household[6]. For example, if a household wants to install 20 kW extra of capacity, and the DSO replaces a 315 kW transformer with a 500 kW transformer, the household has to pay 20/(500-315) = 11% of the cost of the capacity increase. Households that expand in-house capacity in the future will also have to chip in on this transformer upgrade in proportion to their in-house expansion[7]. This would mean that less or none of the investment cost will be dispersed to the other consumers. Instead the scheme provides a price signal to the very households that demand more capacity, informing their decision to whether or not the benefits of expanding their in-house capacity outweighs the cost. Such co-payments also apply to firms and individuals who want to establish fast-chargers, as this in most cases will entail some expansion of local transformer capacity. Hence, the issue of externalities is less pronounced with regards to fast-chargers, which is why it out of the scope of this article.

The scenario where increased PEV ownership leads to higher capacity demand that eventually exceeds the local transformer's capacity, without any household expanding its in-house capacity, is expected to be most prevalent. The reason is that most households will have the possibility to charge an EV at 3.6 kW power without any in-house capacity expansion (conversation with the DSO Ringeriks-Kraft AS on April 5th, 2018). This will lead to situations where, over time, some neighborhoods could drive up grid company investment costs as PEV ownership increases, leading to higher tariffs for all customers.

At the time of writing, no household has incentives to postpone charging until after peak hours: Both electricity prices and grid tariffs are the same throughout the day. And there are many reasons why PEV owners prefer to charge right away after coming home. First, it is convenient. They plug

[5] Hoarau and Perez (2019) show that under the assumption of sunk grid costs and no need for capacity expansion, PEVs have the opposite effect, as the increased electricty consumption from PEV leads to lower tariffs needed for DSO cost recovery, benefitting non-PEV-owners.

[6] https://www.hafslundnett.no/artikler/bygge-og-grave/anleggsbidrag/6l51MrL1vyaCi0WsisqAQQ

[7] Other households in the neighborhood could have reinforced their household power capacity without having to pay a connection charge, as the total capacity demand would still be within the transformer's capacity. This may look like a set-up for a strategy game between households, where early-moving households can expand their in-house capacity without having to pay extra, but we expect that such games are rare.

in, and there is no need to spend mental capacity on timing. Second, they maximize the probability of always having the battery charged for any activity later; planned, spontaneous or emergency.

Many papers look at optimal ways for regulators to handle periods with high power demand and cost recovery for DSOs. Recent contributions include Brown and Sappington (2018) that look at Maximum Demand Charges (MDCs) and Time-of-Use (TOU) pricing for residential consumers. They find that TOU pricing in most cases secures higher aggregate welfare than MDCs. It can often be beneficial to apply some element of fixed charges in order to induce efficient consumption and at the same time ensure cost recovery to suppliers (Borenstein, 2016; Brown & Sappington, 2017a, 2017b). This is a common feature in the billing of Norwegian DSOs. It is also worth mentioning that pricing schemes to shift demand away from peak hours (such as TOU pricing, MDCs, Critical Peak Pricing or Extreme Day Pricing) can have additional benefits such as increased reliability (Albadi & El-Saadany, 2008). As discussed above, peak grid tariffs could serve as an instrument to move some of the charging away from peak hours. The peak tariff would have to be large enough to incentivize at least some PEV owners to postpone their charging. The necessary peak tariff is driven upwards by the fact that Norwegian electricity prices and tariffs on average are lower than in most other European countries (Figenbaum et al., 2019), incomes on average are higher and average incomes of car owners are higher than those of non-car owners, and own-price elasticities for electricity are relatively small (see e.g., Ericson, 2007).

## 2.2 Multiple market failures in uncoordinated sectors

Electrification of transport introduces new challenges and opportunities, both for the transport and the electricity sectors. But these sectors consist of many different players, including policy-makers for road transport, electricity sector regulators, electricity retailers, DSOs, and households. Without any coordination, the costs and benefits could be distributed quite unevenly. As shown in Wangsness, Proost, and Rødseth (2018), there are multiple market failures and policy parameters in an urban transport setting: Most of the policy parameters, be it road prices or public transport fares, are often sub-optimally assigned. Acknowledging the local grid capacity issue means bringing yet another market failure into the mix.

This paper focuses on the greater Oslo area. This area is broadly made up by the municipality of Oslo and the county of Akershus, and has a population of about 1.2 million. Oslo aims to reduce $CO_2$ emissions by 50% by 2020 (Oslo Municipality, 2016). The corresponding goal in Akershus is a 50% reduction by 2030 (Akershus County Council, 2016). Consequently, policy-makers for road transport have been mandated to reduce emissions from transport. As shown in Wangsness et al. (2018), in order to reach the emission reduction target at least cost, a large share of transport users would have to switch to PEVs. From transport policy makers' point of view, the fact that grid companies need to invest in local grid capacity in certain places to accommodate a larger PEV share, is an added difficulty to reach their emission reduction target. The needed investments and the subsequent increases in tariffs drive up the cost of switching to PEVs, meaning that policy packages would have to become more radical in order to reach emission targets for road transport. This means higher welfare costs in the transport sector, not to mention overall higher abatement costs (see Figure 2). This is an argument for coordination and bringing in the electricity sector in on the cost-minimizing strategy.

Electricity retailers benefit from policies for reducing emissions, as higher demand for EVs drives up demand for electricity, making the sector more profitable *ceteris paribus*. As for local grid companies' profitability, this is determined by their costs and their regulated revenue cap. If policies drive up EV ownership and subsequently capacity demand, their capital costs will increase, most likely without a corresponding increase in the revenue cap. Since "PEV density" is not an external variable in NVE's benchmarking model, the cost norm calculation will disfavor grid companies that face increased capacity demand from PEV users. A grid company facing such demand increases, will see the policies for reducing emissions as a threat to their profitability. An exception would be a DSO that already is among the most productive and remains among the most productive in spite of the increase in capacity demand from PEV owners. Such a company would set the cost norm, and will be able to pass the entire investment cost over to consumers. If the cost norm is expanded, DSOs who are *not* exposed to this higher capacity demand will get a larger revenue cap, but no extra costs.

Electricity regulators should take the new challenges into account. If capacity demand from PEV owners becomes a major cost driver for DSOs, there are at least two measures the regulator needs to consider. The first is to allow peak power tariffs and incorporate them in the revenue cap. This way, it becomes possible to pass on and signal the additional distribution costs of PEV charging to the owners. The second is to incorporate a measure of "PEV density" in their benchmarking model for calculating the cost norm for the sector, so that the relatively low costs for grid companies with low PEV density are not mistaken for efficiency.

Before we introduce the numerical model, we give a simple illustration of how the abatement costs in the transport sector are affected by the issue of grid capacity. We use a traditional environmental economics framework with marginal damage cost and marginal abatement cost. In Figure 2, we consider a fixed vehicle stock in a metropolitan area, where the cars can either be ICEVs or BEVs: The overall stock is given by the line segment from the origin to $A_{share}$, and allocation at the origin indicates that all cars are BEVs while allocation at $A_{share}$ indicates that all cars are ICEVs.

For simplicity, we assume homogenous ICEV users and vehicles, and consequently a flat marginal external environmental cost curve due to air pollution ($CO_2$, $NO_X$, PM) from ICEVs. These external costs can be abated by switching to BEVs. The marginal abatement cost curve[8] is assumed to be upward sloping as ICEVs are replaced by BEVs, *ceteris paribus*. This is because the lower user costs of BEVs relative to ICEVs will drive up total mileage and total congestion in the urban transport equilibrium[9].

The optimal allocation of car ownership when the model factors in the environmental cost of ICEVs is found at the intersection between the marginal environmental costs of ICEV ownership and the abatement costs of BEV ownership, respectively. In this case, the desired equilibrium would be B, with a small but positive share of BEVs. However, when normal use of BEVs entails some charging during power peak hours, each BEV will add some additional cost to the capacity expansion of the local grid. As costs of transformers are assumed to be linear in capacity for the relevant capacity interval, this implies a constant marginal cost mark-up for BEVs. Taking this into account lowers the optimal BEV-share of the area's car stock to equilibrium C.

Finally, we use the schematic model to look at the implications of a $CO_2$ cap that is more ambitious than marginal abatement cost equaling marginal damage cost. This is shown as a situation where the government, through incentives or command-and-control regulations, pushes towards a new equilibrium with a higher BEV share in order to reach their climate goals, here illustrated by equilibrium Cap. The triangle CapCX illustrates the deadweight loss of imposing such a cap, compared to the equilibrium that is implied by reference prices for air pollution.

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[8] With this we refer to the social cost of removal of all air pollutants from one ICEV, as it is replaced by one BEV.
[9] One could also argue that the curve would be upward sloping in a model with heterogeneous agents. In one end of the distribution you have the early adopters of BEVs with a car usage pattern where BEVs imply a relatively low total cost of ownership (e.g. the marginal abatement cost curve could start (i.e. at $A_{share}$ in Figure 2) below the x-axis). In the other end you have those with a usage pattern that implies a relatively high total cost of ownership (e.g. many long trips, the need for size, poor charging opportunities). This reasoning is also found in Bjertnæs (2016).

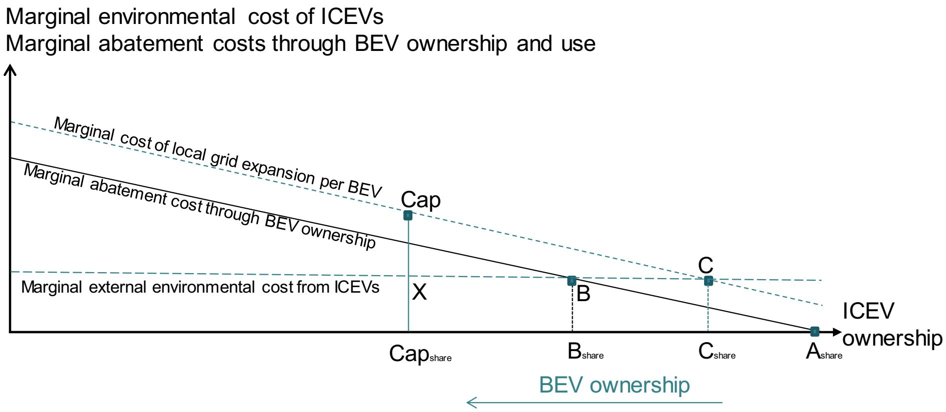


*Figure 2: Optimal ownership distribution between ICEVs and EVs*

The market failure of inadequately being able to make PEV owners face the price of expanding local grid capacity complicates the problem of maximizing welfare for the citizens in the greater Oslo area, and it drives up the cost of achieving ambitious emission reduction targets. The modeling exercise will give an indication of how much.

# 3 The stylized transport and electricity model

## 3.1 Optimizing grid capacity expansion

We use a theoretical model similar to that in Wangsness et al. (2018), where the social planner's objective is to maximize the welfare of the model agents. We extend the model by accounting for the induced cost of demanding higher local capacity for charging PEVs. There is a cost of expanding local capacity that needs to be balanced against the agents' preference for charging during peak hours, modelled as a disutility function of charging during off-peak hours. For the social planner, this can be considered a cost minimization problem. In this section, we solve this problem for a single representative agent. In the stylized first-best solution, the capacity expansion per PEV owner is set to strike the balance between incurred grid investment costs and the disutility of charging off-peak. This can be interpreted as if the PEV owner commits to a charging pattern, and the incurred investment cost in optimum can for the agent be considered a part of the fixed cost of getting a PEV.

Let $kWh^o$ be the amount of energy required in the off-peak period, and let $kWh^p$ be the energy required during the peak period. Assuming a fixed charging speed (3.6 kWh/h) and an exogenous daily charging need of $kWh^o + kWh^p = \Omega$, the problem boils down to how the agent wants to divide her charging hours $h = \Omega / kW$ between peak and off-peak: If she wants to charge during periods with peak demand she must pay for capacity expansion.

We introduce the following simple non-linear programming problem, where $F$ is the fixed investment cost for any transformer, $\beta$ is the investment cost of additional peak capacity, where charging in the off-peak involves some disutility $disU(h^o)$ as a function of off-peak hours charged, and where the control variable is $kWh^p$. We operate with annualized investment costs, denoting them $F^{ann}$ and $\beta^{ann}$. We solve the problem for a representative day.

(1) $$\min_{kWh^p} p^p kWh^p + p^o(\Omega - kWh^p) + disU(\frac{\Omega - kWh^p}{kW}) + \frac{F^{ann} + \beta^{ann} kWh^p / h^p}{365}$$

when $kWh^p \geq 0$

This gives us the following Kuhn-Tucker conditions:

$$p^p - p^o - \frac{disU'}{kW}(\frac{\Omega - kWh^p}{kW}) + \frac{\beta^{ann}/h^p}{365} + \mu = 0$$

$\mu \geq 0$ ($\mu = 0$ if $kWh^p > 0$)

where $\mu$ is the Lagrange multiplier of the non-negativity constraint. We get three possible solutions, two corner solutions and one interior solution:

1. Interior solution: Optimum is where the marginal disutility of charging time during off-peak hours (weighted by *kW)* equals the price difference between peak and off-peak electricity plus the share of the annuity of the marginal investment cost for expanding peak capacity. With the interior solution, we have that some charging is done during peak hours, $0 < kWh^p < \Omega$, when

$$\frac{disU'}{kW}(\frac{\Omega - kWh^p}{kW}) = p^p - p^o + \frac{\beta^{ann}/h^p}{365}$$

2. No charging is done during peak hours, $kWh^p = 0$, when

$$\frac{disU'}{kW}(\frac{\Omega - kWh^p}{kW}) < p^p - p^o + \frac{\beta^{ann}/h^p}{365}$$

3. All charging is done during peak hours, $kWh^p = \Omega$, $\frac{disU'}{kW}(\frac{\Omega - kWh^p}{kW}) > p^p - p^o + \frac{\beta^{ann}/h^p}{365}$

We denote the cost minimizing choice of the agent $kWh^{p*}$. Having established this, we can insert it into the social planner's maximization problem below. We have depicted the optimal solution where the PEV owner faces the marginal investment cost that her charging pattern (which she commits to or is forced not to exceed) imposes on local grid. The fixed component of the investment costs is assumed to be financed through lump-sum taxation or a fixed component on the bill from the local grid company. This can be considered a first-best solution in this dimension. It could be interpreted as a "capacity subscription tariff" to all PEV owners that do not commit to only charge off-peak. This tariff will then optimize incentives not just for purchasing a PEV or not, but also the choice of charging pattern conditional on owning a PEV. The capacities chosen by the PEV owner then give the correct investment signal to the local grid company.

PEV owners are not facing any capacity tariff in the current situation in Norway, but pay regular uniform grid tariffs, as described in section 2. In our model, this corresponds to a situation where $p^p = p^o$. In addition, all fixed investment costs are spread across all DSO customers, so the PEV owner does not face the induced cost of capacity expansion. This leads to the corner solution where the PEV-owner always charges during peak hours, $kWh^p = \Omega$. In the following section, we explore numerically the importance of pricing charging capacity.

## 3.2 Maximizing welfare

The preferences of the modeled agents are represented by a quasi-linear utility function $U$. Here utility is derived from consumption of other (non-transport) goods and services (normalized to net generalized income $m^v_{net}$ for a given vehicle choice *v*), and from consumption of transport. The utility is expressed in monetary terms. The transport goods are car kilometers travelled for short daily trips at peak and off-peak ($q_c^p$ and $q_c^o$, respectively), public transport (PT) kilometers travelled for short daily trips and peak and off-peak ($q_b^p$ and $q_b^o$, respectively) and the number of long car trips per year, $q_{lc}$. The utility from transport consumption is represented by a sub-utility function $B$, which is assumed to be quadratic. $U$ and $B$, for a given representative individual, are represented by the following:

$$U(m_{net}^v, q_c^p, q_c^o, q_b^p, q_b^o, q_c^l) = m_{net}^v + B(q_c^p, q_c^o, q_b^p, q_b^o, q_{lc}) \tag{2}$$

The social planner's task to maximize social welfare can first be broken down into two sub-tasks. For whichever car the agent chooses, policies must be adjusted to get the most efficient transport usage equilibrium. But given efficient transport policies for given car combinations, the social planner also needs to ensure that the agents choose the optimal car combination (i.e., fleet mix). In the case of a car combination where EVs are chosen, the planner also needs to factor in the social cost of charging the EV (cf. Figure 2).

With the utility function consisting of transport consumption and normalized "other" consumption, costs are subtracted from gross generalized income $m_{gross}^v$ in order to get net generalized income. We also subtract from gross generalized income the fixed costs of car ownership $C_{v,fixed}^{ann}$, cost of non-transport electricity consumption (where $a^p$ and $a^o$ represent annual consumption of electricity in peak and off-peak), and annuity of the capacity-independent part of the grid cost $F^{ann}$ paid equally among the $n = 1,\ldots,N$ agents. If the car chosen for at least one of the agents is a PEV, and the agents in question have $kWh^{p^*} > 0$, this term will be greater than zero. If not, the term will be zero, and local grid capacity expansion will be unnecessary.

If an agent owns a PEV, the subtracted costs also include the annuity of the required investment cost of the chosen charging pattern and any annual disutility of charging off-peak $disU$. Since we model annual welfare, the fixed costs are considered as annuities. Finally, the user costs of transport (monetary costs and time costs) for driving car during peak hours, $uc_{cn}^p q_{cn}^p$, off-peak hours, $uc_{cn}^o q_{cn}^o$, and on long car trips, $uc_{lcn} q_{lcn}$, and for PT during peak hours, $uc_{bn}^p q_{bn}^p$, and off-peak hours, $uc_{bn}^o q_{bn}^o$ are defined. The user costs for car includes distance related costs (fossil fuels and/or electricity, repairs, lubricants), toll costs, parking costs and time costs. If the long car trip is done by a BEV, and the trip back and forth is longer than the range of the car, the agent will need to charge enough to cover the remainder of the round trip. This adds a disutility cost as a function of the charging time. The user cost for PT travel includes access time costs, fare costs, waiting costs and in-vehicle time costs, weighted by crowding. We thus have

$$\begin{aligned} m_{net}^v &= m_{gross} - C_{v,fixed}^{ann} - p_{el}^p a^p - p_{el}^o a^o - \tfrac{F^{ann}}{N} + \frac{\sum_n \beta^{ann} kWh^{p^*}}{Nh^p} - \sum_{days} disU\left(\tfrac{\Omega - kWh^{p^*}}{kW}\right) \\ &\quad - uc_c^p q_c^p - uc_c^o q_c^o - uc_b^p q_b^p - uc_b^o q_b^o - uc_{lc} q_{lc} \end{aligned} \tag{3}$$

Consider $n=1,\ldots,N$ agents that are differentiated by the number of long trips they want to make per year, employment situation and by their mode choice preferences. The social planner's welfare maximization problem for all $N$ agents can then be formulated as follows: Induce agents to choose vehicle $v = \left[ICEV(\text{large}), ICEV(\text{small}), PHEV, BEV(\text{short-range}), BEV(\text{long-range})\right]$ and number of trips with car and/or public transport so that the following social welfare function $W^v$ is maximized:

(4)
$$W^{v}=\sum_{n=1}^{N}\left[m_{net,n}^{v}+B_{n}(q_{cn}^{p},q_{cn}^{o},q_{bn}^{p},q_{bn}^{o},q_{lcn})\right]$$
$$-\left(C_{b}-\tau_{c}^{p}q_{c}^{p}-\tau_{c}^{o}q_{c}^{o}-\tau_{b}^{p}q_{b}^{p}-\tau_{b}^{o}q_{b}^{o}-\tau_{c}^{r}q_{lc}-\tau_{g}g_{c}q_{c}-\sum_{k}\tau_{c}^{ann}k\right)+P_{price}-P_{\text{cost}}-E$$

The costs of operating the PT system is given by $C_b$, which includes both the fixed and variable operating costs (so it depends on $q_b^p$ and $q_b^o$). It is assumed to be a linear function of frequency. Environmental external costs of driving, for all cars, are given by $E$ (so it depends on $q_c^p$, $q_c^o$ and $q_{lc}$). The government gets revenue from tolls (peak, off-peak and rural), and fares (peak and off peak), and purchase, fossil fuel, and electricity taxes. All of these revenue sources are denoted by $\tau$ in the equation above. The component $P_{price}$ represents the revenue to the parking company (a transfer), and the component $P_{\text{cost}}$ consists of the opportunity cost of occupied parking space.

For simplicity, we assume constant marginal costs for electricity generation, and constant electricity prices. We also assume lump-sum taxes to finance any public sector deficits. Hence, we ignore labor market distortions, and have a marginal cost of public funds (MCF) equal to 1.

For each combination of the *N* agents and *V* vehicles, tolls and fares are optimized. Optimal tolls for cars are equal to the marginal external congestion costs plus the marginal external non-congestion costs of road use. The optimal fare for PT equal the marginal external crowding cost (which depends on frequency). This is shown in Wangsness et al. (2018). The resulting combinations of policies and vehicle types per agent will give us a range of welfare levels $W^v$, where the social planner chooses the combination that leads to the highest welfare level.

# 4 Numerical modeling

Our numerical model is constructed to capture the most important aspects of vehicle ownership and transport choices for the population of the greater Oslo area. This population is based on the Norwegian travel survey (documented in Hjorthol, Engebretsen, & Uteng, 2014). Of the approximately 60 000 respondents in this survey, about 10 400 (18 years or older) lived in the greater Oslo area, representing about 0.95 million adult inhabitants. Applying frequency weights constructed by travel survey experts at The Institute of Transport Economics, travel survey respondents are extrapolated to a synthetic adult population of the greater Oslo area.

Based on this synthetic population, we construct and calibrate a numerical model in MATLAB, using the steps described in in Table 1.

*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[10]. The selection criteria for the agent groups were whether they were employed or not, and whether they occasionally went on long car trips or not. The groups we get capture important differences in the population in terms of:<br>- Baseline travel pattern (PT and car).<br>- Employment and incomes (which determine value of time).<br>- Car ownership, access to parking at home, etc. |
| 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, for both peak and off-peak, and long car trips per year (more information in Appendix A). |
| 4 | Calibrate each agent's utility function using the data from steps 1, 2 and 3. |
| 5 | Check the calibration of the utility functions by simulating the choice of each agent (person-km per day by car and by PT, for both peak and off-peak, and long car trips per year) and cross-check 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 linear approximation of peak and off-peak speeds in the greater Oslo area. |
| 7 | Construct the cost functions for public transport using a linear function with intercept (fixed costs), and an automatic frequency "rule-of-thumb" optimization for peak and off-peak. A similar approach was used by Parry and Small (2009) and Kilani, Proost, and van der Loo (2014). |
| 8 | Construct the crowding cost function for public transport (see Appendix A for more information). |
| 9 | Construct linear cost functions for the non-congestion external costs; air pollution, noise & accidents. Values are given in Table 6 in Appendix A based on Thune-Larsen, Veisten, Rødseth, and Klæboe (2014). |
| 10 | Construct a welfare function to represent equation (4), that consists of the sum of utility for each agent minus user costs for agents (including taxes, tolls, fares and parking charges) minus transfers to government and parking company minus external costs other than congestion minus the operational costs of PT minus the opportunity cost of parking spaces. |

The three aggregate agents go by the names of X, Y and Z. They are categorized by whether they are employed or not (agent Z is not employed), and among the employed whether they go on occasional long trips by car (agent Y does not go on long trips by car). Using this categorization

[10] 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

on the synthetic population of the greater Oslo area, we get agents with characteristics displayed in Table 2.

*Table 2: Key agent characteristics*

| 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 |
| Number of 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 |
| Peak trips car per day | 0.9 | 0.7 | 0.3 |
| Peak km car per day | 10.5 | 7.7 | 2.8 |
| Off Peak trips car per day | 1.0 | 0.7 | 0.7 |
| Off Peak km car per day | 10.4 | 7.8 | 7.0 |
| Peak PT trips per day | 0.29 | 0.43 | 0.14 |
| Peak PT km per day | 4.5 | 6.9 | 2.3 |
| Off Peak PT trips per day | 0.15 | 0.32 | 0.26 |
| Off Peak PT km per day | 3.1 | 4.0 | 4.6 |

Once all the agents' utility functions have been calibrated to fit the observed data, the model is ready for policy analysis. This is done according to the following procedure:

1. **Transport demand:** The model's objective function is to maximize welfare. For a given scenario we specify which of the policy variables (tolls, fares and/or parking charges) that can vary freely to maximize the objective function. In the optimum, the policy variables have driven agents to choose the transport consumption that maximizes social welfare, see eq. (4). The combination of agents and which car type they own is fixed so that we can find the optimal transport market equilibrium for a given combination (in Wangsness et al. (2018) this is done for 20 fixed combinations)
2. **Car choice**: Of the combinations that yield the highest welfare, new simulations are done to ensure that the optimal transport equilibria are incentive compatible. This means that agents may need to be induced to choose the car combination that under optimized transport policies (cf. the paragraph above) yields the highest welfare level. The simulations will find the minimum differences in purchase taxes and VAT between the car types, so that agents, when choosing the car combination that maximizes their own utility, choose the car combination that is socially optimal. We then get the incentive-compatible optimal car ownership and transport market equilibrium.

Compared to Wangsness et al. (2018), the model is extended to include agents' choices regarding home charging, in the case where they end up owning a BEV or a PHEV (hereafter PEV). The demand for electricity from PEV-owners is determined by their travel demand (and other exogenous electricity consumption). In equilibrium, agents adapt so that private marginal transport benefit equals private marginal transport cost. Among these costs we have the electricity expenses (electricity costs, grid tariffs and taxes).

In the model, the demand for capacity (kW) for charging during peak hours, transforms into a need for the local DSO to replace the old transformer with a new one with higher capacity. The added cost stemming from this increase in demand depends on how much more additional capacity is needed, and how prematurely the old transformer is to be replaced. If it is to be replaced anyway since it has reached the end of its technical life, the latter cost component would be zero. The cost of replacing the transformer prematurely is assumed to be equal to the foregone interest income for the years that are left of the transformer's technical life.

As mentioned in section 2.1, the consequences of more PEVs will vary from neighborhood to neighborhood. In our stylized model we only have one representative neighborhood that we expect to represent the average case where more EV charging during peak hours leads to more investments from the DSO. The parameters for the average case can be considered fairly uncertain. The addition of the EV charging module, adds at least two key assumptions about uncertain parameters in the numerical model.

1. How large is the disutility parameter for an PEV-owning agent to charge her car off-peak, i.e. how responsive will she be to peak tariffs?
2. Given the need for new grid capacity, how many years has the investment been moved ahead, i.e., how much of the fixed investment cost can be attributed to the rise in peak power demand from PEV charging?

In order to illustrate the uncertainty and give an idea of the variation in how costly the grid enhancements for accommodating EV home charging can be, we will provide sensitivity analysis for how the results change with changes in these key parameters. The table below shows our baseline assumptions for the model extensions regarding PEV-charging:

*Table 3: Parameter values for baseline assumptions regarding EV-charging and grid costs*

| **Parameter** | **Value** | **Comment/Source** |
|---|---|---|
| Cost of new transformer, fixed component (NOK) | 190 000 | Sidelnikova et al. (2015) |
| Cost of new transformer, per kW capacity (NOK) | 79 | Sidelnikova et al. (2015) |
| Return on capital applied for regulation (%) | 6 | NVE (2018) |
| Expected years of technical lifetime for transformer station | 30 | Sneve, Stene, and Brekke (2005) |
| No. of years premature the average transformer needs to be replaced due to home charging | 0.5 | Discussion meetings with DSOs[11] |
| Marginal disutility parameter $\alpha$ of charging off-peak (NOK per hour), from $\alpha h^o$ (i.e. quadratic disutility function) | 0.15 | Calibrated from a cross-price elasticity of 0.2, which is applied in the LIBEMOD model[12] |
| No. of agents per transformer | 50 | Approx. average for DSO Hafslund Nett in 2018 |
| Charging capacity at home (kW) | 3.6 | Standard for home charging wall box, see e.g., Figenbaum (2018) |

[11] We have had discussion meetings with representatives from the DSOs Ringeriks Kraft AS and Hafslund Nett. They state that unless households install more in-house capacity, they have not experienced having to replace transformers before schedule even with neighborhoods with high EV-shares. The choice of applying 6 months as our base case is a bit arbitrary, but illustrates the low occurrence of early replacement. We decide to dramatically stress test this number to see what happens if replacements happen 10 years ahead of schedule on average.

[12] The cross-price-elasticity parameters are a result of the model calibration. For more information, see https://www.frisch.uio.no/ressurser/LIBEMOD/

The investment cost is transformed to an annuity over the new transformer's life time. This annuity is what the DSO needs to recover through its tariffs. We will model different pricing schemes for the DSO. As shown in the solutions for eq. (1), the consumer adapts so that marginal disutility of charging off-peak equals the difference in electricity price (including taxes and tariffs). With uniform prices between peak and off-peak, the consumer will cover all charging needs during peak hours. If the DSO applies peak tariffs, the consumers will shift some of her charging to off-peak. We end up with an equilibrium with tariffs and quantities charged at peak and off-peak, and transport costs and amounts travelled.

# 5 Scenario description

We use the model for analyzing different scenarios with different policies. The policies can be either fixed or be determined endogenously as a way to achieve a policy objective at least cost. The starting point for the scenarios is the reference situation of 2014. This can be considered an equilibrium before EVs were made available on a large scale. In the travel survey, on which the model agents are based, 98% of the cars are conventional. The policies will take us from the reference equilibrium to a new equilibrium in each policy scenario.

The main policy scenarios are the "Business-As-Usual"-scenario and the "$CO_2$-cap"-scenario. The former scenario is where there is a continuation of the 2014-policies (which were already very friendly towards the purchase and use of EVs), while the latter is where the 50% $CO_2$ target in the Oslo area is binding. These scenarios were analyzed in Wangsness et al. (2018) without any regard for the impact PEV charging may have on the local grid. We will briefly repeat the key insights from those scenarios:

In the BAU-scenario, Agent X (who works and makes occasional long trips) adapted by switching to a PHEV, Agent Y (who works, but makes no long trips) to a short range EV, while Agent Z (who does not work, and makes occasional long trips) stuck to the small ICEV. In sum, this gave us large emissions reductions (64% reduction), but higher transport volumes (2.1% for a constant population). Compared to the reference situation there is a welfare loss due to higher resource costs for cars and more congestion.

In the $CO_2$-cap-scenario, policies are determined so that the target is reached at least cost leading to Agent X switching to a PHEV, Agent Y sticking to a small ICEV, and Agent Z switching to a small EV. The policies are characterized by; 1) higher tolls for all cars, in particular during peak traffic, 2) higher peak fares and lower off-peak fares for PT, 3) higher purchase taxes for ICEVs and 4) no tolls for BEVs driving in rural areas. These policies achieve the $CO_2$-target, but the equilibrium has a lower welfare level than the reference equilibrium. The welfare cost of reaching the $CO_2$-target amounts to 6690 NOK per $tCO_2$.

We revisit these scenarios, but now the impact of EV charging on the local grid is part of the modelling. We run the model for two different pricing schemes the DSO can apply to respond to increased demand for power for EV charging.

- No ability for DSOs to peak price, i.e. the DSO continues with uniform tariffs
- DSOs apply peak tariffs determined by the *marginal* increase in capacity stemming from charging EVs during peak hours, and covers the rest of the costs by a fixed component

# 6 Results

We now present the results from the numerical modeling in a way that answers the research questions stated in section 1. We will also briefly describe the results from the sensitivity analysis, which is documented in Appendix B.

*When we factor in the current uniform grid tariff system, what are the welfare impacts of today's EV policies and polices for reaching $CO_2$-targets at least cost?*

This research question focuses on the pecuniary external cost of EV charging with BAU EV policies when there is an incomplete market for using grid capacity, i.e., uniform tariffs between peak and off-peak hours. As shown in Wangsness et al. (2018), the model simulations conclude that Agent X (working, long trips) switches from ICEV to PHEV and Agent Y (working, no long trips) from ICEV to a small BEV in the BAU-scenario without any concern of grid costs. These agents would then start home-charging their vehicles to cover their daily transport needs by car. Their choice of when to charge is reflected by the relative price between charging during power peak and off-peak hours, and their disutility of charging during off-peak hours. We test the impact of adding this charging behavior under the different pricing schemes the DSO can respond with, described in section 5.

We find that the main features of the BAU-equilibrium remain the same as in Wangsness et al. (2018), even though the charging issues now have been added. Nevertheless, the added grid costs are tangible costs, and not including them overestimates the welfare in the equilibrium. Without any form of pricing of peak power consumption, there will be no incentive for the agents to shift any of their charging to off-peak hours. This spurs investment in transformer capacity that amounts to a welfare cost of 18 mill. NOK (approx. € 2 mill.) per year in the new BAU-equilibrium, compared to an equilibrium where these costs are not taken into account (as in Wangsness et al., 2018). All agents see a reduction in their general disposable income as tariffs increase. In the new BAU-equilibrium, those who drive PEVs get somewhat higher transport costs, and all agents get higher household expenses on their non-car consumption of electricity. The model finds an increase of about 18 NOK (approx. € 2) per agent per year in increased household expenses in non-car electricity due to the increase in uniform tariffs. This is the cost we expect todays EV policies to impose on electricity users is the Oslo area.

The cost increase is a result of some agents' actions, while other agents have not changed their behavior at all: Agents X and Y are driving up their own costs, but they are also imposing costs on Agent Z as tariffs increase. This is a pecuniary external cost in the market for grid capacity, a market that can be considered incomplete as a uniform tariff structure does not give any signal about capacity scarcity and expansion costs. Of the total welfare cost addition of 18 mill. NOK, Agent Z has to bear a brunt of 4 mill. NOK.

We show in Wangsness et al. (2018) that reaching a 50% $CO_2$ reduction target at least cost implies that Agent X switches from ICEV to a PHEV and Agent Z switches from ICEV to a small BEV. Before considering any charging issues, we find a welfare cost of 6690 NOK (approx. € 700 or USD 850) per $tCO_2$ for reaching this $CO_2$-target. Adding these issues in the $CO_2$-target scenario does not change optimal car combinations under policies for reaching the target at least cost. Like in the BAU-scenario, the changes in tariffs amount to so small changes in generalized costs that travel patterns hardly change at all. Consequently, the policy variables in the $CO_2$-target scenario are close to unaffected by introducing charging issues.

With uniform tariffs, the welfare cost increases by 16 mill NOK per year (approx. € 1.75 mill.), translating into an increase of 27 NOK (approx. € 3) per $tCO_2$ (i.e., from 6690 to 6717) in order to reach the ambitious targets. The main results are summarized in Figure 3.

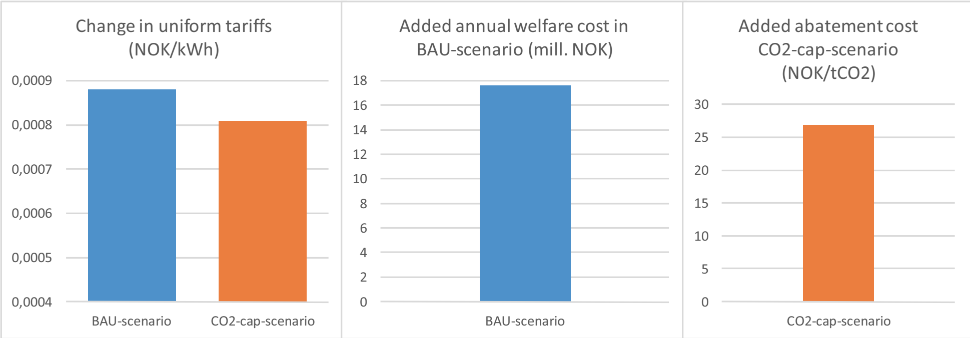


*Figure 3: Main results from simulations with uniform tariffs*

*How can these welfare costs be affected by a better pricing of electricity distribution?*

The welfare cost can be reduced by allowing the DSO to apply peak tariffs. This will cause some shifting of PEV charging to off-peak hours. While this reduces investment costs, it also increases the disutility cost of postponing some charging to off-peak hours. Consider the scheme where the added peak tariff is only determined by the *marginal* increase in capacity stemming from charging PEVs during peak hours, and where the rest of the costs are covered by a fixed component. In this case, the added welfare cost amounts to 12 mill. NOK pear year in the new equilibrium (approx. € 1.3 mill.), lowering the costs by a third compared to the uniform pricing scheme. Now the agents pay approx. 12 NOK more per year in non-car electricity expenses, with a fixed component of about 9 NOK and a 3 NOK increase in expenses due to higher peak tariffs.

It is worth noting that even though the peak tariffs provide a price signal for grid capacity usage, we still get an equilibrium where PEV owners do most of their charging during peak hours. This implies that Agents Z still has to pay more in grid rent over her electricity bill, ceteris paribus, despite not owning an EV. The Agent Z group has to pay more for their non-car electricity consumption during peak hours, which is assumed to be inelastic. One can still consider this a pecuniary externality, but no longer in an incomplete market, as grid scarcity now has a price signal. However, Agent Z still has to pay a higher fixed component for the grid rent. This is a result of the PEV charging actions of the other agents, who still do not have to carry the full cost of their behavior. However, the burden imposed on Agent Z has been reduced to about 2.5 mill. NOK, compared to the case with uniform tariffs.

We also see welfare improvements from applying a better pricing scheme in the $CO_2$-target scenario. When applying peak tariffs only to the marginal capacity expansion induced by EVs and covering the rest with a fixed component, the added welfare cost is 17 NOK per $tCO_2$. This is about 37% less than under uniform pricing. The main results are summarized in Figure 4.

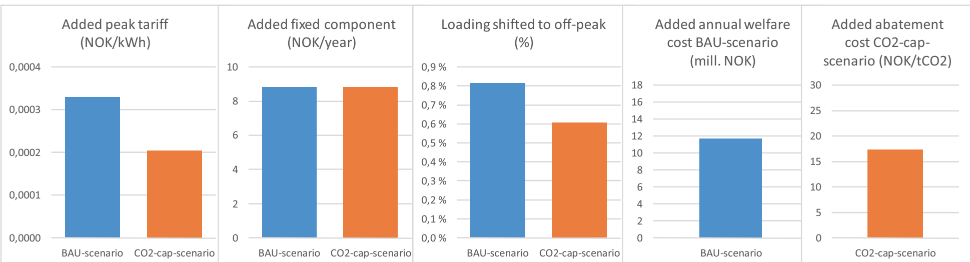


*Figure 4: Main results from simulations with optimal peak tariff*

Under both pricing regimes, the agents' car choices are unaffected compared to the results in Wangsness et al. (2018), and the changes in tariffs never cause more than minor changes (less than 0.1%) in generalized transport costs and subsequently in transport use.

*Sensitivity analysis*

These added welfare costs do not seem so large for an area with a population of 1.2 mill. people. In discussion meetings with the DSOs Ringeriks Kraft AS and Hafslund Nett, we were told that regular home charging has not spurred many new investments that would not have occurred otherwise (unless co-founded by households wanting to increase their own capacity), corroborating this story.

Our base assumption is that DSOs need to replace the transformer on average 6 months ahead of its expected life span of 30 years (a shortening of less than 2%). We conduct sensitivity analysis where we assume the replacement of transformers on average has to be done 10 years ahead of its expected life span and additional 100 000 NOK (approx. € 11 000) needs to be spent on digging and replacing cables between the transformer and the household. This assumption entails far larger investment costs due to PEV charging, and subsequent changes in tariffs and welfare. With the 10-year assumption, the additional welfare cost to the BAU-equilibrium is 304 mill. NOK per year (approx. € 34 mill.) under uniform pricing, compared to an equilibrium where grid costs are not taken into account (as in Wangsness et al., 2018). Further, the added cost is limited to only 193 mill. NOK (approx. € 22 mill.) with peak tariffs for the marginal capacity increase and the rest of the cost covered by a fixed component. This also translates into a higher cost per ton of CO2 abated in the CO2-cap scenario. In Figure 5, we compare the costs of reaching the ambitious climate goals when we disregard the costs to the local grid and when we include the costs to the local grid under the 6 month and 10-year premature replacement assumptions. This will be further discussed in the section 7.

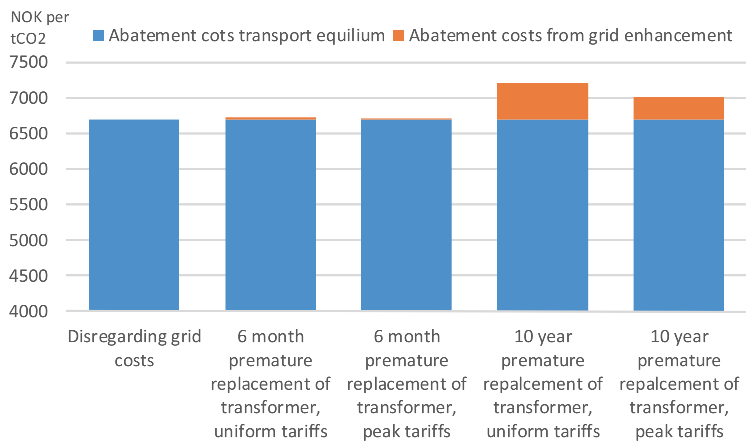


*Figure 5: How grid costs affect the abatement costs of achieving ambitious climate goals under different assumptions*

The disutility function is a highly uncertain part of the model, so we test the impact of doubling the marginal disutility parameter. This will only make a difference where peak tariffs are allowed. Higher marginal disutility of off-peak charging leads to less load shifting under the relevant pricing scheme, thus driving up investment costs in transformer capacity. On the other hand, due to the assumption of a quadratic disutility function from charging in off-peak hours, the low levels of load shifting imply lower absolute disutility costs for PEV owners. The differences in investment costs and disutility costs seem to balance out, so there is hardly any difference in added welfare costs (less than 1 mill NOK per year) compared to the equilibrium under baseline assumptions.

# 7 Discussion and conclusion

We find that as today's policies drive up the PEV-share of the car fleet, they also drive up investment costs in the local grid as old transformers need to be replaced prematurely. Our model finds an equilibrium where the replacement leads to between 12 and 18 NOK (approx. € 1.3 - € 2) in added non-car electricity costs per agent per year, depending on the DSO's pricing scheme.

Are these numbers large or small? We argue that such an increase in expenses is small, and would probably go unnoticed by most households as it represents less than a 0.1% increase in annual electricity costs (including tariffs and taxes) for households with normal consumption between 10 000 and 20 000 kWh per year.

The sensitivity analysis shows that the cost can get substantially higher if old transformers have to be replaced sooner than in the baseline. If the transformers need to be replaced 10 years ahead of their technical life and we assume higher cost for cables, non-car electricity costs per agent increase to between 205 and 310 NOK per year. While this may be a more noticeable expense for consumers, it is still a small number relative to overall electricity expenses, and well within fluctuations in such expenses due to normal year-to-year price fluctuations.

The shift to PEVs is an integral part of reaching the ambitious goals of reducing $CO_2$-emissions by 50% in the greater Oslo area at least cost. We find that adding the charging issues leads to 17-27 NOK in additional costs per $tCO_2e$ under baseline assumptions. Before adding grid capacity costs, the welfare cost of reaching the emissions target amounted to 6690 NOK (about 700 Euro) per $tCO_2$ (Wangsness et al., 2018), so adding the grid costs means 0.3%-0.4% extra cost per $tCO_2$. If the policy makers have committed to the $CO_2$-target and are willing to pay the cost of reaching it, accounting for the grid costs is not going to be very discouraging.

*Caveats*

There are several caveats that are worth mentioning. As discussed in Wangsness et al. (2018), the transport model we use is very stylized with some major simplifications, such as having only five stylized car types and three stylized agent groups. It gives more nuance and insight than single representative cars and agents, but there are still many issues of heterogeneity that go uncaptured. For example, if more heterogeneity is introduced in the users' profiles, the penetration of electric vehicles could be affected more strongly. The added model features in this paper are also quite stylized, with identical neighborhoods with identical investment cost functions for transformers, and with the simplifying assumption of clean-cut differences between peak and off-peak periods.

The model contains many parameters that can be considered fairly uncertain, which is also discussed in Wangsness et al. (2018). The model extension in this paper, accounting for the capacity of the distribution grid, also introduce new uncertain parameters, such as the investment cost function for transformers and the average number of years of premature replacement of transformers. The model is static, so it ignores the dynamics of DSOs over years continuously replacing old infrastructure according to schedule, along with the year-by-year growth in the number of EVs. While the model is consistent with experiences over the last few years and expectations for the next few years, the future developments contain a lot of uncertainty. We do sensitivity analysis to address some of this uncertainty.

Given these caveats we advise that the exact numbers should be interpreted with some caution. However, we believe that this analysis helps understanding the mechanisms within and between the transport and electricity market as transport gets electrified. We also think it provides insights into what can be considered major issues and minor issues when designing optimal transport policy moving forward.

*Concluding remarks*

This paper gives new insights into some of the ways the transport market and electricity market may affect each other when a large part of the car fleet is electrified. We find that the increase in demand for electricity and power from EV owners lead to some increase in grid investment costs and tariffs, but not too large. This corroborates the findings of a recent empirical study on the cost impact of local BEV density on DSO costs (Wangsness & Halse, 2020), although there is significant heterogeneity in these impacts. The cost impacts per BEV is found to be substantially higher for smaller DSOs in rural areas, than for larger DSOs in urban areas, such as the Oslo metropolitan area.

Our results show that the added grid costs do not cause significant changes to the transport market equilibrium. For example, the conclusion that large differences between peak and off-peak tolls and fares are necessary to improve transport market efficiency, remains the same. This was also part of the conclusion from Börjesson, Fung, and Proost (2017), which the model in Wangsness et al. (2018) is an extension of. We find that the increase in grid costs leads to a relatively modest increase in the cost of reaching the Oslo area climate goals. However, the overall abatement costs, which would require a large penetration of EVs in order to be minimized, are many times higher than the Norwegian reference price of $CO_2$. Several studies show that switching to EVs is a fairly costly form of $CO_2$ abatement (Bjertnæs, 2016; Fridstrøm & Østli, 2017). However, these costs are well within the inter-quartile range of costs needed by 2035 in order to stay on a path that curbs emissions in line with the goal of limiting global warming to 1.5ºC (Huppmann et al., 2018), as found in the IPCC report on reaching the 1.5ºC goal (IPCC, 2018).

Furthermore, our paper gives support to the literature that demand management, e.g. through peak grid tariffs, can be beneficial as the EV-owners demand for grid capacity increases (see e.g., Barton et al., 2013; Clement-Nyns et al., 2011; Masoum et al., 2011; O'Connell et al., 2012). That allowing for peak pricing in the electricity sector can improve efficiency, is a common finding in the extensive literature on peak-load pricing (see e.g. Decker, 2014, pp. 83-85 for an overview). As the transport sector gets increasingly electrified, and EV owners prefer charging after coming home from work, i.e., during evening peak hours, peak tariffs can help strike a better balance between investment costs and the EV owners' disutility of charging during off-peak hours. With user-friendly solutions for smart-charging that automatically adjust charging to minimize charging, the differences in peak and off-peak tariffs would not need to be very large in order to get load shifting from EV charging[13]. Within the realms of our model framework, this could be interpreted as a drastic reduction in the disutility[14] of charging off-peak.

From a policy perspective, our findings can be interpreted with cautious optimism. Ambitious climate goals will entail a relatively large shift to PEVs as a cost-minimizing strategy, but there is no way to escape high welfare costs. There will probably be some added abatement cost as local grids needs to be enhanced, but these cost additions can be expected to be relatively small compared to the welfare effects in the market for transport. And these cot additions can also be curbed by introducing a more efficient system for grid tariffs, which Norwegian regulators are working on at the time of writing.

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[13] An example: https://evblog.org/this-ev-charger-saves-up-to-50-on-your-electric-bill/

[14] It is worth noting that there are multiple factors that affect consumers' acceptance of smart charging, and not just monetary aspects (Will & Schuller, 2016).

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# Appendix A: Model details

The cost parameters applied for replacing transformers are taken from the NVE report Sidelnikova et al. (2015). The table below reports the parameter values from that report:

| Rated supply voltage (kV) | Cost for new transformer, capacity independent component (NOK) | Cost for new transformer, capacity dependent component (NOK/kW) |
|---|---:|---:|
| 5-24 | 190 000 | 79 |
| 66 | 1 125 000 | 91 |
| 132 | 2 125 000 | 80 |
| 300 | 6 250 000 | 90 |
| 420 | 8 750 000 | 58 |

*Table 4: Cost parameters for new transformer. Taken from Table 9-4 in Sidelnikova et al. (2015)*

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 public transportation (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 (e.g., to the cabin) , the agents can only choose the number of long trips per year.

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 MPMM23 (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, Fung, and Proost (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 5. Purchase costs and distance-based costs for the different car types are given in Table 6.

*Table 5: 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 |

*Table 6: Car specific parameters for technology, user costs, and externalities, baseline*

| | **ICEV small** | **ICEV large** | **PHEV** | **EV short** | **EV long** |
|---|---|---|---|---|---|
| Purchase price | 273 058 | 503 614 | 456 036 | 263 049 | 720 468 |
| 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[15] | 0 | 0 | 72.7% | 100% | 100% |
| 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 |
| Non-congestion external cost per km in city (NOK) | 0.70 | 0.70 | 0.36 | 0.36 | 0.36 |
| Non-congestion external cost per km far from densely populated areas (NOK) | 0.16 | 0.16 | 0.16 | 0.15 | 0.15 |

[15] For PHEVs we assume that they run on electricity 73% of the time on short trips in the city area, and on fossil fuel when going on long trips.

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 Cost-Benefit Analysis, 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 regards 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 public transport company for Oslo and Akershus, as a linear function 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 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.

# Appendix B: Sensitivity analysis

| Sensitivty analysis | Pricing scheme | Change peak | Change off-peak | Change fixed component (NOK) | EV-charging during peak | Added abatement cost (NOK/t$CO_2$) |
|---|---|---|---|---|---|---|
| Double disutility parameter | Uniform tariffs | 0.0008 | 0.0008 | 0 | 100 % | 27 |
| | Marginal peak tariff and fixed component | 0.0002 | 0.0000 | 9 | 99.8 % | 17 |
| Replace 10 years prematurely | Uniform tariffs | 0.0154 | 0.0154 | 0 | 100 % | 512 |
| | Marginal peak tariff and fixed component | 0.0002 | 0.0000 | 200 | 99.6 % | 320 |
| Double disutility parameter and Replace 10 years prematurely | Uniform tariffs | 0.0154 | 0.0154 | 0 | 100 % | 512 |
| | Marginal peak tariff and fixed component | 0.0002 | 0.0000 | 200 | 99.8 % | 320 |

*Table 7: Main results from sensitivity analysis*

# Chapter 4:
# The impact of electric vehicle density on local grid costs: Empirical evidence from Norway

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# The impact of electric vehicle density on local grid costs: Empirical evidence from Norway

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## Abstract

While a rapid shift towards electric vehicles (EVs) will contribute to reducing carbon emissions from the transport sector, there are concerns that uncoordinated charging of EVs might impose challenges for the local electricity grid. Our study is the first to investigate this empirically in a country-wide analysis, using data from the country with the highest market share of EVs, namely Norway. We present the regulatory framework in which Norwegian grid companies operate and discuss the possible impact of EV charging. Using panel data on 107 grid companies over the period 2008-2017, we then estimate the effect of local growth in EVs on local grid costs. We find that increases in EV stock are associated with increases in costs which are both statistically and economically significant. However, there is a lot of heterogeneity in these results, where the effect on grid costs are higher for small grid companies in rural areas.

Keywords: Electric vehicles, Distribution System Operators, local grid costs, local grid capacity, fixed effects regression, peak power tariffs

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# 1 Introduction

Do electric vehicle (EV) owners impose a negative externality on other electricity consumers when they plug in their cars at home during peak hours for electricity? In the absence of any peak pricing scheme, if the high power consumption of EVs leads to higher local grid costs, the resulting increase in uniform grid tariffs will be shared among all customers. Simulation exercises suggest that uncoordinated EV charging might have an impact on the local grid (see e.g., De Hoog, Alpcan, Brazil, Thomas, & Mareels, 2015; Masoum, Deilami, Moses, Masoum, & Abu-Siada, 2011), but the empirical evidence is scarce. What can we learn from actual data in the country with the highest EV share, namely Norway?

The high EV share must be viewed as a result of national climate policy, which aims to fulfill Norway's part of the Paris agreement. Norway has a goal of ensuring that all new passenger cars are zero emission vehicles by 2025. Incentives like low vehicle taxes, toll road exemptions, and access to bus lanes has resulted in the highest penetration of EVs worldwide. By January 2020, there were about 260 000 battery electric vehicles (BEVs) and 115 000 plug-in hybrids (PHEVs) in Norway, a country with only 5.3 million inhabitants. In 2019, BEVs accounted for 42 percent and PHEVs for 14 percent of all new vehicles (Norwegian Electric Vehicle Association, 2020).

The Norwegian Water Resources and Energy Directorate (NVE) presents a scenario where the growth in BEVs in Norway continues and reaches 100 % of the new car sales after 2025. This implies 1.5 million BEVs in Norway in 2030, resulting in a 3 % increase in domestic electricity consumption (Skotland, Eggum, & Spilde, 2016). So even with rapid electrification of passenger transport, we can expect aggregate electricity generation to cope without major challenges.

However, while a BEV's energy consumption may be modest, its power usage could be quite high. Currently, power demand per electricity consuming unit in a household usually varies from 2.3 to 7.3 kW. Skotland et al. (2016) find through a survey that most BEV owners do their daily charging at home (almost 90 %). Charging at work or at public charging stations seems at this point to be mainly supplemental. NVE's review indicates that most BEV owners start their charging late in the evening and cover most of their charging needs during night hours, while some start charging their vehicle immediately after work, which is a peak period for electricity consumption.

Uncoordinated charging (or "dumb charging") will increase electricity consumption during the morning and evening peaks (Graabak, Wu, Warland, & Liu, 2016). De Hoog et al. (2015) point out that if EV charging is not controlled, adverse impacts on the distribution network are expected: power demand may exceed distribution transformer ratings; line current may exceed line ratings; phase unbalance may lead to excessive current in the neutral line; and voltages at customers' points of connection may fall outside required levels. A similar point is made by Neaimeh et al. (2015). Skotland et al. (2016) develop a stress-test for neighborhoods with high BEV density. If 70 % of the residents charge their BEVs simultaneously during peak hours, they find that power demand can increase by up to 5 kW per household. This results in overload for more than 30 % of the transformer stations currently servicing the distribution network.

Our motivation for this paper is as follows: The number of BEVs is growing fast, and there exists a literature that warns that BEV charging will cause substantial future costs to the local grid unless measures are put in place. If indeed the aggregate uncoordinated charging from BEV owners does induce higher costs to local grid companies (Distribution System Operators - DSOs), then Norwegian data would be the first place to investigate. Detailed data of all Norwegian DSOs and all registered BEVs during the last ten years gives a unique opportunity to analyze this relationship. To our knowledge, such an empirical analysis has not been done before on real data in a country-wide analysis. It will therefore push the knowledge frontier on a debated, but relatively unexplored topic empirically. Findings may have implications for how to regulate DSOs, how to price household power usage and how to assess the net social cost of achieving emission reduction targets through promoting EVs.

This paper complements previous studies that look at the effects that BEVS and PHEVs can have on the electricity market. Our analysis covers a relatively long time-period of real experiences with increasing BEV density (over 10 % of the car fleet in some areas), while most of the relevant literature up until now have been simulation exercises in numerical models of local grids. Hattam and Greetham (2017) analyze how EVs affect load profiles on neighborhood level in low voltage networks. Azadfar, Sreeram, and Harries (2015) look at charging behavior in terms of time of day, duration, frequency and electricity consumption in light of its implication for electricity network management. Barton et al. (2013) look at the challenges for grid balancing when EV charging becomes more prominent, and stress the importance of demand side management with time-shifting of electricity loads from periods of peak demand to off-peak, and from periods of low renewable energy supply to periods of high supply.

Other studies also argue for demand side management (see e.g., Haidar, Muttaqi, & Sutanto, 2014; Masoum et al., 2011) as an alternative to costly upgrades of distribution transformer stations. Some of these studies also argue for pricing schemes that disincentivize charging during peak hours (see e.g., Barton et al., 2013; Clement-Nyns, Haesen, & Driesen, 2011; Masoum et al., 2011; O'Connell et al., 2012). In the future, smart-charging technology and vehicle-to-grid[2] (V2G) and vehicle-to-building (V2B) solutions may also provide a means to mitigate capacity problems in both electricity generation and distribution (Barton et al., 2013; Clement-Nyns et al., 2011; Mwasilu, Justo, Kim, Do, & Jung, 2014; Sioshansi & Denholm, 2010), but bidirectional EV charging is in its infancy (Haidar et al., 2014), and seems to come at a relatively high cost due to increased battery degradation, energy losses, changes in infrastructure, and extra communication between EVs and the grid (Habib, Kamran, & Rashid, 2015).

Exploiting local differences in the growth of the BEV fleet over time, we investigate how an increase in the number of BEVs affects the costs of the local DSO. We look at both total costs and individual cost components. We analyze data on 107 DSOs over the period 2008-2017 using fixed-effects estimation that account for time-invariant characteristics of the DSO. We also control for growth in output indicators that could be correlated with growth in the BEV fleet.

[2] V2G involves using EVs as storage for electricity.

The main finding is that increases in the BEV fleet are associated with positive and statistically significant increases in costs when controlling for other DSO outputs and year dummies. The point estimates also imply that the effect is economically significant. However, there is a lot of heterogeneity in these results, where the marginal cost estimates are a lot higher for small DSOs in rural areas, and a lot lower for larger DSOs in urban areas.

Section 2 presents the regulatory setting for local grid operators in Norway, and why the growth in BEVs may exacerbate existing market failures. Section 3 presents the methods and data. In section 4 we present the results from our empirical analysis. Section 5 discusses the results and concludes.

# 2 EVs and Norwegian DSO regulation

Norwegian DSOs are regulated under a revenue cap model with benchmark (or yardstick) competition against other DSOs (see e.g., Decker, 2014, pp. 103-140), where they set their tariffs based on this revenue cap. The revenue cap is composed of 40 % cost recovery and 60 % cost norm based on benchmark modeling using data envelopment analysis (DEA) (NVE, 2015). This means that an increase in costs increases the revenue cap, which allows the DSO to raise its tariffs. However, the revenue cap, and therefore the tariffs, are constrained by the cost development of the other DSOs that comprise the benchmark competition.

Still, at least some of the increase in capital cost will eventually lead to higher tariffs, and these will have to be paid by all consumers connected to the local grid, and not just the households demanding more capacity. It can be viewed as a pecuniary external cost in an incomplete market (Greenwald & Stiglitz, 1986). That is, the households demanding more capacity do not face the full cost of the capacity expansion, and indirectly impose costs on other consumers.

We describe the mechanisms for how an increased number of BEVs may lead to higher costs to DSOs and subsequently to higher grid tariffs through the following steps:

1. The BEV share increases in a neighborhood.
2. Households will charge their BEVs at 3.6-7.2 kW, and the demand for power capacity will increase.
3. With a certain size of the BEV share and a certain share of the owners charging simultaneously, the existing distribution transformer and/or the cables between the transformer and the household will not be able to handle the power capacity demand at certain times of day, certain times of year. This may lead to more inspection and maintenance before new investments need to be made.
4. The DSO invests in capacity expansion in the local grid. The cost of such capacity expansion will depend on whether enhancements need to be done for the transformer and/or the cables, the amount of transformer capacity that needs to be installed, whether the new transformer fits in the old box that contained the old transformer, and the costs of digging.
    - The new investment increases the capital stock for the DSO.

5. Regulation then says that the DSO can charge higher grid tariffs to cover costs (subtracted any co-funding of upgraded infrastructure from consumers).
   - All of the DSO's customers have to pay the higher tariffs.

Currently, individual households do not have any incentive to avoid charging at peak hours[3]. Both electricity prices and grid tariffs are the same throughout the day. And there are many arguments for why BEV owners would want to charge the car right away after coming home. First, it is convenient. They can plug in, and there is no need to spend mental capacity on timing. Second, they maximize the probability of always having the battery charged for any activity later; planned, spontaneous or emergency.

DSOs' profitability is determined by their costs and their regulated revenue cap. If policies drive up BEV ownership and subsequently capacity demand, their costs will increase, most likely without a corresponding increase in the revenue cap. Since "local BEV stock" is currently not a variable in the benchmark competition analysis, the cost norm calculation will disfavor DSOs that face increased capacity demand from BEV users. A DSO facing such increases in power demand, will see BEV-favoring policies as a threat to their profitability. An exception would be a DSO that already is among the most productive and remains among them in spite of the increase in capacity demand from BEV owners. Such a company would set the cost norm, and will be able to pass the entire cost increase on to consumers. If then the cost norm is expanded, DSOs who are *not* exposed to higher capacity demand from BEV owners will get a larger revenue cap, but no extra costs.

If capacity demand from BEV owners becomes a major cost driver for DSOs, there are at least two measures the regulator can take. The first is to incorporate a measure of "local EV stock" in their benchmarking model for calculating the cost norm for the sector, so that the relatively low costs for DSOs with low BEV density are not mistaken for efficiency. The second is to allow for peak power tariffs. NVE argues that the introduction of power-based tariffs will provide incentives to shift charging outside peak-hours. An official proposal has been drafted and is currently (first half of 2020) out on a public hearing[4]. Power-based tariffs have become technologically feasible after January 1st 2019, when smart meters became compulsory for all Norwegian households. This will enable households to closely monitor their temporal consumption profile of electricity, and both distribution grid companies and electricity retailers to bill accordingly.

# 3 Methods and data

## 3.1 Model concept

The main objective of our empirical analysis is to identify the effect that changes in the BEV stock has on DSO costs. Parts of the data that we use to analyze this is the very same data that NVE uses for regulation by calculating the annual revenue cap for

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[3] Some DSOs are experimenting with hour-by-hour pricing experiments, where participating households will be informed about and charged according to hour-by-hour prices

[4] http://publikasjoner.nve.no/rme_hoeringsdokument/2020/rme_hoeringsdokument2020_01.pdf [in Norwegian - last accessed 13.05.2020].

DSOs. The main outcome variable for our analysis is the DSOs annual total costs (*tot_cost*) as this is the main basis for calculating the revenue cap. The total costs are the sum of operational costs (*opex*), capital costs (*cap_cost*), depreciation costs (*dep_cost*), CENS - cost of energy not supplied (*cens*) and cost of energy network losses (*eloss_cost*).

In the benchmarking competition DSOs performance is measured by the output variables number of subscribers (*subscribers*), number of transformer substations (*substations*) and kilometers of high voltage grid, including overhead lines, underground cables and subsea cables (*voltline*).

In the regulatory DEA calculations, NVE controls for a set of contextual factors that can be seen as external cost-driving factors. This is in order not to mistake a difficult operating climate for some DSOs for inefficiency. All of the contextual variables are assumed to be time-invariant in NVE's analysis. The applied variables are displayed in Figure 1. In the model below, all these variables are covered by the vector $X_i$.

To summarize, in NVE revenue cap calculation the DSO costs are assumed to be driven by three output measures and external cost-driving factors. In our analysis, we want to investigate whether the registered number of BEVs in their operational area is an external cost driving factor that currently is not accounted for. Figure 1 gives an illustration of how we expect the relationship between the variables to be.

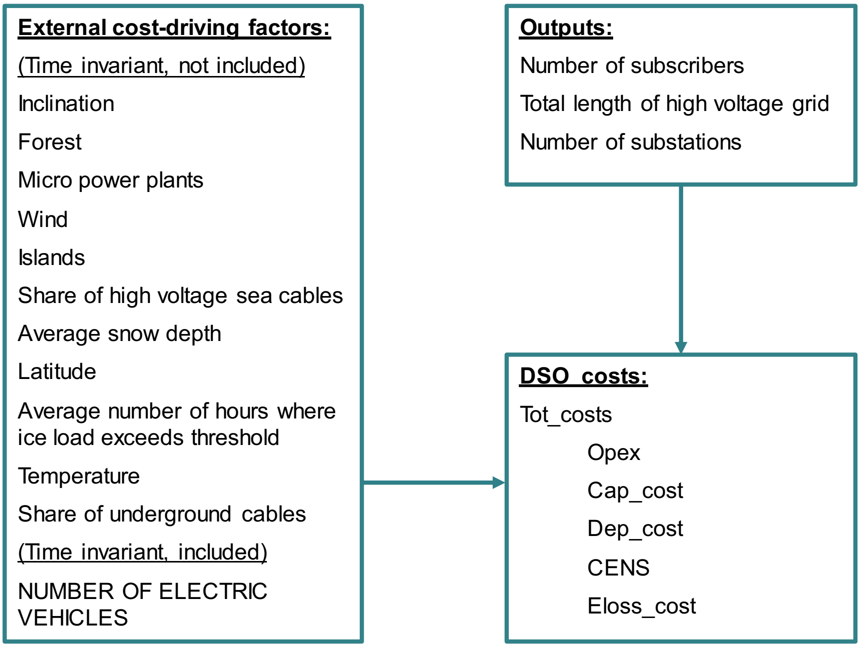


*Figure 1: Direction of impacts from outputs and external cost-driving factors to costs*

Due to substantial skewness in the distribution of DSO costs (see Table 1), we transform the model into a log-log format. Conceptually, our economic model looks like the following:

$$tot\_cost = ASubscribers_{it}^{\beta_1} Voltline_{it}^{\beta_2} Substations_{it}^{\beta_3} BEV_{it}^{\beta_4} X_i^{\gamma} \tag{1}$$

When we do a log-log transformation, we get:

$$\begin{aligned} log(tot\_cost) = \alpha + \beta_1 log(subscribers_{it}) + \beta_2 log(voltline_{it}) \\ + \beta_3 log(substations_{it}) + \beta_4 log(BEV_{it}) + \gamma log(X_i) \end{aligned} \tag{2}$$

Here, $\alpha = \ln(A)$ and the beta coefficients can be interpreted as cost elasticities. We expect them all to be positive. A beta coefficient value of 1 implies a constant marginal costs in absolute terms from an increase of a given variable, whereas values above 1 implies increasing marginal costs. Beta values between 0 and 1 implies decreasing marginal costs for a given variable. Our default assumption is that these elasticities are constant, but we will in section 4 investigate whether the beta coefficients could depend on the level of the explanatory variable, e.g., $\beta_1 = \beta_{10} + \beta_{11} log(subscribers)$, by adding squared transformations of the variable.

## 3.2 Data and variables

We have combined 3 datasets. 1) NVE's data for DSO costs and outputs applied for regulation, with 2) NVE's data for the DSOs legal operational area, with 3) municipalities, which finally can be merged with Statistics Norway's (SSB) data on registered cars at municipal level.

**NVE's data for DSO costs and outputs applied for regulation**

The data is extracted by running an R-script according to instructions from NVE's web pages (NVE, 2017). The data consists of cost measures and other characteristics of 134 grid companies operating in either the local grid or the regional grid. Our analysis will only focus on the local grid, with a dataset consisting of all DSOs that distribute electricity to households, as these are the ones that may be affected by home charging of EVs. That leaves us with 107 DSOs in total.

Following NVE's instructions, operational costs are adjusted to reflect 2015-prices using the consumer price index for the service sector. CENS is adjusted to reflect 2015 prices using the consumer price index. Annual capital costs (or the regulator-allowed return on invested capital) are calculated by multiplying the value of the regulatory assets (*regulat_assets*), which is the value of the total capital stock excluding co-paid assets (*co-paid_assets* – which customers pay for themselves), with the NVE-calculated regulatory interest rate for each year. The contextual variables mentioned in the previous section also follows with this dataset. Since all the contextual variables in vector $X_i$ are time-invariant, they drop out of the fixed effects regressions in this paper.

**NVE's data for the DSOs legal operational area**

NVE's hydrology department have given us access to data on DSOs' legal operational area and matched this with municipalities. In total 149 companies have areas for grid operation. Using the organizational number as a unique identifier, we can merge together cost data and operational area data.[5]

**Statistics Norway's data over registered cars at municipal level**

The StatBank of SSB contains data on registered cars at municipal level categorized by fuel type. We have extracted the number of electric passenger cars for each of the years 2008-2017 for all Norwegian municipalities. We have then merged this with the rest of the dataset.

Not all municipalities and DSO operational areas match one-to-one. Where a municipality has its area covered by more than one DSO, it is assumed that the DSO's share of the municipality reflects the share of households in the municipality and subsequently the share of EVs. Arguably, this introduces some measurement error into the data, but we expect this error to be small, as 90 % of the municipalities have 95 % or more of their area covered by a single DSO. This means that observed EVs at municipal level are aggregated up to DSO level and weighted by area to the variable we call *BEVs*.

**The variables**

For this analysis we will conduct separate regressions with the different dependent variables; *tot_cost* and its sub-components *opex*, *cap_cost*, *dep_cost*, *cens*, and *eloss_cost*. Descriptive statistics of these variables are given in Table 1.

The independent variables will be the DSO output variables *subscribers*, *substations,* and *voltline* and our main variable of interest *BEVs*. We expect the coefficients for the three DSO output variables to be positive for total costs and all the sub-components, as more output should *ceteris paribus* drive up costs.

We exclude the variable *substations* as there could be cases where DSOs would build more substations to meet local capacity demand increases stemming from BEV charging. In such cases, the variable s*ubstations* could be considered what Angrist and Pischke (2008) call a "bad control". When bad controls are applied the coefficient estimates of the independent variables will be biased and lose their causal interpretation. It is not clear whether we should expect increases in EVs to drive increases in the number of substations (as it probably would be more common to reinforce existing ones). However, in order to stay on the safe side, we only include the variable *substations* in robustness checks with alternative specifications (we find out that including this variable has little or no impact on the estimates of interest).

A linear model in absolute terms would give the easiest interpretation. Then, the interpretation would be "For every new BEV registered among the customers of the DSO, we can expect a $\beta_{EV}$ NOK increase in the DSO's cost, *ceteris paribus*". However, the cost variables have very high numbers for skewness and kurtosis (see Table 1), making it less suited for OLS. This is not surprising given that the Norwegian DSO sector consists of many small operators and a few very large ones. Transforming the main cost variable to a cost-per-customer variable, or taking the logarithm gets it closer

[5] These two data sets have also been combined in Orea, Álvarez, and Jamasb (2018) for the purpose of efficiency analysis using a spatial econometric approach.

to a normal distribution. The log-transformed cost variable is somewhat closer to a normal distribution compared to the per-customer transformation. This can be seen in the two bottom rows of Table 1. We therefore proceed with the log-log[6] model in this paper, and use a per-customer model as a robustness check (see Appendix A).

*Table 1: Descriptive statistics*

| | *Mean* | *1st percentile* | *Median* | *99th percentile* | *Skewness* | *Kurtosis* |
|---|---|---|---|---|---|---|
| *Tot_cost* | 120 048 | 7 652 | 42 935 | 909 365 | 5.05 | 35.39 |
| *Opex* | 62 234 | 4 445 | 24 281 | 415 189 | 5.78 | 45.90 |
| *Cap_cost* | 20 433 | 809 | 6 361 | 207 649 | 4.29 | 25.46 |
| *Dep_cost* | 21 733 | 816 | 7 231 | 217 133 | 4.04 | 22.44 |
| *CENS* | 4 861 | 61 | 1 271 | 58 898 | 4.02 | 21.65 |
| *Eloss_cost* | 10 786 | 342 | 2 928 | 89 277 | 6.74 | 58.96 |
| *Subscribers* | 26 980 | 999 | 6957 | 208 411 | 6.57 | 54.79 |
| *Voltline* | 932 | 51 | 339 | 7138 | 3.87 | 21.16 |
| *Substations* | 1177 | 59 | 377 | 10 626 | 4.47 | 27.38 |
| *BEVs* | 367 | 0 | 6 | 7900 | 14.98 | 276.80 |
| *Tot_cost_per subscriber* | 6.53 | 3.10 | 6.29 | 12.90 | 0.96 | 4.41 |
| *Ln_tot_cost* | 10.86 | 8.94 | 10.66 | 13.72 | 0.83 | 3.66 |

Note: Cost figures in 1000 NOK. All costs are in 2015-prices. N = 1070 (107 DSOs over 10 years; 2008-2017).

With a log-transformations of the model, along with the included variables gives us the following preferred model specification:

$$\begin{aligned} log(tot\_cost) &= \alpha + \beta_1 log(subscribers_{it}) + \beta_2 log(voltline_{it}) \\ &+ \beta_4 log(BEV_{it}) + \delta_t + \lambda_i + \varepsilon_{it} \end{aligned} \tag{3}$$

This equation includes DSO fixed effects $\lambda_i$, year dummies $\delta_t$ and the random error term $\varepsilon_{it}$. As discussed above, time-invariant contextual variables ($X_i$) drop out of our fixed effects analysis, and *substations* is not included because it is considered a bad control.

## 3.3 Fixed effects regression

In this paper we conduct a panel data analysis using a fixed effects regression model on a panel with annual data for 107 DSOs over the time period 2008-2017. This gives us a balanced panel containing in total 1070 observations.

The goal is to investigate how the time varying explanatory variable *BEVs* influence the time-dependent endogenous variable *tot_cost*. A good way to do this is applying

[6] For variables for which some values are zero for some DSOs in some years, we add a constant of 1 (e.g. *log_ev* = log(*BEVs+1*)).

fixed effects regression, as the fixed effects will capture all time-constant variation, both time-invariant explanatory variables and unmeasured time-invariant variables (Mehmetoglu & Jakobsen, 2016, pp. 241-242). There has been large variation in when and where the growth in BEVs has taken place, making it a suitable candidate for such analysis. In 2008, more than 25 % of the DSOs had zero BEVs registered in their area, which grew to between 1 and 625 by 2017. On the other end of the spectrum, the single DSO with over a 1000 BEVs in 2008 saw the BEV stock grow to over 55 000 in 2017. To illustrate this variation in status and growth, we show the distribution of BEVs in 2008 and 2017 in Figure 2. Because of the large differences in scale, we display these differences in status and growth of BEVs across DSOs in the form of BEVs per subscriber.

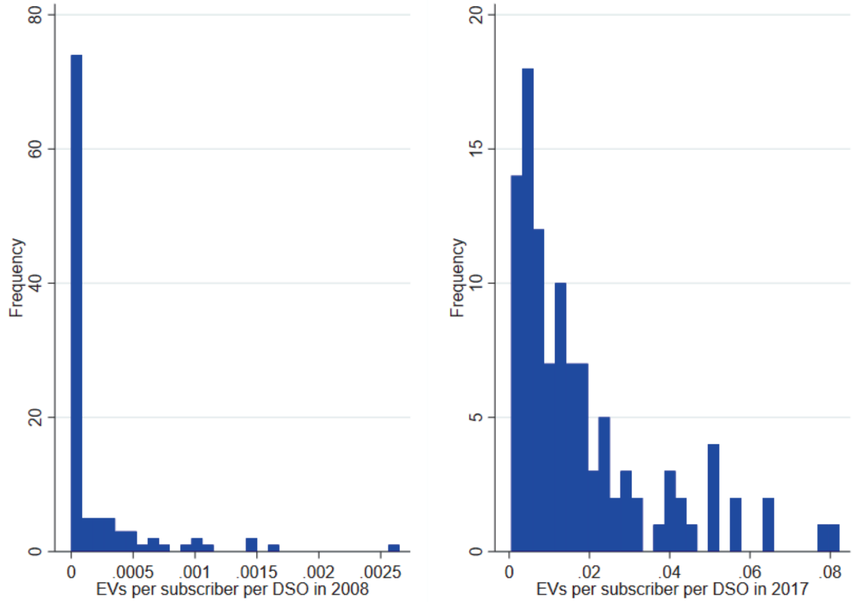


*Figure 2: Large variation in BEV numbers across DSOs and over time*

The fixed effects model will capture the variation from the time-invariant variables that NVE uses for regulation, some of which may have a relatively strong correlation with the number of BEVs. Most notably are perhaps *Latitude*, which we expect is negatively correlated with the number of BEVs as most of BEVs are registered in the southern half of Norway, and *Temperature*, which we expect is positively correlated with the number of BEVs as colder winters have a negative impact on the range of the BEVs (Figenbaum & Weber, 2017). In addition, there are *unmeasured* time-invariant variables that we expect to have an effect on both our explanatory variable of interest and the endogenous variable, so controlling for it in the fixed effects model reduces the problem of omitted variable bias. An example of this could be distances between populated areas within a DSO's operational area, i.e. how sprawled people live. This can be expected to drive up DSO costs (need for more infrastructure per customer) and drive down BEV demand as such distances would indicate a need for driving range that would make most BEVs less favorable.

As for the question of reverse causality, there are *a priori* reasons to believe that this is unlikely. As we discussed in the previous section we expect higher BEV density to drive up the cost for DSOs, but even if higher costs for DSOs would lead higher tariffs for their customers, dramatic price hikes would be needed to make noticeable changes in EV demand. In the calculations in Wangsness (2018), the cost of electricity comprises about 15 % of the distance-based cost for EVs. And grid rent makes up less than half of the total electricity bill before taxes. And it is not certain that the DSO can pass on all of their cost increase to their customers, as they are regulated by a revenue cap based on yardstick competition with other DSOs. In other words, we expect BEVs to affect grid costs, and have very little feedback the other way around.

# 4 Results

Table 2 shows the effect of the size of the local BEV fleet on the total cost of the DSO, based on six different specifications. Table 4 presents estimates for each of the cost components. All of the models use robust standard errors clustered at DSO level, acknowledging that even though observations are assumed to be independent across DSOs, there could be correlation between yearly observations for the same DSO.

**Main results**

*Table 2: Fixed effects regression on the relationship between BEV stock (log_ev) in a DSOs operational area and DSO costs (log_tot)*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| log_ev | $0.013^{***}$ | 0.011 | $0.018^{**}$ | $0.019^{**}$ | $0.014^{*}$ | $0.019^{**}$ |
| | (0.004) | (0.007) | (0.008) | (0.009) | (0.008) | (0.008) |
| log_subscribe | $0.383^{**}$ | 0.326 | 0.967 | 0.840 | 0.534 | 1.154 |
| | (0.193) | (0.245) | (0.917) | (1.117) | (1.049) | (1.001) |
| log_voltline | $0.291^{**}$ | $0.280^{*}$ | $1.698^{***}$ | $1.706^{***}$ | $1.526^{**}$ | $1.539^{**}$ |
| | (0.147) | (0.146) | (0.628) | (0.635) | (0.713) | (0.726) |
| log_subscribe2 | | | -0.036 | -0.029 | -0.019 | -0.047 |
| | | | (0.049) | (0.061) | (0.060) | (0.052) |
| log_voltline2 | | | $-0.131^{**}$ | $-0.132^{**}$ | $-0.114^{*}$ | $-0.118^{*}$ |
| | | | (0.058) | (0.059) | (0.067) | (0.065) |
| log_ev2 | | | | -0.000 | | |
| | | | | (0.001) | | |
| _cons | $5.594^{***}$ | $6.173^{***}$ | -0.197 | 0.283 | 2.595 | -0.546 |
| | (1.616) | (2.217) | (4.310) | (4.908) | (4.392) | (4.558) |
| Year dummies | No | Yes | Yes | Yes | Yes | Yes |
| Removed outliers | No | No | No | No | Removed 3 largest DSOs | Removed 3 smallest DSOs |
| *N* | 1070 | 1070 | 1070 | 1070 | 1040 | 1040 |
| r2_within | 0.200 | 0.276 | 0.291 | 0.291 | 0.299 | 0.289 |

Standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

In the first column we report the results where we only control for the size of the customer base and kilometers of high voltage line. The estimated effect of *log_ev* is positive, as expected, and significant at the 1 % level. This is the naivest regression model where we do not control for any time effects. We provide more controls by adding year dummies in column 2. The estimated coefficient for *log_ev* is similar to that in column 1, but is statistically insignificant.

The coefficient becomes significant in column 3, where we add the squared terms *log_subscribe2* and *log_voltline2* as controls. There is a good theoretical argument for testing whether these cost elements display declining cost elasticities, as DSOs are expected to show increasing returns to scale. After all, they are regulated as natural monopolies. As expected, the squared terms are negative. There is some correlation between the growth in BEVs and growth in high voltage line and customers, probably because the growth in the BEV stock has been highest in cities, that have the largest DSOs with the largest customer base and network of high voltage line. When we control for the increasing returns to scale for network and customers, we are better able to isolate the cost impact from BEVs. We also improve the explanatory power of the model (larger within $R^2$).

In column 4 we use the same model as in column 3, but we add the squared term *log_ev2* to see if the cost elasticity for BEVs change significantly with changes in BEV stock. The estimated coefficient for *log_ev2* is negative but close to zero, and highly insignificant. The size and precision of the coefficient for *log_ev* does not change much. We therefore proceed with column 3 as our preferred specification.

Finally, in column 5 and 6 we test if the preferred model is robust to the removal of outliers. In the former column we have removed the three largest DSOs in terms of annual costs during the period 2008-2017. In the latter column we have removed the three smallest DSOs in terms of costs. In the former column the coefficient becomes somewhat smaller and less precise. In the latter column both the point estimate and standard error remains largely unchanged. The confidence intervals for the coefficient in these models largely overlap both each other and the original model, implying that the original model is relatively robust to removal of outliers.

The point estimates from our preferred specification indicates that a 1 % increase in the number of BEVs in a DSOs area is associated with a 0.018 % increase in cost. In order to translate this into monetary value, we look at the median values for DSOs in 2017. The median values were 44 mill. NOK (about €4.4 mill.) in total costs for about 7300 customers with in total 78 registered BEVs. If this DSO experienced a 10 % increase in BEVs in 2018 (8 cars), *ceteris paribus*, the model would predict about 80 000 NOK increase in costs. This would translate into a cost of about 10 000 NOK per BEV imposed on the DSO, which can be considered economically significant. However, if these estimates are applied to the DSO with the highest BEV stock in its area, the cost per BEV is about 600 NOK. Such scale effects follow naturally from a log-log model with a coefficient between zero and one, as this implies a positive but declining marginal cost per BEV in absolute terms. However, a constant cost elasticity is a fairly strong assumption. We therefore investigate the heterogeneity in the effect from BEVs in different parts of the sample.

**Heterogeneity**

As the example above illustrates, there is substantial heterogeneity among the DSOs. We will use the regressors from column 3 when investigating the heterogeneity in the results, which is shown in Table 3.

*Table 3: Fixed effects regression on the relationship between BEV stock (log_ev) in a DSOs operational area and DSO costs (log_tot). Heterogeneity test with sample splits along 3 dimensions*

| | (1) (lower half customers) | (2) (upper half customers) | (3) (lower half BEV density) | (4) (upper half BEV density) | (5) (lower half costs per customer) | (6) (upper half costs per customer) |
|---|---|---|---|---|---|---|
| log_ev | 0.036*** | 0.005 | 0.032** | 0.008 | 0.015 | 0.032*** |
| | (0.012) | (0.009) | (0.014) | (0.011) | (0.009) | (0.011) |
| log_subscribe | 0.408 | 2.576 | 0.445 | 2.333** | 0.011 | 1.779 |
| | (2.247) | (1.729) | (1.882) | (0.965) | (1.093) | (1.877) |
| log_voltline | 1.111 | -0.628 | 1.920** | 0.798 | 2.049 | 1.086 |
| | (1.075) | (2.207) | (0.930) | (0.913) | (1.424) | (0.987) |
| log_subscribe2 | -0.002 | -0.104 | -0.018 | -0.086* | 0.018 | -0.078 |
| | (0.140) | (0.084) | (0.112) | (0.050) | (0.056) | (0.113) |
| log_voltline2 | -0.067 | 0.022 | -0.135 | -0.077 | -0.166 | -0.072 |
| | (0.104) | (0.154) | (0.092) | (0.082) | (0.108) | (0.096) |
| _cons | 2.828 | -0.279 | 1.399 | -4.839 | 3.287 | -2.775 |
| | (8.477) | (8.117) | (7.096) | (4.843) | (5.977) | (6.676) |
| Year dummies | Yes | Yes | Yes | Yes | Yes | Yes |
| *N* | 540 | 530 | 540 | 530 | 540 | 530 |
| r2_within | 0.315 | 0.314 | 0.287 | 0.333 | 0.264 | 0.343 |

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In Table 3 we show split-sample heterogeneity[7] in the regression results along the following dimensions; DSO size as measured by the number of customers, BEV density in DSO areas (average over the period of analysis) and cost per customer. We see that there is considerable heterogeneity in the results. The effect of BEV stock on cost seems to vary considerably between different parts of the sample, underlying our point earlier that a constant elasticity is a fairly strong assumption. If anything, the cost elasticity for accommodating BEVs seems to be declining.

We find effects of BEVs on cost that are statistically significant and with point estimates almost twice as large in the sample halves with the fewest customers, lowest BEV density and highest cost per customer, compared to the full sample. The strongest effect is found in the sample half with lower-than-median number of customers. However, it is worth noting that these 54 DSOs serve less than 7 % of the total customers in the sample.

[7] We split the sample at the median at any chosen dimension (customers, BEV density etc.) in order to investigate split-sample heterogeneity with the largest possible sub-samples. When we tested splitting the sample in three, we got very imprecise results.

In the other halves of the sample the estimated coefficient are closer to zero and far form statistically significant. This could indicate that at the levels observed until now, the cost elasticity for accommodating BEVs may be declining rather than constant. Since a constant elasticity between zero and one already implies decreasing marginal costs in absolute terms, a declining elasticity implies that the marginal cost decreases even faster as the BEV stock increases.

Another possibility which has been mentioned in conversations with representatives from DSOs may complement the explanation that it is costlier for small, rural DSOs to accommodate BEVs. It could be costlier to accommodate BEVs in some rural areas where the need for investing in high capacity in all parts of the distribution grid has historically been relatively low. In such areas, if there is a need to upgrade parts of the old high voltage network or a distribution transformer to accommodate a few dozen BEVs, it may be a noticeable increase in total costs. We will look closer at this in the last part of this section.

**Regressions for cost components**

In Table 4 we investigate through which cost components BEVs contribute to higher costs. The first five columns show the major cost components sorted from left to right according to their relative importance for total costs.

*Table 4: Fixed effects regression on the relationship between the number of BEVs registered in a DSOs operational area and 5 different cost components*

| | (1) log_opex | (2) log_cap | (3) log_cens | (4) log _depres | (5) log_eloss_cost |
|---|---|---|---|---|---|
| log_ev | 0.020* | 0.011 | 0.024 | 0.017 | -0.026* |
| | (0.011) | (0.012) | (0.032) | (0.013) | (0.015) |
| log_subscribe | 2.790** | -0.216 | -2.184 | 0.294 | 2.261 |
| | (1.303) | (1.226) | (3.497) | (1.399) | (1.699) |
| log_subscribe2 | -0.138** | 0.022 | 0.137 | -0.009 | -0.058 |
| | (0.065) | (0.064) | (0.170) | (0.076) | (0.086) |
| log_voltline | 2.101** | 0.044 | 6.063** | 2.167 | 1.844 |
| | (1.016) | (1.064) | (3.025) | (1.369) | (1.338) |
| log_voltline2 | -0.181* | 0.036 | -0.453* | -0.175 | -0.116 |
| | (0.094) | (0.097) | (0.257) | (0.128) | (0.113) |
| _cons | -9.309 | 7.462 | -4.251 | 0.497 | -14.087** |
| | (6.231) | (6.443) | (15.417) | (7.004) | (6.697) |
| *Year dummies* | Yes | Yes | Yes | Yes | Yes |
| *N* | 1070 | 1070 | 1070 | 1070 | 1070 |
| r2_within | 0.163 | 0.833 | 0.127 | 0.513 | 0.199 |

Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In column 1 we find that BEVs have a positive and significant relation (at 10 % level) with DSOs' operational costs. We also find a positive relationship between BEVs and capital costs in column 2, but this is not significant at the 10 % level. Given the operational costs share of total costs (see Table 1), it looks like it would be through this component where BEVs would have the strongest impact on total cost. We are a bit surprised that BEVs would have a stronger effect on operational costs than capital costs on average, but it matches the experience of one of the DSOs with whom we have talked[8]. This is a relatively small DSO on the west coast of Norway, and they have had a few incidents over the last few years where they have upgraded their infrastructure more than they would otherwise have, because of BEVs. In some of these incidents they have received co-payments from customers for the hardware to upgrade the infrastructure, but all other costs (in particular labor costs) were registered as operational costs.

In column 3 and 4 we also find small positive but highly non-significant effects on *log_depres* and *log_cens,* respectively. The results in column 5 may require some more explanation. Here we find a negative and significant (at the 10 % level) relationship between EVs and grid energy losses. A drop in energy losses for DSOs with many EV owners in their operational area could be consistent with these DSOs upgrading their infrastructure faster, meaning a faster upgrade from a 230 Volts grid to a 400 Volts grid. The energy losses are lower in an electric grid with higher voltage (Haugen, Haugland, Vingås, & Jonhnsen-Solløs, 2004).

**Alternative specifications**

We test some alternative specifications of the model in order to assess the robustness of our findings. We show these in Table 5.

[8] In total we have had discussions with representatives from six DSOs; two relatively large, and four relatively small. Only one of them, one of the small ones, could confirm that BEVs had caused noticeable costs.

*Table 5: Alternative specifications on fixed effects regressions on the relationship between BEV stock in a DSOs operational area and DSO costs*

| | (1) FE | (2) FE | (3) FE | (4) Difference approach over sample period |
|---|---|---|---|---|
| log_ev | 0.039$^{*}$ | 0.018$^{**}$ | 0.018$^{**}$ | 0.045$^{***}$ |
| | (0.023) | (0.008) | (0.008) | (0.012) |
| log_subscribe | 0.338 | 1.035 | 0.994 | 1.714 |
| | (1.196) | (0.873) | (0.921) | (1.279) |
| log_subscribe2 | 0.000 | -0.044 | -0.039 | -0.078 |
| | (0.065) | (0.046) | (0.049) | (0.073) |
| log_voltline | 1.533$^{**}$ | 1.667$^{***}$ | 1.677$^{***}$ | 2.361$^{**}$ |
| | (0.649) | (0.630) | (0.629) | (1.162) |
| log_voltline2 | -0.117$^{*}$ | -0.129$^{**}$ | -0.130$^{**}$ | -0.196$^{*}$ |
| | (0.061) | (0.058) | (0.058) | (0.105) |
| log_ev x log_voltline | -0.003 | | | |
| | (0.003) | | | |
| wintertemp | | 0.000 | | |
| | | (0.005) | | |
| event | | 0.004* | | |
| | | (0.002) | | |
| log_hh_inc | | -0.409 | | |
| | | (0.327) | | |
| log_substation | | | 0.025$^{**}$ | |
| | | | (0.012) | |
| _cons | 2.869 | 5.200 | -0.336 | -0.207$^{***}$ |
| | (5.682) | (6.458) | (4.328) | (0.067) |
| Year dummies | Yes | Yes | Yes | No |
| *N* | 1070 | 1070 | 1070 | 107 |
| r2_within | 0.292 | 0.296 | 0.291 | 0.186 |

Standard errors in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

In column 1 we add an interaction term between *log_ev* and *log_voltline* in order to investigate whether the marginal cost of accommodating more BEVs is higher for small DSOs in rural areas with little grid capacity (measured as km with high voltage line). We find that the marginal cost of more BEVs is decreasing in the amount of high voltage line (though not statistically significant), supporting that more capacity makes it less costly to accommodate more BEVs. This corroborates our interpretation of the main results and heterogeneity tests, and also the conversations with representatives from DSOs.

In column 2 we add three new control variables that can be expected to impact DSO costs, although some of this impact is probably captured by the year dummies. The variable *wintertemp* is a measure of average winter temperature in a given year at county level[9]. We expect lower winter temperatures to drive DSO costs upwards, and perhaps capture some of the costs per BEV, as lower average temperatures would generally require more electricity per BEV-km. However, the effect of this control variable is far from statistically significant. Based on conversations with representatives from DSOs we have also included extreme weather events as a control variable[10], as many spikes in costs for different DSOs at different times can be attributed to such events. We see that *event* has a statistically significant impact on costs. We also add average household income (aggregated from municipal level data, retrieved from Statistics Norway) as a control variable. BEV growth could be correlated with variations in an underlying growth in power usage and demand for modern appliances that require more power capacity, like induction stoves. If this is true, then our estimated coefficients for *log_ev* would be biased upwards, overstating the effect. Ideally, we would like to control for household ownership of modern appliances and their power usage, but it is reasonable to expect that this should correlate with income. Figenbaum and Kolbenstvedt (2016) show at least that most BEV buyers until now have generally higher-than-median income. However, the control variable *log_hh_inc* is highly statistically insignificant. The addition of all these control variables does not affect the coefficient estimate for *log_ev*.

In column 3 we introduce the variable *log_substations*. As discussed in Section 3, substations are an important part of regulators DEA calculation, but it is potentially a bad control when trying to estimate the impact of BEVs of cost. Compared to the preferred model, the coefficient for *log_ev* is largely unchanged. There still may be a theoretical argument for leaving *log_substations* out of the regression, but it does not seem to make much difference in practice.

Finally, in column 4, we estimate the impact from BEVs using data aggregated over several years. Here, we look at the change over the entire sample period instead of year-to-year changes. We want to minimize the year-to-year noise in the data, so we take the average of the first three years of the sample (2008-2010) and the last three years (2015-2017). We then take the differences between these two averages and run the regression. With this specification we find a stronger and somewhat more precise relation between differences in BEV stock and differences in DSO costs, compared to the preferred model in Table 2. We find comparable results when using this alternative specification on capital costs and operational costs. These findings imply that the main findings are robust.

# 5 Discussion and conclusions

In this paper, we have used a complete dataset of Norwegian DSOs outputs, costs and registered BEVs in their operational area over the time period 2008-2017 to analyze

[9] Retrieved from https://www.yr.no/klima/

[10]. County-level data on extreme weather events according to the definition from the Norwegian Meteorological Institute: https://no.m.wikipedia.org/wiki/Liste_over_ekstremvær_i_Norge [In Norwegian. Last accessed October 1st 2019]

the effect increasing BEV numbers have on DSO costs. We have also investigated through which mechanisms, i.e. cost components, do we see this effect.

The results of our preferred model specification show that an increase in the BEV stock in the operational area of a DSO is associated with an increase in local grid costs. This finding is robust to the addition of several controls and removal of outliers. The estimated cost increases are also economically significant, as they imply additional costs of several thousand NOK per BEV when the BEV stock is low. With a constant cost elasticity of 0.018, the per-BEV cost becomes relatively low when the stock has reached the higher levels in the sample.

The results indicate that there is fairly large heterogeneity in the effect of BEVs on DSO costs. In particular, the effect is a lot smaller for DSOs that have a higher-than-median number of customers, and over the period has had a higher-than-median BEV density. We tested whether the effect of BEVs could be higher in areas with less installed capacity, usually rural areas. The point estimates gave some support to this, but they were not very precise.

The costs imposed on DSOs can be contrasted with the reduction in environmental costs from a one-to-one replacement of a conventional car with a BEV. The annual tailpipe emissions of a typical diesel car in Norway driving on average 12 140 km per year amounts to 1.7 tons of $CO_2$, 7.9 kg of $NO_X$ and 150 grams of $PM_{2.5}$ (Rødseth et al., 2020). According to Rødseth et al. (2020) this would be valued at about NOK 1060 if all the driving was done in rural areas (with little exposure). However, it would be valued at NOK 4460 if all the driving was done in larger cities. The external costs of pollution are highest where we find the imposed grid costs to be lowest, namely in urban areas, suggesting that these are the areas with the highest social benefit-cost ratio of BEVs.

The heterogeneity also indicates that costs imposed on DSOs by BEV owners, is not a problem that will affect a large number of consumers. The half of the sample with largest DSOs serve over 93 % of the customers in the entire sample. The effect of BEVs on costs in that sample half is a lot smaller than the full-sample estimate, and statistically insignificant. If BEV owners are imposing pecuniary externalities in the incomplete local grid market, these externalities do not seem to be very large for most Norwegians. A minority of unlucky DSO customers may have to bear some cost as their DSOs seem to have a hard time accommodating BEVs.

When looking closely at individual cost components, we see that increases in BEV numbers are associated with statistically significant increases in operational costs, but statistically insignificant increases in other major components. We found this somewhat surprising, but it does corroborate the experiences of one of the DSO representatives we contacted during this project.

The analysis in this paper should be revisited in later years as the stock of BEVs in Norway continues to grow. In this dataset the highest level of BEVs in any of the DSOs operational area amounts to 8.3 per 100 customers. Even though the cost of an additional BEV seems to be positive but decreasing up until now, it could be that when we reach substantially higher levels in a matter of years we would detect larger cost impacts, unless measures are put in place. It has gone relatively painless so far, as the current BEV stock – the most concentrated in the world – has not yet substantially stress-tested the local grid in most places. In Section 2 we referred to NVE stress-test that found that if 70 % of normal neighborhood simultaneously charged BEVs during peak hours, they would expect overload for more than 30 % of the current substations. Norway is not there yet.

It is worth noting a few caveats at the end. The main caveat is that our model captures the statistical relationship between DSO costs and the number of BEVs *registered* in the DSOs area. We do not have data on the charging behavior of the BEV-owners, or what kind of equipment they have installed. In addition, the number of registered BEVs in one DSO operational area does not need to correspond completely to where the BEV charging is taking place. There could be cases where DSOs experience costs from BEVs charging, but these are not BEVs registered in their area. This could e.g., apply to municipalities with many cabins, which typically lie in areas where the local grid is not dimensioned for high capacity[11]. Our model would not be able to pick up any of that cost if it is there. However, to include cabin owners with BEVs to the analysis could be an interesting venue for future research, when more data is available.

Several papers have documented that the $CO_2$ abatement costs from policies that promote a shift from conventional to electric cars are fairly large (see e.g., Bjertnæs, 2016; Fridstrøm & Østli, 2017; Wangsness, 2018; Wangsness, Proost, & Rødseth, 2018). These costs may come in the form of higher costs for a given quality level of the car stock, a loss in government revenue that has to be funded by distortionary taxes elsewhere, and higher congestion levels in cities because of low energy costs and low tolls. Should we in addition to these costs worry about BEVs imposing higher costs on the local grid and passing on the cost to all customers, and subsequently want the regulators to take action?

As many economists before us, we expect there to be efficiency gains if the regulator allowed for a well-designed peak pricing system. That would incentivize more efficient use of local grid capacity with regards to all electric appliances, including BEVs. And with a fast-growing number of BEVs, the gains from introducing such a pricing scheme would be even larger. Many BEV owners would probably respond by installing smart charging systems, which would ease the household cost minimization and ensure more efficient grid capacity utilization, even with small hour-to-hour price differences.

With regards to including "BEV stock" as a variable in the regulatory analysis, our cautiously optimistic interpretation of the findings suggest that this would be a bit premature. Although we find a statistically significant relationship between BEV stock and DSO costs, the marginal cost is positive but decreasing, and for the half of the DSOs that serve more than 93 % of the Norwegian customers, the point estimates are actually quite close to zero. DSOs and regulators should keep an eye on developments, but for now grid costs stemming from higher BEV ownership rates do not need to be at the top of their list of worries.

[11] https://www.distriktsenergi.no/artikler/2019/1/16/elbilene-gjor-at-stromnettet-i-hytteomradene-ma-oppgraderes/ [Electric cars leads to a need to upgrade the electric grid in cabin areas (Article from DistriktsEnergi in Norwegian, last accessed 05.12.2019)]

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# Appendix A: Regressions with a per-customer model

As discussed in section 3, there was a need to transform the data because of the very skewed distribution of DSOs. The log-log transformation was preferred because the dependent variable was closer to a normal distribution than was a per-customer-transformation. Still, a per-customer model can work as a robustness check. Table 6 below is the counterpart of Table 2, but with a per-customer transformation. The variable of interest is *EV_percent*, which is the number of BEVs per 100 customers.

*Table 6: Fixed effects regression on the relationship between EV density in a DSOs operational area and DSO costs per customer (measured in 2015-NOK)*

| | (1) | (2) | (3) | (4) | (5) (removed 3 largest DSOs) | (6) (removed 3 smallest DSOs) |
|---|---|---|---|---|---|---|
| EV_percent | 61.94$^{**}$ | 52.40 | 42.45 | 23.00 | 24.80 | 39.48 |
| | (30.46) | (44.27) | (46.74) | (98.96) | (48.85) | (47.55) |
| 1000subscribers | -15.64$^{***}$ | -20.11$^{***}$ | -20.18$^{***}$ | -20.93$^{***}$ | -31.99$^{**}$ | -20.12$^{***}$ |
| | (4.36) | (4.98) | (5.18) | (4.62) | (12.76) | (5.35) |
| Meters of high voltage line per subscriber | 42.35$^{***}$ | 49.38$^{***}$ | 6.69 | 5.95 | -15.11 | -3.95 |
| | (15.58) | (15.55) | (54.61) | (54.93) | (48.16) | (53.99) |
| Meters of high voltage line per subscriber^2 | | | 0.27 | 0.28 | 0.46 | 0.32 |
| | | | (0.37) | (0.37) | (0.30) | (0.36) |
| EV_percent2 | | | | 3.68 | | |
| | | | | (11.59) | | |
| _cons | 4453.49$^{***}$ | 4034.52$^{***}$ | 5431.13$^{***}$ | 5471.29$^{***}$ | 6044.53$^{***}$ | 5818.63$^{***}$ |
| | (917.65) | (922.36) | (1826.46) | (1837.35) | (1761.20) | (1814.01) |
| Year dummies | No | Yes | Yes | Yes | Yes | Yes |
| *N* | 1070 | 1070 | 1070 | 1070 | 1040 | 1040 |
| r2_w | 0.03 | 0.13 | 0.13 | 0.13 | 0.15 | 0.13 |

Standard errors clustered at DSO level in parentheses. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

We find that the coefficient for *EV_percent* is positive under all specifications, just like we find with the log-log model. However, with the exception of the most naïve specification in column 1, we do not find any statistically significant effects from registered BEVs (per customer) on DSO costs (per customer). However, compared to the log-log model, the per-customer model does a worse job explaining the variation in the data. Given a choice between specifications, it is clear that the log-log model is preferable.

# Paal Brevik Wangsness

Paal Brevik Wangsness was born in Oslo, Norway in 1986. He is a senior research economist at the Institute of Transport Economics (TØI). Paal is a Master of Economic Theory and Econometrics from the University of Oslo and the University of Minnesota. He joined PwC Consulting after graduating in 2011. In nearly three years as a consultant for PwC, he has conducted several projects in the field of economic analysis and evaluations. Paal is continuing this work at TØI, specializing in transport and environmental economics. He has also contributed to further method development for cost-benefit analysis, both for passenger and freight transport.

This thesis focuses on the economics and polices for the electrification of transport. Over the last few years we have observed a rapid rise in the number of battery electric vehicles (BEVs) in Norway. The rising share of BEVs relative to the share of conventional vehicles could lead to socio-economic benefits such as reduced greenhouse gas emissions and local pollution, but it could also pose new challenges such as pressure on the capacity of the electricity distribution network. In addition, BEVs have similar negative externalities as fossil-fueled vehicles with regards to congestion, road wear and accidents, but with fewer instruments for internalizing them. BEVs can mitigate some market failures and exacerbate others, creating a messy optimization problem. This illustrates the need for new knowledge on mechanisms and welfare enhancing policies in the transport and electricity markets as they become more integrated. This thesis consists of an introductory chapter and four independent chapters. The latter chapters are written as scientific papers that are either published or in the process of getting published in peer-reviewed journals.

The main overarching contribution is new and improved understanding of how the emergence of BEVs in the transport sector changes the calculus of social costs and benefits and how policies optimally should respond to these changes. This is done by extending well-established modeling frameworks to include BEVs and issues related to their charging, and econometric analysis of a new and highly relevant dataset on BEV density and local grid costs. With this we can better understand the mechanisms at play, and what balances need to be struck to form welfare-enhancing policies.

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