Norwegian University of Life Sciences
School of Economics and Business

Philosophiae Doctor (PhD)
Thesis 2023:57

The green transition in the transport sector

Det grønne skiftet i transportsektoren

Gøril Louise Andreassen

The green transition in the transport sector

Det grønne skiftet i transportsektoren

Philosophiae Doctor (PhD) Thesis

Gøril L. Andreassen

Norwegian University of Life Sciences
School of Economics and Business

Ås (2023)

Thesis number 2023:57
ISSN 1894-6402
ISBN 978-82-575-2086-1

Supervisors and Evaluation Committee

Supervisor:
Knut Einar Rosendahl, Norwegian University of Life Sciences
Co-supervisors:
Frode Alfnes, Norwegian University of Life Sciences
Annette Alstadsæter, Norwegian University of Life Sciences

Evaluation Committee:
Stefanie Peer, WU Vienna University of Economics
Colin Green, NTNU Norwegian University of Science and Technology
Arild Angelsen, Norwegian University of Life Sciences

Acknowledgements

I would like to thank all those who have contributed to my work with this PhD thesis. The inputs, insights, and inspiration from others, as well as the opportunity to take part in different research communities, have been instrumental in helping me carrying out this work from the start until the submission.

First, I would like to express my gratitude to my main supervisor, Knut Einar Rosendahl, for his unwavering support, high-quality advice, responsiveness, constructive feedback and belief in me. When I was going through a period of illness, he provided invaluable backing, which I deeply appreciate. It is when in a deep valley, support is cherished the most. Kalle Moene has said about him that he possesses a unique combination of kindness and accomplishments, and I could not agree more. I am very happy that he has been my supervisor, and that we have written two papers together. Collaborating with him is both academically stimulating and enjoyable.

I would also like to thank my co-supervisors, Frode Alfnes and Annette Alstadsæter, for their contributions to my research. Frode Alfnes has provided prompt and insightful comments, which has helped refine my articles. Annette Alstadsæter has both given important input and included me into her dedicated and highly competent research group, and later research centre, Skatteforsk – Centre for Tax Research, which has been good for my learning.

I am very happy for the cooperation with my co-authors, Askill Harkjerr Halse, Steffen Kallbekken, Jo Thori Lind, and Knut Einar Rosendahl. Their contributions to our joint work have played a pivotal role in my learning process, and it has been fun to work together. I consider myself fortunate to have had the opportunity to collaborate with such highly competent individuals.

Several research communities have been valuable for me during my PhD. In addition to the already mentioned Skatteforsk, the climate, resource, energy and environment research group (the KREM group) at the School of Economics and Business at NMBU was an interesting and friendly research fellowship, both at and between the meetings.

Further, a big thank to the people at the Institute of Transport Economics for letting me be a guest researcher there from the autumn of 2021. Being around warm people with interests in the same research topics as me was excellent, educational and inspiring, and I really look forward to start working there in August.

The last semester of my PhD I spent at the Frisch centre. This was an academically rewarding time. I would like to thank everyone at Frisch for being this welcoming, unique, high-level, truth-seeking and motivating research community. A special thank goes to Andreas Kotsadam for being inclusive, giving valuable advice and for keep reminding me about what the process of research is and is not, Ole Røgeberg for phenomenal explanations and Anna Godøy, Karen Evelyn Hauge, and Oddbjørn Raaum for outstanding input.

Further, as teaching has been an important part of my learning, I would like to thank those who gave me the opportunity: Arild Angelsen, Bård Harstad, Knut Einar Rosendahl, Sigurd Rysstad, Christian Treager and Mette Wik.

I would also like to thank the other participants at EAERE-ETH Winterschool 2020 in Monte Verità, Ascona, Switzerland for a great experience. Luckily we did not know what was expecting us relating to lock-downs soon after.

For great conversations and sharing of knowledge and wisdom, I would like to thank Arild Angelsen, Julie Brun Bjørkheim, Svenn Jensen, Åshild Auglænd Johnsen, Tora Knutsen, Maria Nareklishvili, and Andreas Økland.

Good times with friends and family have been precious. Thank you to my parents, Karl Johan and Barbara, especially for their endless love, help and support to both me and my family. Thank you to my brother, Kåre and his partner Clas, my parents-in-law, Brit and Jan (and in addition thank you for all the help), my sister-in-law Ingrid and her partner Panagiotis, family in Vesterålen, Bergen, Oslo and Germany, Ann Mari, Bente, the Thursday Club: Anne, Anja, Gunnell, Madel, Therese, and the Book Club: Ane, Inga, Ingeborg, Marie, Olivia, Sunniva, Åshild, and Anka, Nils Hermann, Ragnhild, Solveig, Tonje and Unni, to friends and neighbours at Vålerenga, and to the yoga people at OnYoga in Gamlebyen. Thank you to the marching band of Vålerenga for giving me the opportunity to feel useful at *dugnader* and especially the flea market committee. Thank you to my favorite gang, Audun, Amanda, Åse and Tord, who are a continuous source of happiness.

Oslo, June 2023
Gøril L. Andreassen

Contents

List of papers

Paper 1: Andreassen, G. L., Kallbekken, S., & Rosendahl, K.E. (2023). Can policy packaging help overcome Pigouvian tax aversion? A lab experiment on combining taxes and subsidies.

Paper 2: Andreassen, G. L., & Halse, A. H. (2023). Company cars and household car choices.

Paper 3: Andreassen, G. L., & Lind, J. T. (2023). Climate, technology and value: Insights from the first decade with mass-consumption of electric vehicles.

Paper 4: Andreassen, G. L., & Rosendahl, K. E. (2022). One or two non-fossil technologies in the decarbonized transport sector?. Resource and Energy Economics, 69, 101314.

Abstract

Mobility is essential for ensuring human well-being. At the same time the transport sector is a large source of greenhouse gas emissions. To address climate change, it is imperative to accelerate the shift towards sustainable practices within the transport sector. This thesis aims to explore various aspects pertaining to the green transition in the transport sector.

The first chapter (with Kallbekken and Rosendahl) focuses on public support for policies aimed at reducing negative externalities. Tax aversion makes it politically difficult to introduce Pigouvian taxes at sufficiently high levels. To address this resistance, one proposed solution is the implementation of policy packages. In this study, we employ an online lab experiment to explore whether individuals find the combination of a tax and a subsidy more acceptable compared to implementing tax or subsidy alone. We find that public support for a combination of a tax and a subsidy is equal to the average of support for the two instruments alone. Consequently, it appears that combining Pigouvian taxes with other popular policies does not alleviate tax aversion, unless the overall tax burden is reduced.

In the second chapter (with Halse), we explore the relationship between access to a company car and household car choices. Our study employs a difference-in-difference design, utilizing job changes as a source of potential exogenous variation. The sample comprises household where one adult switches job once and work in company car occupations. The treatment group is most likely offered a company car following the job change, while the control group, also working in company car occupations, does not have the opportunity to obtain a company car but undergoes a job change. We find that being offered a company car is associated with a 9% increase in the number of cars in households. However, the treatment group also experiences higher wage growth compared to the control group after changing job. Therefore, we do not interpret the difference in number of cars in the households as causal effects of the company car scheme, but as correlations between the change in the number of cars in the household and gaining access to a company car. Nevertheless, observed income elasticities in car demand suggest that a portion of the increased number of cars can indeed be attributed to the company car scheme.

In the third chapter (with Lind), we examine how the market values electric vehicles throughout their lifetime. Our objective is to investigate whether the market value of electric vehicles, characterized by fast-paced technological improvements, declines faster compared to gasoline vehicles, representing a mature technology. To do this, we utilize novel data from Norway's largest online platform for used vehicles covering the period from 2011 to June 2021. Our findings indicate that electric vehicles experience a faster decline in value compared to gasoline cars, primarily driven by vehicles with a range of less than 200-250 km. We hypothesize that the significant price fall is due to the substantial technological advancements in electric vehicles.

The fourth chapter (with Rosendahl) focuses on the factors influencing whether governments should promote one or more technologies in a decarbonized road transport sector, and what policies governments should choose. We investigate these questions theoretically and numerically using a static, partial equilibrium model of the road transport market. We find that a crucial factor is the degree of substitutability between different technologies. Additionally, the optimal number of vehicles of one technology depends on the number of vehicles of the other technology. The first-best policy involves a subsidy of the markup on charging and filling, where the markup is higher the more utility increases with the number of stations. However, as there are several possible market equilibria, additional policies may be needed to avoid an unwanted lock-in.

Norsk sammendrag

Mobilitet spiller en sentral rolle for at samfunnet skal fungere og folk skal ha god livskvalitet. Samtidig er transport en stor kilde til klimagassutslipp. Derfor er en grønn omstilling i transportsektoren viktig. Denne doktoravhandlingen handler om aspekter knyttet til det grønne skiftet i transportsektoren.

Første kapittel (med Kallbekken og Rosendahl) handler om folkelig støtte til virkemidler for å redusere miljøskadelige utslipp. Avgiftsaversjon gjør det politisk vanskelig å innføre Pigou-avgifter på et høyt nok nivå. Et forslag til løsning for å overvinne denne motstanden er politikkpakker. Ved hjelp av et nettbasert labeksperiment undersøker vi om folk anser det å kombinere en avgift og en subsidie som mer akseptabelt enn en avgift eller en subsidie alene. Vi finner at oppslutningen om en kombinasjon av en avgift og en subsidie er lik gjennomsnittet av støtten til de to virkemidlene alene. Å kombinere en avgift og en subsidie ser derfor ikke ut til å redusere avgiftsaversjonen, annet enn gjennom å redusere selve avgiften.

I andre kapittel (med Halse) utforsker vi relasjonen mellom tilgang på firmabil og husholdningenes bilvalg. Vi bruker et forskjell-i-forskjell-design der jobbendring skaper den potensielle eksogene variasjonen. Utvalget består av arbeidstakere som bytter jobb én gang og jobber i et firmabilyrke. "Behandlingen" er å få tilbud om en firmabil etter et jobbskifte. Kontrollgruppen har aldri mulighet til å ha firmabil, men jobber i firmabilyrker og bytter jobb. Vi finner at det å få tilbud om firmabil er assosiert med en økning i antall biler i husholdningen med 9%. Gruppen som får tilbud om firmabil har imidlertid også høyere lønnsvekst enn kontrollgruppen etter jobbskiftet. Vi kan derfor ikke tolke økningen i antall biler som en kausal effekt av firmabilordningen, men som en korrelasjon. Inntektselastisiteten i biletterspørselen tyder likevel på at en del av det økte bilholdet skyldes firmabilordningen.

I det tredje kapittelet (med Lind) ser vi på hvordan markedet verdsetter elbiler gjennom hele levetiden når teknologien forbedres fort. Vi undersøker om markedsverdien av elbiler, som er preget av rask teknologisk utvikling, synker mer over levetiden sammenlignet med bensinbiler, som representerer en moden teknologi. For å gjøre dette bruker vi nye data fra den største nettplattformen for brukte kjøretøy i Norge, finn.no, fra 2011 til juni 2021. Vi finner at elbiler faller raskere i verdi sammenlignet med bensinbiler. Dette ser ut til å være drevet av kjøretøyene med rekkevidde under 200-250 km. Vår hypotese er at det store prisfallet for elbiler først og fremst skyldes de store teknologiske forbedringene.

Det fjerde kapittelet (med Rosendahl) undersøker hvilke faktorer som påvirker om myndighetene skal fremme en eller flere teknologier i en avkarbonisert veitransportsektor, og hvilken politikk myndighetene bør velge. Vi undersøker dette teoretisk og numerisk gjennom en statisk, partiell likevektsmodell for veitransportmarkedet. Vi finner at en viktig faktor er hvor nære substitutter de forskjellige teknologiene er. Videre avhenger det optimale antallet kjøretøy av en teknologi av antall kjøretøy av den andre teknologien. Den optimale politikken inkluderer en subsidie av prispåslaget på lading og fylling, der påslaget er høyere jo mer nytten øker av flere stasjoner. Men siden det er flere mulige markedslikevekter, kan det være behov for ytterligere politikk for å unngå uønsket innlåsing.

Introduction to the thesis

1 Introduction

Mobility plays a crucial role in securing human welfare. Transportation enables the movement of people and goods and the exercise of government authority, facilitates trade and commerce, connects communities, and provides access to essential resources and opportunities. It supports tourism, employment, healthcare services, social connections, education, and cultural exchange. Overall, transport is a vital enabler that underpins the functioning and development of societies at large.

At the same time the transport sector is a major contributor to global greenhouse gas emissions, accounting for around 1/4 of global energy-related CO_2 emissions. In 2019, road vehicles accounted for 70% of transport emissions, whereas rail, shipping, and aviation contributed 1%, 11%, and 12% of the emissions, respectively. From 1990 to 2019, global emissions from the transport sector increased by 74% (Pathak et al., 2022).

Given these figures and the goal of the Paris agreement of limiting the average temperature increase to well below 2 degrees and to aim at 1.5 degree, the green transition in the transport sector is crucial. Climate strategies often include reducing the transport volume, shifting away from cars towards public transport, cycling and walking, as well as transitioning from combustion-engine cars to zero-emission vehicles (Hegsvold et al., 2022).

Technological progress making batteries cheaper and better has made the shift towards electric vehicles possible (Pathak et al., 2022). 14% of the world's new car sales in 2022 were electric vehicles, up from 9% in 2021 and less than 5% in 2020. China is the largest electric vehicle market, Europe the second and the USA the third largest market with 8% sale share (IEA, 2023).

Norway has and has had many economic and other incentives for zero-emission vehicles, which has resulted in electric vehicles being cheaper than equivalent gasoline and diesel vehicles (OFV, 2021, 2022, 2023f). The new car market in Norway has the last decade gone through a technology shift, which is a preview of what might happen in other markets as well. From having 1.5% market share in 2011, the electric vehicle share in the new car market in the first five months of 2023 was 83% in Norway (OFV, 2023a, 2023b, 2023c, 2023d, 2023e). The political goal of the Norwegian government is that "all new passenger cars and light vans sold in 2025 shall be zero-emission vehicles" (Meld. St. 33, 2016-2017, p.30).

The green transition in the transport sector involves not only the adoption of zero-emission vehicles. Reducing the overall transport volume and the number of trips taken with a car are also part of countries' climate strategies (Hegsvold et al., 2022).

Having one or more cars available most likely influences the number of trips taken with a car. Investigating factors important for household car ownership is therefore important.

Environmental taxes are often implemented in the transport sector. However, carbon taxes are not the most popular climate policies (Dechezleprêtre et al., 2022). The yellow vest protesters against increased fuel tax in France in 2018 is one example of riot against carbon taxes (Douenne & Fabre, 2022). Another is the toll road rebellion in Norway in 2019 leading to the foundation of a new political party based on the opposition to toll roads. However, how the revenue from the Pigouvian taxes are spent are important for the level of public support (Anderson et al., 2023; Dechezleprêtre et al., 2022; Kallbekken et al., 2011).

In this thesis, I, together with co-authors, investigate aspects related to the green transition in the transport sector. Topics in this thesis include public support for policy packages that include an environmental tax, the company car scheme and households' car choices, the price path of used electric vehicles compared to used gasoline vehicles, and technology choice in the decarbonized transport sector. A schematic overview of the chapters in the thesis can be seen in Table 1.

The first chapter (with Kallbekken and Rosendahl) is about public support for Pigouvian taxes in combination with subsidies. We investigate this with a lab experiment. Public opposition towards Pigouvian taxes often stops taxes from being implemented at a high enough level. It is important to find out how the tax can be introduced without the political incumbent losing the next election. We find that combining a tax and a subsidy only increases the support for a policy with the average of the support for the two. Therefore, combining Pigouvian taxes with subsidies does not seem to help against tax aversion beyond the effect of reducing the tax.

In the second chapter (with Halse) we investigate the relation between the number of cars in the household and access to a company car. If the way the company cars are taxed makes it cheaper or easier to have a car, the scheme might increase the number of cars in the households. We find that access to a company car is associated with an increase in the number of cars in the family. However, wage growth and access to company cars are also positively correlated. Thus, the increased number of cars might be due to the increased wage, rather than the company car scheme. Still, income elasticities in the demand for cars indicate that some of the increase in the number of cars can be due to the company car scheme. We find no statistically significant difference in the number of electric vehicles between those with access to a company car and those without access.

Table 1: Overview of thesis

Chapter	Research question	Concepts	Data	Method	Key findings
1	Can policy packaging help overcome Pigouvian tax aversion?	Pigouvian tax aversion, policy packaging	Primary data collection through the online platform Prolific and Lioness Lab (Giamattei et al., 2020)	Lab experiment	Combining a Pigouvian tax and a subsidy increases support to the policy by the simple average of the two instruments alone The expectations about how large share of the tax revenue the participant receives is more pessimistic for the tax alone than when combined with a subsidy The tax is expected to be more effective in reducing demand than the combinations of a tax and a subsidy.
2	What is the relation between access to a company car and the number of cars in the household?	Taxation of fringe benefits	Norwegian register data covering the universe of employers, employees, families and passenger cars from 2015-2021	Difference-in-differences	Getting access to a company car is associated with an increase in the number of cars in the household by 9%. Wage growth and access to company cars are also positively correlated. Therefore, we cannot interpret the increase in the number of cars as a causal effect of the company car scheme, but as correlations.
3	Does the price of secondhand electric vehicles decline faster than secondhand gasoline vehicles?	Technological development	A novel data set from the largest web platform for secondhand vehicles in Norway (finn.no)	Descriptive work and a theoretical model	Prices of electric vehicles decline faster than gasoline vehicles, but this seems to be driven by the electric vehicles with driving range below 200-250 km
4	What factors determine whether one or more technologies are optimal in a decarbonized road transport market, and what policies should governments choose?	Indirect network effects	Projections for the Norwegian vehicle market in 2030, information from charging and hydrogen station suppliers and other sources	Partial, static equilibrium model and numerical simulations	One important factor is how close substitutes the two vehicle technologies are. Another is that the number of vehicles of one technology depends on the number of vehicles of the other technology. The first-best policy involves a subsidy of the. markup on charging and filling. Additional policies may be needed to avoid an unwanted lock-in.

In the third chapter (with Lind) we look at how the market values electric vehicles throughout their lifetime when the technology is rapidly improving. We investigate whether the market value of electric vehicles, which are characterized by fast technological advances, declines more over their lifetime compared to gasoline vehicles, which represent a mature technology. To do so, we utilized novel data from the largest web platform for secondhand vehicles in Norway from 2011 to June 2021. We find that electric vehicles experience a steeper decline in value compared to gasoline vehicles. This seems to be driven by the vehicles with driving range below 200-250 km. We hypothesize that this large price drop is primarily due to the fast-paced technological improvements in electric vehicles.

The fourth chapter (with Rosendahl) aims to identify the factors that determine whether it is optimal with one or more technologies in a decarbonized road transport sector. Electric vehicles are energy-efficient and therefore cheap to use, while hydrogen vehicles are fast to fill with energy. The two technologies represent different benefits and the variety might be valued by the consumer. In the transport market there are indirect network effects, which can create a tradeoff between the utility from the size of the energy station network and the benefit of the variety of car technologies offered in the market. To determine the optimal number of transport technologies the policy-makers should promote, one important factor is how close substitutes these technologies are. Another important factor is that the number of vehicles of one technology affects the optimal number of vehicles of the other technology. The first-best policy involves a subsidy of the markup on charging and filling, where the markup is higher the more utility increases with the number of stations. However, as there are several possible market equilibria, additional policies may be needed to avoid an unwanted lock-in.

In the subsequent sections of this introduction to the thesis, I will provide an overview of the economic theory pertinent to the green transition in the transport sector. Subsequently, I will discuss the methods employed in this thesis, followed by an outline of the diverse sets of data utilized in each chapter. Lastly, I will synthesize each chapter of the thesis, including limitations and further research ideas, before I conclude.

2 Theoretical background

2.1 Introduction

Addressing climate change is a complex problem, as it involves multiple market failures, government short-comings, human cognitive biases, and uncertainty about the climate sensitivity and the value of future damages. Emission of greenhouse gases is an environmental externality, which is not only large but also global in scope. Increased concentrations of greenhouse gases, in particular CO_2, is causing increased global temperature.

Although our understanding of the climate system has significantly improved, a large increase in the global mean temperature has not been experienced during the lifetime of humans on Earth. As a result, we have never observed how the system responds to a large increase in CO_2 concentrations in the atmosphere. Feedback mechanisms in the climate system can both cool down and further heat up the planet, making it challenging to predict the exact outcomes of higher CO_2 concentrations (MIT climate portal, 2021). This makes risk assessments difficult, and combined with the high uncertainty of the value of future damages, and disagreement on the discounting rate, the value of emitting one ton of CO_2 today (the social cost of carbon) is highly uncertain (Carleton et al., 2022; Drupp et al., 2018; Nesje et al., 2022; Nordhaus, 2007; Pindyck, 2013; Stern, 2008).

Economists have long advocated for the implementation of a price on carbon. While a price on carbon is paramount, it is likely to not be sufficient to tackle climate change. The development of green technologies lags behind brown technologies, making it more profitable to do research and improve brown technologies. To address the interaction between the environmental externalities and the intertemporal knowledge externalities, Acemoglu et al. (2012) find that optimal policies should include both subsidies to research that increase the productivity of green technologies and a carbon tax (more explanation below).

Another market failure relevant to mitigating climate change is network effects (Greaker & Midttømme, 2016). Network effects mean that the utility a user gets from a good depends on the number of users in the same network (Katz & Shapiro, 1985). The road transport market exhibits indirect network effects, since the number of charging stations depends on the number of electric cars and the number of electric cars depends on the number of charging stations. This may create a coordination problem that leads to under-investments in zero-emission vehicles and energy stations compared to the socially optimal investment level (Greaker & Midttømme, 2016).

Compounding the issue further is the interaction between market failures and the limitations of governments. First, one major problem in addressing cross-country environmental externalities is the lack of a global authority with the power to enforce policies and regulations. Barrett (1994) finds that a self-enforcing environmental agreement with deep emission reductions will only have 2 or 3 member countries. The 2015 Paris Agreement uses a decentralized approach, in which all countries commits to reducing their greenhouse gas emissions based on their own determined plan. Second, even if politicians on a national level can introduce carbon taxes, they cannot credibly commit to a long-term carbon price (Besley & Persson, 2022; Fæhn & Isaksen, 2016).

Additionally, the presence of human cognitive biases, such as confirmation bias, loss aversion and status quo bias can make it even more challenging to implement climate policy (Heutel, 2019; Kahneman et al., 1991; Millner & Ollivier, 2016; Samuelson & Zeckhauser, 1988). It is possible to continue to list factors that make climate change a complex problem, such as distributional effects of the consequences of climate change or climate policy (e.g. Andor et al., 2022; Dechezleprêtre et al., 2022; Drupp et al., 2023), but I will stop here. I will now go more into detail on the different market failures that are important for the green transition, but first I will define market failures.

Market failures are situations where the market do not provide an efficient allocation of resources. This means that there are unexploited gains in the economy. Efficient allocations are called Pareto efficient or Pareto optimal. Pareto efficiency means that it is not possible for one person to be better off without making another person worse off. There can be many Pareto efficient allocations and the criteria does not give any guidance on how to range them. Pareto efficiency does not take inequality or fairness into account (The CORE team, 2017).[1] It can also be noted that Pareto efficiency is a static term which judges the present allocation, not the change from one allocation to another. This means that if a change from one allocation to another is not a Pareto improvement, the new allocation can still be Pareto optimal.

2.2 Environmental externalities and policies to correct for them

The term externality can be defined as situations "where a consumption or production activity has unintended effects on others for which no compensation is paid" (Perman et al., 2003, p.10). Pigou (1920) is often pointed to as the founding father of the term *externalities*. But Pigou (1920) never uses the term *externalities* in his almost 1000 pages long book "The economics of welfare" (Spash, 2021). He writes about a person who in supplying something to another person "incidentally also renders services or disservices to other persons (...)" (Pigou, 1920, p.159) and he writes about "divergencies between marginal social net product and marginal trade net product"

[1] Sen (1987, p.35) argues that "[t]he criterion of Pareto optimality is an extremely limited way of assessing social achievement". He also writes that economics "can be made more productive by paying greater and more explicit attention to the ethical considerations that shape human behaviour and judgment. It is not my purpose to write off what has been or is being achieved, but definitely to demand more" (Sen, 1987, p.9). Sen later won the The Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel in 1998 "for his contributions to welfare economics" (Nobelprize.org, 2023).

(Pigou, 1920, p. xiii).

Even if the term is not the same as modern economists use, the idea is clear. Pigou (1920, p.168) writes that:

> "[i]t is plain that divergences between trade and social net product of the kinds we have so far been considering cannot (...) be mitigated by a modification of the contractual relation between any two contracting parties, because the divergence arises out of a service or disservice rendered to persons other than the contracting parties. It is, however, possible for the State, if it so chooses, to remove the divergence in any field by "extraordinary encouragements" or "extraordinary restraints" upon investments in that field. The most obvious forms, which these encouragements and restraints may assume, are, of course, those of bounties and taxes."

Coase (1960) argued against this, stating that with sufficiently low transaction costs and clearly defined property rights, bargaining between the agents will lead to a Pareto optimal outcome, i.e., internalizing the externality. However, in many situations involving externalities, such as climate change, there are many actors involved and therefore difficult to bargain and make agreements between everyone.

Furthermore, Pigou (1920) does not think taxes and subsidies are the only measures for government intervention, especially in "highly complex" situations:

> "It should be added that sometimes, when the interrelations of the various private persons affected are highly complex, the Government may find it necessary to exercise some means of authoritative control in addition to providing a bounty. (...) No "invisible hand" can be relied on to produce a good arrangement of the whole from a combination of separate treatments of the parts. It is, therefore, necessary that an authority of wider reach should intervene and should tackle the collective problems of beauty, of air, and of light (...)" (Pigou, 1920, p.170-171).

He sums up in the beginning of the book: "The above classes of divergence can be mitigated by a judicious employment of taxes and bounties, and sometimes by direct coercion" (Pigou, 1920, p.xiv).

The modern idea of a Pigouvian tax is that it should equal the marginal external cost. For pollution the marginal external cost equals the marginal damage cost. Emissions should be reduced until the marginal damage cost equals the indirect marginal benefits of emissions (i.e., from the activity that leads to the emissions). Then the total net benefit is maximized, assuming that the cost and benefit curves are smooth. The aim is to internalize the external costs into the price of the good or service. This creates an incentive for producers and consumers to take into account the full social costs when making decisions. The idea is that this will result in an efficient allocation of resources that maximizes the total net benefit for the society (Perman et al., 2011).

There are at least four reasons for a tax being the preferred instrument among economists correcting for environmental externalities, rather than regulations or subsidies. First, information asymmetry: The government does not know the abatement costs of different firms and it is therefore difficult to regulate each firm so that we achieve the optimal pollution level.[2] Second, taxes create revenue that can be used for other purposes or to reduce other distortionary taxes. The third and fourth reasons are related to political economy: Subsidies may be politically difficult to remove after they are implemented, and subsidies may result in adverse incentives, for instance that firms spend money on lobbying for subsidies.

When economists argue that a Pigouvian tax is welfare improving, we look at the aggregate effect for the society, from the view of the social planner (Sapienza & Zingales, 2013). The welfare of the society is usually summed using utilitarian ethics, meaning that every person is weighted equally (Perman et al., 2011). For individuals on the other hand it will make perfect sense to oppose a tax if the effect of the tax for them personally is net negative. If a person has higher utility from the activity inducing the externality than the average, lower marginal damage cost from the externality or lower utility from what the income of the taxes is spent on than the average person, the tax might not be in a person's self-interest. Therefore, from a theoretical point of view, resistance against environmental taxes on a personal level can be rational from a utility-maximizing perspective.

2.3 The interaction between environmental and knowledge externalities

The estimated cost of limiting the temperature increase to a certain degree is highly sensitive to assumptions about future technological progress (Gillingham & Stock, 2018). If low-carbon technologies become cheaper, the cost of reducing emissions by a certain amount becomes lower.

Acemoglu et al. (2012) argue that in order to avoid an environmental disaster, a market intervention is needed to influence the *direction* of technical change. The starting point of their theoretical model is that clean technology is less productive than dirty

[2] Ambec and Coria (2021) argue that an environmental tax can reveal information about firms' abatement cost and that this information can be used to inform the policy-makers about the optimal emission standard.

technology, and that technology is developed through a standing-on-the-shoulders-of-giants-effect. This means that there are intertemporal knowledge externalities present, which means that the researcher in the present do not take into account the productivity gain in the future from their innovation. The researcher is focused on the possible profit in the present.

The profitability of research in each of the two sectors (clean and dirty) determines the direction of technological change. Since clean technology lags behind the dirty sector, without any intervention, research in the dirty sector is the most profitable and research only occurs in the dirty sector. As long as there is no policy, the dirty technology improves and the productivity gap between the clean and the dirty technology increases. With only a carbon tax to direct the technological development, the economy will be highly distorted. Acemoglu et al. (2012) find that it is optimal with a subsidy that makes research on clean technology the most profitable. In addition, a carbon tax is needed to address the environmental externality. Delay is costly, as then the dirty technology becomes even more productive compared to the clean technology, and the clean technology will need more time to catch up with the dirty.

2.4 Network effects

Network effects can either be directly linked to the product itself, or indirectly through increased supply of complementary services such as charging stations (Katz & Shapiro, 1985). Indirect network effects mean that there is an interdependence between the demand for the primary good and the supply of the complementary good, and this is the case for electric vehicles and fast charging stations, and for hydrogen vehicles and stations. We often refer to this as the chicken or the egg paradox. Few consumers want to buy hydrogen vehicles because there are no stations, and no one wants to build hydrogen stations because there are so few hydrogen cars. In order to correct for the presence of network effects and solve the coordination problem, the government should introduce policies (Greaker & Midttømme, 2016).

2.5 Interaction between market failures and political failures

Besley and Persson (2022) investigate the interaction between market and political failures in the green transition, combined with a coordination problem between consumers and producers. They develop a dynamic model that explores the political and market conditions that could facilitate a green transition. The starting point is that politicians cannot commit to future climate policy. They argue that this is a realistic focus, rather than the normative focus on the optimal dynamic choices of a social planner.

What can drive the green transition in their model is the share of voters/consumers having green values increasing over time and the share of firms using green technology also increasing over time. The share of households demanding green products and the share of firms producing green products are interrelated (just as the interdependence between consumers when network effects are present), and this creates a coordination problem. If a green transition is socially desirable, they find that it is optimal to subsidize green technology. This lowers the cost of using green technology for the firms and creates a positive dynamic that increases the speed of the green transition. A limitation of this model is that the consumers and producers can only be either green or brown, while in reality most actors are on a continuous line where some choose more green than others.

I have now discussed multiple market failures and interaction between them that make the green transition in the transport sector challenging. Now I turn to the methods used in the thesis.

3 Methodological approaches

In this Section I will briefly present the different methods I have used in the different chapters, and some of their advantages and disadvantages.

3.1 Descriptive work

In certain instances, providing a clear and accurate description is crucial. Chapter 3 of this thesis focuses on the valuation of electric vehicles in the market, drawing upon comprehensive data gathered by the largest commercial actor on the secondhand car market in Norway. As highlighted by Økland (2022) in his thesis introduction, descriptive and empirical research holds great power in presenting pure facts. Økland (2022) supports this notion by referencing the renowned economist Thomas Piketty's work on wealth inequality, and literature pertaining to tax havens. Additionally, Rosling et al. (2018)'s book "Factfulness" serves as another notable example of the significance of factual description. Nevertheless, while describing a phenomenon is valuable, it can only take us so far. We do not know the cause of something by describing it. Other methods can be used to find effects and causes.

3.2 The causal framework

3.2.1 The potential outcome framework

The average effect of a policy intervention for those that were affected by the policy is called the average treatment effect of the treated. The treated persons are those that take part in or are affected by a program or a policy. This can for instance be an educational program about climate change, change in the cost of parking or implementation of environmental taxes. The effect for the treated of a policy intervention can be defined as the potential outcome of the treated when treated minus the potential outcome of the treated had the treated not been treated:

$$\tau = \mathbb{E}[Y_{i,2}(1) - Y_{i,2}(0)|D_i = 1] \tag{1}$$

where $Y_i(1)$ is the potential outcome of interest if treated and $Y_i(0)$ is the potential outcome of interest if not treated, $D_i = 1$ indicates that an individual is treated and $t = 2$ is the period post treatment (Roth et al., 2023). The last term is something we cannot observe. We can only observe either the outcome when not getting treatment or the outcome when getting treatment.

If the allocation of treatment is not random and we compare those getting treatment and those not getting treatment, we often have a problem with selection effects (Angrist & Pischke, 2009):

$$\begin{aligned}&\mathbb{E}[Y_{i,2}(1)|D_i = 1] - \mathbb{E}[Y_{i,2}(0)|D_i = 0] = \\ &(\mathbb{E}[Y_{i,2}(1)|D_i = 1] - \mathbb{E}[Y_{i,2}(0)|D_i = 1]) + (\mathbb{E}[Y_{i,2}(0)|D_i = 1] - \mathbb{E}[Y_{i,2}(0)|D_i = 0])\end{aligned} \tag{2}$$

The term in the first parenthesis in the second line is the effect we are interested in, while the term in the second parenthesis is the difference between the treated and the untreated, had none of them been treated. This second part is the selection effect. If those that choose to get treatment have different (unobservable) characteristics that influence the outcome than those that do not choose to get treatment, we have selection effects.

People self-select into many kinds of treatments. Therefore it is not possible to just compare those that get a treatment and those that do not in order to find the effect of the treatment. Without an experiment, either a natural experiment or an experiment that is initiated by the researcher, it is not random who gets a treatment and not. Randomized experiments "offer a powerful method for deriving results that are defensible both in the seminar room and in a legislative hearing" (Angrist & Pischke, 2010, p.4). A natural experiment can for instance be that a policy is rolled out at different times (staggered treatment), or a lottery behind who gets treatment, because e.g. it is not enough budget for everyone that would like to participate to take part.

The idea behind all methods using this potential outcome framework, is that the difference between the two terms in the selection effect should be zero. This means that the outcome of the untreated group (the control group) represents the outcome of the treatment group, had the treatment group not been treated. There are several methods using this framework, such as instrumental variables, randomized control trials and regression discontinuity design. I will now present the two different methods I have used in this framework, namely difference-in-difference and lab experiment.

3.2.2 Difference-in-difference

In Chapter 2 we use a difference-in-difference design. The idea behind this method is that we compare the outcome of two groups. The two groups have similar trends in the outcome variable before treatment. Then one of the groups gets a treatment, while the other does not. In order to find the effect of the treatment (β), we conduct two differences. First the difference between the outcome after and before treatment for both groups. Then we find the difference between the two differences:

$$\mathbb{E}[Y_{i,2}(1) - Y_{i,1}(1)|D_i = 1] - \mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 0] = \beta \tag{3}$$

The difference between the outcome of the treatment group before and after treatment could partly be a time effect. The outcome could already be on an upward or a downward trend. Having a control group then represents what the trend in the outcome variable would have been, had the treatment group not been treated.

The problem is that we cannot observe the trend for the treatment group had they not been treated. We need to assume that the control group follows the trend the treatment group would have followed had they not been treated. This is called the parallel trend assumption:

$$\mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 1] = \mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 0] \tag{4}$$

Combining the parallel trend assumption with an assumption of no anticipatory effects ($\mathbb{E}[Y_{i,1}(1)|D_i = 1] = \mathbb{E}[Y_{i,1}(0)|D_i = 1]$), which means that the treatment group do not have any treatment effects before treatment), we get something that is observable and possible to estimate:

$$\begin{aligned}\beta = \mathbb{E}[Y_{i,2}(1) - Y_{i,2}(0)|D_i = 1] \\ = \mathbb{E}[Y_{i,2}(1) - Y_{i,1}(1)|D_i = 1] - \mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 1] \\ = \mathbb{E}[Y_{i,2}(1) - Y_{i,1}(1)|D_i = 1] - \mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 0] \quad (5)\end{aligned}$$

This is the canonical difference-in-difference design with two groups and two time periods, one before and one after the treatment. However, there are different treatment timing in most applied work using this method (Baker et al., 2022). Before the work of Callaway and Sant'Anna (2021) and Goodman-Bacon (2021) and many others, the usual way to do a difference-in-difference with multiple time periods was using two-way fixed effects like in this regression equation:

$$Y_{i,t} = \alpha_i + \delta_t + \beta D_{i,t} + \epsilon_{i,t} \quad (6)$$

where $Y_{i,t}$ is the outcome of interest, α_i is unit fixed effects, δ_t is time fixed effects, $D_{i,t}$ is a binary indicator of whether the unit i is treated at time t and β is the coefficient of interest. The problem with this set-up is the presence of heterogenous effects across groups depending on when they are treated and/or dynamic treatment effects. Then the β could be biased (Baker et al., 2022; Roth et al., 2023). One of the reasons for the bias is that this regression makes "forbidden comparisons" with those already treated as control group (Roth et al., 2023). This is not problematic if the treatment effects are not dynamic or if the effects are not different across treatment cohorts or that the treatment is not staggered (Baker et al., 2022). In our case, in Chapter 2, the treatment is staggered and we therefore use the Callaway and Sant'Anna (2021)-estimator which is robust for hetereogenous treatment effects across time and treatment cohorts. It is difficult to know ex ante whether the treatment effects are hetereogenous across treatment cohorts and/or time, and it is therefore best to use estimators that are heterogeneity-robust (Roth et al., 2023). We explain more about how the Callaway and Sant'Anna (2021)-estimator works in Chapter 2.

3.2.3 Lab experiment

In Chapter 1 we use a lab experiment. The great advantage for all experiments, both in the lab and in the field, is that randomization of who gets treatment and not, solves the selection problem. This means that randomization makes sure that it is by coincidence who gets treated or not and which treatment they end up with. Experiments are therefore great for finding causal effects. However, Deaton (2009) argues that experiments do not find the *mechanism* behind the effect that is found.

Lab experiments have e.g. been used to investigate under what circumstances humans deviate from Homo Economicus (Falk & Heckman, 2009). Lab experiments are useful because one can keep constant everything but the variable one wants to test (Falk & Heckman, 2009). The problem is that lab experiments can be artificial and may not reflect real-world conditions, and participants may not behave in the same way as they would in natural settings (Levitt & List, 2007). Therefore, as the findings of lab experiments may not generalize to real-world settings, we do not know the external validity of the lab findings. This needs to be tested for different types of lab experiment, which has been done by e.g. Levitt and List (2007) and Buser and Yuan (2019).

3.3 Static, partial equilibrium model with numerical calibration

Almost all countries in the world have climate targets and policies and some countries have reduced their emissions (Boasson et al., 2022). Yet, even if the growth of emissions has been lower the last years, the global emissions do not seem to have reached their peak (Ritchie et al., 2023). In order to meet the goals of the Paris agreement, more climate policies are needed (Boasson et al., 2022). Therefore, limiting research to examining what has already been done, is not always sufficient. In addition, what has happened in the past might not represent what will happen in the future. Models can therefore be a good tool for assessing climate policy.

In Chapter 4 we use a partial equilibrium model of the future decarbonized road transport market. The model is static which makes it less complicated. The downside is that the phenomenon we are investigating, indirect network effects, is inherently dynamic. As number of users of station networks increases, the network effect decreases (Greaker & Midttømme, 2016). The conclusions from a static model might not directly translate into a dynamic setting. Static models might anyway be useful in many circumstances. The classic demand and supply model is a static model that gives insight.[3] However, static models should be supplemented with dynamic models in order to verify whether the insights from the static models hold in a dynamic setting.

A partial equilibrium model investigates what happens in one part of the economy

[3] Tjøtta (2021) investigates the dynamics of the market in an experiment with voluntarily exchange of goods. The dynamic process outside of the market equilibrium is important to investigate, for instance how prices are set. Although the static model does not capture everything interesting, Tjøtta (2021) finds that the static market equilibrium is reached quite quickly in the dynamic market process.

and disregards interactions with the rest of the economy. In Chapter 4, we look at the road transport market and disregard whether changes in this market affects for instance the electricity prices which again can influence the road transport market. In a general equilibrium model the changes in the whole economy is taken into account.

4 Data

In this section I present the different data sources I have used in this PhD thesis.

4.1 Administrative register data

In Chapter 2 we use Norwegian register data. The Norwegian administrative data is extremely rich and covers the whole population. An id for each person, family, firm and car makes it possible to track each unit from dataset to dataset. However, for environmental research this data has not been extensively used until recently, see for instance Fevang et al. (2021), Halse et al. (2022), Isaksen and Johansen (2021), and Johansen and Munk-Nielsen (2022).

One problem with register data is that it is a time lag between when the data is collected and when the researchers get access to the data. When studying phenomena that develop fast, such as the Norwegian electric car market, 1-2 years lag can make the data seem old before we have started doing research on it, and then when the research is published the findings might be somewhat outdated.

4.2 Primary data collection

In Chapter 1 we do primary data collection through the online platform Prolific and Lioness Lab (Giamattei et al., 2020). Prolific is a United Kingdom based company that gathers potential participants for surveys and lab experiments from all over the world (www.prolific.co). Their base of participants are so large that collecting answers from over 1600 residents in the United Kingdom in just one day was possible. Lioness Lab is an online platform for developing interactive online lab experiments. The platform has building blocks of "stages" that can be coded with JavaScript. The answers that the participants on Prolific give is collected through Lioness Lab on a server we set up.

4.3 Data from private sources

Data from private sources can be a great place to look for new and unstudied topics. In Chapter 3 we utilize novel data from Norway's largest internet market place for used goods, among those cars (finn.no). The web platform accounts for close to 90%

of the secondhand car market. We got the newest data they had, from 2011 to June 20th 2021. Finn.no provided the data, it is not web scraped. It took very short time from we inquired about the data until we received them, and we got the newest possible data.

In Chapter 4 we collect information from suppliers of fast charging stations and hydrogen stations that we use to calibrate the model. We also collect information from other sources, which is elaborated in Appendix B of the chapter.

5 Synthesis of the papers, including limitations and ideas for future research

5.1 Chapter 1: Does policy packaging boost public support for Pigouvian taxes? A lab experiment on combining taxes and subsides

Public resistance towards Pigouvian taxes often stops this policy from being implemented at a high enough level. In this article we investigate whether the support for a policy with a Pigouvian tax increases if it is combined with a subsidy. We conduct an online lab experiment with over 1600 participants. Participants were randomly assigned to different treatments, including a tax-only treatment, a subsidy-only treatment, and different combinations of the two. The tax is imposed on buying a good with a negative externality, while the subsidy is provided for each unit of the good not bought.

We find that the support for combinations of a tax and a subsidy is the average of the support for the two instruments alone. Participants' beliefs about revenue redistribution were most pessimistic when the tax was alone. Moreover, participants expected a lower increase in their payoff for the tax alone compared to the combinations. Interestingly, the tax was expected to be more effective than the subsidy in reducing demand.

The main limitations of this study is that the generalizability outside of the lab is not known. This is a general limitation of lab experiments, see Section 3.2.3.

For future research, the disparity between our findings and previous studies regarding view on taxes and beliefs about their effectiveness raises an important question regarding the causal direction. Are people opposed to taxes because they perceive them as ineffective, or do individuals express in surveys that taxes are ineffective because they simply do not want taxes? Our findings challenge the prevailing notion in the literature, as we discover that people do not support taxes while simultaneously consider them effective in reducing demand. Given this contradiction, it is evident that further investigation is needed to determine the causal relationship between attitudes towards taxes and beliefs about their effectiveness.

Several valuable extensions to the experiment could enhance our understanding of the topic. Firstly, it would be informative to compare our fractional combination design of a tax and a subsidy with an additive design, where the tax remains constant but different policies are added to form a policy package. It would be interesting to see whether this changes the relative level of support we find in our experiment for the combination policies. Additionally, exploring combinations of Pigouvian taxes with instruments other than subsidies in a policy package could yield different outcomes.

5.2 Chapter 2: Company cars and household car choices

Considering the environmental impact of car production and the potential for increased car usage with greater accessibility, it is crucial to understand the factors that influence household car choices. This understanding is essential for designing effective policies. In this paper, we investigate the relationship between getting access to a company car and the change in the number of cars within a household, including the number of electric vehicles.

This paper is the first study to investigate the company car scheme using quasi-experimental methods. Specifically, we employ a difference-in-differences design to address the potential endogeneity of the decision to acquire a company car. Instead, we focus on who most likely receives an offer of a company car, considering it as an exogenous variation resulting from job changes. Our sample comprises individuals who change jobs once during the period of investigation and work in what we call company car occupations. The treatment group most likely get an offer of a company car when they change job, while the control group, also working in company car occupations and changes job, never has such an opportunity.

It might seem like the access to a company car scheme increases the numbers of cars in the household. However, this might be driven by wage growth, rather than the company car scheme itself, as the access to a company car and higher wage growth are correlated. Still, based on income elasticities in car demand, it seems like some of the increase in the number of cars in the households can be due to the company car scheme.

If there is any change in the rules for how the company cars are taxed in the future, this can be exploited through a regression discontinuity design in further investigations.

5.3 Chapter 3: Climate, technology, and value: Insights from the first decade with mass-consumption of electric vehicles

The widespread deployment and ongoing advancement of low-carbon technologies play a crucial role in mitigating greenhouse gas emissions. However, one potential unintended consequence of rapid technological progress is that products may become outdated before the technical lifetime is over. We investigate whether the market value of electric vehicles (which represent rapid technological progress) declines faster over their lifetime than gasoline vehicles (which represent mature technology). We use novel data from the largest web platform for secondhand vehicles over the period 2011-June 2021 (finn.no).

We find that electric vehicles experience a steeper decline in value compared to gasoline vehicles. This seems to be driven by the electric vehicles with driving range below 200-250 km. We hypothesize that the substantial price drop is primarily a consequence of the rapid technological advancements in electric vehicle technology.

One of the limitations of this study is that there is no data for old, large electric vehicles with long range because they mainly entered the market only a few years ago. Therefore we do not know the entire price path of large electric vehicles with long range yet.

For further investigations, I would like to examine predictions for secondhand values made a few years ago regarding the secondhand values of vehicles with different technologies and compare them with the current observed secondhand prices. Such an analysis aims to evaluate the accuracy of these earlier predictions and potentially improve future predictions.

5.4 Chapter 4: One or two non-fossil technologies in the decarbonized transport sector?

Subsidies to fast charging stations for electric vehicles are part of several countries' climate policies. Should the government subsidize hydrogen stations too? Or should the government concentrate on electrification of the transport market? The presence of indirect network effects point in direction of only one technology type in the transport market because one big network is better than two small. On the other hand, the benefit of variety in technologies offered points in direction of two technologies.

In this chapter we investigate what factors determine whether the government should promote one or two technologies in a decarbonized road transport market, and what policies governments should choose. We investigate these questions theoretically and numerically through a static, partial equilibrium model.

We find that whether one or two non-fossil technologies is optimal depends on the substitutability between the technologies and the existing number of vehicles of the other technology. The first-best policy involves a subsidy of the markup on charging and filling.

One limitation is that the calibration of a future equilibrium is highly uncertain. The uncertainty is both related to how the technology will develop the next years, the market structure in the future, and the parameters in the model related to consumers' utility. Further, we do not know whether the results from the static model translates to a dynamic model.

For further investigations, developing a dynamic model with indirect network effects in the transport market would be interesting.

6 Concluding remarks

While the goal of the leading politicians in the world is to limit the temperature increase to well below 2 degrees and to aim at 1.5 degrees of warming, the global CO_2 emissions do not yet seem to have peaked (Ritchie et al., 2023). Studying the effects and side-effects of climate policy, as well as what shapes climate policy will become even more important in the coming years.

Further, it is not just climate policy, but many types of policies that will need to be scrutinized. The company car scheme for instance, which the second chapter in this thesis investigates, is not climate policy per se, but illustrates how efforts to reduce emissions are integrated into many different policies.

As countries continue to strengthen and reevaluate their policies, more data will become increasingly available. These policy changes might generate natural experiments, which can give us needed insights.

Public budgets are essential for various sectors, including healthcare, defense, education, infrastructure, and addressing climate change. Consequently, the cost associated with climate policies cannot be dismissed as an insignificant concern. At the same time, the attitudes of people towards policies play a crucial role in determining their implementation. Striking a balance between effective environmental measures and public acceptance is vital in shaping sustainable and successful climate policies. Therefore combining Pigouvian taxes and subsidies might be a way forward.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of parts of this introduction the author used Chat-GPT-3.5 and Google translate in order to improve language and find synonyms. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, *102*(1), 131–166.

Ambec, S., & Coria, J. (2021). The informational value of environmental taxes. *Journal of Public Economics*, *199*, 104439.

Anderson, S. T., Marinescu, I., & Shor, B. (2023). Can Pigou at the Polls Stop Us Melting the Poles? *Journal of the Association of Environmental and Resource Economists.*

Andor, M. A., Lange, A., & Sommer, S. (2022). Fairness and the support of redistributive environmental policies. *Journal of Environmental Economics and Management*, *114*, 102682.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion.* Princeton university press.

Angrist, J. D., & Pischke, J.-S. (2010). The credibility revolution in empirical economics: How better research design is taking the con out of econometrics. *Journal of economic perspectives*, *24*(2), 3–30.

Baker, A. C., Larcker, D. F., & Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, *144*(2), 370–395.

Barrett, S. (1994). Self-enforcing international environmental agreements. *Oxford economic papers*, *46*, 878–894.

Besley, T. J., & Persson, T. (2022). *The Political Economics of Green Transitions*, CEPR Discussion Paper No. DP17242.

Boasson, E. L., Clapp, C., Kverndokk, S., Peters, G., Strømman, A. H., & Wettestad, J. (2022). *Optimisme å spore i klimarapporten* (NRK, Ed.) [Accessed 18 May 2023]. https://www.nrk.no/ytring/optimisme-a-spore-i-klimarapporten-1.15915215

Buser, T., & Yuan, H. (2019). Do women give up competing more easily? Evidence from the lab and the Dutch math olympiad. *American Economic Journal: Applied Economics*, *11*(3), 225–252.

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230.

Carleton, T., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Kopp, R. E., McCusker, K. E., Nath, I., et al. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics*, *137*(4), 2037–2105.

Coase, R. H. (1960). The problem of social cost. *The journal of Law and Economics.*

Deaton, A. S. (2009). *Instruments of development: Randomization in the tropics, and the search for the elusive keys to economic development*, National Bureau of Economic Research.

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A. S., & Stantcheva, S. (2022). *Fighting climate change: International attitudes toward climate policies*, National Bureau of Economic Research.

Douenne, T., & Fabre, A. (2022). Yellow vests, pessimistic beliefs, and carbon tax aversion. *American Economic Journal: Economic Policy*, *14*(1), 81–110.

Drupp, M. A., Freeman, M., Groom, B., & Nesje, F. (2018). Discounting disentangled. *American Economic Journal: Economic Policy*, *10*(4), 109–134.

Drupp, M. A., Meya, J., Quaas, M. F., & Sager, L. (2023). Inequality and the environment: An introduction to the special issue.

Fæhn, T., & Isaksen, E. T. (2016). Diffusion of climate technologies in the presence of commitment problems. *The Energy Journal*, *37*(2).

Falk, A., & Heckman, J. J. (2009). Lab experiments are a major source of knowledge in the social sciences. *Science*, *326*(5952), 535–538.

Fevang, E., Figenbaum, E., Fridstrøm, L., Halse, A. H., Hauge, K. E., Johansen, B. G., & Raaum, O. (2021). Who goes electric? The anatomy of electric car ownership in Norway. *Transportation Research Part D: Transport and Environment*, *92*, 102727.

Giamattei, M., Yahosseini, K. S., Gächter, S., & Molleman, L. (2020). Lioness lab: A free web-based platform for conducting interactive experiments online. *Journal of the Economic Science Association*. https://doi.org/10.1007/s40881-020-00087-0.

Gillingham, K., & Stock, J. H. (2018). The cost of reducing greenhouse gas emissions. *Journal of Economic Perspectives*, *32*(4), 53–72.

Goodman-Bacon, A. (2021). Difference-in-differences with variation in treatment timing. *Journal of Econometrics*, *225*(2), 254–277.

Greaker, M., & Midttømme, K. (2016). Network effects and environmental externalities: Do clean technologies suffer from excess inertia? *Journal of Public Economics*, *143*, 27–38.

Halse, A., Hauge, K. E., Isaksen, E. T., Johansen, B. G., & Raaum, O. (2022). *Local incentives and electric vehicle adoption*, Available at SSRN 4051730.

Hegsvold, K., Nenseth, V., & Wangsness, P. B. (2022). *Klimamål og strategier i transportplanlegging i utvalgte land.* Transport Economic Institute. Report 1931/2022.

Heutel, G. (2019). Prospect theory and energy efficiency. *Journal of Environmental Economics and Management*, *96*, 236–254.

IEA. (2023). *Global EV Outlook 2023*. https://iea.blob.core.windows.net/assets/dacf14d2-eabc-498a-8263-9f97fd5dc327/GEVO2023.pdf

Isaksen, E. T., & Johansen, B. G. (2021). *Congestion pricing, air pollution, and individual-level behavioral responses*, Available at SSRN 3832230.

Johansen, B. G., & Munk-Nielsen, A. (2022). *Portfolio complementarities and electric vehicle adoption*, Working paper.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). Anomalies: The endowment effect, loss aversion, and status quo bias. *Journal of Economic perspectives*, *5*(1), 193–206.

Kallbekken, S., Kroll, S., & Cherry, T. L. (2011). Do you not like pigou, or do you not understand him? tax aversion and revenue recycling in the lab. *Journal of Environmental Economics and Management*, *62*(1), 53–64.

Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American Economic Review*, *75*(3), 424–440.

Levitt, S. D., & List, J. A. (2007). What do laboratory experiments measuring social preferences reveal about the real world? *Journal of Economic Perspectives*, *21*(2), 153–174.

Meld. St. 33. (2016-2017). *National Transport Plan 2018–2029. Report to the Storting (white paper) English Summary.*

Millner, A., & Ollivier, H. (2016). Beliefs, politics, and environmental policy. *Review of Environmental Economics and Policy.*

MIT climate portal. (2021). *Climate sensitivity* [Accessed April 4 2023]. https://climate.mit.edu/explainers/climate-sensitivity

Nesje, F., Drupp, M. A., Freeman, M. C., & Groom, B. (2022). *Philosphers and economists can agree on the intergenerational discount rate and climate policy paths*, CESifo Working Paper.

Nobelprize.org. (2023). *Amartya Sen – Facts* [Accessed 23 May 2023]. https://www.nobelprize.org/prizes/economic-sciences/1998/sen/facts/

Nordhaus, W. D. (2007). A review of the Stern review on the economics of climate change. *Journal of economic literature*, *45*(3), 686–702.

OFV. (2021). *Kostnader ved bilhold – eksempler på beregning [Car ownership costs – examples of calculation]*. The Norwegian Road Federation.

OFV. (2022). *Kostnader ved bilhold – eksempler på beregning [Car ownership costs – examples of calculation]*. The Norwegian Road Federation.

OFV. (2023a). *Bilsalget i april 2023* [Accessed May 25 2023]. https://ofv.no/bilsalget/bilsalget-i-april-2023

OFV. (2023b). *Bilsalget i februar 2023* [Accessed May 25 2023]. https://ofv.no/bilsalget/bilsalget-i-februar-2023

OFV. (2023c). *Bilsalget i januar 2023* [Accessed May 25 2023]. https://ofv.no/bilsalget/bilsalget-i-januar-2023

OFV. (2023d). *Bilsalget i mai 2023* [Accessed June 13 2023]. https://ofv.no/bilsalget/bilsalget-i-mai-2023

OFV. (2023e). *Bilsalget i mars 2023* [Accessed May 25 2023]. https://ofv.no/bilsalget/bilsalget-i-mars-2023

OFV. (2023f). *Kostnader ved bilhold – eksempler på beregning [Car ownership costs – examples of calculation]*. The Norwegian Road Federation.

Økland, A. (2022). *Tax and secrecy issues in real estate markets* (Doctoral dissertation).

Pathak, M., Slade, R., Shukla, P., Skea, J., Pichs-Madruga, R., & Ürge-Vorsatz, D. (2022). Technical Summary. In P. Shukla, J. Skea, R. Slade, A. A. Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, & J. Malley (Eds.), *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK; New York, NY, USA.

Perman, R., Ma, Y., Common, M., Maddison, D., & McGilvray, J. (2011). *Natural resource and environmental economics*. Pearson Education.

Perman, R., Ma, Y., McGilvray, J., & Common, M. (2003). *Natural resource and environmental economics*. Pearson Education.

Pigou, A. C. (1920). The economics of welfare [Accessed through Internet Archive May 23 2023]. https://archive.org/details/cu31924073868113/page/160/mode/2up?q=tax

Pindyck, R. S. (2013). Climate change policy: What do the models tell us? *Journal of Economic Literature*, *51*(3), 860–72.

Ritchie, H., Roser, M., & Rosado, P. (2023). *Co2 and greenhouse gas emissions*. https://ourworldindata.org/co2-and-greenhouse-gas-emissions

Rosling, H., Rosling, O., & Rönnlund, A. R. (2018). *Factfulness: Ten reasons we're wrong about the world – and why things are better than you think*.

Roth, J., Sant'Anna, P. H., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of risk and uncertainty*, *1*, 7–59.

Sapienza, P., & Zingales, L. (2013). Economic experts versus average Americans. *American Economic Review*, *103*(3), 636–42.

Sen, A. (1987). *On Ethics and Economics*. Oxford University Press.

Spash, C. L. (2021). *The history of pollution 'externalities' in economic thought*, WU Vienna University of Economics and Business. SRE - Discussion Papers No. 2021/01.

Stern, N. (2008). The economics of climate change. *American Economic Review*, *98*(2), 1–37.

The CORE team. (2017). *The economy*. https://www.core-econ.org/.

Tjøtta, S. (2021). Adam smiths markedsteori: Mistet og funnet. *Samfunnsøkonomen*, *2*.

Papers

Paper 1: Can policy packaging help overcome Pigouvian tax aversion? A lab experiment on combining taxes and subsidies

Can policy packaging help overcome Pigouvian tax aversion? A lab experiment on combining taxes and subsidies *

Gøril L. Andreassen[†] Steffen Kallbekken[‡] Knut Einar Rosendahl[§]

June 22, 2023

Abstract

Tax aversion makes it politically challenging to introduce Pigouvian taxes. One proposed solution to overcome this resistance is to package policies. Using an online lab experiment, we investigate whether combining a tax and a subsidy is perceived as more acceptable than the tax or the subsidy alone. The purpose of the policies is to reduce demand for a good with a negative externality to the socially optimal level. We find that support for a combination of a tax and a subsidy equals the simple average of support for the two instruments alone. Combining a tax and a subsidy therefore does not reduce tax aversion, other than through lower tax rates in the combinations. We also examine potential mechanisms behind the tax aversion. Participants hold more pessimistic beliefs about what share of the tax revenue they will receive when the tax is implemented alone than when it is combined with a subsidy. Furthermore, we find that the participants expect the tax to be more effective in reducing demand for the good with a negative externality than both the subsidy alone and the combinations of tax and subsidy. This belief does not, however, translate into support for the tax. (*JEL* D72, H23, Q54, Q58)

Keywords: Pigouvian taxes; policy packaging; public support; lab experiment; tax aversion

*Funding: This work was supported by the Research Council of Norway, grant number 308789

†Corresponding author. goril.louise.andreassen@nmbu.no. School of Economics and Business, Norwegian University of Life Sciences, PB 5003 NMBU, 1432 Ås, Norway

‡steffen.kallbekken@cicero.oslo.no. CICERO Center for International Climate Research, PB 1129 Blindern, 0318 Oslo

§knut.einar.rosendahl@nmbu.no. School of Economics and Business, Norwegian University of Life Sciences, PB 5003 NMBU, 1432 Ås, Norway

1 Introduction

Pigouvian taxes are crucial policy instruments to cost-effectively reduce negative externalities such as emissions of greenhouse gases and other types of pollution, as they internalize the external costs (Timilsina, 2022). Shapiro and Metcalf (2023) find that not only do carbon taxes reduce emissions, they also induce firms to choose green technologies, and they find positive (but modest) effects on consumption, output and employment. However, public opposition towards Pigouvian taxes makes it challenging for policy makers to introduce them. The yellow vest protests against the fuel tax increase in France in 2018 is the iconic example of peoples' disapproval of carbon taxes (Douenne & Fabre, 2022). Another indication of the unpopularity and political difficulty of introducing taxes is that carbon pricing only covers 23% of global greenhouse gas emissions, with only 4% of emissions having a price sufficiently high to keep global warming below 2°C (The World Bank, 2022). The world's inability to correctly price externalities is tremendously costly: According to Parry et al. (2021), explicit and implicit global fossil fuel subsidies amounted to 6.8 percent of global GDP in 2020, mostly due to lack of environmental and other taxes.

It is therefore essential to explore policy designs or other interventions that can increase public support for Pigouvian taxes. One idea that has been garnering growing attention in multiple fields is to create policy packages (Givoni et al., 2013; Kern et al., 2019). Put simply, the idea is to combine effective but unpopular policies with less effective but more popular policies, to use secondary policies to offset undesirable impacts of the primary policies, or that the way the instruments work together is helpful.[1] In this paper we use a lab experiment to investigate how combining a tax with a subsidy influences the relative level of support.[2] We also examine the role of beliefs about the tax, the subsidy and the combinations of the two instruments to understand the low level of public support for taxes.

Economists have labelled the opposition against taxes "tax aversion". Tax aversion can be defined as opposition towards tax schemes that would increase both individual and social economic welfare, based on incorrect and pessimistic beliefs about the

[1] Ambec and Coria (2021) find that taxes reveal information about a firm's abatement costs and this information can be used to set an emission standard. Further, Acemoglu et al. (2012) find that a combination of a tax and a subsidy is optimal to target the interaction effects between environmental externalities and intertemporal knowledge externalities.

[2] Using both taxes and subsidies to target the same externality is a common practice. One example is a congestion tax on cars and a subsidy for public transport to target pollution from cars as well as congestion. Another is energy taxes combined with subsidies for investing in energy saving, such as improved insulation or installing heat pumps. Helm and Mier (2021) investigate the optimal mix of subsidies and taxes for intermittent renewable energy and energy storage. Combining taxes and subsidies to target a negative externality will probably not be as cost effective as having only taxes, see for instance Gugler et al. (2021).

properties of the tax such as its effectiveness and fairness.[3] Several of the factors shaping people's views about Pigouvian taxes are well established (Bergquist et al., 2022; Drews & Van den Bergh, 2016). From economic theory one would expect economic self-interest to play a central role. Whereas it does play a role, it cannot fully explain the opposition against Pigouvian taxes (Anderson et al., 2023; Dechezleprêtre et al., 2022; Douenne & Fabre, 2022; Heres et al., 2017; Kallbekken & Sælen, 2011; Umit & Schaffer, 2020). The belief that taxes do not reduce demand has consistently been shown to be one of the most important determinants of public opinion about taxes (Bergquist et al., 2022; Dechezleprêtre et al., 2022; Douenne & Fabre, 2022). Beliefs about fairness have also persistently been shown to be important (Dechezleprêtre et al., 2022; Douenne & Fabre, 2022).[4]

Research has identified some strategies that can be helpful for overcoming tax aversion. Earmarking of the tax revenue seems to increase support (Baranzini & Carattini, 2017; Dechezleprêtre et al., 2022; Kallbekken et al., 2011).[5] What the earmarked tax revenue is spent on can have strong impact on the level of support, but varies between groups of people (Anderson et al., 2023; Dechezleprêtre et al., 2022). Heres et al. (2017) find in a lab experiment that informing the participants that the tax revenue is returned in equal proportions to them, increases their support for taxes. However, the support for both a tax and a subsidy increases when there is no uncertainty about what happens to the income from the tax and the cost of funding the subsidy.[6] Allowing people to experience positive effects of an environmental tax, can increase support (Cherry et al., 2014; Schuitema et al., 2010; Winslott-Hiselius et al., 2009). The results on providing more information about how environmental taxes work are mixed (Dechezleprêtre et al., 2022; Douenne & Fabre, 2022; Kallbekken et al., 2011). Avoiding the term "tax" can under some circumstances lead to higher support (Baranzini & Carattini, 2017; Hardisty et al., 2010; Kallbekken et al., 2011).

A scarce literature explores the impact on the level of public support of combining coercive instruments like taxes with other and more popular policies. The interesting dynamic is how preferences for different types of policies interact when they are

[3]This combines and further develops the definitions of Kallbekken et al. (2011) and Douenne and Fabre (2022).

[4]Ideology or political attitudes can also be an important argument against taxes (Cherry et al., 2017). The view that the government should by principle not decide what one can and cannot do, could be a driver in the opposition against taxes. However, Douenne and Fabre (2022, p.83) find that "these results suggest that the rejection of carbon taxation does not typically result from clashing principles, such as a disinterest in the climate or a dislike of price instruments, but rather from overly pessimistic beliefs about the properties of the reform."

[5]We do not define earmarking of tax revenue to a specific purpose as a policy package or policy bundle. To be defined as a policy package, different instruments have to be combined.

[6]From the research design in Heres et al. (2017), we cannot disentangle whether the increased support comes from the removal of the uncertainty or that the tax revenue is shared between the participants, or both.

combined. Is, for instance, the joint assessment of combined instruments (policy packages) dominated by the instrument the respondents are most (or least) averse to, or is it a simple averaging of the preferences for each instrument?

The early contribution by Eriksson et al. (2008) finds that support for a combination of two instruments is higher than for the most restrictive instrument alone, but the level of support is lower than the average of support for the two constituent parts (a fossil fuel tax combined with either improved public transport or subsidies for renewable fuels). However, when the instruments are presented in isolation, it appears that no information is provided on how the tax revenues are to be spent or how the subsidies are to be financed, whereas this information is provided for the two policy packages.

Two more recent and experimental papers indicate a positive dynamic: Milkman et al. (2012) find that bundled policies are valued more highly than the most popular policy is valued on its own.[7] The policies vary in their costs and benefits (jobs lost, acres of forest protected, etc.), and hence the results are somewhat difficult to interpret. Using a choice experiment, Fesenfeld (2022) finds that bundling policies may reduce opposition to taxation. He studies the impact of policy complexity by comparing responses to low complexity policy proposals (one goal and one instrument) with high complexity policy proposals (one goal and four policy instruments). When a large tax increase is added to a low complexity policy proposal, he finds that it decreases the probability of choosing that package (the average marginal component effect) by 15 and 27 percentage points among German and US respondents, respectively. However, when the same large tax increase is added to a high complexity policy proposal, it decreases the probability of choosing that policy package by only 9 and 18 percentage points, respectively. In this choice experiment, payoffs and policy effectiveness are not made explicit, but the subsidies offer lower consumer prices (for food and transport) at no explicit cost.

The existing literature does not disentangle the mechanisms that can explain how a joint preference for combined instruments is formed: Instrument type varies together with costs and benefits, and these studies are therefore unable to pinpoint what causes the level of support for the combination to differ from the level of support for the constituent parts. Based on the diverging previous findings, we explore the dynamics of how the preferences for a tax and a subsidy interact to form the preference for a combination of the two in a setting where 1) participants' decisions are incentivized, 2) the study is sufficiently powered to detect a 6 percentage point difference in support

[7] In the article they write that "bundled legislation is valued more than the sum of its parts", but the correct wording seems to be "higher than the most popular policy on its own". For example, Bill 1 and Bill 2 has 54% and 45% support, respectively, while the combined Bill has 83% support.

for policies (see pre-analysis plan (p.7) in Appendix D for details), 3) payoffs are equal across instruments (for the same behaviour), and 4) the combinations of instruments are fractional rather than additive. This means that when the tax and subsidy are combined, the tax and subsidy rates are lower than when the tax or the subsidy are implemented alone.

Further, we want to investigate the mechanisms behind the lack of support for taxes by comparing beliefs about a tax with beliefs about a subsidy and combinations of the two. Expectations about the effectiveness of the instrument in reducing the externality and about what happens with the tax revenue and the subsidy cost are interesting to shed light on in order to deepen our understanding of attitudes towards Pigouvian taxes.

In our experiment we introduce a market for a fictitious good with a negative externality where participants earn a financial reward (payoff) through the profit they make by purchasing units of the good. At the same time they are negatively affected by the externality from the units purchased by the other participants in their group. Participants vote on the introduction of policies that can incentivize participants to purchase the socially optimal number of units through a tax, a subsidy, or combinations of the two instruments. If implemented, the tax is charged for any units purchased, whereas the subsidy is paid for any of the units *not* purchased. The participants are randomized into five different groups: (1) 100% tax, (2) 75% tax & 25% subsidy, (3) 50% tax & 50% subsidy, (4) 25% tax & 75% subsidy, and (5) 100% subsidy.

Taxes have two core properties: First, they change the price the consumer faces so that demand decreases (as long as demand is not fully inelastic), which in turn reduces the external costs. Second, they generate revenue that can be spent by the government, such as distributing it back to the citizens. Subsidies also change the (direct or implicit) price the consumer faces, but instead of generating income for the government, subsidies need to be financed. If the tax is implemented in our lab experiment, the revenue collected from each participant is split equally between the other group members. We do not include the revenue from the participant itself to mimic the real world setting where the revenue from the tax paid by the participant itself is a marginal contribution to the total tax revenue.[8] The subsidy payments received by each participant are financed through equal contributions from the other group members. In this way we ensure that all policies in the experiment produce identical payoffs for the same behaviour for all group members. However, we cannot verify whether the participants actually take this payoff into account when they vote.

[8]As each group in our experiment consists of three members, $\frac{1}{3}$ is a large part of the total tax revenue, while in the real world the "group" typically consists of millions of people.

The first contribution of this paper is that we find that the point estimates of the public support increases linearly as the subsidy share increases and the tax share decreases in the fractional combinations of the instruments. As explained above, this is in a setting where decisions are incentivized and the payoff structures are identical across policies. Our experiment with 1641 participants thus produces results that do not align with the previous findings of Milkman et al. (2012) and Fesenfeld (2022).[9] The dynamics we observe indicate no beneficial effect on public support from combining policy instruments beyond the simple averaging of preferences for the constituent parts of the package. Thus, the increased support found in Milkman et al. (2012) might have come from the increased gain in the policy package and not from the strategy of packaging as such.

The second contribution of this paper is that we find pessimistic beliefs about what happens to the tax revenue. This finding is consistent with Douenne and Fabre (2022, p.83), who find that the opposition against the carbon tax comes "from overly pessimistic beliefs about the properties of the [carbon tax] reform." Revealing pessimistic beliefs in different contexts is important for understanding the opposition towards Pigouvian taxes. We find more pessimistic beliefs about what share of the tax revenues the participants in the experiment will receive (a piece of information that is not clearly shared with them initially, cf. Section 2) when a tax is the only policy, than when it is combined with a subsidy. Similarly, the beliefs about whether the proposed policy will increase the payoff compared with no policy are more pessimistic when the tax is the only instrument than when the tax is combined with a subsidy or the subsidy alone. Furthermore, for the combination of a tax and a subsidy, the share expecting the policy to increase the payoff declines with the share of the tax in the proposed policy. Participants do expect to pay a substantial share of the subsidy cost, but unlike the expectations about tax revenues this share does not differ significantly across treatments. Because our design has fractional combinations of the tax and the subsidy, we can investigate what happens with a gradual decrease of the tax share of the instrument. The result shows that the pessimistic beliefs about the tax revenue are specific to the 100% tax treatment group.

The third contribution is that we find that participants expect the tax to be more effective in reducing the demand for the good causing the externality than the subsidy alone and the combinations of a tax and a subsidy. This contradicts previous findings that people believe taxes not to be effective in reducing demand, which has been found to be one of the main reasons why people oppose taxes (Bergquist et al., 2022;

[9] Milkman et al. (2012) had far fewer participants (168), while Fesenfeld (2022) had 9115 participants.

Douenne & Fabre, 2022).[10] We do not simply ask the participants whether they expect the policy to be effective. Instead we ask how many units they expect the other participants in their group to buy with and without the policy. The expectation about the effectiveness of the tax does not translate into support for the tax. By contrast, in the subsidy treatment, almost all who expect the policy to be effective also vote for the policy.

In the next section, we describe our experimental design, the theoretical predictions of what the participants will do, the experimental procedure, the sample and the balance tests. Then we analyse the findings, before the we discuss and conclude. We posted a pre-analysis plan on AEA Social Registry before the experiment started with RCT ID AEARCTR-0009099 and this can be found in Appendix D. Deviations from the plan are mentioned in the text and elaborated in Appendix E.

2 Methods

2.1 Experimental design

The experiment consists of a market round, a policy vote and then a second market round. In the market, participants decide how many units of a good to buy. Buying the good creates value for the participants, but also an external cost that is imposed on the others in their group. In the first round there is no policy. Participants are then asked to vote on a policy proposal that would incentivize all to limit the number of units bought to the social optimum. If the majority votes for the policy, the prices and the payoff structure in the second market round changes. The outcome we are interested in is whether the participants vote yes or no to the policy proposal. The experimental design is based on Kallbekken et al. (2011), Cherry et al. (2013), Cherry et al. (2014), Heres et al. (2017) and Cherry et al. (2017).

Each participant is part of a group with two other participants. All the participants act as buyers in a market. Each participant can buy up to six units of the good. The price of each good is 40 tokens,[11] whereas the value of each of the units of the goods differ. The first unit has the highest value and then each additional unit is worth less, mimicking declining marginal utility of consumption, see Table 1. For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group, meaning that the total external cost per unit is 40 tokens.

In the first round, the payoff is calculated as the value of the units each participant

[10] Dechezleprêtre et al. (2022) also find that the majority of the respondents believe that a carbon tax would result in less driving.

[11] The currency used in the experiment is tokens, where 100 tokens equal £1.

Table 1: The value of each unit the participants can buy.

Number	Value of the unit
1.	130
2.	110
3.	90
4.	70
5.	50
6.	30

buys minus the price of the units and minus the external costs from the purchases by the two other group members, see Table 2. At the end of the round, participants receive feedback on all the components of this payoff equation.

Table 2: Example of how the payoff is calculated in round 1. The example is based on all group members choosing five units.

	Element in the payoff	Example
	The value of the units the participant buys	130+110+90+70+50= 450
-	the price of the units	- 40*5 = -200
-	the external costs from the purchase by the others in the group	-20*5*2= -200
=	Payoff	50

In order to reduce strategic behavior within the group, the participants only have one round to get to know the market before they vote on a policy proposal. Further, we decided to nudge the participants into choosing five units (the dominant strategy, see Section 2.2) in the first round by informing them (truthfully) that in a pilot we ran for the experiment, a majority chose five units.

After experiencing this market for one round, participants are asked to vote on the rules that will govern the next round of the market. These rules vary across treatment groups. The participants' choices are to either 1) keep the rules as they were for the previous round, or 2) introduce a new specific policy.

The specific policy can either be a tax, a subsidy, or a fractional combination of the two. The option that receives the majority of votes (i.e., policy or no policy) will be implemented. Whether or not a participant votes for the proposed policy is the outcome variable. This a between-subjects design where participants are randomly allocated to one of five treatments. The five treatments are:

1. 100% tax: A tax of 40 tokens per unit.
2. 75% tax & 25% subsidy: A tax of 30 tokens per unit and a subsidy of 10 tokens per unit not purchased.[12]

[12]To give subsidies for not buying or producing something is e.g. done within farming and

3. 50% tax & 50% subsidy: A tax of 20 tokens per unit and a subsidy of 20 tokens per unit not purchased.

4. 25% tax & 75% subsidy: A tax of 10 tokens per unit and a subsidy of 30 tokens per unit not purchased.

5. 100% subsidy: A subsidy of 40 tokens per unit not purchased.

As all policies entail the same monetary payoff for choosing the dominant strategy (see Section 2.2), what differs is how the payoff structure is implemented (via a tax or a subsidy), and for simplicity of exposition we will refer to this difference as the "tax share" of the proposal (i.e. 100, 75, 50, 25 or 0% tax). Whereas previous studies add policies to the policy package, our design using fractional combinations of two policies (tax and subsidy) is essential for keeping monetary payoffs for choosing the dominant strategy identical across treatments.

We inform the participants that the value of each unit will remain the same if policy is implemented, and what the new price per unit will be if the tax is implemented (50 to 80 tokens depending on the treatment). For the subsidy, the price per unit remains the same, but the value of each unit is reduced since the participants receive money for each unit they do not buy.

The payoff is calculated in the same way as in the first round, but the price of the good changes. In addition, in the four treatment groups where there is a subsidy, the subsidy paid for not buying a good is also added to the payoff. Further, the tax revenue is distributed and the subsidy cost is financed. The revenue from the tax a participant in the group pays is shared equally among the two other participants. The cost of the subsidy a participant in the group receives is shared equally among the two other participants. The participants are, however, not informed fully about how the tax revenues or the cost of the subsidy will be shared among the three group members (see the next paragraph). Table 3 shows an example of payoff calculation in the second round. If someone has a negative payoff at the end of the experiment, the payoff is 0.

When voting for policy or no policy, the participants are by design not fully informed about how the tax revenues will be distributed nor how the subsidy will be financed. This is the same design as in Heres et al. (2017). This resembles real world situations where tax revenue use and subsidy funding are rarely explicit. To avoid deception, we provided the following information before participants were asked to vote: "The tax generates revenue. The group's budget will be balanced through personal transfers

foresting. For instance, the subsidy scheme REDD+ is paying for not deforesting forests. Another example is to subsidize no-till farming.

Table 3: How the payoff is calculated in round 2. The example is based on all group members choosing three units and that the policy with 50% tax & 50% subsidy is implemented.

	Element in the payoff	Example
	The value of the units the participant buys	130+110+90= 330
-	the price of the units	- 60*3 = -180
+	the subsidy for the units not bought	+ 20*3 = 60
-	the external costs from the purchase by the two other participants	-20*3*2= -120
+	the income from the tax from the two others in the group	+10*3*2=120
-	the cost of the subsidies to the two others in the group	-10*3*2=-120
=	Payoff	90

of tokens between the members of the group."[13] After the votes have been cast and the number of units chosen, we inform participants about the distribution of the tax revenues and the financing of the subsidy payments.

After the vote, but before participants decide how many units to purchase, we elicit expectations in order to help uncover the mechanisms behind their voting decision. First we ask how many units they expect the other members in the group to buy with and without the policy implemented. Second, we ask what share of the tax revenue from the other group members the participant expects to receive, and/or what share of the subsidy cost for the other group members the participant expects to pay (depending on the treatment they are in). Finally, we ask whether the participant expects their payoff to increase, decrease or remain the same if the policy is implemented.

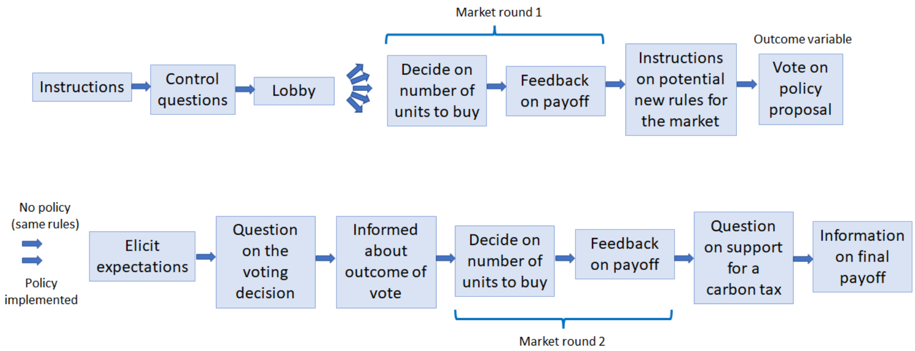
After the purchasing decsions are made in the second round, participants are asked: "Imagine that to combat climate change the government proposed to increase the cost of emitting CO_2 by £100 per ton from next year. This would increase the cost of petrol by 23 pence per litre and diesel by 26 pence per litre. If there was a vote on this tax proposal today, what would you have voted?" This question is to test whether voting for the tax in the experiment is correlated with expressing a willingness to vote for a hypothetical CO_2 tax.

Figure 1 shows a timeline of the experiment. Screenshots of each page the participants see are found in Appendix G.

One factor which has been found to be important for the level of support for Pigouvian taxes is distributional effects (see for instance Andor et al. (2022) and Dechezleprêtre et al. (2022)). We wanted to investigate other factors important for attitudes towards

[13]For the subsidy treatment we write: "The subsidy costs money. Your group's budget will be balanced through personal transfers of tokens between the members of your group." For the three combinations we write: "The tax generates revenue and the subsidy costs money. Your group's budget will be balanced through personal transfers of tokens between the members of your group."

Figure 1: The timeline of the experiment.



taxes and subsidies, and therefore we have designed an experiment in which there are no distributional effects (for the same behaviour). We keep the endowment and payoff structure identical for all participants within each group.

2.2 Theoretical predictions

For the individual participant, buying five units maximizes own payoff in the first round of the experiment, irrespective of how many units the other participants buy. We refer to this choice as the dominant strategy.[14] The socially optimal number of units to purchase is, however, three per participant.

The social optimum represents an efficiency gain over the market equilibrium if participants choose the dominant strategy. Total group payoff then increases from 150 to 270 tokens. By reducing their purchases by a total of 6 units (2 units per person), the buyers forego profits of 120 tokens, but external costs are reduced by 240 tokens, yielding a net gain of 120 tokens.

If the policy is implemented, the payoff structure changes, and the dominant strategy will be to choose three units, i.e., the socially optimal choice. If all participants choose the dominant strategy, introducing the policy increases the individual payoff from 50 tokens to 90 tokens. This payoff is the same for all policies, given that all group members follow the dominant strategy.

If the whole group chooses three units (the socially optimal number) in the first round, their individual payoff increases from 50 to 90 tokens. This is the same payoff

[14]When taking into account how choices in the first round may influence voting and the choice in the second round, it is not obvious that this is a dominant strategy. However, as we only had one round before the vote, choosing five units in the first round would most likely maximize final payoff, too.

as when any of the considered policies are implemented, assuming participants follow their new dominant strategy. Hence, one could argue that there is no incentive to vote for a policy if all three participants choose three units. However, there is no guarantee that the other participants will continue choosing three units in the second round if a policy is *not* implemented, as the dominant strategy in the absence of a policy is to choose five units. With a policy implemented, the dominant strategy is always to choose three units.[15]

2.3 Experimental procedures

We conducted an online interactive experiment on November 24th 2022, using the software Lioness lab (Giamattei et al., 2020). The participants were recruited from the online platform Prolific, a United Kingdom based firm that recruits participants for research.

Each participant is guaranteed to earn £1.5 if completing the experiment, in addition to the payoff. The median time to complete was just below 15 minutes, which means that the guaranteed payment equalled £6 per hour on average. The average payoff was £1.16, which is added to the guaranteed earnings. The payoff is based on the choices the participants make in the experiment, as explained in Section 2.1. The total average payment was thus almost £11 per hour.

All interactions are anonymous. Before the participants can enter the experiment, they receive instructions and have to correctly answer three control questions to test that they understand the rules.

Participants are assigned to a treatment group depending on the order in which they enter into the experiment after answering the control questions correctly. The first three participants entering get treatment 1, the next three participants entering get treatment 2 and so on. As several hundred participants take part simultaneously, and assignment to groups happens sequentially, the allocation to treatments is random.

2.4 The sample

The sample consists of 1641 participants, all of them UK residents. Table 4 shows the number of observations in each of the five treatment groups. Table 5 displays the observational characteristics of the participants.

Table 4: Number of observations in each treatment group.

Treatment group	Number of observations
Tax	331
75% tax and 25% subsidy	323
50% tax and 50% subsidy	325
25% tax and 75% subsidy	328
Subsidy	334
Total	1641

Table 5: Descriptive statistics of the participants.

Characteristics	Average/Share	Number of observations
Age	38.4	1619
Female	50.0%	1579
Student status	11.4%	1641
Full-time employed	47.2%	1619
Part-time employed	15.7%	1619
Unemployed	4.6%	1619
Country of birth United Kingdom	80.2%	1641
Ethnicity white	83.2%	1619
Nationality United Kingdom	86.5%	1619
Language English	88.0%	1619

Notes: Some participants have missing values on some variables and therefore the total number of observations are not 1641 for all variables.

Table 6: Balance tests

Treatment group	Age	Diff tax	t-statistics
Tax	39.4	–	–
75% tax and 25% subsidy	39.2	-0.2	0.14
50% tax and 50% subsidy	37.1	-2.3	2.14
25% tax and 75% subsidy	37.6	-1.8	1.70
Subsidy	38.8	-0.6	0.57
Treatment group	**Share of females**	**Diff tax**	**t-statistics**
Tax	53.0%	–	–
75% tax and 25% subsidy	46.8%	-6.2	1.56
50% tax and 50% subsidy	48.7%	-4.3	1.07
25% tax and 75% subsidy	50.3%	-2.7	0.67
Subsidy	51.2%	-1.7	0.44
Treatment group	**Chose 5 units in part 1**	**Diff tax**	**t-statistics**
Tax	54.4%	–	–
75% tax and 25% subsidy	57.9%	3.5	0.90
50% tax and 50% subsidy	59.1%	4.7	1.21
25% tax and 75% subsidy	54.3%	-0.1	0.03
Subsidy	57.2%	2.9	0.73

2.5 Balance tests

We test whether the other treatment groups differ from the tax group (which we use as the "control" group) for the variables age and gender, in accordance with the pre-analysis plan. We also check whether the choices in part 1 of the experiment are balanced across treatments.

Table 6 shows that for two of the treatment groups the average age is around 2 years younger than in the tax group. This is statistically significant, but it is not a large difference, and therefore we do not see it as a cause for concern. We check whether the age variable interacted with the treatment groups is statistically significant, see Table A-6. The coefficient is significant for the 50% tax & 50% subsidy treatment group interacted with age, but the size of the coefficient is only -0.005. For the other treatment groups the interaction term is not statistically significant.

For gender there are no statistically significant differences between the tax treatment group and the other treatment groups. In addition, there is balance between the treatment groups on the share of people choosing five units (the dominant strategy, see Section 2.2) in the first part.

We also test whether the treatment groups are different from each other, for instance if the 100% subsidy group is different from the 25% tax & 75% subsidy group on both age and gender. They are not statistically different, see Table A-1 in Appendix A.

3 Results

In this section we present the purchases the participants make, individual payoffs, voting results, expectations about the policies, and the result of the test for external relevance.

We analyse the results from the experiment using an OLS regression as generally recommended by Duflo et al. (2007). OLS coefficients are intuitive to interpret. As long as the probability is not close to 0 or 1, using OLS in combination with a binary outcome variable is regarded as unproblematic (Stock & Watson, 2015).

3.1 Purchases and individual payoffs

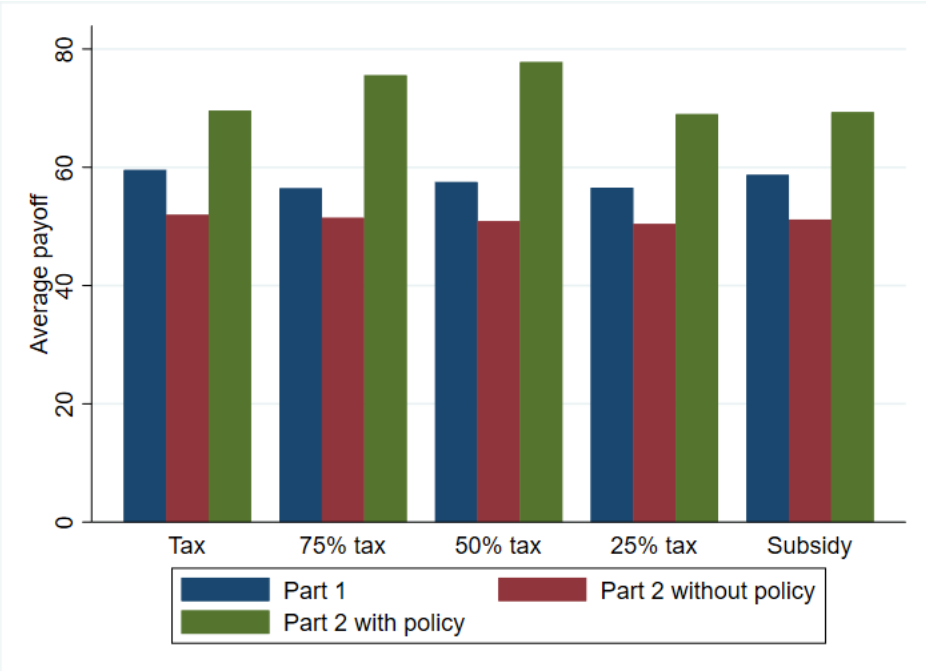
Participants on average buy 4.6 units in the first part, 3.5 units in the second part when a policy is implemented and 4.8 units in the second part when no policy is implemented. See Figure A-1 in Appendix A for the average number of units by

[15] In the experiment, a majority of the participants chose five units in the first round, and the share of participants choosing five units is balanced across the five treatment groups (see Table 6).

treatment. This means that the policies reduced the demand significantly, although less than the theoretical predictions, of the good with a negative externality.

On average across treatments, only 36.2% of the participants voted for the policy, meaning that 63.8% voted to keep the rules as they were. The average individual payoff is higher with policy than without, see Figure 2. However, the payoff in part 1 is higher than the theoretically predicted payoff (i.e., if participants choose their dominant strategy), and lower than the predicted amount in part 2 with policy (see Section 2.2).

Figure 2: The average individual payoff for the different groups in part 1 and part 2 with and without policy.



Notes: The 75% tax group also has 25% subsidy. The 50% tax group also has 50% subsidy. The 25% tax group also has 75% subsidy.

3.2 Support of the policy

We now turn to the main result of the experiment. The outcome variable is whether or not a participant votes for the proposed policy. We test whether there is a difference in the level of support between tax, subsidy and combinations of tax and subsidy. We estimate the following regression equation:

$$v_i = \beta_0 + \beta_1 c3_i + \beta_2 c4_i + \beta_3 c5_i + \beta_4 s_i + u_i \tag{1}$$

v_i is a binary variable for whether the person voted for the policy or not, $c3_i - c5_i$ are binary variables for whether the participant is in the treatment group with respectively 75% tax & 25% subsidy, 50% tax & 50% subsidy, and 25% tax & 75% subsidy, and s_i is a binary variable for being in the treatment group with 100% subsidy.

Table 7: Testing the difference in support for policy between the treatment groups.

	(1) Vote
Subsidy	0.388***
	(0.0339)
25% tax and 75% subsidy	0.322***
	(0.0341)
50% tax and 50% subsidy	0.206***
	(0.0334)
75% tax and 25% subsidy	0.106**
	(0.0317)
Constant	0.157***
	(0.0200)
Observations	1641
R^2	0.086

Tax treatment group is the baseline.
Robust standard errors in parentheses.
$*p < 0.05$, $** \ p < 0.01$, $*** \ p < 0.001$

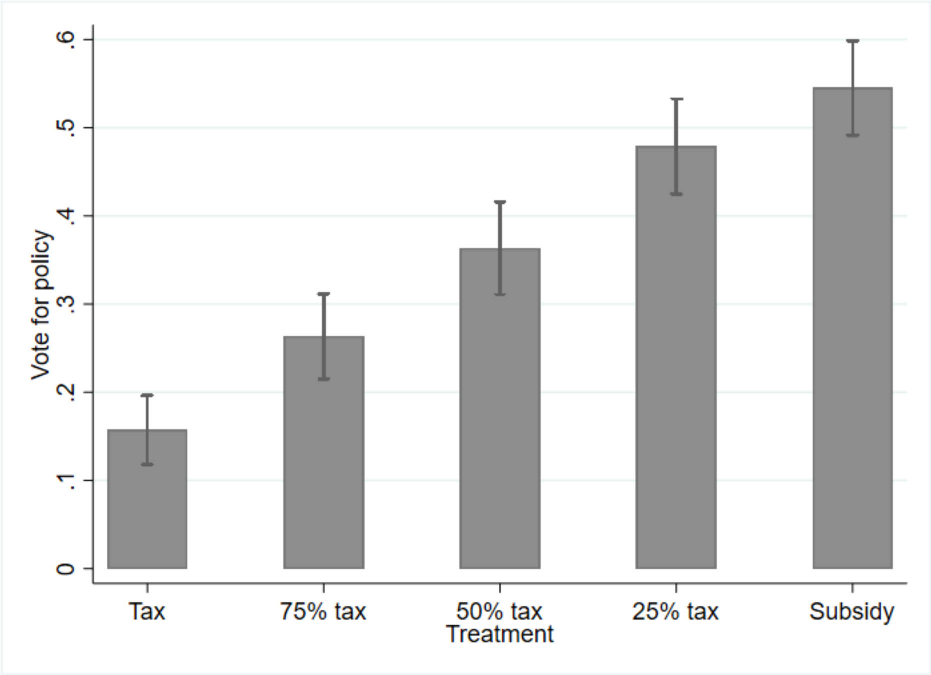
The tax treatment group is the baseline, and all coefficients are compared to the level of support in the 100% tax treatment. The H_0-hypothesis (no difference between the treatment groups) is rejected, see Table 7.[16] We find that the support for policy increases with the subsidy share in the policy proposal.

Figure 3 shows the share of participants voting for the policy proposal by treatment. This illustrates visually what the coefficients of the regression analyses show: Support increases approximately linearly with the share of the subsidy in the policy proposal. The effect of combining policy instruments is, in our experiment, close to a perfectly linear combination of the support for a tax alone and a subsidy alone.

Before the experiment was conducted, our hypothesis was that the support for the combinations of instruments would be somewhere between the support for the tax alone and the subsidy alone (see p. 4-5 in the pre-analysisplan in Appendix D). We

[16]To adjust for the fact that we test several hypotheses, we follow Fink et al. (2014) and use Benjamin - Hochberg adjusted p-values. This can be seen in Appendix C.

Figure 3: The share voting for the policy in each treatment group.



Notes: The 75% tax group also has 25% subsidy. The 50% tax group also has 50% subsidy. The 25% tax group also has 75% subsidy. The lines are 95% confidence intervals.

did not have an a priori belief about whether the support would be different between having a 25% tax & 75% subsidy, 50% tax & 75% tax or a 75% tax & 25% subsidy. What we find is a clear difference in support between the combinations and that the support for the policy is increasing in the subsidy share. Further, both the support for policy of the 50% tax & 50% subsidy and the 75% tax & 25% subsidy groups are statistically significantly different from both the 100% tax and the 100% subsidy group.

3.3 Expectations about the policy

We elicited four different expectations about consequences of the policy proposals. We use these to investigate mechanisms that can potentially explain why participants voted for or against the policy proposals.[17] We first test whether the treatment groups differ in their expectations about how the policy work. Then we test whether the support for the policy differs between the treatment groups among those that hold the specific expectation and those that do not. At the end of the section, we do an exploratory analysis where we simulate the expected payoff based on the answers the participants gave.

3.3.1 Mechanisms: Expectations about the effect of the policy

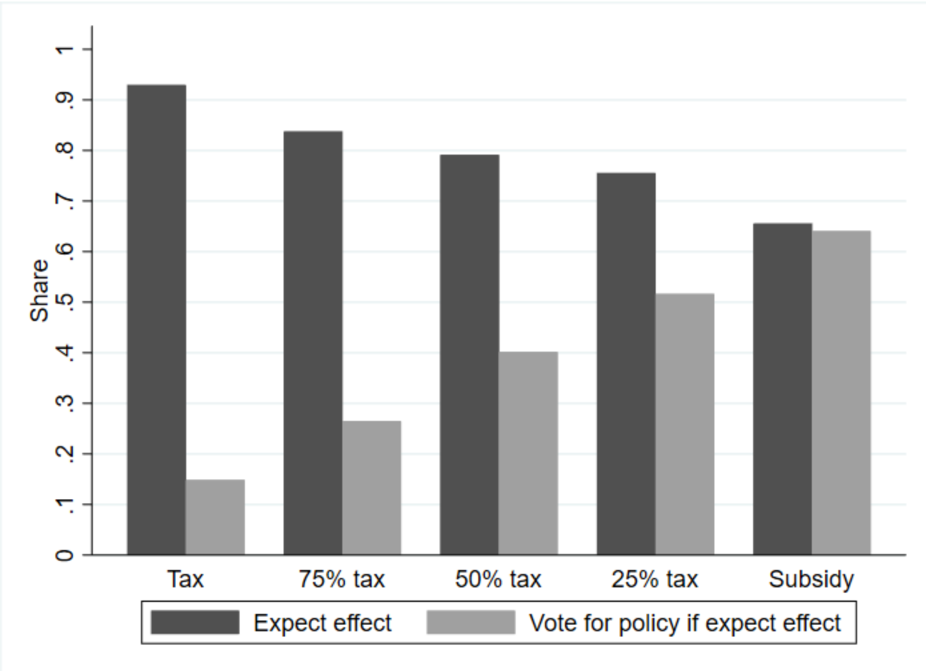
To what extent participants expect the policy to reduce the demand differs across treatments. Results are shown in Figure 4 and Table A-2, column 1. In the tax treatment group, 93% of participants expect a reduction in demand. In the subsidy group, 27 percentage points fewer (66%) expect a reduction in demand. In the combination treatments, expectations are in between those for the tax and subsidy treatments, and are all statistically different from the tax group.[18] This indicates that the type of policy instrument influences expectations about policy effectiveness. Keep in mind that the experiment is designed so that all policies provide the same incentives and should be equally effective in reducing demand.

Further, Figure 4 and Table A-2, column 2 shows that the probability of voting for the policy among those who expect the policy to reduce demand increases with the share of subsidies in the policy proposal. Those who expect the subsidy to reduce

[17]There is a slight deviation from the pre-analysis plan, see Appendix D. We have reformulated the regression equations. This is done to obtain a more relevant comparison group when testing whether the difference is statistically significant. The topics we test follow the pre-analysis plan, and all are included. The reformulation of the regression equation follows the same pattern for all topics. This is explained in detail in Appendix D. The results from the regression equation in the pre-analysis plan can be seen in Appendix F.

[18]The 50% tax & 50% subsidy group is not significantly different from neither the 25% tax & 75% subsidy group nor the 75% tax & 25% subsidy group. The 25% tax & 75% subsidy group and 75% tax & 25% subsidy group are statistically different from each other (tests not shown).

Figure 4: The share expecting effect in each treatment group and the share voting for policy if they expect an effect.



Notes: The 75% tax group also has 25% subsidy. The 50% tax group also has 50% subsidy. The 25% tax group also has 75% subsidy. The voting of those that do not expect an effect can be seen in Table A-2.

demand have a 49 percentage points higher probability of voting for the policy, than those who expect the tax to reduce demand. The results for the treatments with combinations of tax and subsidy lie in between the levels for the tax and subsidy treatments. The higher the tax share in the proposal, the higher the share of people expecting the policy to be effective, but also the lower the support for the policy. This indicates that expectations about effectiveness is not what drives policy support in our experiment.

For those that do not expect an effect, there is no statistically significant difference between the tax treatment group and the other treatment groups, see Table A-2, column 3.

3.3.2 Mechanisms: Expectations about the tax revenue

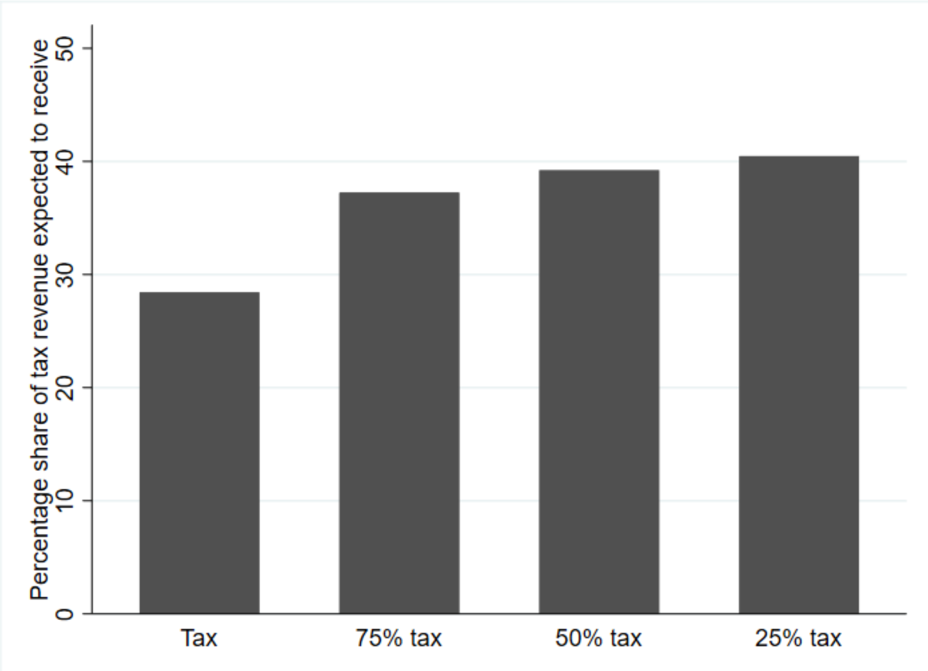
Participants in the combination treatments expect to receive a higher share of the tax revenues than those in the 100% tax treatment, see Figure 5 and Table A-3, column 1. The difference in expected share of revenues is not statistically different between the three combination treatments, but the combination treatments are all significantly different from the 100% tax treatment group. The experimental design and instructions should not give participants any reason to hold different expectations regarding the share of revenues shared across the tax and combination treatments. This shows pessimistic beliefs about how the tax works when it is implemented alone, compared to when the tax is combined with subsidies.

In addition, the share of voting for the policy among those who expect to receive a share of the revenue is increasing with the subsidy share in the policy proposal, from 48% voting for policy in the 25% tax & 75% subsidy treatment group to 18% voting for the policy in the 100% tax treatment (see Table A-3, column 2 and Figure A-2).

For those that do not expect to receive a share of the tax revenue, the combination treatment groups have a higher voting share for the policy than the 100% tax treatment groups, but the voting pattern is not linear (see Table A-3, column 3 and Figure A-2).

Asking participants what share of the revenue they expect to receive might induce some people who otherwise would not consider that they might receive any of the tax revenue, to believe that they may do so. As a starting point, we placed the slider handle they use to indicate share of revenues they expect to receive in the middle (50%). This could influence participants to keep the slider closer to the middle than they would otherwise have done. However, asking this question cannot influence voting as it is asked after the votes have been cast. This caveat applies equally to all treatment groups, so even if the point estimates might be influenced by the starting

Figure 5: The share of the tax revenue expected to receive.

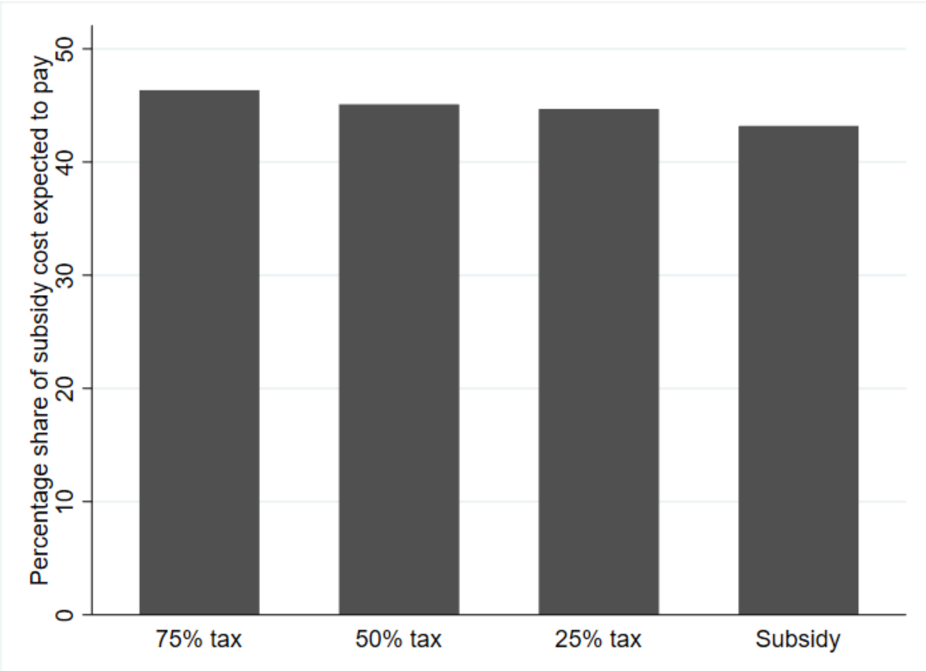


Notes: The 75% tax group also has 25% subsidy. The 50% tax group also has 50% subsidy. The 25% tax group also has 75% subsidy. The difference between the tax group and the 75% tax group is statistically significant.

point of the slider, the difference between the treatments should not be influenced.

3.3.3 Mechanisms: Expecting to pay for the subsidy cost

Figure 6: The share of the subsidy cost expected to pay in the different treatment groups.



Notes: The 75% tax group also has 25% subsidy. The 50% tax group also has 50% subsidy. The 25% tax group also has 75% subsidy. The differences between the groups are not statistically significant.

The average share of the subsidy cost participants expect to pay is 43% in the subsidy treatment group, and expectations are not significantly different from this in the combination treatments, see Figure 6 and in Table A-4, column 1.

In addition, 80% of those in the subsidy group who do *not* expect to pay for the subsidy, voted for the subsidy, see Figure A-3 and Table A-4, column 2. For the combination groups, the probability of voting for the policy declines with the tax share going up, and the difference compared to the subsidy is statistically significant for the 75% tax & 25% subsidy and the 50% tax & 50% subsidy groups, see Table A-4, column 2.

For those expecting to pay a share of the subsidy cost, the support for the policy is lower the higher the tax share in the policy, see Table A-4, column 3 and Figure A-3. This can be because expecting to pay for the subsidy cost is not what determines the support for the policy. It can also be because the total subsidy cost is lower, the lower the subsidy share of the policy.

3.3.4 Mechanisms: Expectations about the payoff

Only 17% of participants in the tax treatment group expect that the policy will increase their payoff, whereas 60% in the subsidy treatment group do so, see Figure 7 and Table A-5, column 1.[19] The share of participants in the combination treatment groups who expect that the policy will increase their payoff, is increasing in the subsidy share in the policy proposal. This shows again pessimistic beliefs related to taxes.

Among those who expect the policy proposal to increase payoffs, the share voting in favor of the policy is higher for the combination treatment groups than for the tax treatment group, see Figure 7 and Table A-5, column 2. The support for policy does not, however, increase linearly with the subsidy share, as we have seen earlier, see Figure 7. The share supporting the policy among those who expect the policy proposal to increase payoffs, does not significantly differ between the tax treatment group and the 75% tax & 25% subsidy group, but for the two other combination groups the support is statistically different, see Table A-5, column 2.

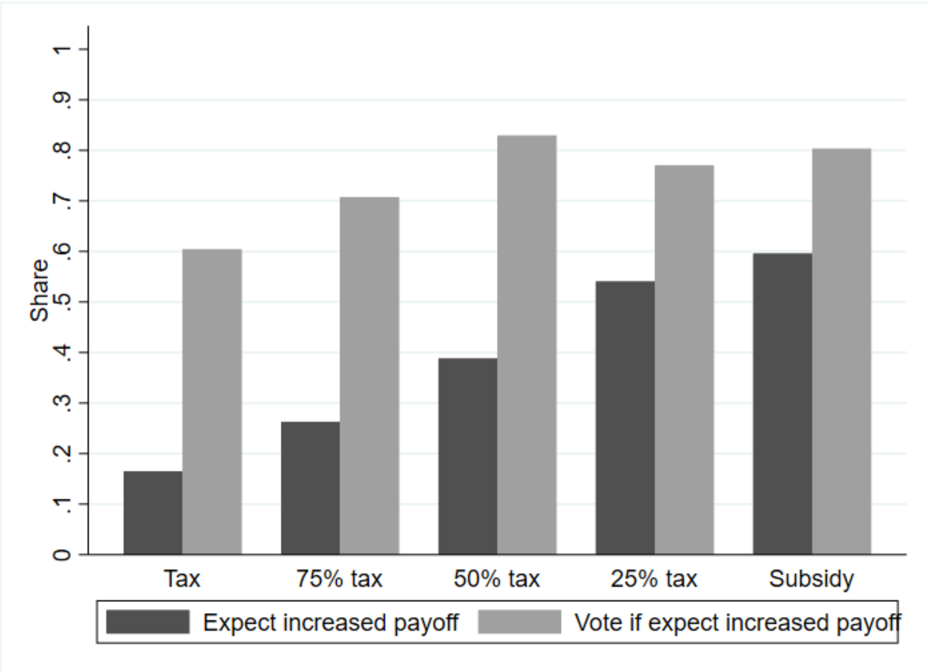
In general, expecting the policy to increase payoff seems to be a clear predictor of voting behavior, but not all who believe the policy to increase payoff voted for the policy. Furthermore, only 39% of the participants expect that the policy will increase their payoff. 77% of those who believe the payoff will increase, vote for the policy (not shown), but this is not even across treatments, as can be seen in Figure 7. This result leads us to investigate the relationship between expectations about tax revenue and subsidy cost and expectations about payoff, see Subsection 3.3.5.

3.3.5 Exploratory analysis: Simulating the expected payoff

We use participants' expectations about policy effectiveness, tax revenue and the subsidy cost to explore if participants expect the payoff to be higher with the policy. As this was not part of our pre-analysis plan, it is an exploratory analysis. This differs from simply asking the participants whether they expect the payoff to increase (which we also did, see Subsection 3.3.4). Here, we instead use the expectations about how many units the others in the groups would buy with or without the policy, what

[19]For both the subsidy and the 25% subsidy & 75% tax group, a higher share of participants expect their payoff to increase if policy is implemented (60% for the subsidy group, see Table A-5) than the share of participants who actually voted for the subsidy (39% for the subsidy group, see Table 7). The reason for this may be that asking questions about the expectations can change participants' thinking about the policies by making certain aspects more salient, or through experimenter demand effects.

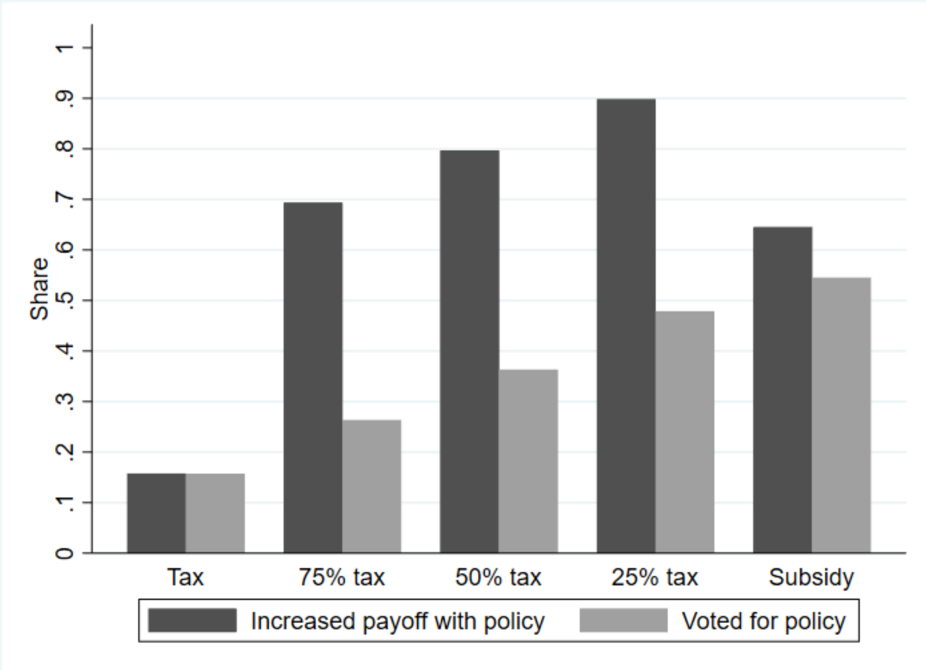
Figure 7: The share expecting the payoff to increase in the different treatment groups and the voting behavior for those that expect increased payoff.



Notes: The 75% tax group also has 25% subsidy. The 50% tax group also has 50% subsidy. The 25% tax group also has 75% subsidy. The voting of those that do not expect the payoff to increase can be seen in Table A-5.

share of the tax revenue one expects to receive, and how much of the subsidy cost one expects to pay, to calculate the expected payoff with and without the proposed policy.[20]

Figure 8: The simulated share expecting increased payoff based on the elements in the payoff (reduced externality because of reduced demand, a share of the tax revenue and a share of the subsidy cost) compared to the voting behavior in the different treatment groups.



Notes: The 75% tax group also has 25% subsidy. The 50% tax group also has 50% subsidy. The 25% tax group also has 75% subsidy.

Figure 8 shows the share expecting increased payoff with policy based on our calculation, and we can compare it with the share voting for the policy, i.e., the same as in Figure 3. We see that participants in the tax group seem to vote according to their payoff expectations, and as noted above these expectations are pessimistic compared to the groups where tax and subsidy are combined.

For the combination groups the number of participants who expect the payoff to increase with policy is much higher than the number of participants that actually

[20]We need to make some assumptions to do this simulation. When policy is not implemented in the second round, we do not know how many units the participant would have chosen to buy with policy. Then we assume that the participant would buy as many units as (s)he expect his/her group members to choose with policy. To calculate the payoff without policy, we use the purchases in the first round. Then we calculate the difference in expected payoff with and without policy.

voted for the policy proposal. This may indicate either that the expectations elicited after the voting were not clear for the participants when they voted, or that something other than the payoff expectations were driving the voting behavior.

3.4 Test for external relevance

We test whether voting for the tax in the experiment is correlated with expressing a willingness to vote for a hypothetical CO_2 tax. The result can be seen in Table 8.

Table 8: Correlation between voting for a tax in the experiment and a hypothetical carbon tax

	(1) Voting for tax
Carbon tax	0.0836
	(0.0470)
Constant	0.130***
	(0.0239)
Observations	303
R^2	0.012

The sample is only the tax treatment group.
Robust standard errors in parentheses
*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Support for the tax proposal in the experiment correlates with support for the hypothetical CO_2 tax on a 10% significance level. Note, however, that only 48 participants (16%) voted for the tax in the experiment. The support for a hypothetical CO_2 tax is higher (35% of all participants and 34% of the tax group) than the support for a tax in the experiment (16%).

4 Discussion

We find that support for a combination of tax and subsidy approximately equals the simple average of support for the two instruments alone. This main result appears to contradict Milkman et al. (2012) and Fesenfeld (2022), who find that policy packaging increases support (beyond the averaging of support for its constituent parts). Our result also stand in contrast to Eriksson et al. (2008), who find a negative effect of combining policies. It is, however, not possible to make clean comparisons because of important differences in methods and design between the studies. First, our study is incentivized, i.e., participants' choices have real financial consequences for them, whereas none of the three other studies are.

When comparing our results with Milkman et al. (2012), it is important to note that we keep the payoff from the policy equal across treatments (given that the participants follow their dominant strategy). Further, we use fractional combinations where we reduce the tax rate to the same extent as we increase the subsidy rate, whereas in Milkman et al. (2012) the stated gain varies across the policies. The gain from the policy in their study is higher when the two bills are combined than when each bill is considered separately. This difference can potentially explain the difference in voting outcome between our study and Milkman et al. (2012). Another important difference is that Milkman et al. (2012) investigate gains and losses of specific policies, for instance clearing forest (loss) to create jobs (gain), whereas we study policy instruments in a non-contextualized setting. Still, both studies consider bundling of policies that are often viewed as respectively desirable and undesirable. Milkman et al. (2012) find that the reason for the increased support for the policy bundle is that "policy bundling reduces the salience of losses (...) and heightens the salience of gains".

When comparing our results with Fesenfeld (2022), it is important to note that the payoffs from the policies in his study are neither stated (as in Milkman et al. (2012)), nor set to be equal by design (as in our experiment), but left open for respondents to consider themselves. The core idea explored is how greater complexity influences policy perceptions (including public support). The choice experiment in Fesenfeld (2022) has four policy attributes that vary simultaneously and target different behaviours, e.g., taxes for consumers combined with emissions standards for producers. This differs crucially from our experiment where the two instruments target the same behaviour.

In Eriksson et al. (2008) all participants were presented with all policy options (single instruments first and then the packages), and the costs and benefits are not clearly stated nor kept the same across instruments: For the instruments by themselves the specific tax or subsidy rates were not provided, whereas the rates were stated for the policy packages. This latter difference could to some extent explain the result that public support for the packages is closest to the level of support for the least popular instrument: Making policy proposals more specific, e.g., by stating the tax rate, may reduce support and this is only done for the policy packages in Eriksson et al. (2008).

Our findings are generally consistent with Heres et al. (2017), another lab experiment with a market with negative externalities, whose main finding is that subsidies are substantially more popular than taxes, even when payoff is kept constant across policies (if participants choose the dominant strategy). Further, Heres et al. (2017) state that this can in part “be explained by the participants’ expectation that the subsidy will increase their own payoffs more than a tax, but not because it is expected to be more effective in changing behavior", which is similar to our findings. We introduced the same vagueness regarding the distribution of tax revenues and subsidy funding as Heres et al. (2017), and the (intentional) asymmetry this creates may be an important explanation for the differences in support between taxes and subsidies: The uncertainty for a participant regarding what share of the tax revenue (s)he will receive can be seen as a potential loss (e.g., expecting to receive no share of the revenues, or a smaller share than one's own tax payment), whereas the uncertainty related to paying the subsidy cost can be seen as a potential gain (e.g., expecting not to have to help fund the subsidy, or to fund less than one receives). Thus, the difference in support to the different instruments that both Heres et al. (2017) and we find, can be related to loss aversion.

Status quo bias might explain why many do not support the proposed policies even when they are designed to increase individual and group payoffs (Kahneman et al., 1991; Samuelson & Zeckhauser, 1988), but it does not explain the difference in support between the policies. There seems to be a "broader aversion to market intervention", in line with the findings in Cherry et al. (2012). This could be related to status quo bias.

Another explanation might be that participants view taxes as a more coercive instrument that reduces their own freedom to buy a "dirty" good, rather than an instrument aiming to reduce others' incentives to buy the same "dirty" good (Cherry et al., 2012). Even though the latter effect may be more significant in terms of total welfare effect, the former effect may be more visible or salient to the participant. This, however, needs further investigation. Interestingly, Dechezleprêtre et al. (2022) find that respondents rank a carbon tax as the most costly climate policy, followed by investments in green infrastructure and a ban on combustion-engine vehicles. This indicates that the participants' focus is on the personal costs and benefits, not society's total cost and benefits, which is in line with the findings of Sapienza and Zingales (2013).

Do participants understand the incentive structure fully? One reason participants vote as they do could be that they do not fully understand or take into account the payoff structure. Kallbekken et al. (2011) investigated how much the participants understand and whether more information about how Pigouvian taxes work influenced support. They find that with more information the participants understand more, but it does not change the support for taxes by much. Still, the participants might not take the revenue from the tax and the financing of the subsidy sufficiently into account. Our experimental design does not make it possible to disentangle whether the participants understand the whole payoff structure. Instead, we build on the findings of Kallbekken et al. (2011), where they test the understanding of the payoff structure, and on Heres et al. (2017) where the role of budgetary information is investigated.

5 Conclusion

In this study, we have conducted an online interactive lab experiment to explore support for taxes, subsidies, and combinations of the two instruments. We find that support increases approximately linearly with the share of subsides in the policy proposal. This finding questions the claim, based on findings in previous studies, that policy packaging can increase public support for unpopular policies. However, given the design of the previous studies, where instrument type and benefits vary together, the findings in those studies might relate to the policy package increasing gains and not the act of packaging as such.

We furthermore find that people hold pessimistic beliefs regarding taxation (especially whether it will increase payoffs), and that this belief scales linearly with the share of taxes in the policy package. Our findings therefore imply that combining a Pigouvian tax with a subsidy does not help reduce tax aversion as such: Support follows the share of the tax in the fractional combinations; the share of participants who expect the payoff to increase with the policy increases only in linear proportion with the subsidy (non-tax) share of the policy, and the belief that taxes are (more) effective does not translate into policy support. The only aspect where combining instruments can be said to influence (an aspect of) tax aversion, is that when combined with a subsidy, respondents expect a larger share of the revenues to be returned to themselves.

The discrepancy between our finding and previous findings on taxes and beliefs about effectiveness raises a question about the causal direction: Do people oppose taxes because they think they are not effective, or do people answer in surveys that taxes are not effective because they do not want taxes? Our findings contrast with what is common in the literature as we find that people both oppose taxes *and* think they are effective. Further investigation on the causal direction between attitudes towards taxes and beliefs about the effectiveness is clearly warranted.

Several extensions of the experiment would be valuable. We chose a design where the packages are fractional combinations of a tax and a subsidy. It would be informative to compare this design to an additive design where the tax remains constant but different policies are added to it in a policy package. Another refinement of our design would be to ask participants if they want to change their vote after eliciting their expectations, as the act of eliciting the preferences may change their thinking about the policies. In addition, it could be that combining Pigouvian taxes with other kinds of instruments than subsidies in a policy package would yield different results.

Whether the results hold outside of lab experiments is a question for further investigation. Levitt and List (2007, p.168) underline that "many real-world markets operate in ways that make pro-social behavior much less likely" than in a lab experiment. It has been investigated to what degree some types of lab experiments find the same results in real-world settings, such as reaction to competition (Buser & Yuan, 2019). The type of lab experiment we are using has not been investigated for validity outside of the lab, and this is a point for further investigation.

Policy packaging may make sense for a number of reasons, including enhancing effectiveness (van den Bergh et al., 2021), addressing distributional concerns (Bouma et al., 2019), eliciting information about firms' abatement cost (Ambec & Coria, 2021), or directing technological change (Acemoglu et al., 2012). However, unlike what some previous studies have indicated, we do not find that packaging policies increases the level of public support beyond the simple averaging of support for the constituent parts of the package.

Acknowledgements

We would like to thank Frode Alfnes, Arild Angelsen, Kjetil Bjorvatn, Julie Brun Bjørkheim, Askill Harkjerr Halse, Karen Evelyn Hauge, Julia Del Carmen Naime Sanchez Henkel, Tora Knutsen, Andreas Kotsadam, Magnus Merkle, Marit Sandstad, Siv-Elisabeth Skjelbred, Håkon Sælen, and the rest of the research group KREM at the School of Economics and Business at NMBU for valuable input and comments.

References

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, *102*(1), 131–166.

Ambec, S., & Coria, J. (2021). The informational value of environmental taxes. *Journal of Public Economics*, *199*, 104439.

Anderson, S. T., Marinescu, I., & Shor, B. (2023). Can Pigou at the Polls Stop Us Melting the Poles? *Journal of the Association of Environmental and Resource Economists.*

Andor, M. A., Lange, A., & Sommer, S. (2022). Fairness and the support of redistributive environmental policies. *Journal of Environmental Economics and Management*, *114*, 102682.

Baranzini, A., & Carattini, S. (2017). Effectiveness, earmarking and labeling: Testing the acceptability of carbon taxes with survey data. *Environmental Economics and Policy Studies*, *19*, 197–227.

Bergquist, M., Nilsson, A., Harring, N., & Jagers, S. C. (2022). Meta-analyses of fifteen determinants of public opinion about climate change taxes and laws. *Nature Climate Change*, *12*(3), 235–240.

Bouma, J., Verbraak, M., Dietz, F., & Brouwer, R. (2019). Policy mix: Mess or merit? *Journal of Environmental Economics and Policy*, *8*(1), 32–47.

Buser, T., & Yuan, H. (2019). Do women give up competing more easily? Evidence from the lab and the Dutch math olympiad. *American Economic Journal: Applied Economics*, *11*(3), 225–252.

Cherry, T. L., Kallbekken, S., & Kroll, S. (2012). The acceptability of efficiency-enhancing environmental taxes, subsidies and regulation: An experimental investigation. *Environmental Science & Policy*, *16*, 90–96.

Cherry, T. L., Kallbekken, S., & Kroll, S. (2014). The impact of trial runs on the acceptability of environmental taxes: Experimental evidence. *Resource and Energy Economics*, *38*, 84–95.

Cherry, T. L., Kallbekken, S., & Kroll, S. (2017). Accepting market failure: Cultural worldviews and the opposition to corrective environmental policies. *Journal of Environmental Economics and Management*, *85*, 193–204.

Cherry, T. L., Kallbekken, S., Kroll, S., & McEvoy, D. M. (2013). Cooperation in and out of markets: An experimental comparison of public good games and markets with externalities. *Economics Letters*, *120*(1), 93–96.

Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Chico, A. S., & Stantcheva, S. (2022). *Fighting climate change: International attitudes toward climate policies*, National Bureau of Economic Research.

Douenne, T., & Fabre, A. (2022). Yellow vests, pessimistic beliefs, and carbon tax aversion. *American Economic Journal: Economic Policy*, *14*(1), 81–110.

Drews, S., & Van den Bergh, J. C. (2016). What explains public support for climate policies? A review of empirical and experimental studies. *Climate policy*, *16*(7), 855–876.

Duflo, E., Glennerster, R., & Kremer, M. (2007). Using randomization in development economics research: A toolkit. *Handbook of development economics*, *4*, 3895–3962.

Eriksson, L., Garvill, J., & Nordlund, A. M. (2008). Acceptability of single and combined transport policy measures: The importance of environmental and policy specific beliefs. *Transportation Research Part A: Policy and Practice*, *42*(8), 1117–1128.

Fesenfeld, L. P. (2022). The effects of policy design complexity on public support for climate policy. *Behavioural Public Policy*, 1–26.

Fink, G., McConnell, M., & Vollmer, S. (2014). Testing for heterogeneous treatment effects in experimental data: False discovery risks and correction procedures. *Journal of Development Effectiveness*, *6*(1), 44–57.

Giamattei, M., Yahosseini, K. S., Gächter, S., & Molleman, L. (2020). Lioness lab: A free web-based platform for conducting interactive experiments online. *Journal of the Economic Science Association*. https://doi.org/10.1007/s40881-020-00087-0.

Givoni, M., Macmillen, J., Banister, D., & Feitelson, E. (2013). From policy measures to policy packages. *Transport Reviews*, *33*(1), 1–20.

Gugler, K., Haxhimusa, A., & Liebensteiner, M. (2021). Effectiveness of climate policies: Carbon pricing vs. subsidizing renewables. *Journal of Environmental Economics and Management*, *106*, 102405.

Hardisty, D. J., Johnson, E. J., & Weber, E. U. (2010). A dirty word or a dirty world? Attribute framing, political affiliation, and query theory. *Psychological science*, *21*(1), 86–92.

Helm, C., & Mier, M. (2021). Steering the energy transition in a world of intermittent electricity supply: Optimal subsidies and taxes for renewables and storage. *Journal of Environmental Economics and Management*, *109*, 102497.

Heres, D. R., Kallbekken, S., & Galarraga, I. (2017). The role of budgetary information in the preference for externality-correcting subsidies over taxes: A lab experiment on public support. *Environmental and Resource Economics*, *66*(1), 1–15.

Kahneman, D., Knetsch, J. L., & Thaler, R. H. (1991). The endowment effect, loss aversion, and status quo bias. *Journal of Economic Perspectives*, *5*(1), 193–206.

Kallbekken, S., Kroll, S., & Cherry, T. L. (2011). Do you not like Pigou, or do you not understand him? Tax aversion and revenue recycling in the lab. *Journal of Environmental Economics and Management*, *62*(1), 53–64.

Kallbekken, S., & Sælen, H. (2011). Public acceptance for environmental taxes: Self-interest, environmental and distributional concerns. *Energy Policy*, *39*(5), 2966–2973.

Kern, F., Rogge, K. S., & Howlett, M. (2019). Policy mixes for sustainability transitions: New approaches and insights through bridging innovation and policy studies. *Research Policy*, *48*(10), 103832.

Levitt, S. D., & List, J. A. (2007). What do laboratory experiments measuring social preferences reveal about the real world? *Journal of Economic perspectives*, *21*(2), 153–174.

Milkman, K. L., Mazza, M. C., Shu, L. L., Tsay, C.-J., & Bazerman, M. H. (2012). Policy bundling to overcome loss aversion: A method for improving legislative outcomes. *Organizational Behavior and Human Decision Processes*, *117*(1), 158–167.

Parry, I. W., Black, S., & Vernon, N. (2021). *Still not getting energy prices right: A global and country update of fossil fuel subsidies*. IMF. Working Paper No. 2021/236.

Samuelson, W., & Zeckhauser, R. (1988). Status quo bias in decision making. *Journal of risk and uncertainty*, *1*, 7–59.

Sapienza, P., & Zingales, L. (2013). Economic experts versus average americans. *American Economic Review*, *103*(3), 636–42.

Schuitema, G., Steg, L., & Forward, S. (2010). Explaining differences in acceptability before and acceptance after the implementation of a congestion charge in Stockholm. *Transportation Research Part A: Policy and Practice*, *44*(2), 99–109.

Shapiro, A. F., & Metcalf, G. E. (2023). The macroeconomic effects of a carbon tax to meet the us paris agreement target: The role of firm creation and technology adoption. *Journal of Public Economics*, *218*, 104800.

Stock, J. H., & Watson, M. W. (2015). *Introduction to econometrics 3rd ed.* Pearson Education.

The World Bank. (2022). *Carbon pricing dashboard* [Accessed January 10 2023]. https://carbonpricingdashboard.worldbank.org/

Timilsina, G. R. (2022). Carbon taxes. *Journal of Economic Literature*, *60*(4), 1456–1502.

Umit, R., & Schaffer, L. M. (2020). Attitudes towards carbon taxes across Europe: The role of perceived uncertainty and self-interest. *Energy Policy*, *140*, 111385.

van den Bergh, J., Castro, J., Drews, S., Exadaktylos, F., Foramitti, J., Klein, F., Konc, T., & Savin, I. (2021). Designing an effective climate-policy mix: Accounting for instrument synergy. *Climate Policy*, *21*(6), 745–764.

Winslott-Hiselius, L., Brundell-Freij, K., Vagland, Å., & Byström, C. (2009). The development of public attitudes towards the stockholm congestion trial. *Transportation Research Part A: Policy and Practice*, *43*(3), 269–282.

A Additional balance tests

Table A-1: Comparing the difference in the mean for two and two treatment groups. There is no statistically significant difference between the treatment groups. Treatment group 1 is compared with the other groups in Table 6.

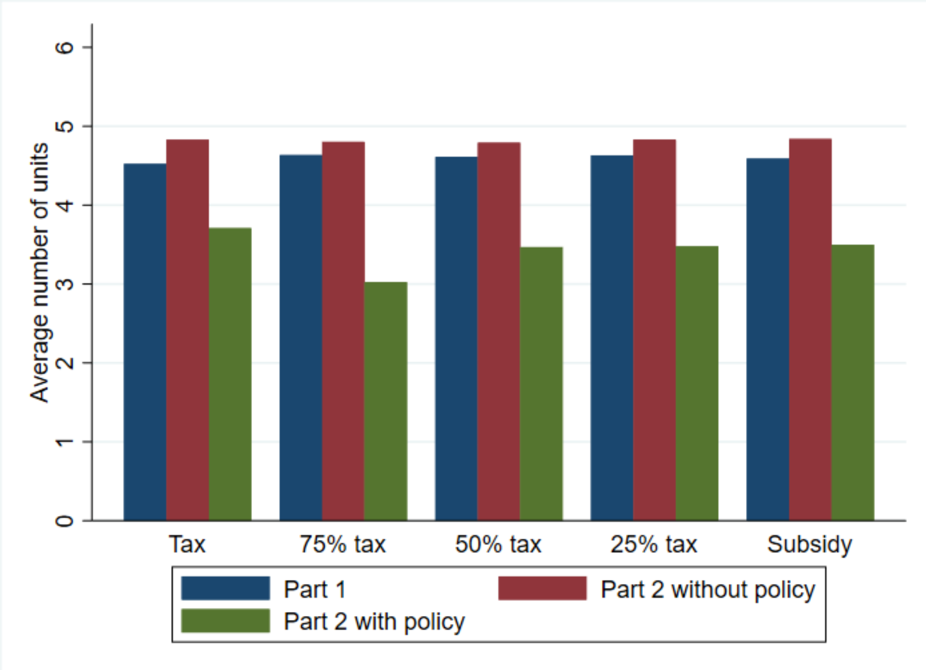
Variable	Treatment group	t-statistics
Age	2&3	1.1274
Age	2&4	1.5787
Age	2&5	-0.4051
Age	3&4	0.4766
Age	3&5	-1.4746
Age	4&5	-1.8961
Gender	2&3	0.2335
Gender	2&4	0.6337
Gender	2&5	1.1260
Gender	3&4	0.3986
Gender	3&5	0.8895
Gender	4&5	0.4918
5 units in part 1	2&3	0.7548
5 units in part 1	2&4	-0.4913
5 units in part 1	2&5	-0.1836
5 units in part 1	3&4	-1.2394
5 units in part 1	3&5	-0.9313
5 units in part 1	4&5	0.3049

The treatment groups are:

1. 100% tax
2. 75% tax and 25% subsidy
3. 50% tax and 50% subsidy
4. 25% tax and 75% subsidy.
5. 100% subsidy

B Additional results

Figure A-1: The average number of units participants buy in the different treatment groups in part 1 and part 2 with and without policy.



Notes: The 75% tax group also has 25% subsidy. The 50% tax group also has 50% subsidy. The 25% tax group also has 75% subsidy.

Table A-2: Expect effect on the demand and voting if expecting or not expecting effect on the demand.

	(1) Expect effect	(2) Vote if expect effect	(3) Vote if do NOT expect effect
Constant (Tax)	0.929***	0.149***	0.217*
	(0.0142)	(0.0205)	(0.0867)
75% tax and 25% subsidy	-0.0919***	0.116***	0.0518
(Hypothesis 1, 5 & 9)	(0.0251)	(0.0339)	(0.107)
50% tax and 50% subsidy	-0.138***	0.253***	-0.00844
(Hypothesis 2, 6 & 10)	(0.0268)	(0.0370)	(0.100)
25% tax and 75% subsidy	-0.174***	0.368***	0.150
(Hypothesis 3, 7 & 11)	(0.0278)	(0.0380)	(0.102)
Subsidy	-0.274***	0.492***	0.160
(Hypothesis 4, 8 & 12)	(0.0298)	(0.0385)	(0.0980)
Observations	1621	1286	335
R^2	0.050	0.130	0.024

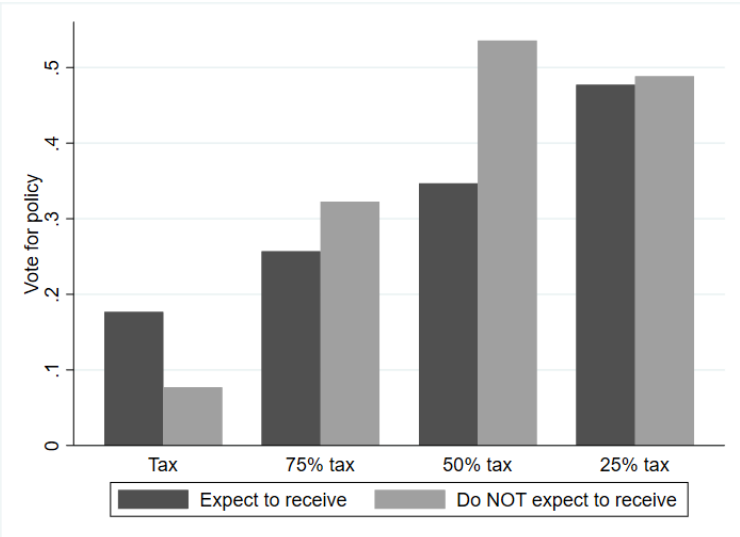
Robust standard errors in parentheses.

$^*p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Tax treatment group is the baseline.

The coefficient states the difference between the treatment group and the tax group.

Figure A-2: The share voting for the policy in each treatment group for those expecting to receive a share of the tax revenue and those NOT expecting to receive.



Notes: The 75% tax group also has 25% subsidy. The 50% tax group also has 50% subsidy. The 25% tax group also has 75% subsidy.

Table A-3: Share of the tax revenue.

	(1) Expected share	(2) Vote if expecting share	(3) Vote if NOT expecting share
Constant (Tax)	28.42***	0.175***	0.0769*
	(1.278)	(0.0237)	(0.0335)
75% tax and 25% subsidy	8.827***	0.0811*	0.246**
(Hypothesis 13, 16 & 19)	(1.988)	(0.0353)	(0.0913)
50% tax and 50% subsidy	10.80***	0.178***	0.459***
(Hypothesis 14, 17 & 20)	(1.946)	(0.0368)	(0.101)
25% tax and 75% subsidy	12.05***	0.302***	0.411***
(Hypothesis 15, 18 & 21)	(2.065)	(0.0382)	(0.0841)
Observations	1273	1106	167
R^2	0.031	0.057	0.179

Tax treatment group is the baseline.
Robust standard errors in parentheses.
The subsidy treatment group is not part of the analysis because this question is not relevant for the subsidy treatment group.
$^*p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A-4: Share of the subsidy cost.

	(1) Expected share	(2) Vote if NOT expecting to pay	(3) Vote if expecting to pay
75% tax and 25% subsidy	3.167	-0.527***	-0.242***
(Hypothesis 22, 25 & 28)	(2.205)	(0.123)	(0.0395)
50% tax and 50% subsidy	1.900	-0.354***	-0.140***
(Hypothesis 23, 26 & 29)	(2.206)	(0.128)	(0.0410)
25% tax and 75% subsidy	1.510	-0.221**	-0.0386
(Hypothesis 24, 27 & 30)	(2.273)	(0.103)	(0.0421)
Constant (Subsidy)	43.18***	0.804***	0.504***
	(1.634)	(0.0595)	(0.0300)
Observations	1275	120	1155
R^2	0.002	0.148	0.037

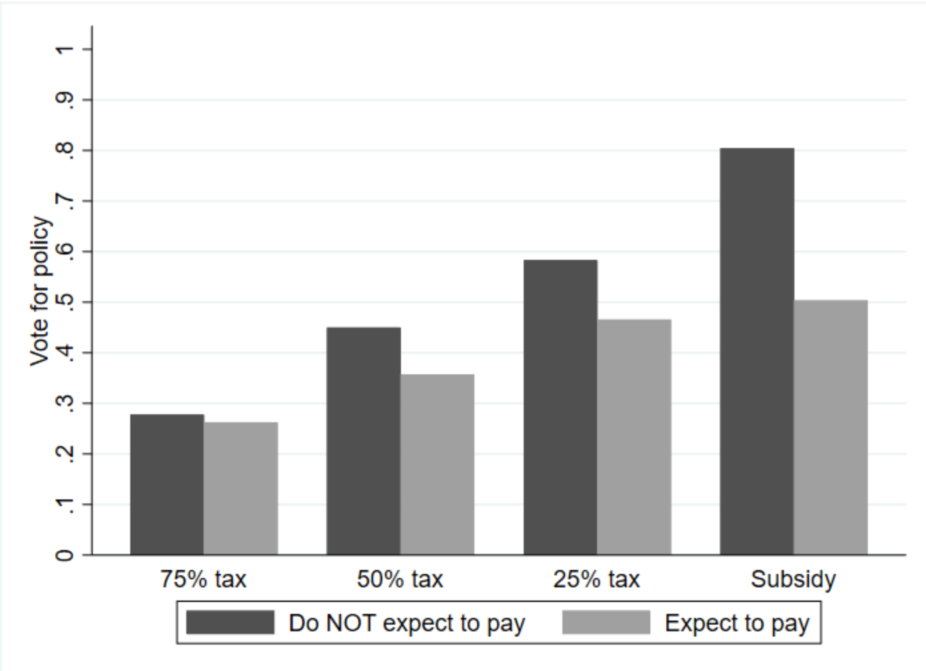
Subsidy treatment group is the baseline.
Robust standard errors in parentheses
The tax treatment group is not part of the analysis because this question is not relevant for the tax treatment group.
$^*p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A-5: Increase in payoff

	(1) Expect payoff to increase	(2) Vote if expect to increase payoff	(3) Vote if do NOT expect to increase payoff
Subsidy	0.431***	0.199***	0.101**
(Hypothesis 31, 35 & 39)	(0.0343)	(0.0733)	(0.0361)
25% tax and 75% subsidy	0.376***	0.166**	0.0682*
(Hypothesis 32, 36 & 40)	(0.0347)	(0.0747)	(0.0320)
50% tax and 50% subsidy	0.223***	0.225***	0.0104
(Hypothesis 33, 37 & 41)	(0.0343)	(0.0756)	(0.0246)
75% tax and 25% subsidy	0.0982***	0.104	0.0374
(Hypothesis 34, 38 & 42)	(0.0324)	(0.0842)	(0.0253)
Constant (tax)	0.165***	0.604***	0.0669***
	(0.0207)	(0.0675)	(0.0153)
Observations	1597	625	972
R^2	0.111	0.022	0.013

Tax treatment group is the baseline.
Robust standard errors in parentheses.
*$p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A-3: The share voting for the policy in each treatment group for those expecting to pay a share of the subsidy cost and those NOT expecting to pay.



Notes: The 75% tax group also has 25% subsidy. The 50% tax group also has 50% subsidy. The 25% tax group also has 75% subsidy.

Table A-6: Age interacted with the treatment groups.

	(1)
Subsidy	0.402***
	(0.101)
25% tax & 75% subsidy	0.315**
	(0.100)
50% tax & 50% subsidy	0.366***
	(0.0920)
75% tax & 25% subsidy	0.115
	(0.0886)
Tax × Age	-0.00106
	(0.00123)
Subsidy × Age	-0.00142
	(0.00207)
25% tax & 75% subsidy × Age	-0.000861
	(0.00212)
50% tax & 50% subsidy × Age	-0.00543**
	(0.00178)
75% tax & 25% subsidy × Age	-0.00125
	(0.00164)
Constant	0.197***
	(0.0543)
Observations	1619
R^2	0.093

Robust standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Adjustment for several hypothesis

The main hypothesis consists of 7 hypothesis tests. We follow Fink et al. (2014) and use Benjamin - Hochberg adjusted p-values, see Table A-7. Since all the p-values are 0.000, this is does not change anything.

Table A-7: Ordered p-values of the 4 main hypothesis.

k	p-value	Benjamini-Hochberg adjusted p-value required	H_0 rejected?
1	0.000	$\frac{1}{4} * 0.05 = 0.0125$	Yes
2	0.000	$\frac{2}{4} * 0.05 = 0.025$	Yes
3	0.000	$\frac{3}{4} * 0.05 = 0.0375$	Yes
4	0.000	$\frac{4}{4} * 0.05 = 0.05$	Yes

In addition we do the same for the 43 secondary hypothesis that is tested in Table A-2, Table A-3, Table A-4, Table A-5 and Table 8. Table 8 is hypothesis number 43. Each Table has 9-12 0-hypothesis that are tested. When we order all the p-values, none of the coefficients that have a significance level below 5% is rejected because of having many hypotheses. The ordering of the p-values can be seen in Table A-8.

Table A-8: Ordered p-values of the secondary hypothesis.

k	Hypothesis no	p-value	Benjamini-Hochberg adjusted p-value required	H_0 rejected?
1	1	0.000	$\frac{1}{43} * 0.05 = 0.001$	Yes
2	2	0.000	$\frac{2}{43} * 0.05 = 0.002$	Yes
3	3	0.000	$\frac{3}{43} * 0.05 = 0.003$	Yes
4	4	0.000	$\frac{4}{43} * 0.05 = 0.005$	Yes
5	5	0.000	$\frac{5}{43} * 0.05 = 0.006$	Yes
6	6	0.000	$\frac{6}{43} * 0.05 = 0.007$	Yes
7	7	0.000	$\frac{7}{43} * 0.05 = 0.008$	Yes
8	13	0.000	$\frac{8}{43} * 0.05 = 0.009$	Yes
9	14	0.000	$\frac{9}{43} * 0.05 = 0.010$	Yes
10	15	0.000	$\frac{10}{43} * 0.05 = 0.012$	Yes
11	16	0.000	$\frac{11}{43} * 0.05 = 0.013$	Yes
12	17	0.000	$\frac{12}{43} * 0.05 = 0.014$	Yes
13	18	0.000	$\frac{13}{43} * 0.05 = 0.015$	Yes
14	19	0.000	$\frac{14}{43} * 0.05 = 0.016$	Yes
15	22	0.000	$\frac{15}{43} * 0.05 = 0.017$	Yes
16	23	0.000	$\frac{16}{43} * 0.05 = 0.019$	Yes
17	31	0.000	$\frac{17}{43} * 0.05 = 0.020$	Yes
18	32	0.000	$\frac{18}{43} * 0.05 = 0.021$	Yes
19	33	0.000	$\frac{19}{43} * 0.05 = 0.022$	Yes
20	8	0.001	$\frac{20}{43} * 0.05 = 0.023$	Yes
21	24	0.001	$\frac{21}{43} * 0.05 = 0.024$	Yes
22	34	0.002	$\frac{22}{43} * 0.05 = 0.026$	Yes
23	35	0.003	$\frac{23}{43} * 0.05 = 0.027$	Yes
24	36	0.005	$\frac{24}{43} * 0.05 = 0.028$	Yes
25	25	0.006	$\frac{25}{43} * 0.05 = 0.029$	Yes
26	37	0.007	$\frac{26}{43} * 0.05 = 0.030$	Yes
27	20	0.008	$\frac{27}{43} * 0.05 = 0.031$	Yes
28	21	0.022	$\frac{28}{43} * 0.05 = 0.033$	Yes
29	38	0.026	$\frac{29}{43} * 0.05 = 0.034$	Yes
30	26	0.033	$\frac{30}{43} * 0.05 = 0.035$	Yes
31	39	0.034	$\frac{31}{43} * 0.05 = 0.036$	Yes
32	43	0.076	$\frac{32}{43} * 0.05 = 0.037$	No
33	9	0.104	$\frac{33}{43} * 0.05 = 0.038$	No
34	40	0.140	$\frac{34}{43} * 0.05 = 0.040$	No
35	10	0.145	$\frac{35}{43} * 0.05 = 0.041$	No
36	27	0.151	$\frac{36}{43} * 0.05 = 0.042$	No
37	41	0.219	$\frac{37}{43} * 0.05 = 0.043$	No
38	28	0.360	$\frac{38}{43} * 0.05 = 0.044$	No
39	29	0.389	$\frac{39}{43} * 0.05 = 0.045$	No
40	30	0.506	$\frac{40}{43} * 0.05 = 0.047$	No
41	11	0.627	$\frac{41}{43} * 0.05 = 0.048$	No
42	42	0.672	$\frac{42}{43} * 0.05 = 0.049$	No
43	12	0.933	$\frac{43}{43} * 0.05 = 0.05$	No

D Pre-analysis plan

Pre plan: Can combining tax and subsidy generate less public opposition than tax alone?

Gøril L. Andreassen* Steffen Kallbekken† Knut Einar Rosendahl‡

November 23, 2022

1 Introduction

Pigouvian taxes are politically difficult to introduce at a high enough rate because of opposition from the public. Subsidies on the other hand are often popular. How will a combination of tax and subsidies be considered by ordinary people, compared to each of the policy instruments in isolation? Will a combination of a tax and a subsidy generate less public opposition than tax alone? Is there a difference in the support if the combination is more tax than subsidies or if there is more subsidies than tax? We investigate this in an online interactive experiment.

This plan describes the hypotheses we would like to test and how we will test them. It includes a description of how variables will be coded, and the specification of the estimation equations. All deviations from the plan will be highlighted in the final paper.

We have run pilots to help us design the experiment.

The pre-analysis plan is archived before the experiment starts. We archive the pre-plan at the registry for randomized controlled trials in economics held by The American Economic Association: https://www.socialscienceregistry.org/ before the experiment starts. We will start the experiment on November 24 2022.

2 The sample

The sample consists of people that have United Kingdom as their country of residence.

*School of Economics and Business, NMBU

†Cicero

‡School of Economics and Business, NMBU

Our main analysis will include the participants that complete the voting in the experiment. Those that have voting as a non-missing variable defines our sample.

We will conduct the experiment during one day, but if the number of observations are not 1500, we will conduct the experiment one more day and this will continue until we have 1500 observations. We will conduct the experiment during weekdays between 9 am - 5 pm Norwegian time.

Some will not complete because they fail the control questions or do not bother to do the control questions. This means that there will probably be some selection into the experiment based on cognitive abilities and/or dedication.

We do not get information about those that do not complete the experiment from Prolific, so we can not check whether there is balance between those that are in our sample and those that drop out before the voting.

The groups are formed after the control questions. Some will not complete the experiment because the other group members dropped out. We will make a Table that shows how many that are part of the analysis, and the number will probably be reduced for each stage, see Table 1 as example. For each stage someone will experience that a group member drops out because of other disturbances, bad internet connection, not paying attention or other reasons. For each group member dropping out, two other participants will also drop out of the experiment. We choose to analyse all that have voted because we want as many observations as possible and it is random who is in a group that is aborted.

The number that is part of an analysis do not need to be dividable by 3 (the number of participants in a group) because one group member can drop out and the other group members get to answer questions before they are terminated as well.

Table 1: Example of the number of participants being reduced for each stage in the experiment.

Number	**Variable**	**Stage in the experiment**	**N**
1	sam	Voting	1500
2	E	Expectations 1	1400
3	I	Expectations 2	1300
4	CT	Carbon tax	1200

2.1 Balance tests

We will investigate whether the sample is balanced between the five treatment groups on age and gender.

We will also check whether the sample is balanced between the five treatment groups on share of participants choosing 5 units, which is the Nash equilibrium.

3 Coding variables

3.1 Main dependent variable

v_i is a binary variable equal to 1 if the participant voted for a policy and 0 if the participant voted against. Note that this is not whether the policy is implemented, because that depends on whether the policy gets a majority. v_i is generated by combining those voting for a policy in each treatment group.

3.2 Variable that defines the main sample

Those that have v_i as a non-missing variable is our main sample. We generate a variable ("sam") equal to 1 if v_i is non-missing.

3.3 Main independent variables

t_i is a binary variable that indicates whether the participant is in the tax treatment (1) or not (0).

s_i is a binary variable that indicates whether the participant is in the subsidy treatment (1) or not (0).

$c3_i$ is a binary variable that indicates whether the participant is in the treatment with a combination of both tax (25%) and subsidy (75%) (1) or not (0).

$c4_i$ is a binary variable that indicates whether the participant is in the treatment with a combination of both tax (50%) and subsidy (50%) (1) or not (0).

$c5_i$ is a binary variable that indicates whether the participant is in the treatment with a combination of both tax (75%) and subsidy (25%) (1) or not (0).

3.4 Variables used for balance tests

f_i is binary variable that is equal to 1 when the person is female and 0 when male.

a_i is the age and is a discrete variable.

We get the age and gender from Prolific, so we merge the Prolific data with the data from the experiment using Prolific ID as the variable to merge on. If the age and/or gender is missing, the observation is not part of the balancing test on that specific variable.

If the participant chooses 5 units in the first part, the variable $N_i = 1$ and 0 if not.

3.5 Expectations about the effect of the policy

To collect more information on participants' reasons for voting for or against the policy we ask about their expectation for the other group member's choices with or without policy. We generate a variable called $diff_i$ which is the difference between the expectation without or with policy. If $diff_i > 0$, the participant expect the policy to have an effect and the binary variable E_i is equal to 1. If $diff_i \leq 0$, E_i is equal to 0.

3.6 Expectations about the budget

We generate the variable R_i which is a discrete variable that indicate the share of the tax revenue from the other members in the group the participant expects to receive.

We generate the variable S_i which is a discrete variable that indicate the share of the cost of the subsidy for the other members in the group the participant expects to pay.

3.7 Expectations about the payoff

We generate a variable I_i which is equal to 1 if participants believe that the policy will increase their payoff, 0 if they expect no change in the payoff or if they expect the payoff to decrease.

3.8 Carbon tax

The variable CT_i is equal to 1 if the participant support a carbon tax and 0 otherwise.

4 Test of hypothesis

4.1 Main hypothesis: Support for a combination of tax and subsidy compared to only tax and only subsidy

Main hypothesis 1: The percentage support for subsidies and combinations of subsidies and taxes is higher than the percentage support for taxes.

This is the main equation:

$$v_i = \beta_0 + \beta_1 s_i + \beta_2 c3_i + \beta_3 c4_i + \beta_4 c5_i + u_i \tag{1}$$

The tax treatment group is the baseline and all coefficients are compared to the support for taxes. β_1 estimates the difference in support between the tax and the subsidies and β_2-β_4 estimate the difference in support between the tax and the combinations of subsidies and taxes. The hypothesis states that β_1-$\beta_4 > 0$.

Whether the support for combinations of tax and subsidy is higher the less tax and the more subsidy the combination has is an open question.

Number of hypothesis: 4

Main hypothesis 2: The percentage support for the combination of subsidies and taxes is lower than the percentage support for subsidies.

$$v_i = \beta_0 + \beta_1 t_i + \beta_2 c3_i + \beta_3 c4_i + \beta_4 c5_i + u_i \tag{2}$$

Here the subsidy treatment group is the baseline and all coefficients are compared to the support for the subsidy. β_2-β_4 estimate the difference in support between the subsidy and the combinations of subsidies and taxes. The hypothesis states that β_2-$\beta_4 < 0$.

Number of hypothesis: 3

4.2 Secondary hypothesis

4.2.1 Mechanisms: Expectations about the effect of the policy

Hypothesis: Expecting the policy to reduce the number of units the other participants buy, increases the support for the policy, across all treatment groups, compared to not expecting the policy to reduce demand in the tax group. Thus, we expect $\gamma_5 - \gamma_9 > 0$ in equation (3). Whether the effects are different across the different treatment groups is an open question which we will investigate.

$$\begin{aligned} v_i = {} & \gamma_0 + \gamma_1 s_i + \gamma_2 c3_i + \gamma_3 c4_i + \gamma_4 c5_i + \\ & \gamma_5 E_i \times t_i + \gamma_6 E_i \times s_i + \gamma_7 E_i \times c3_i + \gamma_8 E_i \times c4_i + \gamma_9 E_i \times c5_i + u_i \end{aligned} \tag{3}$$

Number of hypothesis: 5

4.2.2 Mechanisms: Expectations about the revenue from taxes and cost of subsidies

Hypothesis: Expecting to receive tax revenue increases the support for policy, across all treatment groups, compared to not expecting to receive any tax revenue in the tax treatment. Thus, we expect $\gamma_4 - \gamma_7 > 0$ in equation 4. Whether the effects are different across the different treatment groups is an open question which we will investigate.

Here the subsidy treatment group is not part of the analysis because this question has not been asked the subsidy treatment group.

$$v_i = \gamma_0 + \gamma_1 c3_i + \gamma_2 c4_i + \gamma_3 c5_i + \\ \gamma_4 R_i \times t_i + \gamma_5 R_i \times c3_i + \gamma_6 R_i \times c4_i + \gamma_7 R_i \times c5_i + u_i \quad (4)$$

Number of hypothesis: 4

Hypothesis: Expecting to pay for the cost of the subsidy for the others in the group, decreases the support for the policy, across all treatment groups, compared to no expecting to pay in the . Thus, we expect $\gamma_4 - \gamma_7 < 0$ in equation 5. Whether the effects are different across the different treatment groups is an open question which we will investigate.

Here the tax treatment group is not part of the analysis because this question has not been asked the tax treatment group.

$$v_i = \gamma_0 + \gamma_1 c3_i + \gamma_2 c4_i + \gamma_3 c5_i + \\ \gamma_4 S_i \times s_i + \gamma_5 S_i \times c3_i + \gamma_6 S_i \times c4_i + \gamma_7 S_i \times c5_i + u_i \quad (5)$$

Number of hypothesis: 4

4.2.3 Mechanisms: Expectations about the payoff

Hypothesis: Expecting the policy to increase the payoff, increases the support for the policy, across all treatment groups, compared to the the support for tax if the participants expects the payoff to decrease or stay the same. Whether the effects are different across the different treatment groups is an open question which we will investigate.

$$
\begin{aligned}
v_i = \gamma_0 + \gamma_1 s_i + \gamma_2 c3_i + \gamma_3 c4_i + \gamma_4 c5_i + \\
\gamma_5 I_i \times t_i + \gamma_6 I_i \times s_i + \gamma_7 I_i \times c3_i + \gamma_8 I_i \times c4_i + \gamma_9 I_i \times c5_i + u_i
\end{aligned}
\tag{6}
$$

Number of hypothesis: 5

4.2.4 Test for external validity

Hypothesis: Voting for tax in the experiment is correlated with voting for a CO2 tax in reality, all though the support for CO2 tax in reality is lower than in the experiment. We expect $\xi_1 > 0$.

$$
tax_i = \xi_0 + \xi_1 CT_i + u_I \tag{7}
$$

Number of hypothesis: 1

5 Multiple hypothesis testing and power analysis

5.1 Correction for multiple hypothesis testing

Because there are 5 treatment groups, the main hypothesis consists of 7 hypothesis tests. In addition, there are 19 secondary hypothesis. We follow Fink et al. (2014) and will use Benjamin - Hochberg adjusted p-values. This means that we will order all the p-values of the hypothesis. The number of hypothesis is m. The hypothesis will get a number $k = 1, 2, 3, ..., m$ based on the order. The p-value required to reject the null hypothesis is $p_k \leq \frac{k}{m} * 0.05$.

Since there are so many hypothesis on the secondary level, we will treat them as exploratory. We will test the main hypothesis based on $m = 7$.

5.2 Power analysis

We use Stata to calculate the needed sample size. With 80% power, standard deviation of 0.5, significance level of 0.05 and 5 treatment groups, with 1500 participants, we have power to detect a 6 percentage points difference between the different treatment groups and the tax group or the subsidy group.

6 Text analysis

We ask an open question about why they voted as they did. We will make clouds of words that are more frequently used by those voting for a policy in a treatment group compared to those voting for tax, and by those voting against a policy in a treatment group compared to those voting against tax.[1] This is based on Knutsen and Kovacevic (2021).

References

Fink, G., McConnell, M., & Vollmer, S. (2014). Testing for heterogeneous treatment effects in experimental data: False discovery risks and correction procedures. *Journal of Development Effectiveness*, *6*(1), 44–57.

Knutsen, T., & Kovacevic, S. (2021). Pre plan: An experiment on how wage discretion affects distribution preferences.

[1] In order to make a more interesting comparison we will drop words that do no have a lot of content such as: "actually","question", "think", "also" , "participant", "participants", "percent", "therefore", "want", "percentage", "someone", "option", "thought", "made", "person", "decided", "amount","didnt", "scenario", "chose","still", "can","put", "get", "one", "last", "final", "etc", "pair", "isnt", "get", "pairs", "know", "player", "something", "seems", "may", "wanted",, "pay", might", "felt", "thats","hence", "will", "cases", "way", "gave", "need", "participation", "simply", "used", "main"

E Comments on the pre-analysis plan

The main hypothesis remains unchanged from the pre-analysis plan. Here we state the secondary hypotheses as phrased in the pre-analysis plan and explain how they were altered. The rephrasing of the secondary hypotheses is done to have a more relevant comparison group. The topics we test and the coding of the variables adheres to the pre-analysisplan, it is only what we compare with that is changed. The rephrasing of the secondary hypotheses follows the same pattern for all topics. The results following the comparison in the pre-analysisplan can be seen in Table A-9 in Appendix F.

E.1 Secondary hypothesis

E.1.1 Mechanisms: Expectations about the effect of the policy

Hypothesis in the pre-analysisplan: "Expecting the policy to reduce the number of units the other participants buy, increases the support for the policy, across all treatment groups, compared to not expecting the policy to reduce demand in the tax group."

Comment on the hypothesis: Comparing the voting of both those that expect an effect and those that do not expect an effect with the tax group that do not expect an effect, is not focusing on the most interesting comparison. In addition it is interesting to investigate the expectation about an effect across the treatment groups, not just the voting behavior. Therefore, we

1. Test if there is a statistically significant difference between the treatment groups on the expectation of the effect of the policy
2. Test if there is a statistically significant difference in the support for the policy between the treatment groups for the participants that expect an effect.
3. Test if there is a statistically significant difference in the support for the policy between the treatment groups for the participants that *do not* expect an effect.

E.1.2 Mechanisms: Expectations about the revenue from taxes and cost of subsidies

Hypothesis in the pre-analysisplan: "Expecting to receive tax revenue increases the support for policy, across all treatment groups, compared to not expecting to receive any tax revenue in the tax treatment."

Comment on the hypothesis: Comparing the voting of both those that expect to receive revenue for the tax and those that do not expect to receive revenue with the tax group that do not expect to receive any revenue, is not focusing on the most interesting comparison. In addition it is interesting to investigate the share of the tax revenue the participants expect to receive across the treatment groups, not just the voting behavior. Therefore, we

1. Test if there is a statistically significant difference between the treatment groups on the share of the tax revenue the participants expects to receive.

2. Test if there is a statistically significant difference in the support for the policy between the treatment groups for the participants that expect to receive a share of the tax revenue.

3. Test if there is a statistically significant difference in the support for the policy between the treatment groups for the participants that *do not* expect to receive a share of the tax revenue.

Hypothesis in the pre-analysisplan: “Expecting to pay for the cost of the subsidy for the others in the group, decreases the support for the policy, across all treatment groups, compared to no expecting to pay in the [Here a word is lacking, but it should be “subsidy group”]"

Comment on the hypothesis: Comparing the voting of those that expect to pay for the subsidy and those that do not expect to pay with the subsidy group that do not expect to pay is not focusing on the most interesting comparison. In addition it is interesting to investigate the share of the subsidy cost the participants expect to pay across the treatment groups, not just the voting behavior. Therefore, we

1. Test if there is a statistically significant difference between the treatment groups the share the participants expects to pay.

2. Test if there is a statistically significant difference in the support for the policy between the treatment groups for the participant that *do not* expect to pay.

3. Test if there is a statistically significant difference in the support for the policy between the treatment groups for the participant that expect to pay.

E.1.3 Mechanisms: Expectations about the payoff

Hypothesis: “Expecting the policy to increase the payoff, increases the support for the policy, across all treatment groups, compared to the the support for tax if the participants expects the payoff to decrease or stay the same."

Comment on the hypothesis: Comparing the voting of those that expect the payoff to increase and those that do not expect the payoff to increase in the tax group is not focusing on the most interesting comparison. In addition it is interesting to investigate the expectation about the payoff across the treatment groups, not just the voting behavior. Therefore, we

1. Test if there is a statistically significant difference between the treatment groups on the expectation for the payoff to increase.

2. Test if there is a statistically significant difference in the support for the policy between the treatment groups where the participant expect the payoff to increase.

3. Test if there is a statistically significant difference in the support for the policy between the treatment groups where the participant *do not* expect the payoff to increase.

E.2 Text analysis

We compared the words more frequently used in the open ended question about why the participants voted as they did. We compare those that voted *against* policy in the 100% tax group, the 100% subsidy group and the 50% tax & 50% subsidy group in Figure A-4. And in Figure A-5 we compare those that voted *for* policy in the 100% tax group, the 100% subsidy group and the 50% tax & 50% subsidy group. We do not think the word clouds provide particularly interesting insights and have therefore placed them in Appendix F.

F Results from following the pre-analysisplan

F.1 The regression equations (3)-(6)

Table A-9: The regression equations in the preplan estimated.

	(3) Effect	(4) Tax revenue	(5) Subsidy cost	(6) Payoff
Subsidy	0.160			0.101**
	(0.0976)			(0.0362)
25% tax & 75% subsidy	0.150	0.411***	-0.221*	0.0682*
	(0.102)	(0.0833)	(0.101)	(0.0321)
50% tax & 50% subsidy	-0.00844	0.459***	-0.354**	0.0104
	(0.0996)	(0.100)	(0.126)	(0.0246)
75% tax & 25% subsidy	0.0518	0.246**	-0.527***	0.0374
	(0.106)	(0.0905)	(0.121)	(0.0253)
Tax interaction term	-0.0689	0.0982*		0.537***
	(0.0887)	(0.0408)		(0.0691)
Subsidy interaction term	0.263***		-0.301***	0.635***
	(0.0560)		(0.0659)	(0.0436)
25% tax & 75% subsidy interaction term	0.149*	-0.0117	-0.118	0.635***
	(0.0632)	(0.0821)	(0.0876)	(0.0426)
50% tax & 50% subsidy interaction term	0.193**	-0.183	-0.0864	0.752***
	(0.0586)	(0.0987)	(0.115)	(0.0391)
75% tax & 25% subsidy interaction term	-0.00431	-0.0664	-0.0159	0.603***
	(0.0674)	(0.0882)	(0.109)	(0.0543)
Constant	0.217*	0.0426	0.732***	0.0669***
	(0.0863)	(0.0277)	(0.0448)	(0.0153)
Observations	1621	1273	1275	1597
R^2	0.112	0.073	0.061	0.469

Robust standard errors in parentheses.

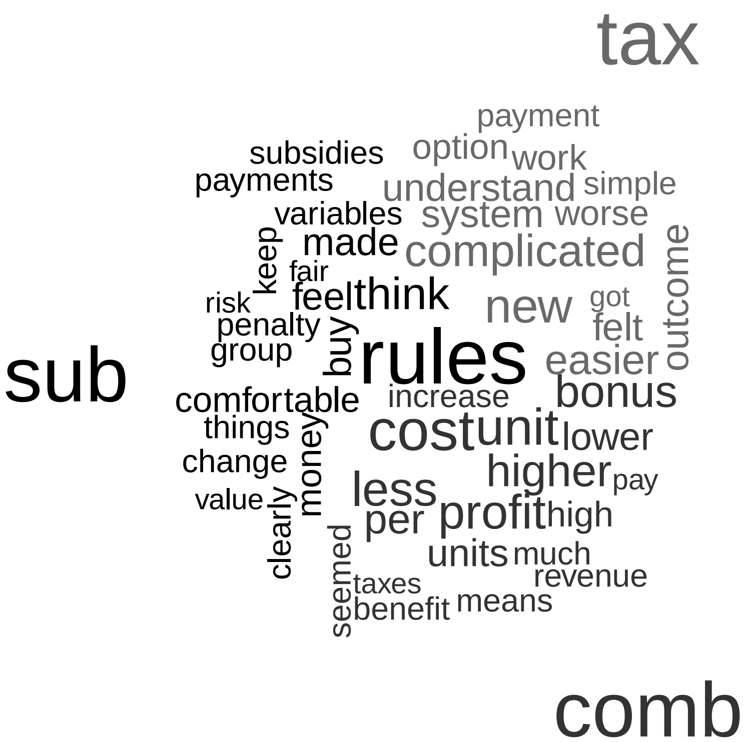
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The column numbers refer to the regression equations 3-6 in the pre-analysis plan.

The interaction terms are the treatment groups interacted with the variable in the header. This means that column 1 interaction terms are the treatment groups interacted with expecting effect. Column 2 interaction terms are the treatment groups interacted with whether the participants expect a share of the tax revenue, and so on.

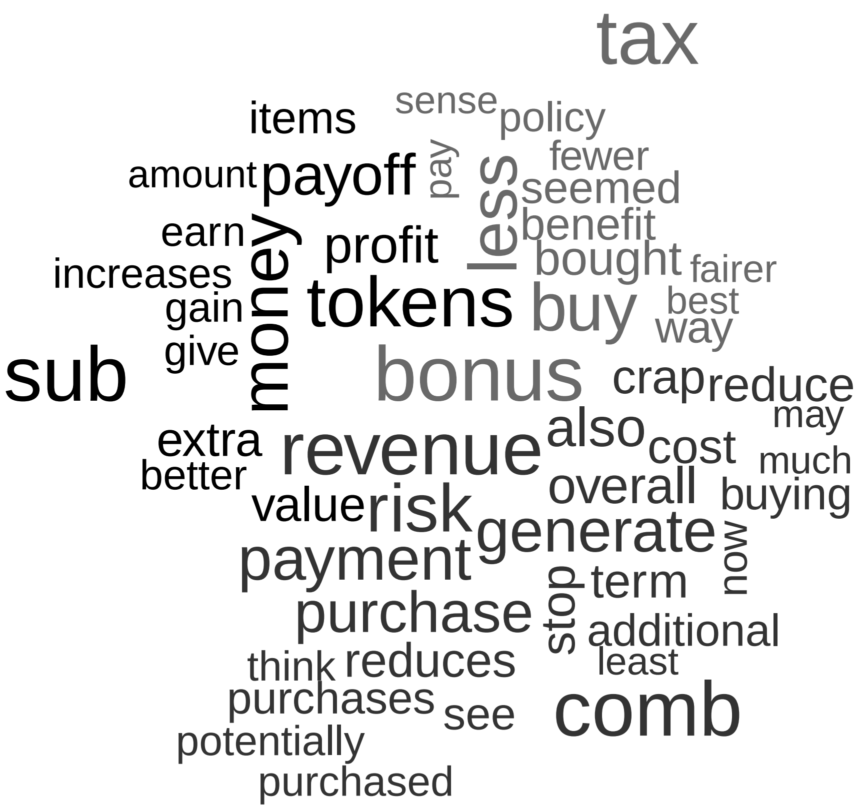
F.2 Word cloud

Figure A-4: Comparing explanations for voting AGAINST the policy for the 100% tax group (“tax”), the 100% subsidy group (“sub”) and the 50% tax & 50% subsidy group (“comb”).



The words in the same grey scale as “tax” are the words that people in the tax group mentioned more, relative to people in the two other groups (similar for "sub" and "comb"). The size of the word tells us the relative number of people mentioning it.

Figure A-5: Comparing explanations for voting FOR the policy for the 100% tax group (“tax”), the 100% subsidy group (“sub”) and the 50% tax & 50% subsidy group (“comb”).



The words in the same grey scale as “tax” are the words that people in the tax group mentioned more, relative to people in the two other groups (similar for "sub" and "comb"). The size of the word tells us the relative number of people mentioning it.

G Details about the experiment design

G.1 All instructions for the 100% tax treatment group

G.1.1 Introduction

Welcome

Thank you for taking part in this market experiment developed for research purposes.

You are guaranteed to earn £1.5 if you and your group members complete the experiment. The estimated time to complete is 15 minutes.

In addition, you can earn a bonus payment depending on your decisions in the experiment (but not your answers in the survey).

You will be in a group with two real people that are doing the experiment at the same time. It is therefore important that you complete without interruptions.

If one of the participants in your group drops out, you cannot continue, and you will receive compensation for the time you spent on the study in line with Prolific payment principles. In this case you will not receive bonus payment because the bonus payment is calculated at the end of the experiment.

The money in the experiment is in tokens. 100 tokens equals £1.

All interactions are anonymous.

Before you can enter the experiment, you will receive instructions and we will ask you some control questions to test that you understand the instructions.

You will receive compensation for the time you spent only if you answer the control questions correctly and start the actual study.

We recommend you to have a calculator ready, for instance on your mobile phone or your laptop.

At the end of the study, you will get a code that you can enter into Prolific to show that you have finished the study.

Please write your participant ID below so that we can pay your earnings later:

remaining characters 24

Continue

Do you understand the information below and do you consent to taking part in this study? If so, please press the button "I consent" and then the button "Continue".

I consent

I do not consent

Continue

Are you interested in taking part in the research project «attitudes towards regulation of markets»?

Purpose of the project: You are invited to participate in a research project where the main purpose is to study behaviour in a market. Governments can make use of different policies to influence how people behave in markets. People's attitudes to the choice of policies, and to whether it is necessary or not to regulate a market, are important for which policy decisions that are taken. In this study we will first ask you to make decisions in a fictitious market, and later ask you about your personal views on different types of persons.

Which institution is responsible for the research project? CICERO Center for international climate research is responsible for the project (data controller). The project is funded by the Research Council of Norway.

Why are you being asked to participate? You signed up as a potential participant for research studies at Prolific, and expressed an interest in taking part in this specific study when you clicked the link shared by Prolific.

What does participation involve for you? The study is an online experiment where you make decisions in a fictitious market and answer survey questions. It will typically require 15 minutes to complete. The information is stored digitally. We will ask for your Prolific ID in order to be able to pay for your participation.

Participation is voluntary. If you choose to participate, you can withdraw your consent at any time without giving a reason. All information about you will then be made anonymous. There will be no negative consequences for you if you choose not to participate or later decide to withdraw. We will, however, not be able to pay you if you do not finish the study.

Your personal privacy – how we will store and use your personal data. We will only use your personal data for the purpose(s) specified here and we will process your personal data in accordance with data protection legislation (the GDPR). Your personal data in this study is your Prolific ID. The Prolific ID will make it possible for us to pay you and to get the demographic information you have given to Prolific. We do not have access to information that can identify you such as name, email address or IP-address.

We will only use your Prolific ID for the purposes specified here. We will process your Prolific ID confidentially and in accordance with data protection legislation (the General Data Protection Regulation and Personal Data Act). CICERO will only have access to your Prolific ID while the study is ongoing. Once the study is completed, and we have informed Prolific about how much you earned in the study (and downloaded the demographic data from Prolific), we will delete your Prolific ID from our records, and keep only the anonymized answers.

Three people in the project team will have access to the answers you give in this study. The answers will be stored on an encrypted server with two-factor authentication. No participants will be recognizable in the research publications that we will write based on the experiment.

G.1.2 Instructions part 1

Instructions, page 1/5

You and two other participants are buyers in a market. You can buy up to 6 units of a good.

Each unit of the good has a different value, but the price is the same. The first unit has the highest value and then each additional unit is worth less. The value of the units you buy is used to calculate your bonus payment each round.

You will make a decision once on how many units to buy, before receiving new instructions and make a new decision. The decision you make in part 1 do not influence the rules and alternatives in part 2.

Continue

Instructions, page 2/5

This is how your bonus payment is calculated:

The value of the unit(s) you buy

minus

the price of the unit(s) you buy

Continue

Back to instructions page 1

Instructions, page 3/5

The price you pay for each unit of the good is 40 tokens.

The value of each unit is:

130	110	90	70	50	30

In a pilot we had, a majority chose 5 units.

Continue

Back to instructions page 1 | Back to instructions page 2

Instructions, page 4/5

There is one more feature of the market that affects your bonus payment. Buying the good creates an additional cost. For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

Continue

Back to instructions page 1 | Back to instructions page 2 | Back to instructions page 3

Instructions, page 5/5

Example:

If you choose 5 units, and the other two members in your group choose 3 units, your bonus payment in that round would be:

The value of the 5 units: 130 + 110 + 90 + 70 + 50 = 450

minus

The cost of your 5 units: 40*5 = 200

minus

the additional cost imposed on you by the purchases of the two others in your group: 3*20 + 3*20 = 120

= 450 - 200 - 120 = 130

Summary:

The price you pay for each unit of the good is 40 tokens.

The value of each unit is:

130	110	90	70	50	30

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other participants in the group.

Continue

Back to instructions page 1 | Back to instructions page 2

G.1.3 Control questions

(1) How much do you earn in bonus payment if you buy 3 units and the two others in your group buy 5 units each?

(2) How much do you earn in bonus payment if you buy 5 units and the two others in your group buy 5 units each?

The price is 40 tokens per unit.

The value of each unit is:

130	110	90	70	50	30

The additional cost the others impose on you is 20 tokens per good they buy.

Submit answer

Attempts left to answer the control questions: 3

Back to instructions part 1 | Back to instructions part 2

Back to instructions part 3 | Back to instructions part 4 | Back to instructions part 5

G.1.4 Results from the control question

That is correct!

At this stage it could be a good idea to think through how many units you would like to buy, since when the experiment starts you are on a time limit to choose.

The price you pay for each unit of the good is 40 tokens.

The value of each unit is:

130	110	90	70	50	30

In a pilot we had, a majority chose 5 units.

I am ready to join the study!

G.1.5 Purchase of goods part 1, equal for all treatment groups

Please write in the box how many units you want to buy. Remember that the maximum is 6.

If you buy fewer than 6 units, the units you buy will always be the those with the highest value.

Number of goods:

The price is 40 tokens per unit.

The value of each unit is:

130	110	90	70	50	30

Continue

Remaining time: 04:52

G.1.6 Result bonus payment part 1, equal for all treatment groups

Your bonus payment this round is 50 tokens.

You chose 3 unit(s). The value was 330 tokens and the total price was 120 tokens. The others chose 8 unit(s) in total. This results in 160 additional costs for you.

(If your bonus payment is negative, it will be set to 0 after the survey, so that you do not lose money. In addition, you will receive the guaranteed participation fee of £1.5 when you have completed the study.)

Continue

Remaining time: 05:00

G.1.7 Instructions part 2, 100% tax treatment group

Instructions part 2

We will now ask you to vote on the rules that will govern the next round of the market. The option that receives the majority of votes will be implemented.

Your choices are to either
1) keep the rules as they were for the previous round or
2) introduce a tax of 40 tokens per unit.

If the majority in your group vote for a tax, the new price per unit will be 80 tokens.

The value of each unit remains the same:

130	**110**	**90**	**70**	**50**	**30**

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

The tax generates revenue. Your group's budget will be balanced through personal transfers of tokens between the members of your group.

Continue

Remaining time: 04:58

G.1.8 Voting, 100% tax treatment group

For the next round, which of the two rules do you vote for:

A tax of 40 tokens per unit so that the price becomes 80 tokens

No changes in the rules from the previous round

The value of each unit is:

130	**110**	**90**	**70**	**50**	**30**

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

Continue

Remaining time: 05:00

G.1.9 Expectations, 100% tax treatment group

1) If the tax is implemented, how many goods do you expect each of the other persons in your group will buy? (Your answer does not influence your payment)

2) If the tax is NOT implemented, how many goods do you expect each of the other persons in your group will buy? (Your answer does not influence your payment)

If tax is implemented, the price per unit is 80 tokens.

If tax is NOT implemented, the price per unit is 40 tokens.

The value of each unit is:

130	**110**	**90**	**70**	**50**	**30**

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

Continue

Remaining time: 04:57

1) If the policy is implemented, how much of the revenue from the tax the others pay do you expect to receive?

0% 100%

%

2) If the tax is implemented, what do you think will happen to your payoff?

Increase

Decrease

No change

If tax is implemented, the price per unit is 80 tokens.

If tax is NOT implemented, the price per unit is 40 tokens.

The value of each unit is:

130	**110**	**90**	**70**	**50**	**30**

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

Continue

Remaining time: 04:58

G.1.10 Open text question, 100% tax treatment group

Why did you vote to introduce the tax? (Your answer does not influence your payment)

Continue

Remaining time: 04:56

G.1.11 Result from voting if majority for the policy, 100% tax treatment group

A majority in your group voted to introduce the tax.

Continue

Remaining time: 02:00

G.1.12 Purchase of goods part 2, 100% tax treatment group

Please write in the box how many units you want to buy. Remember that the maximum is 6.

If you buy fewer than 6 units, the units you buy will always be the those with the highest value.

Number of goods:

The price is 80 tokens per unit.

The value of each unit is:

130	**110**	**90**	**70**	**50**	**30**

Continue

Remaining time: 05:00

G.1.13 Result bonus payment part 2, 100% tax treatment group

Your bonus payment this round is 80 tokens.

You chose 4 unit(s). The value was 400 tokens and the total price was 320 tokens. The others chose 6 unit(s) in total. This results in 120 additional costs for you.

(If your bonus payment is negative, it will be set to 0 after the survey, so that you do not lose money. In addition, you will receive the guaranteed participation fee of £1.5 when you have completed the study.)

To balance the group's budget you received half of the tax revenue collected from the two others in your group, whereas they received half each of any tax you paid.

Continue

Remaining time: 04:59

G.1.14 Question about hypothetical CO2 tax, equal for all treatment groups

One final question before the experiment is finished: Imagine that to combat climate change the government proposed to increase the cost of emitting CO2 by £100 per ton from next year. This would increase the cost of petrol by 23 pence per liter and diesel by 26 pence per liter. If there was a vote on this tax proposal today, what would you have voted?

Increasing taxes on CO2 emissions by £100 per ton

No changes in the tax rates

Continue

G.1.15 End of experiment, equal for all treatment groups

End of experiment

You earned 100 tokens.

These tokens are worth £1. This will be paid on top of your guaranteed participation fee of £1.5.

Many thanks for participating in this study. We were interested in preferences for policies in the market.

Please enter the following code into Prolific to prove you completed the study:
36D47043

G.2 Instructions for the 100% subsidy treatment group, when it differs from the 100% tax treatment group

G.2.1 Instructions part 2, 100% subsidy treatment group

Instructions part 2

We will now ask you to vote on the rules that will govern the next round of the market. The option that receives the majority of votes will be implemented.

Your choices are to either
1) keep the rules as they were for the previous round or
2) introduce a subsidy of 40 tokens per unit that you do NOT buy.

If the majority in your group vote for a subsidy, the price per unit will remain 40 tokens but you will receive 40 tokens per unit you do NOT buy.

The value of each unit remains the same:

130	**110**	**90**	**70**	**50**	**30**

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

The subsidy costs money. Your group's budget will be balanced through personal transfers of tokens between the members of your group.

Continue

Remaining time: 04:58

G.2.2 Voting, 100% subsidy treatment group

For the next round, which of the two rules do you vote for:

A subsidy of 40 tokens per unit you do NOT buy

No changes in the rules from the previous round

Price per unit is 40 tokens.

The value of each unit is:

130	**110**	**90**	**70**	**50**	**30**

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

Continue

Remaining time: 05:00

G.2.3 Expectations, 100% subsidy treatment group

1) If the subsidy is implemented, how many goods do you expect each of the other persons in your group to buy? (What you answer does not influence your payment)

2) If the subsidy is NOT implemented, how many goods do you expect each of the other persons in your group will buy? (Your answer does not influence your payment)

If subsidy is implemented, 40 tokens will be given to you for each unit of the good NOT bought. The price per unit is unchanged: 40 tokens.

The value of each unit is:

130	110	90	70	50	30

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

Continue

Remaining time: 04:59

1) If the policy is implemented, how much of the cost of the subsidy for the others in your group do you expect to pay?

0% 100%

%

2) If the subsidy is implemented, what do you think will happen to your payoff?

Increase

Decrease

No change

If subsidy is implemented, 40 tokens will be given to you for each unit of the good NOT bought. The price per unit is unchanged: 40 tokens.

The value of each unit is:

130	110	90	70	50	30

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

Continue

Remaining time: 05:00

G.2.4 Open text question, 100% subsidy treatment group

Why did you vote to introduce the subsidy? (Your answer does not influence your payment)

Continue

Remaining time: 04:55

G.2.5 Result from voting if majority for the policy, 100% subsidy treatment group

A majority in your group voted to introduce the subsidy.

Continue

Remaining time: 01:59

G.2.6 Purchase of goods part 2, 100% subsidy treatment group

Please write in the box how many units you want to buy. Remember that the maximum is 6.

If you buy fewer than 6 units, the units you buy will always be the those with the highest value.

Number of goods:

The price is 40 tokens per unit. You will receive 40 tokens per unit you do not buy.

The value of each unit is:

130	110	90	70	50	30

Continue

Remaining time: 04:59

G.2.7 Result bonus payment part 2, 100% subsidy treatment group

Your bonus payment this round is 50 tokens.

You chose 5 unit(s). The value was 450 tokens and the total price was 200 tokens. The others chose 3 unit(s) in total. This results in 60 additional costs for you.

(If your bonus payment is negative, it will be set to 0 after the survey, so that you do not lose money. In addition, you will receive the guaranteed participation fee of £1.5 when you have completed the study.)

To balance the group's budget you paid half of the subsidy cost for the two others in your group, whereas they paid half each of any subsidies you received.

Continue

Remaining time: 04:55

G.3 Instructions for the 75% tax & 25% subsidy treatment group, when it differs from the 100% tax treatment group, as an example of the combination treatment groups

G.3.1 Instructions part 2, 75% tax & 25% subsidy treatment group

Instructions part 2

We will now ask you to vote on the rules that will govern the next round of the market. The option that receives the majority of votes will be implemented.

Your choices are to either

1) keep the rules as they were for the previous round or

2) introduce a tax of 30 tokens per unit and a subsidy of 10 tokens per unit that you do NOT buy.

If the majority in your group vote for a policy, the new price per unit will be 70 tokens and you will receive 10 tokens per unit you do NOT buy.

The value of each unit remains the same:

130	110	90	70	50	30

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

The tax generates revenue and the subsidy costs money. Your group's budget will be balanced through personal transfers of tokens between the members of your group.

Continue

Remaining time: 04:59

G.3.2 Voting, 75% tax & 25% subsidy treatment group

For the next round, which of the two rules do you vote for:

A tax of 30 tokens per unit so that the price becomes 70 tokens, and a subsidy of 10 tokens per unit you do NOT buy

No changes in the rules from the previous round

The value of each unit is:

130	110	90	70	50	30

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

Continue

Remaining time: 04:59

G.3.3 Expectations, 75% tax & 25% subsidy treatment group

1) If the tax and subsidy is implemented, how many goods do you expect each of the other persons in your group to buy? (Your answer does not influence your payment)

2) If the tax and subsidy is NOT implemented, how many goods do you expect each of the other persons in your group will buy? (Your answer does not influence your payment)

If the tax and the subsidy is implemented, the price per unit is 70 tokens and 10 tokens will be given to you for each unit of the good not bought.

If the tax and the subsidy is NOT implemented, the price per unit is 40 tokens.

The value of each unit is:

130	110	90	70	50	30

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

Continue

Remaining time: 04:59

1) If the policy is implemented, how much of the revenue from the tax the others pay do you expect to receive?

0% 100%

%

2) If the policy is implemented, how much of the cost of the subsidy for the others in your group do you expect to pay?

0% 100%

%

3) If the tax and subsidy is implemented, what do you think will happen to your payoff?

Increase

Decrease

No change

If the tax and the subsidy is implemented, the price per unit is 70 tokens and 10 tokens will be given to you for each unit of the good not bought.

If the tax and the subsidy is NOT implemented, the price per unit is 40 tokens.

The value of each unit is:

130	110	90	70	50	30

For each unit a buyer in the group purchases, a cost of 20 tokens is imposed on each of the two other members of the group.

Continue

Remaining time: 04:59

G.3.4 Open text question, 75% tax & 25% subsidy treatment group

Why did you vote to introduce the tax and the subsidy? (Your answer does not influence your payment)

Continue

Remaining time: 04:57

G.3.5 Result from voting, 75% tax & 25% subsidy treatment group

A majority in your group voted to introduce the tax and the subsidy.

Continue

Remaining time: 01:59

G.3.6 Purchase of goods part 2, 75% tax & 25% subsidy treatment group

Please write in the box how many units you want to buy. Remember that the maximum is 6.

If you buy fewer than 6 units, the units you buy will always be the those with the highest value.

Number of goods:

The price is 70 tokens per unit and you will receive 10 tokens per unit you do not buy.

The value of each unit is:

130	**110**	**90**	**70**	**50**	**30**

Continue

Remaining time: 04:56

G.3.7 Result bonus payment part 2, 75% tax & 25% subsidy treatment group

Your bonus payment this round is 50 tokens.

You chose 5 unit(s). The value was 450 tokens and the total price was 350 tokens. The others chose 5 unit(s) in total. This results in 100 additional costs for you.

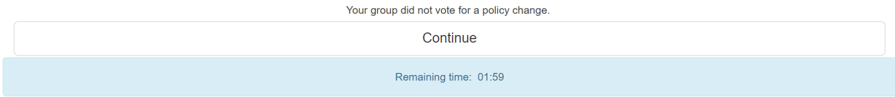
(If your bonus payment is negative, it will be set to 0 after the survey, so that you do not lose money. In addition, you will receive the guaranteed participation fee of £1.5 when you have completed the study.)

To balance the group's budget, you received half of the tax revenue collected from the two others in your group and you paid half of the subsidy cost for the two others in your group. Similarly, the two others in your group received half each of any tax you paid and paid half each of any subsidies you received.

Continue

Remaining time: 05:00

G.4 If a majority in the group do not vote for a policy change



Paper 2: Company cars and household car choices

Company cars and household car choices*

Gøril L. Andreassen[†] Askill Harkjerr Halse[‡]

June 28, 2023

Abstract

Tax systems that favour company cars for personal use could cause households to have more cars. It could also affect the technology choice. We investigate the relationship between household car choices and access to a company car through a difference-in-difference design using Norwegian microdata. We find that access to a company car is associated with an increase in the total number of cars and in the number of combustion-engine cars. For electric cars, the results are inconclusive. However, wage growth and access to company cars are also positively correlated. Therefore, we cannot interpret the difference in number of cars between the treatment and control group as a causal effect of the company car scheme, but as correlations. Still, existing evidence on the income elasticity of car demand suggests that the increase in the number of cars is unlikely to be driven by wage growth alone. (*JEL* D12, H24, J33, Q58, R41)

Keywords: Fringe benefits; Company car; Car Ownership; Electric Vehicles; Tax

*We would like to thank Eivind Bjørkås, Maria Bratt Börjesson, Fenella Carpena, Anna Godøy, Bjørn Gjerde Johansen, Åshild Auglænd Johnsen, Andreas Kotsadam, Ismir Mulalic, Maria Nareklishvili, Oddbjørn Raaum, Ole Røgeberg, Andreas Økland and Vegard Østli, participants at the Skatteforsk-Centre for Tax Research Workshop, Frisch seminar and Institute of Transport Economics seminar for valuable input. We would also like to thank Hege Nygård in the Norwegian Tax Administration and Jan Petter Røssevold in The Norwegian Road Federation for providing important information. This study is part of the projects *Transport, inequality and political opposition*, funded by The Research Council of Norway (grant #302059) and *Skatteforsk – Centre for Tax Research* (grant #341289)

†Corresponding author. goril.louise.andreassen@nmbu.no, School of Economics and Business, Norwegian University of Life Sciences, PB 5003 NMBU, 1432 Ås, Norway

‡askill.harkjerrhalse@toi.no, Institute of Transport Economics, Gaustadalléen 21, 0349 Oslo, Norway

1 Introduction

The convenience and flexibility provided by cars have made them a crucial element in modern mobility. The global number of vehicles has been on a steady rise and reached approximately 1.4 billion in 2022 (Hedges & Company, 2021).[1] However, the increased number of cars has led to a rise in CO_2 emissions and other types of pollution, both from production and use (ACEA, 2022; IEA, 2021, p.194). In addition, use of cars contributes to other externalities such as road congestion, accidents and noise, and they take up space both when parked and in use. Greenhouse gas emissions from transport accounts for almost one quarter of global energy-related CO_2 emissions (Pathak et al., 2022).[2] To reduce emissions, countries have several strategies, including reducing transport volume, shifting from cars towards public transportation, cycling, and walking, and transitioning from internal combustion engine cars to zero-emission vehicles (Hegsvold et al., 2022).

In this paper we study the relationship between having a company car and the number of cars in the family, as well as the number of electric vehicles and combustion-engine cars.[3] Getting a company car that can be used privately may increase the number of cars in the household compared to the number of cars the household would have had if no household member had a company car. Understanding this magnitude is important as producing and using cars has significant external consequences. Company cars can make having a car cheaper, easier and with less risk regarding unexpected costs. The personal use of a company car is taxed in most countries (Harding, 2014). If the company cars are taxed too lightly, there is both a fiscal loss to the government revenue and an environmental cost because having and/or using a car becomes cheaper (Harding, 2014).

We use a difference-in-difference design on administrative microdata, meaning that we cover the universe of workers, cars, families and firms. If we look at who acquires a company car, the decision could be related to an increase in car demand (endogeneity problem), and we therefore focus on who gets an *offer* of a company car. We look at workers who are likely to be offered a company car when they change job and compare them to workers that change job, but are not likely to be offered a company car. The sample consists of workers who are employed in what we call company car occupations and change job from one firm to another. We then distinguish between those who are hired by what we call company car firms, and therefore are likely to be offered of a company car,

[1] The USA has the highest number of cars per capita (0.89), whereas Europe has 0.52 cars per capita and India 0.05 (Hedges & Company, 2021).

[2] These numbers do not include production of vehicles.

[3] We use the term family and household interchangeably in this article, but statistically we use families as the unit of observation. The statistical difference between a household and a family is that a family can only consist of two generations and maximum one couple, while a household is everyone that lives in the same residence. There can therefore be more than one family in a household. Definitions (in Norwegian) can be seen here: https://www.ssb.no/befolkning/barn-familier-og-husholdninger/statistikk/familier-og-husholdninger.

and those who are hired by firms where company cars are not offered. This constitutes our treatment and control groups. We do not observe whether those working in company car occupations in company car firms actually get an offer of a company car. If only a subset of this group is offered a company car, our underlying assumption is that this offer is exogenous with respect to the outcome variables.

At the first glance it seems like the access to a company car increases the number of cars in the household by 9%. However, the treatment group has higher wage growth than the control group after the job change. Therefore, we cannot interpret the coefficients as a causal effect of the company car scheme, but rather as correlations. We do not know whether it is the company car scheme, the increased wage or both that leads to the increased car possession. However, income elasticities on car demand estimated by Johansen and Munk-Nielsen (2022) indicate that some of the increase in the number of cars is due to the company car scheme, as the increase in the number of cars is higher than the income elasticities and the wage growth would imply.

In addition to the differences in wage growth, the treatment and control group also differ with respect to some pre-treatment characteristics. However, when adding the control variables age, age squared, log wage, mean age of the cars the households own, couple status and number of household members, all measured the year before the job change, the results do not change much.[4] This suggests that these imbalances are not driving the changes in car outcomes that we observe. In addition, the sample is balanced with respect to changes in family size, number of children, number of children under the age of 18, whether they move out of the neighbourhood and change in the couple status.

This paper investigates the company car scheme in a context with a very high market share for electric vehicles. We find no statistical significant difference in the number of electric vehicles between those having access to a company car and those not having access. As the total number of cars is higher among those having access to a company car, this indicates that even with a discount for electric vehicles, the company car scheme does not stimulate much to electric vehicle adoption. This could be related to the electric car models available during the period of investigation not being full-fledged substitutes to combustion-engine cars, particularly for those that use the car a lot in their work.[5] But it could also be related to the employer covering the fuel costs of the company cars, which is most valuable for non-electric vehicle users. Or it could be selection effects, where the people working in company car firms preferring combustion-engine cars to electric vehicles.

[4] We do not add control variables measured after the job change as this could be a bad control, meaning that the outcome affects the control variable, not just the control variable influencing the outcome (Angrist & Pischke, 2009).

[5] This depends on the car make and model preferences and the budget, as Tesla has been available the whole period.

Previous research has shown that having a company car[6] increases the total number of cars households possess (Börjesson & Roberts, 2022; Metzler et al., 2019). Börjesson and Roberts (2022) is the first paper to use administrative microdata to investigate this question. The context is Sweden, and the paper uses household fixed effects to control for unobserved characteristics that do not change over time. They find that having a company car both increases the probability of having at least one car by respectively 38 percentage points (single households) and 14 p.p. (couple households), and the number of cars the household has by 0.41 (couple households).

In addition to our main analysis, we use the same research design as the Swedish study by Börjesson and Roberts (2022). We find that company cars are associated with an increase in the number of cars and the likelihood of having a car of the same magnitude as in Sweden. It could be that the results in both Börjesson and Roberts (2022) and our replication with Norwegian data pick up unobserved differences in car demand between households with and without a company car (selection effects), and not effects of the company car scheme. Although time-invariant characteristics are controlled for, the choice of acquiring a company car could be associated with (unobservable) changes in household car demand (Angrist & Pischke, 2009). If employees have the ability to influence the decision of being offered a company car and they choose to do so when they already intend to purchase a car, the employee may acquire a company car when their alternative would have been buying another car. This would cause an upward bias in the estimated effect of company cars on the number of cars in the household. We therefore try to remedy this by using quasi-experimental methods.

Metzler et al. (2019) investigate the question for Germany. Their data is a household survey. The research design is comparing the log of the number of kilometres driven with private cars and company cars, and with no household fixed effects. They find that company cars are driven longer, but that they use less fuel per kilometre than private cars, probably because the company cars are newer and mid-sized. Further, they find that households holding a company car have 25% more cars. Further, Gutiérrez-i-Puigarnau and Van Ommeren (2011) find that those with a company car in the Netherlands have a more expensive car than those without a company car. Both studies could suffer from selection bias. See Börjesson and Roberts (2022) for a more comprehensive review of the company car literature.

Harding (2014) provide a benchmark for neutral taxing of personal use of company cars and considers whether the benefit is taxed lower than the benchmark in different OECD countries. She finds that the capital component in the Norwegian company car tax system implies that on average, the whole value of the private use of company cars is taxed. Thus,

[6]In this setting "having a company car" means to use a car paid by the employer for private trips.

Norway has no fiscal loss in the company car tax, but the design of the tax does not give environmental incentives, according to Harding (2014). Except for Norway and Canada, Harding (2014) finds that all other OECD countries tax the company cars too lightly.

One contribution of this paper is that it is the first investigation of the company car scheme that uses quasi-experimental methods. It is also the first investigation of the company car scheme in a context with high market penetration of electric vehicles. In addition to the company car literature, this paper contributes to a growing literature that uses administrative microdata to study car ownership and use (Fevang et al., 2021; Gillingham et al., 2022; Gillingham & Munk-Nielsen, 2019; Pyddoke, 2009). For instance, Østli (2023) investigates whether better public transport influences the number of cars in the household. Jordbakke (2023) investigates how new parking rules for people living in the city influences their car consumption. This paper also adds to the literature that uses job changes for exogenous variation. Paetzold and Winner (2016) use change of job to find out if the work environment influences the decision to cheat on the tax.

The rest of the paper is organized as follows. First we present the company car scheme and the Norwegian car market more in detail. Then we present the data and define important variables. Furthermore, we present the empirical strategy and the samples for the two different research strategies. Then we turn to the results, before we discuss income elasticities on car demand and conclude.

2 Background

In this section we give brief information about the taxation of personal use of company cars in Norway, compare the costs of different options and present descriptive statistics about company cars in Norway and the Norwegian car market.

2.1 Taxing the private use of company cars

Private use of company cars are prevalent in many countries. How this benefit is taxed varies. The tax could have only a capital component, only a distance component, combinations of the two, or other tax designs. The capital component can be based on the list price, the cost price or the fair value of the car. The distance component can be added based on personal kilometers, deducted based on business kilometers, or using other methods (Harding, 2014).

In Norway the benefit of the personal use of the company car is valued based on the list price of the same car bought as new. The tax on the capital cost of the car includes the fuel cost and other car-related costs on private trips.[7] 30% of the list price up to a

[7] In Sweden, the company car tax has both a capital component and a distance component (Börjesson

certain amount and then 20% of the remaining list price is added to the wage as a fringe benefit.[8] This amount is taxed according to the marginal tax rate, which depends on the wage level.[9] If the car is older than 3 calender years, the company car tax is lower.

All costs related to the company car are covered by the employer, except costs not defined as 'car costs', which includes parking costs, toll road costs, and ferry costs. There is no rule saying who in the family can use the car. The company car tax is not reduced if the employee pays some of the expenses themselves. However, if the company car is only used sporadically for private trips, defined as maximum 10 days annually and maximum 1000 km, there is no company car tax.[10]

Gutiérrez-i-Puigarnau and Van Ommeren (2011) state that it is common to not pay VAT on the company car, at least in the Netherlands. Firms in Norway are not allowed to deduct the VAT on leasing or purchasing of passenger cars on their VAT accounting.[11] If that had been possible, the cost of a company car would have been lower than the cost of owning a car as a private person, which would have given large incentives to firms to offer a company car instead of wage. How this is in other OECD countries is not covered by the study of Harding (2014).

With only a capital component and with the same tax rules for electric and combustion-engine cars, the scheme probably favors combustion-engine cars, as non-electric cars have higher fuel costs. However, electric company cars had a 40–50% discount in the valuation in 2021 and earlier. This was reduced to 20% in 2022 and stopped in 2023.

2.2 Comparing the cost of different options

The value of the company car can mean three different things: 1) the taxable value based on the tax rules, see Section 2.1, 2) the annual cost of owning and using a new car, see Figure 1, or 3) the personal value of the private use of the company car. The personal value can be both higher and lower than the taxable value and the annual car cost.

The annual company car tax is lower than the average annual cost to a private person of owning and using a new car, see Figure 1.[12] In addition to costing less than a new car,

& Roberts, 2022; Harding, 2014).

[8]The kink where the percentage changes from 30% to 20% increases by around 1-3% every year. See more details here: https://www.skatteetaten.no/en/person/taxes/get-the-taxes-right/property-and-belongings/cars-boats-and-other-vehicles/company-car/private-use-of-a-company-car/

[9]The top marginal tax rate in 2021 was 46.4% and the wage above 1,021,550 NOK has this tax rate. For wages between 651,250 NOK and 1,021,550 NOK the marginal tax rate was 43.4%.

[10]The commuting trip to and from work is defined as a private trip, not a work-related trip, as long as the work place is the same for at least two weeks.

[11]More information (in Norwegian) here: https://www.skatteetaten.no/rettskilder/type/handboker/merverdiavgiftshandboken/gjeldende/M-8/M-8-4/

[12]The annual cost of owning and using a new car is based on calculations from The Norwegian Road Federation (OFV, 2021), and will of course vary from household to household.

the company car scheme removes any uncertainty about annual car expenses, for instance fuel costs if the fuel price is increasing, accidents which might increase insurance costs and unexpected maintenance. This might be a large benefit to some households.

The idea behind the company car tax is neutrality between fringe benefits and wages. The employee should be indifferent between getting a company car and receiving a wage increase equal to the taxable value of the company car. However, it is possible that the employer does not offer the same amount as wage as the personal value of the company car for the employee. Depending on risk preferences related to car costs, the value of the company car for the employee could be higher than the cost to the employer.[13] The value of no uncertainty related to car expenses can be high for some employees, while for the firm this might induce no costs at all, at least if it is a large firm. In these cases, the wage that the firm will be willing to offer as an alternative to a company car will be lower than the value of the company car to the employee.

One factor that can make a company car a less economic choice is that the alternative is not a new car but a used car or no car. Also, the annual cost of owning and using a new car for a specific household can be different than the calculations shown in Figure 1. In Figure 1 we compare the cost of a car costing 636,000 NOK for an employee who has the highest marginal tax rate (46.4%) and drives 20,000 km per year. For privately owned cars, we assume that the employee drives half of the kilometers for work and gets mileage allowance for this. The governmental mileage allowance that many employers follow, is 4.03 NOK per km, and 3.50 NOK/km is without tax. Different annual mileage, new car price and marginal tax rate changes the absolute cost of the different options, but the order of the different options when ordering from the cheapest to the most expensive, as seen in Figure 1, does not change. See Figure A-1 for the cost of a more expensive car and Figure A-2 in the Appendix for different marginal tax rates.

2.3 Descriptive statistics on company cars in Norway

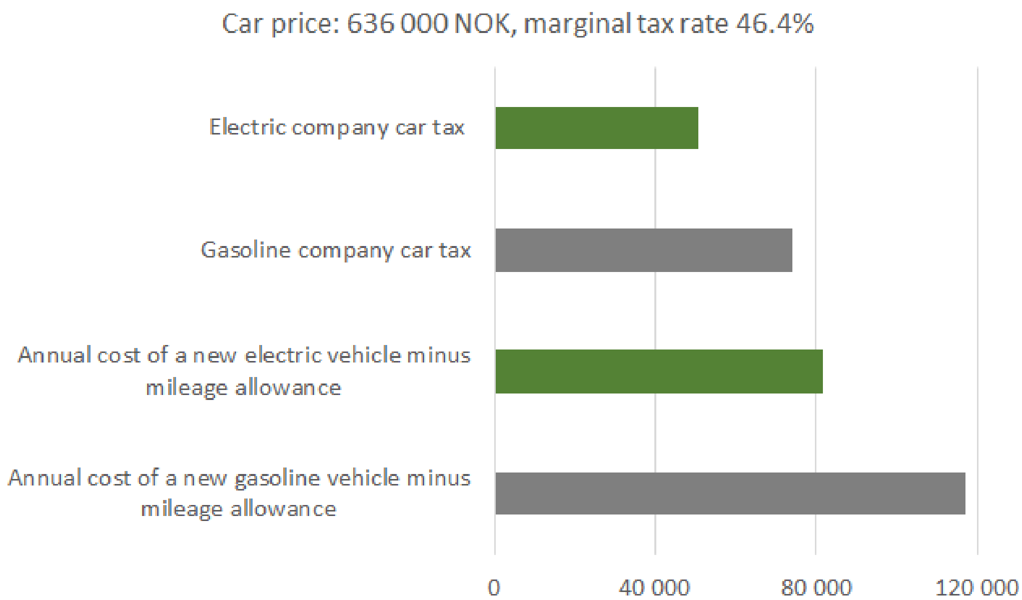
Every year during 2015–2021, around 40,000 employees use a passenger company car for personal purposes. The number has been stable during this period. Since many employees keep the company car for multiple years, 73,309 unique persons have a company car during 2015–2021.

The most common occupations are seller and top manager. Please see Table A-1 in the Appendix for details on the occupations. The average company car user is male (82%) and 48 years old. The mean gross wage in 2021 among all company car users is 846,578 NOK, among sellers 731,050 NOK and among top managers 998,454 NOK.[14]

[13] This point is not relevant for employees that own their own company.

[14] This is after the outliers having wage over 2 million NOK is taken out of the sample.

Figure 1: The annual company car tax compared to the annual cost of owning and using a new car.



The source of the annual cost of owning and using a new car is The Norwegian Road Federation. This compares the cost of a car costing 636,000 NOK, with the top marginal tax rate which is 46.4% and driving 20,000 km per year. For privately owned cars we assume driving half of the kilometers for work and getting mileage allowance for this. The governmental mileage allowance that many employers follow, is 4.03 NOK per km, and 3.50 NOK/km is without tax. The 46.4% marginal tax rate is for wages above 1,021,550 NOK. For wages between 651,250–1,021,550 NOK in 2021, the marginal tax rate is 43.4%. See Figure A-1 for the cost of a more expensive car and Figure A-2 in the Appendix for different marginal tax rates.

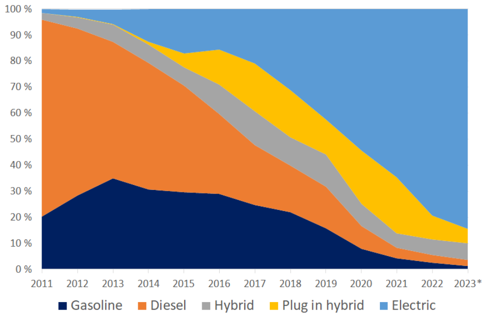
There are 32,165 unique firms in Norway that give a company car to at least one employee during the period 2015–2021. The number of companies with company cars is stable during the period 2015–2021. Each year the number of unique companies is 17–18,000. This means that around 7% of employers give one or more employees passenger company car.[15] 57% of all the firms with at least one company car user only have one company car user. 19% of the firms have two users.

The industries with the highest company car share among the employees are wholesale trade (except motor vehicles and motorcycles), manufacture of beverages and rental and leasing activities. The sector with the most company cars in absolute terms is private companies in the non-financial sector.

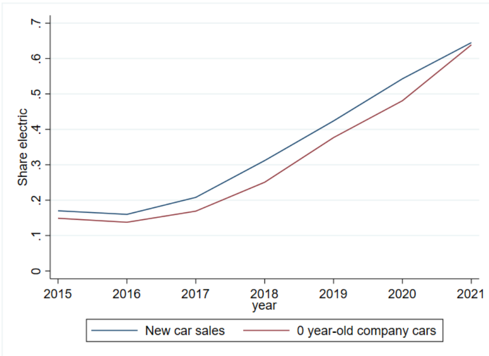
The mean age of the company cars is 2.6 years-old and the median is 2. Passenger company cars between 0 and 7 years old in 2021 constitute 4% of the passenger car stock that are 0-7 years-old. There are roughly around 10,000 new company cars every year (with 2018 and 2020 as exceptions), and new company cars is 5-7% of the total new car market (see Table A-2 in the Appendix for details).

The median amount that is reported as the taxable value of the company car is 104,580 NOK.

Figure 2: Sale shares by technology



(a) Sale shares by technology 2011-2023.



(b) The electric vehicle share among new company cars compared to the whole market 2015-2021.

Notes: New company cars are part of the new car sales. There are around 10 000 new company cars every year, which is 6-7% of the total new car market, see Table A-2 in the Appendix. Source of Figure 2a is The Norwegian Road Federation (OFV) and the figure builds on Figure 1a in Andreassen and Lind (2022). 2023 includes the first quarter of the year.

[15] There are 260,000 employers in Norway, according to this: https://www.skatteetaten.no/en/business-and-organisation/employer/the-a-melding/about-the-a-ordning/about-a-ordningen/

During the last decade, the Norwegian new car market has gone through a technology shift, see Figure 2a. From having a 98.55% market share in 2011, combustion-engine vehicles (not including plug-in hybrids) had a 10% market share the first five months of 2023. Electric vehicles had a market share of 1.45% in 2011, and in the first five month of 2023, the share was 83%. The electric vehicle share among 0 year-old company cars follows the electric vehicle share in the car market, see Figure 2b.

3 Data and empirical strategy

In this section we present the data that we use in the analysis and explain how we define important variables. Then we turn to the empirical strategy. First we present the strategy using the Swedish research design (Börjesson & Roberts, 2022), before we present and discuss the empirical strategy of the main analysis.

3.1 Data

We use rich administrative microdata from 2015-2021 in Norway. The data covers the universe of employees, employers (firms), families and passenger cars.[16] Whether a car is a company car cannot be identified in the vehicle register. The vehicle register says who owns the car.[17] To identify the company cars, we use annual data reported from the employer to the tax administration through the same system as the monthly digital wage reporting.[18] This data can be linked with the vehicle register, wage data, household data and other administrative data through anonymous person id, car id and company id. The variables that we use from the company car data are person id, car id, year, company/firm id[19], and the taxable value of the personal use of the company car.

Company cars are valued based on the list price (see Section 2.1). If the value in the company car data is lower than 100,000 NOK for a non-electric car that is 3 years or younger, we assume that the employee does not use the car for the whole year. In this case, we set the number of company cars to a fraction equal to the taxable value divided by 100,000 NOK, see Section B.2.1 in the Appendix for details. If the amount is higher than 100 000 NOK, the cars are counted as one car the whole year. A more precise way to measure the share of the year a person has a company car, is to find the median list price of the company car model and then divide the list price on the taxable value.

[16]Self-employed persons are included in the sample if they have a limited liability company and employ themselves in this company, but not if they have a sole proprietorship.

[17]From 2020 and onwards we know who leases the car, which in the case of company cars is most often the employer, but it is not registered who uses the car.

[18]For more information, see here: https://www.skatteetaten.no/en/business-and-organisation/employer/the-a-melding/about-the-a-ordning/about-a-ordningen/

[19]Company and firm are used interchangeably in this article.

The family register has a variable for whether a person lives in a couple or alone, and the size of the family. The monthly wage reporting tells us the id of the employer, the gross wage (with and without fringe benefits), the working hours (which we use to define the main employer each month) and the occupation code. We also use the wage data to count the number of employees in each firm. The company car data tells us who has a company car and what firm the person works in. See Section B in the Appendix for more detailed information about the data.

3.1.1 Defining important variables

We define *company car occupation* as occupations where over 10% of the work stock in the whole labor market has a company car that specific year. From this list of occupations, we exclude occupations where it seems likely that the employees decide about the offer of a company car themselves, e.g. top managers.

We define *company car firms* as firms that has given a company car to at least two persons every year the treated works in the firm. We exclude the firms with only one employee having a company car as it can be more likely that this employee is special or that this employee can decide about the offer of a company car themselves.

We assume that those working in a company car occupation and in a company car firm gets *an offer of a company car.*

3.2 Using the Swedish research design

3.2.1 The empirical strategy

In this section, we present the empirical strategy where we use the same research design as Börjesson and Roberts (2022) on Norwegian data in order to compare the results for Sweden and Norway. Börjesson and Roberts (2022) compare the change in the number of cars over time within households that have a company car with the within-household changes over time for those not having a company car. The households not having company car can be different on time-varying variables than the households having a company car.

We follow Börjesson and Roberts (2022) in separating the analysis between couples and singles and controlling for household fixed effect, time fixed effects, log annual income of the household and number of members of the household including children.[20] Results are shown in Section 4.1. The regression equation is:

$$Y_{i,t} = \alpha_i + \delta_t + \theta C_{i,t} + X_{i,t} + \epsilon_{i,t} \tag{1}$$

[20]Börjesson and Roberts (2022) also control for centrality.

where $Y_{i,t}$ is the number of cars or the likelihood of having a car, α_i is household fixed effects, δ_t is time fixed effects, $C_{i,t}$ is whether the household has a company car or not, $X_{i,t}$ is a vector of control variables and $\epsilon_{i,t}$ is the error term.[21]

This research design looks at the change in the number of cars for the households, where some change their company car status, either getting a company car or losing a company car, and some have company car the whole period of investigation. An implicit assumption is therefore that the effect of getting a company car and losing a company car is symmetric.

This design does not take into account the different timing of when the households get or lose a company car, which can be problematic if there are dynamic effects on the number of cars over time or heterogenous effects across groups of households gaining access to a company car at different times (Callaway & Sant'Anna, 2021; Roth et al., 2023). The main analysis (see Section 3.3), using a heterogeneity-robust estimator, takes the possibility of heterogenous treatment effects into account.

Börjesson and Roberts (2022) take out observations where the household does not have a company car the whole year, in order to not overstate the number of cars that year. Based on our company car measure, where the number of company cars can be positive but lower than one, (see Section 3.1), we keep the observations that year.

The couple status can change during the period of investigation. We therefore use the couple status in 2015 (when the period of investigation starts) to define who is in a couple and who is single. This means that those that are single in 2015 can become a couple during the period of investigation, but they are still part of the single sample, and the other way around.

3.2.2 The sample using the Swedish research strategy

The sample where we use the research strategy of Börjesson and Roberts (2022) consists of everyone that are employed every year from 2015-2021. This means that not everyone with a company car is part of the sample, because they are not employed every year. For couples at least one of the adults work. Those that are not in the family register are defined as single. See Table 1 for descriptive statistics of the sample.

[21] Controlling for wage could be a bad control, as there can be simultaneous causality: Higher demand for cars can influence people's choice of work and wage, in addition to the wage influencing the number of cars (Angrist & Pischke, 2009).

Table 1: Descriptive statistics of the sample in 2015 when we are using the Swedish research design (Börjesson & Roberts, 2022).

	All	No company car	Company car
Single household			
	All	No company car	Company car
Having a car or not	0.56	0.55	1
Number of cars	0.69	0.68	1.21
Number of persons in the family	1.45	1.45	1.43
Share male	0.52	0.52	0.74
Number of households	543,090	537,639	5,451
Couple household			
	All	No company car	Company car
Having a car or not	0.92	0.92	1
Number of cars	1.61	1.60	1.96
Number of persons in the family	3.42	3.42	3.53
Share male head of household (oldest person in the household)	0.76	0.76	0.94
Number of households	590,844	574,352	16,492

3.3 Empirical strategy of the main analysis

In this subsection we present the empirical strategy of the main analysis.[22] First, we present the target parameter, the identification strategy, including all assumptions behind it, and discuss the use of covariates in the analysis. Further, we present the estimation strategy and descriptive statistics of the main sample, before we investigate the plausibility of the parallel trend assumption.

3.3.1 Target parameter

A parameter of interest is the effect of having a company car on the number of cars in the households:

$$\tau = \mathbb{E}[Y_{i,2}(1) - Y_{i,2}(0)|D_i = 1]$$

where Y_i is the number of cars in the household, $D_i = 1$ indicates having a company car and $t = 2$ is the post-period in a 2x2 difference-in-difference set-up (Roth et al., 2023). The first term we can observe, while the second term is the unobservable counterfactual: How many cars would the households with a company car have if they did not have a company car.

For the individual the counterfactual is unobservable, but for a group and with the right research strategy, it is possible to uncover the average unobservable counterfactual. We have not found a strategy to recover the number of cars if the families did not have a company car ($\mathbb{E}[Y_{i,2}(0)|D_i = 1]$) or the change in the number of cars between the period after they got a company car and before they got the company car, had they not gotten a company car ($\mathbb{E}[Y_{i,2}(0) - Y_{i,1}(0)|D_i = 1]$).

[22]This part has benefited from the synthesis of the recent developments in the diff-in-diff literature in Roth et al. (2023) and Baker et al. (2022).

Another interesting parameter is the effect of getting an *offer* of a company car:

$$\beta = \mathbb{E}[Y_{i,2}(1) - Y_{i,2}(0) | Z_i = 1]$$

where $Z_i = 1$ is getting an offer of a company car. β estimates the effect of getting an offer of a company car, which is the difference between the number of cars after getting an offer of a car and the number of cars the households would have had, had they not gotten an offer of a company car. This is an intention-to-treat effect. The strategy to uncover the unobservable counterfactual is our identification strategy.

3.3.2 Identification strategy

We limit our sample to households where one adult household member has a company car occupation during the whole sample period, and look at what happens with the number of cars in the household when this household member changes job. The treatment group works in companies that do not offer company cars and then they change job **to** a firm that offer company cars. The control group **never** gets an offer of a company car, neither before nor after the job change. As the acquisition of a company car can be caused by an increase in car demand in the family, we want the timing of the access to the company car to be exogenous. We attempt to achieve this by looking at those that change job. Changing job can cause an increase in car demand, and therefore the control group changes job as well. Since we look at everyone that we assume gets an *offer* of a company car, this will estimate the intention-to-treat effect.

In addition to the comparison already mentioned, we do another comparison. We look at the effect of *losing* the possibility of a company car. The treatment group changes job **from** a company car firm to a non-company car firm. The control group **always** works in a company car firm. Both groups work in company car occupations.

To sum up, we make two different comparisons with four different types of job changers:

- Getting an offer of a company car:
  - Treatment group: Change job from non-company car firm **to** a company car firm
  - Control group: **Never** work in a company car firm, but change job (and work in company car occupations).
- Losing access to a company car:
  - Treatment group: Change job **from** a company car firm to a non-company car firm

- Control group: **Always** work in a company car firm, but change job (and work in company car occupations).

The first assumptions behind the identification strategy is that it is not the possibility of the company car itself that triggers the change of employer. If this assumption does not hold, we get a selection into who works in company car firms compared to those working in firms not giving company cars to their employees. If this selection is in direction of people with preferences for more cars, the bias will go in direction of increasing the estimated effect of the company car scheme.

Second, we assume that those working in company car occupations in a company car firm get an offer of a company car. If only a subset of this group is offered a company car, our underlying assumption is that this offer is exogenous with respect to the trend in the outcome variables. Then it does not matter for the identification strategy if there are some in the treatment group that does not get the offer of the company car.

Third, we assume that the treatment group would have followed the same trend for the number of cars as the control group, had they not gotten the offer of a company car. This is the parallel trend assumption that difference-in-difference research designs rely on (Roth et al., 2023). If those working in company car firms for instance have higher wage growth and use this to have more cars, the parallel trends assumption is violated. See more discussion about this in Section 3.3.6.

Fourth, before treatment takes place the treatment effect is zero (no anticipation effect). This means that the treated do not anticipate the treatment before the treatment happens. In our case, the treated might plan to change job before they actually do it. Especially if the job change happens early in the year, the household would know about it the year before. Therefore we do robustness tests only looking at the outcome for those changing job from June 1st in year 0, see Appendix D.2. The coefficients do not change much.

The fifth assumption is that treatment does not turn on and off. This means that if a person has first started to work in a company car firm, the offer of a company car is not taken away. We observe that the company car firms give company car to at least two employees every year the treated works in the firm, so this assumption seems plausible.

The last assumption is that there are no spillover and general equilibrium effects. This means that if one household gets an offer of a company car, it does not influence the car ownership of for instance the neighbour, also working in company car occupations, through the neighbour borrowing the company car and therefore reducing their own car ownership. This assumption seems likely to hold. A general equilibrium effect would be for instance that the supply of company cars influences prices in the car market, which could be in specific segments of the car market, but probably not.

3.3.3 Covariates

It is possible to relax the parallel trend assumption to hold only conditional on covariates (Roth et al., 2023). The covariates should be measured prior to treatment, as covariates after treatment can lead to a problem with bad controls (Angrist & Pischke, 2009; Roth et al., 2023). Time-varying covariates that are not bad controls can also be used. We can use covariates to make it more plausible that the workers starting to work in company car firms (getting an offer of a company car) are random conditional on the covariates. Imposing parallel trends conditional on covariates "gives us an extra degree of robustness, since conditional random assignment can fail so long as the remaining unobservables have a time-invariant additive effect on the outcome" (Roth et al., 2023, p.23).

In order to use covariates in the analysis, we need another assumption, which is the overlap assumption. This means that for each treated unit with covariates X_i, there is also a unit in the control group with the same value on the X_i (Roth et al., 2023).

We think that age of the individual changing job the year before the job change might be a relevant variable to condition the parallel trend assumption on. The wage growth can follow an age profile and changing job at different ages might lead to different wage growth in the new job. As this might not be a linear relationship, we also include an age squared term. In addition we use log wage the year before the job change as a control.

Another relevant variable can be the average age of the cars the household have the year before the job change. The age of the cars can be a proxy for car preferences at that time. Those having car(s) that are 10 years old might have a different trend in the number of cars than those having car(s) that are 1 year old. Furthermore, the number of persons in the household the year before the job change and the couple status the year before the job change are relevant control variables.

3.3.4 Estimation strategy

We use a difference-in-difference estimator that is robust for heterogeneity across treatment cohorts and across time: Callaway and Sant'Anna (2021). We have 5 treatment cohorts, depending on when the person in the household changes job. g defines when the first treatment takes place, meaning when the person changes job. We estimate the effect for each treatment cohort g at each t relative to the time period before the treatment starts, $g-1$, (ATT (g, t)) for all $t \geq g$:

$$Y_{i,t} = \alpha_i + \delta_t + \beta_{g,t} Z_{i,t} + \epsilon_{i,t} \tag{2}$$

where $Y_{i,t}$ is the number of cars in the household i at time t, $Z_{i,t}$ is whether one adult in the household i has the possibility of a company car at time t, α_i is household-fixed effects, δ_t is time-fixed effects. To create an event study, the estimator aggregates ATT(g, t)'s for all cohorts each period e after treatment ($e = t - g$). We use both not-yet treated and the never treated as control.

The event studies we show in Section 3.3.6 and Section 4.2, have a varying base period in the pre-period (Callaway, 2021).[23] Varying base period means that the base period is the period before, instead of $g - 1$ being the base period for all periods also in the pre-period. For year –1 the base period is –2 and for the year –2, the base period is –3. The pre-period farthest away from treatment for each treatment cohort is left out since that pre-period does not have a base period. This way of estimating the pre-trends might make it more difficult to see if there is a long-term pre-trend. We therefore also should look at the raw data. If there are anticipation effects but no long-term pre-trend, this might be the best way to present the pre-treatment periods (Callaway, 2021).

If we use covariates (see Section 3.3.3), we use the Callaway and Sant'Anna (2021) doubly robust estimator where either outcome regression or inverse probability weighting are used, depending on which one is correctly specified (Roth et al., 2023).

3.3.5 Descriptive statistics of the main sample

The main sample consists of households where one of the adults changes employer once during the period 2016-2020 (since we have data from 2015-2021 and we therefore get pre-periods and post-periods for everyone) and work in company car occupations all 7 years. There are 239 households getting an offer of a company car and the control group is 426 households. There are 251 households losing access to a company car, and their control group is 1,123 households.

The average number of cars before treatment is 1.53 cars for the treatment group gaining access to a company car and 1.51 cars in the control group. 91% of the treatment group have a car in the pre-period, and a somewhat lower share in the control group (88%), see Table 2. For the treatment group losing access to a company car, the average number of cars, including company cars, is 1.6 before treatment. For the respective control group, the average is 1.7. 93% in the treatment group and 95% in the control group have at least one car. The treatment and control group in both comparisons are different on many variables, see Table 2.

3.3.6 Investigating the plausibility of the parallel trend assumption

That the levels on the variables in Table 2 are different is not a problem in itself, as long as we believe that the trend on the number of cars in the post-period will be the

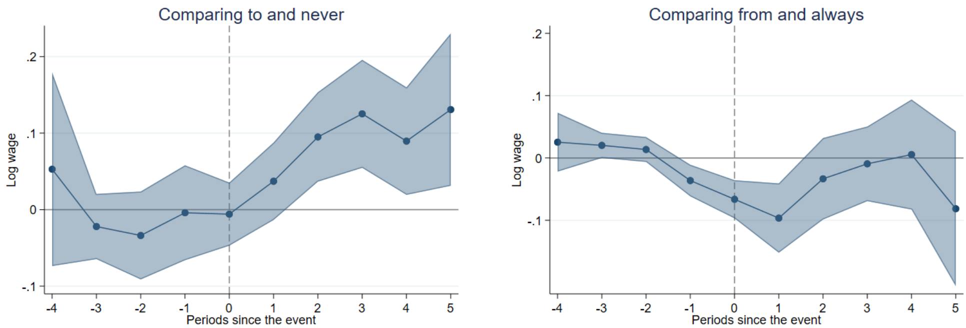
[23] In Stata the varying base period in the pre-period is not possible to change to a universal base period at the time of writing.

Table 2: Descriptive statistics of the main sample, pre-treatment.

	Treatment "Changes to"	Control "Never"			Treatment "Changes from"	Control "Always"		
	mean	mean	diff	p-value	mean	mean	diff	p-value
Number of company cars	0	0	0	.	0.354	0.512	-0.158	0.0000
	(0)	(0)			(0.462)	(0.486)		
Share having company car	0	0	0	.	0.382	0.538	-0.156	0.0000
	(0)	(0)			(0.486)	(0.499)		
Number of cars, including company cars	1.534	1.512	0.022	0.6171	1.643	1.670	-0.027	0.4426
	(0.883)	(0.927)			(0.924)	(0.869)		
Number of cars, excluding company cars	1.534	1.512	0.022	0.6171	1.290	1.158	0.131	0.0004
	(0.883)	(0.927)			(0.980)	(0.908)		
Probability of having a car,	0.906	0.876	0.030	0.0487	0.926	0.946	-0.020	0.0380
including company car	(0.292)	(0.330)			(0.262)	(0.227)		
Number of electric cars, including company cars	0.120	0.144	-0.024	0.1764	0.163	0.113	0.050	0.0005
	(0.361)	(0.372)			(0.415)	(0.338)		
Mean age of the car(s) the households own	5.668	5.930	-0.262	0.3269	4.870	4.477	0.393	0.0855
(excl. company cars)	(5.538)	(5.576)			(5.509)	(5.733)		
Age of the job changer	43.9	45.9	-2.0	0.0000	43.8	45.0	-1.1	0.0012
	(9.0)	(9.4)			(8.1)	(8.6)		
Gross wage for the job changer (NOK)	660,013	702,223	-42,210	0.0005	767,702	707,442	60,260	0.0000
	(212,201)	(271,003)			(260,230)	(219,923)		
Share couples	0.831	0.788	0.043	0.0239	0.813	0.798	0.015	0.3379
	(0.375)	(0.409)			(0.390)	(0.402)		
Share male of the job changer	0.842	0.801	0.040	0.0315	0.732	0.797	-0.065	0.0001
	(0.365)	(0.399)			(0.443)	(0.402)		
Number of persons in the family	3.07	2.93	0.14	0.0254	3.20	3.01	0.19	0.0001
	(1.28)	(1.26)			(1.23)	(1.26)		
Number of children in the family	1.25	1.15	0.10	0.0470	1.40	1.22	0.18	0.0000
(no matter the age)	(1.07)	(1.05)			(1.02)	(1.03)		
Number of families	239	426			251	1 123		

Standard deviation in parenthesis.

Figure 3: Comparing wage growth for the treatment and the control group.



same for the control group and the treatment group, had the treatment group not gotten an offer of a company car, or lost the possibility of a company car. The parallel trend assumption "allows for confounding factors that affect treatment status, but these must have a constant additive effect on the mean outcome" (Roth et al., 2023, p.22). This means that it is decisive that the confounding factors only affect the levels, not the trends.

However, it is difficult to decide whether a factor only affects the levels and not the trends. There could be time-varying confounding factors, which cannot be controlled for through using unit fixed effects. The pre-trends on the number of cars look quite good, at least between year -3 and year -1, as can be seen in Figure 6 and Figure 4b. But that the pre-trends hold, is no guarantee that the counterfactual post-trends hold. One time-varying confounding factor could be change in the wage growth. We therefore test how the wage growth of the treatment and control group develops. This can give some indications on whether the parallel trend assumption is plausible.

In Figure 3 we see an event study where the outcome is wage growth, not including fringe benefits. Year 0 is the year the job change happens. For those gaining the possibility of a company car, the gross wage growth is more than the control group, see Figure 3a. The aggregated effect is 6.4 percentage points higher and statistically significant on a 1% level, see Table 3. However, this effect is 4.4 pp and not statistically significant when including control variables (age, age squared, mean age of the cars the households own, couple status and number of household members, measured the year before the job change). In Figure A-10 in the Appendix we see that also with covariates the event-study show an increase in wage growth for the treatment group.

For those losing the possibility of a company car, the wage growth is lower, at least in the beginning after the job change, see Figure 3b. The aggregated effect is 5.3 p.p. lower wage growth, statistically significant on a 5% level, see Table 3. When including control variables, the wage growth is 6.1 pp lower and statistically significant on a 1% level. In

Figure A-3 in the Appendix, we can see the raw data for log wage for the different groups.

In Table 3, row 2 and Figure A-4 we see the wage in nominal terms, not log wage. The wage in nominal terms is not statistically significantly different for those getting an offer of a company car compared to the control group. For those losing the possibility of a company car, the reduction in the wage in nominal terms is statistically significant, with and without control variables.

Having higher wage growth could translate into higher growth in the number of cars and a lower wage growth could result in fewer cars, without the company car scheme being the reason. Having different trends in wage could also indicate that the treatment and control group are different on other (unobservable) variables as well, not just the wage growth. Thus, the control group might not be a good control group for the treatment group. This makes us conclude that the parallel trend assumption probably does not hold. Therefore, we cannot interpret the coefficients we get in the analysis as causal, but rather as correlations between getting an offer of a company car and the change in the number of cars. We will return to this in Section 4.3, considering income elasticities for the demand of cars.

Table 3: Aggregated effects for the balance tests. The variables in the first column are outcome variables in the Callaway and Sant'Anna (2021)-difference-in-difference estimator.

	(1)	(2)	(3)	(4)
	Getting an offer of a company car		Losing the possibility of a company car	
		With covariates		With covariates
Log wage	0.064**	0.044	-0.053*	-0.061**
	(0.025)	(0.024)	(0.023)	(0.022)
Wage	20,492	8,964	-32,764*	-37,782**
	(12.239)	(12,068)	(13,362)	(12,941)
Number of individuals in the household	0.041	-0.015	0.025	0.003
	(0.054)	(0.049)	(0.045)	(0.041)
Number of children in total	0.010	-0.047	0.050	0.030
	(0.045)	(0.039)	(0.037)	(0.033)
Number of children under the age of 18	0.017	-0.023	0.010	0.001
	(0.044)	(0.039)	(0.039)	(0.033)
Moving out of the neighbourhood (binary)	0.010	0.011	0.001	0.003
	(0.020)	(0.021)	(0.022)	(0.022)
Changing the couple status (binary)	0.010	0.009	0.023	0.021
	(0.011)	(0.012)	(0.012)	(0.012)
Number of observations	4,655	4,655	9,618	9,618
Number of households	665	665	1,374	1,374

Covariates are age, age squared, mean age of the cars the households own, couple status and number of household members.
For row 3-7, the covariates also include log wage.
All covariates are measured the year before job change.
Standard errors are in parenthesis.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We also investigate whether access to company cars is associated with changes in other household characteristics. The results show that the treatment and control groups are balanced with respect to changes in family size, number of children, number of children under the age of 18, whether they move out of the neighbourhood and whether they change couple status (either from single to couple or from couple to single), see Table 3 and Figure A-5 – Figure A-9 in the Appendix.

4 Results

In this section we first present the results from using the Swedish research design (Börjesson & Roberts, 2022) before we present the results from the main analysis.

4.1 Results from comparing households with and without company cars (The Swedish research design)

The results when using the same research design as in Börjesson and Roberts (2022) can be seen in Table 4. First, we show the result with only household fixed effects (the columns with the odd number) and then we show the results with both fixed effects and control variables (the columns with the even numbers). The control variables are number of household members and log annual gross income for the household. The coefficients do not change much when adding control variables. Following Börjesson and Roberts (2022), we focus on the results with control variables.

The results are almost the same or at the same magnitudes as in Börjesson and Roberts (2022). Having a company car is associated with an increase in the likelihood of having a car by 11 percentage points for couples (Table 4, column 2) in Norway and 14 percentage points in Sweden (Börjesson & Roberts, 2022). For single households, the increase is 31 percentage points (column 4) in Norway and 38 p.p. in Sweden (Börjesson & Roberts, 2022). The increase in the number of cars in the family is almost the same as in Sweden: 0.40 (column 6) in Norway and 0.41 in Sweden (Börjesson & Roberts, 2022). Börjesson and Roberts (2022) do not report the increase in the number of cars for singles. We find that the increase in the number of cars is about the same for singles as couples (0.39, column 8).

4.2 Results from the main analysis

In this Section we first present the raw data and the first stage results, before we turn to the results for the different outcome variables. The analysis for the years at the beginning and the end (year -5 and -4 and year 4 and 5) have few observations and can therefore be quite noisy.

Table 4: The results from using the Swedish strategy (Börjesson & Roberts, 2022).

	Likelihood of having a car				Number of cars, incl company cars			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Couples	Couples	Singles	Singles	Couples	Couples	Singles	Singles
Company car	0.112***	0.110***	0.319***	0.308***	0.411***	0.399***	0.394***	0.394***
	(0.001)	(0.001)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Households	590,844	590,844	543,090	543,090	590,844	590,844	543,090	543,090
Observations	4,135,908	4,135,908	3,801,630	3,801,630	4,135,908	4,135,908	3,801,630	3,801,630

Control variables are number of household members and log annual gross income for the household.
The company car variable is a binary variable and do not take into account that the family might not have a company car the whole year.
When counting the number of cars, including the company cars, in column 5-8, the company cars are not counted as 1 the whole year if the taxable value is below a threshold, see Section 3.1 for more explanation.
Robust standard error in parenthesis.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2.1 Raw data

In Figure 4a we see the number of company cars in the treatment and control groups. We see that the 'changes to'-group does not have company cars until they change job. The 'never'-group does not have a company car. The 'changes from'-group has company car before they change job. The 'always' group has a company car the whole time, both before and after the job change.

The number of cars in the households, including company cars, for the different treatment groups can be seen in Figure 4b. The blue line represents the group that never gets an offer of a company car and is the control group for those that change to a company car offer (red line). The yellow line represents those that always have a company car possibility, which is the control group for those that change from a company car firm (green line). Those that never have a company car offer (the blue line) increase their number of cars somewhat when they change job, which shows why it is important with a control group to control for change in car demand when changing job. In addition, there is a slight increase in the number of cars from year -5 to year 5, which is a general time trend, which is important to control for.

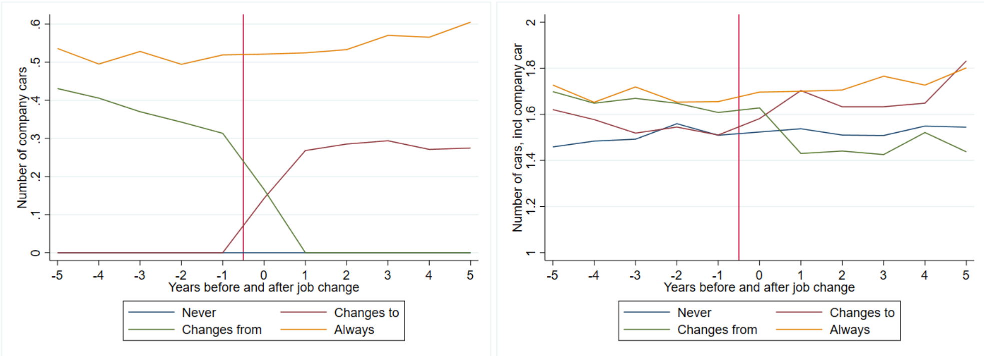
4.2.2 First stage

In Table 5, row 1 and Figure 5 we see the share having company car before and after treatment for the two treatment and control groups using the Callaway and Sant'Anna (2021)-estimator. This is a binary indicator, while in Figure 4a we see the number of company cars.[24]

The 'changes to'-group do not have any company cars before they change job. After

[24]None have more than one company car, but several do not have company car the whole year (see Section 3.1 and Appendix B for how we count the company cars).

Figure 4: Raw data



(a) Raw data: Company cars

(b) Raw data: Number of cars in the households

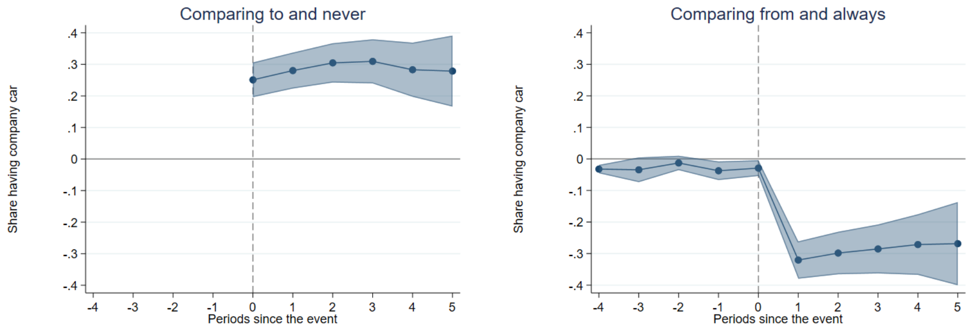
Table 5: Aggregated effects using the Callaway and Sant'Anna (2021)-estimator.

	(1)	(2)	(3)	(4)
	Getting an offer of a company car		Losing the possibility of a company car	
		With covariates		With covariates
Change in the share having company car, (Figure 5)	0.283***	0.283***	-0.229***	-0.233***
	(0.029)	(0.029)	(0.026)	(0.026)
Change in the number of cars in the households, incl. company cars (Figure 6a and 7a)	0.143**	0.132**	-0.136**	-0.144**
	(0.050)	(0.050)	(0.047)	(0.047)
Change in the number of cars in the households, excl. company cars (Figure 6b and 7b)	-0.104*	-0.115*	0.114*	0.110*
	(0.052)	(0.052)	(0.049)	(0.048)
Likelihood of having a car, incl. company cars (Figure 8)	0.042	0.037	-0.037	-0.039
	(0.022)	(0.022)	(0.020)	(0.020)
Change in the number of electric vehicles, incl. company cars (Figure 9)	0.020	0.013	-0.023	-0.033
	(0.026)	(0.026)	(0.029)	(0.029)
Change in the number of non-electric vehicles, incl. company cars (Figure 9)	0.106	0.101	-0.184***	-0.185***
	(0.054)	(0.053)	(0.050)	(0.049)
Household fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Number of observations	4,655	4,655	9,618	9,618
Number of households	665	665	1,374	1,374

Covariates are age, age squared, log wage, mean age of the cars the households own, couple status and number of household members.
All covariates are measured the year before job change.
Standard errors are in parenthesis.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

the job change, 28% have a company car.[25] The 'changes from'-group has a company car before they change job, and then they lose the possibility of having a company car. Compared to their control group who always have the possibility of a company car, the reduction after the job change is 23 percentage points.[26]

Figure 5: First stage: Change in the share having company car.



4.2.3 The number of cars in the households

In Figure 6a and Table 5, row 2, column 1, we see that getting an offer of a company car is associated with an increase in the number of cars, including company cars, by 0.143. This is statistically significant on a 1% level. With covariates the change is 0.132 and also statistically significant on a 1% level. Pre-treatment, the number of cars in the treatment group is 1.53 (see Table 2). Therefore the increase in the number of cars is 8.6–9.3%. When excluding the company cars, the reduction in the number of cars is -0.104 (-0.115 with covariates) and statistically significant on a 5% level.

Losing access to a company car is associated with a reduction in the number of cars, incl. company cars, by 0.14 (Figure 7a and Table 5, row 2, column 3 and 4). This is statistically significant on a 1% level. Pre-treatment, the number of cars, including company cars, in the treatment group is 1.64. The decrease in the number of cars is around 9% (8.7-8.8%). The reduction in the number of cars for those losing access to a company car and the increase in the number of cars for those gaining access to a company car therefore seems to be symmetric. Excluding the company cars, the number of cars increases by 0.11, with or without covariates (Figure 7b and Table 5, row 3, column 3 and 4). This is statistically significant on a 5% level.

When we include covariates in the analysis, the results do not change much (Table 5 (column 2 and 4) and Figure A-11 and Figure A-12 in the Appendix). The covariates we

[25]For the continuous company car variable the result is an increase by 0.247 (not shown).
[26]For the continuous company car variable the result is a decrease by 0.250 (not shown).

Figure 6: The change in the number of cars for those getting access to a company car. a) including company cars and b) excluding company cars.

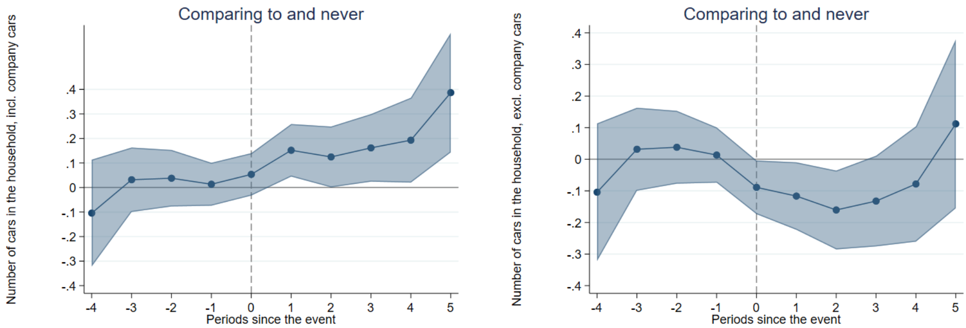
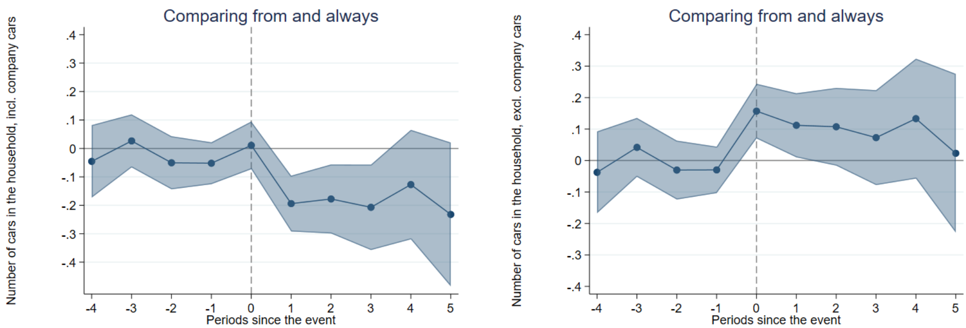


Figure 7: The change in the number of cars in the household for those losing access to a company car. a) including company cars and b) excluding company cars.



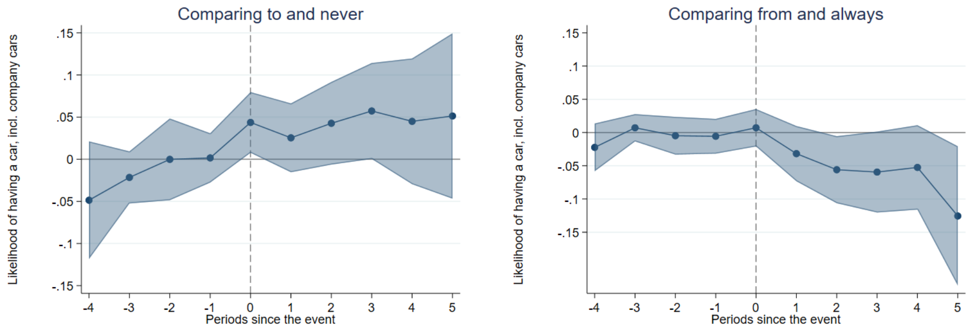
include are age the year before the job change, the same age squared (to take into account the possibility of a non-linear age effect), mean age of the cars the households own the year before job change, couple status the year before job change and number of household members the year before job change.

To take anticipation effects into account, we investigate the change for only those changing job from June 1st in year 0. The coefficients do not change much, just a little bit higher increase and decrease in the number of cars, see Table A-4 and Figure A-13–A-16 in Appendix D.2.

4.2.4 Likelihood of having a car

In the sample the large majority has a car before treatment. Before treatment, 91% of the 'changing to'-group have a car and 93% of the 'changing from'-group, including company cars (Table 2, row 4). This is probably because we limit the sample to individuals

Figure 8: Likelihood of having a car when (a) getting access to a company car or (b) losing access to a company car.



that work every year in company car occupations, which means for instance no students. There is no statistically significant change in the likelihood of having a car for either of the treatment groups, with or without covariates (Table 5, row 4).

4.2.5 Electric vehicles

The estimated effects on the number of electric cars go in the same direction as the total number of cars, but the point estimates are much smaller, and the coefficients are not statistically significant. See Figure 9 and Table 5, row 5. The small point estimates could partly reflect that electric vehicles have a moderate market share in the sample period. Before job change, the gaining access group has on average 0.12 electric vehicles, while the losing access group has 0.16 (Table 2, row 6). The point estimates then correspond to a 17% increase in electric cars for those that change to a company car firm (11% with covariates) and a 14% decrease for those that change from a company car firm (20% with covariates).

In Figure 10 and Table 5, row 6, column 1 and 2, we see that the increase in non-electric vehicles (including plug-in hybrids) for those changing to company car possibility constitute $\frac{3}{4}$ of the increase in the number of cars, but this increase is only statistically significant on a 10% level. For those changing from the company car firms, the reduction in non-electric vehicles is higher than the reduction in cars (Table 5, row 6, column 3 and 4 compared to row 2, column 3 and 4). This could be because of the electric vehicles not being perfect substitutes for combustion-engine cars during the period of investigation and therefore not a suitable car when using the car a lot for work, because the company car scheme favours non-electric vehicles or because of selection effects where those that work in company car firms prefer non-electric vehicles, or a combination of these explanations.

Figure 9: Change in the number of electric vehicles when (a) getting access to a company car or (b) losing access to a company car.

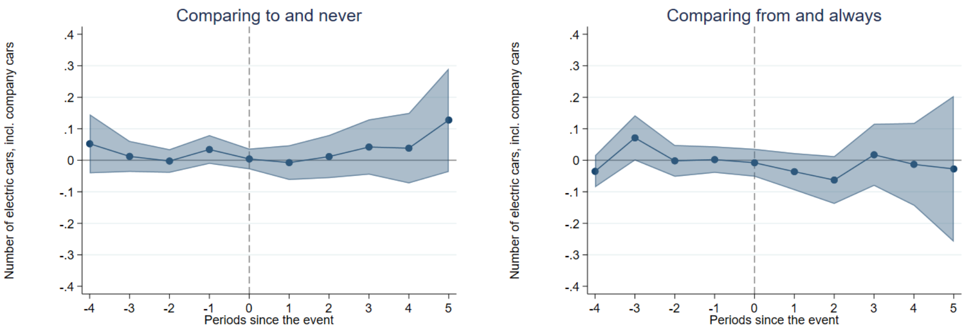
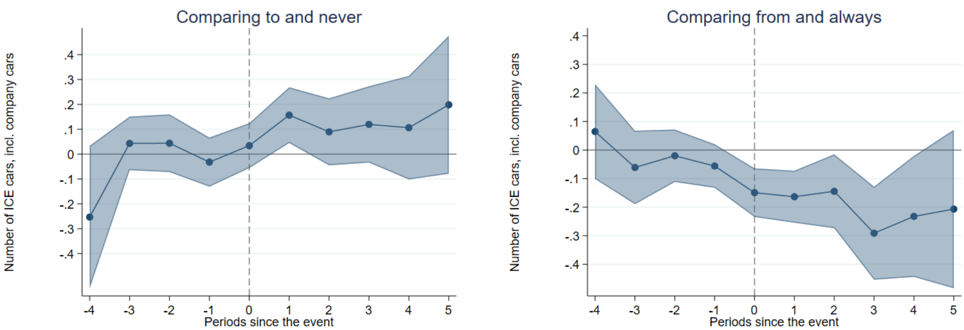


Figure 10: Change in the number of non-electric vehicles (gasoline, diesel, hybrid and plug in hybrids) when (a) getting access to a company car or (b) losing access to a company car.



4.2.6 From intention-to-treat to effects on the treated

We can roughly translate the intention-to-treat effects that we have estimated, to average effects on the treated. Then we need to make one more assumption, which is that nothing else than the company car influences the average number of cars in the household (the levels, not just the trends). This assumption might not hold.

The increase in the number of cars is 0.132 for those getting an offer of a company car (Table 5, row 2, column 2). The share of the treatment group having a company car (the take-up rate) is 0.283 (Table 5, row 1, column 2). Then we find:

$$ATT = \frac{0.132}{0.283} = 0.466$$

$$\text{Standard error} \approx \frac{0.050}{0.283} = 0.177$$

The standard error on this estimate is not exactly calculated with this method, it is only an approximation. Then the 95% confidence interval of this estimate is [0.119, 0.813].[27]

The confidence intervals on the average treatment effect of the treated-estimates are very large, and we therefore do not know if the estimates of the increase in the number of cars for those that have a company car are larger or smaller than the coefficients based on the Swedish research design (around 0.40 for both single and couple households).

4.3 Income elasticities

We find that the number of cars increase by 9% for those gaining access to a company car, and since we cannot disentangle the effect of changes in wage and the effect of the company car scheme, we look at estimates for how much demand for cars increase when the income increases. Johansen and Munk-Nielsen (2022) estimate elasticities in a structural model using Norwegian administrative data from 2005-2017. They find that when net income increases by 1% the demand for cars increases by 0.42%. Our wage variable is gross wage, while the income variable in Johansen and Munk-Nielsen (2022) is net income.

We find a 6.4 percentage point higher wage growth among those that change to a company car firm (4.4 pp with control variables), compared to the control group. Assuming an income elasticity of 0.42 %, this would translate into a 2.7% increase in the number of cars, while we find an 9.3% increase.[28] This could mean that some of the increase in the number of cars that we observe is due to the company car scheme.

[27] $0.466 \pm 1.96 * 0.177 = [0.119, 0.813]$

[28] With control variables the increase in number of cars because of increased income would be 1.8%, while we find 8.6% increase in the number of cars when including control variables.

However, estimates of income elasticities on car demand might be specific to the base levels and the sample, as well as the assumptions behind the structural model in Johansen and Munk-Nielsen (2022), and might not be directly transferable to this context.

5 Conclusion

Whether getting a company car from the employer causes an increase in the number of cars in the households is still an open question. We think that the strategy of Börjesson and Roberts (2022) leads to a selection bias because households with and without company car are probably different on time-varying unobservable factors and the decision to acquire a company car might be caused by increase in car demand (endogeneity problems). We have tried to remedy this by comparing the within-household change in the number of cars between groups that could be more similar, namely households where one adult works in a company car occupation and change job. However, the wage development of the treatment group is different from the control group. Therefore, we cannot disentangle the effects of the company car scheme from the wage growth.

We find that gaining access to a company car is associated with an increase in the numbers of cars in the household by 9%. At the same time, gaining access to a company car is associated with 4-6 pp higher wage growth. Losing access to a company car is associated with a decrease in the numbers of cars in the household by 9% and a 5-6 pp wage decrease. How much of the change in the number of cars in the household is due to wage growth and how much is due to the company car scheme is not settled. Based on income elasticities on car demand estimated by Johansen and Munk-Nielsen (2022), we induce that probably both the wage growth and the company car scheme contributes.

The company car scheme during the period of investigation (2015-2021) had a discount for electric vehicles. Gaining or losing access to a company car is not associated with a statistically significant change in the number of electric vehicles, although the point estimates go in the same direction as the change in the total number of cars. From 2023, there is no discount for electric vehicles in the company car scheme. How the company car scheme will influence the number of electric cars when there is no discount is a topic for further research as data becomes available.

If the company car tax is at the right level, but sets a fixed sum, not giving any incentives to buy cars that pollutes less and to drive less, the company car tax system "will provide adverse environmental incentives", according to Harding (2014, p.38). Whether the company car scheme as it is designed in Norway leads to more driving is an interesting question. As the odometer data is collected the first time when the car is 4 years and in addition it is not possible to distinguish between private and work-related driving, we unfortunately do not have data to investigate this question. One possibility is to ask the companies that offer electronic driving books for access to anonymous data. This data will distinguish between private and work-related travel. If we get relevant data and develop a credible research strategy, we will investigate whether the company car scheme influences the driving pattern.

If there is any change in the rules for how the company cars are taxed, this can be exploited through a regression discontinuity design in further investigations. Furthermore, it could be possible to look for exogenous job changes, not job changes initiated by the employee themselves.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used Chat-GPT-3.5 and Google translate in the writing process of the first paragraph of the introduction and also sporadically other places in the text in order to improve language. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

References

ACEA. (2022). The automobile industry. pocket guide 2022/2023. https://www.acea.auto/files/ACEA_Pocket_Guide_2022-2023.pdf#page=79

Andreassen, G. L., & Lind, J. T. (2022). *Climate, technology and value: Insights from the first decade with mass-consumption of electric vehicles*, CESifo Working Paper.

Angrist, J. D., & Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Baker, A. C., Larcker, D. F., & Wang, C. C. (2022). How much should we trust staggered difference-in-differences estimates? *Journal of Financial Economics*, *144*(2), 370–395.

Börjesson, M., & Roberts, C. (2022). *The impact of company cars on car ownership*, Available at SSRN 4065324.

Callaway, B. (2021). *Universal vs. varying base period in event studies* [Accessed May 30th 2023]. https://bcallaway11.github.io/posts/event-study-universal-v-varying-base-period

Callaway, B., & Sant'Anna, P. H. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, *225*(2), 200–230.

Fevang, E., Figenbaum, E., Fridstrøm, L., Halse, A. H., Hauge, K. E., Johansen, B. G., & Raaum, O. (2021). Who goes electric? The anatomy of electric car ownership in Norway. *Transportation Research Part D: Transport and Environment*, *92*, 102727.

Gillingham, K., Iskhakov, F., Munk-Nielsen, A., Rust, J., & Schjerning, B. (2022). Equilibrium trade in automobiles. *Journal of Political Economy*, *130*(10), 2534–2593.

Gillingham, K., & Munk-Nielsen, A. (2019). A tale of two tails: Commuting and the fuel price response in driving. *Journal of Urban Economics*, *109*, 27–40.

Gutiérrez-i-Puigarnau, E., & Van Ommeren, J. N. (2011). Welfare effects of distortionary fringe benefits taxation: The case of employer-provided cars. *International Economic Review*, *52*(4), 1105–1122.

Harding, M. (2014). *Personal tax treatment of company cars and commuting expenses: Estimating the fiscal and environmental costs*. OECD.

Hedges & Company. (2021). *How many cars are there in the world in 2023*. https://hedgescompany.com/blog/2021/06/how-many-cars-are-there-in-the-world/

Hegsvold, K., Nenseth, V., & Wangsness, P. B. (2022). *Klimamål og strategier i transportplanlegging i utvalgte land*. Institute of Transport Economics. Report 1931/2022.

IEA. (2021). *The role of critical minerals in clean energy transitions*.

Johansen, B. G., & Munk-Nielsen, A. (2022). *Portfolio complementarities and electric vehicle adoption*, Working paper.

Jordbakke, G. N. (2023). *How parking regulation affects the consumption of private cars – identification through a natural experiment*, Working paper.

Metzler, D., Humpe, A., & Gössling, S. (2019). Is it time to abolish company car benefits? An analysis of transport behaviour in Germany and implications for climate change. *Climate Policy*, *19*(5), 542–555.

OFV. (2021). *Kostnader ved bilhold – eksempler på beregning [Car ownership costs – examples of calculation]*. The Norwegian Road Federation.

Østli, V. (2023). *The effect of public transport frequency on car ownership: The case of the Oslo metro system*, Working paper.

Paetzold, J., & Winner, H. (2016). Taking the high road? Compliance with commuter tax allowances and the role of evasion spillovers. *Journal of Public Economics*, *143*, 1–14.

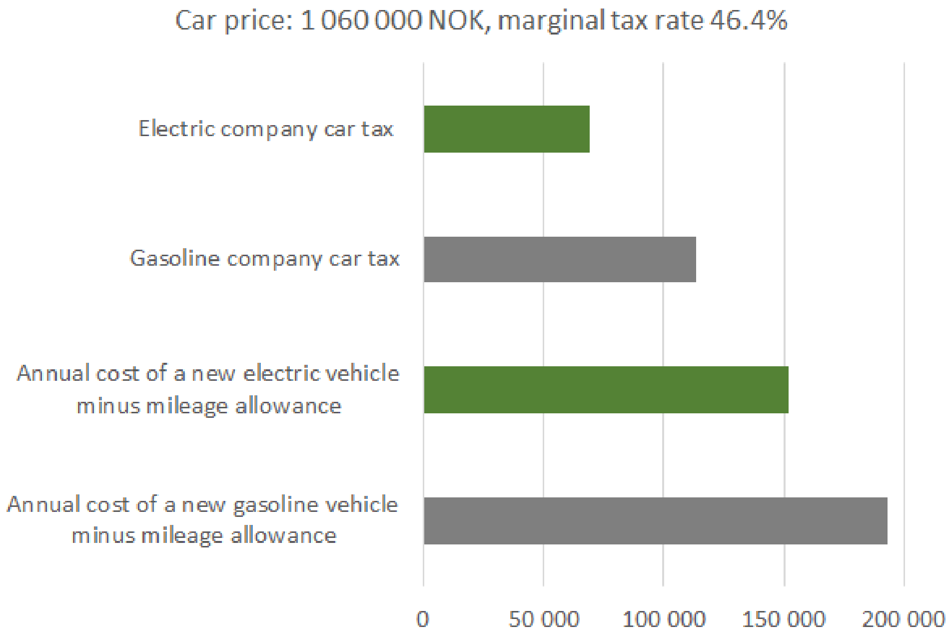
Pathak, M., Slade, R., Shukla, P., Skea, J., Pichs-Madruga, R., & Ürge-Vorsatz, D. (2022). Technical Summary. In P. Shukla, J. Skea, R. Slade, A. A. Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, & J. Malley (Eds.), *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK; New York, NY, USA.

Pyddoke, R. (2009). *Empirical analyses of car ownership and car use in Sweden.* VTI Rapport 653/653A.

Roth, J., Sant'Anna, P. H., Bilinski, A., & Poe, J. (2023). What's trending in difference-in-differences? A synthesis of the recent econometrics literature. *Journal of Econometrics*.

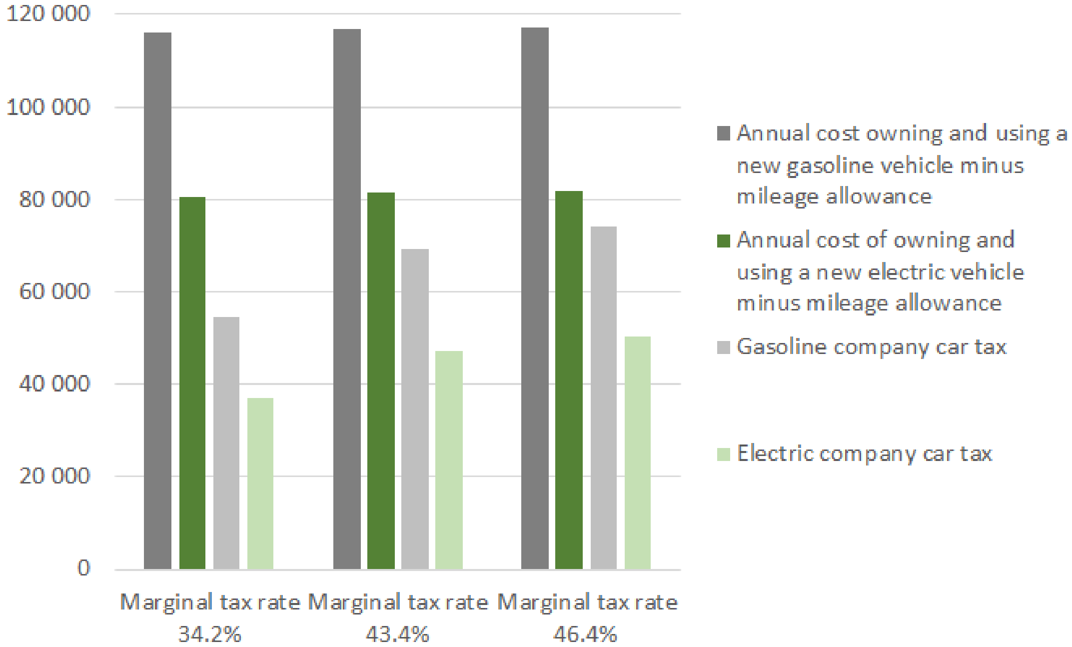
A More details on the background

Figure A-1: The annual company car tax compared to the annual cost of owning and using a new car. Car price: 1 060 000 NOK. Marginal tax rate: 46.4%.



The source of the annual cost of owning and using a new car is The Norwegian Road Federation. This compares the cost of a car costing 1 060 000 NOK, with the top marginal tax rate which is 46.4% and driving 20 000 km per year. For privately owned cars we assume driving half of the kilometers for work and getting mileage allowance for this. The governmental mileage allowance that many employers follow, is 4.03 NOK per km, and 3.50 NOK/km is without tax. The 46.4% marginal tax rate is for wages above 1 021 550 NOK. For wages between 651 250-1 021 550 NOK in 2021, the marginal tax rate is 43.4%.

Figure A-2: The annual company car tax compared to the annual cost of owning and using a new car. Car price: 636 000 NOK. Different marginal tax rates.



The source of the annual cost of owning and using a new car is The Norwegian Road Federation. This compares the cost of a car costing 636 000 NOK, and driving 20 000 km per year. For privately owned cars we assume driving half of the kilometers for work and getting mileage allowance for this. The governmental mileage allowance that many employers follow, is 4.03 NOK per km, and 3.50 NOK/km is without tax. The 46.4% marginal tax rate is for wages above 1 021 550 NOK. For wages between 651 250-1 021 550 NOK in 2021, the marginal tax rate is 43.4%. For wages between 260 100 – 651 250 NOK the tax rate is 34.2%

Table A-1: Company car occupations

Variable	Share
Seller (wholesale)	22.3%
Top manager	11.5%
Sales and marketing manager	8%
Retail managers	5.9%
Other administrative managers	3.1%
Engineer building and construction	2.8%
Manager building and construction	2.7%
Worker in stores	2.2%
Seller within technical and medical products	2.1%
Manager industrial production	1.8%

The share is of the total number of company car users.
In this Table we use 4-digit occupation codes, while in the analysis we use 7-digit codes.
This table is made after the outliers on wage is taken out of the sample.

Table A-2: The car market in Norway

Year	Number of new cars sold	Number of new company cars	Share
2015	150,686	9,890	6.6%
2016	154,603	9,973	6.5%
2017	158,650	10,987	6.9%
2018	147,929	7,865	5.3%
2019	142,381	9,267	6.5%
2020	141,412	8,434	6.0%
2021	176,276	10,358	5.9%

The source for number of new cars sold is The Norwegian Road Federation (OFV).

B Details about the data

B.1 Source of the data

In this section we present the source of the data, and the variables that we use.

B.1.1 Vehicle register

The vehicle register is maintained by the Norwegian Public Road Administration. It is not allowed to drive on the road if the car is Norwegian and not registered. In addition, Statistics Norway include data about car scrapping into the vehicle register data from the Norwegian Tax Administration (because they have the responsibility of paying out money for the scrapping).

From 2020, the variables changed, and more were included. Leased cars have both owner id and leaser id. This means that cars that are owned by a leasing company can be tracked to the leaser. In the company car case, the leaser is most often the company that pays the car expenses. Cars that are leased by private persons before 2020 are not counted as a private car. Therefore, the number of cars in the households are higher in 2020 and onwards not just because the private car park is getting larger, but because the counting is made more precise.

The variables from the vehicle register that we use are:

- Car id
- Owner id
- Leaser id (only in 2020 and 2021)
- First registered (in order to find the age of the car) (date)
- First time registered on this owner (date)
- Deregistration date (temporary or permanent de-register)
- Scrapping date
- Fuel

B.1.2 Company car data

Whether a car is a company car cannot be identified in the vehicle register. To identify the company cars, we use annual data reported from the employer to the tax administration through the same system as the monthly wage reporting.[29]

The variables that are in the company car data are:

- Person id
- Car id
- Year
- Company/firm id[30]
- The id of the subunit of the company[31] (We do not use this variable)
- The value of the personal use of the company car. This is the amount that is added to the wage as a fringe benefit, see more information about this in Section 2.1.

The company cars that are used privately, but not reported to the tax authority is not in the data. How many cars this is, is difficult to estimate. The enforcement of the company car tax is done by the tax administration. There are some examples in the media about company cars not being correctly reported to the tax administration and therefore not correctly taxed.[32] The Norwegian Tax Administration did not want to say any numbers on how many cars they control annually to identify tax evasion, and how many cases related to company cars they reveal every year.

B.1.3 Family register

The family register consists of all individuals that are registered as living in Norway in the National Register (*Det sentrale folkeregister*), by the rules of what living in Norway means. Those excluded from the family and household register is persons studying abroad or for other reasons residing outside mainland Norway (in Svalbard, in the military or in the Foreign Service). There is also some missing information as some addresses have more than one dwelling. This is particularly a problem in cities, but the problem has become smaller in recent years. The group of persons with the least information is unmarried students, as they are allowed to register that they live with their parents in the National Register, while they live in another city. Also, if individuals do not update their information in the

[29]See more information about the monthly digital wage reporting system (in Norwegian) here: https://www.skatteetaten.no/bedrift-og-organisasjon/arbeidsgiver/a-meldingen/om-a-ordningen/om-a-ordningen/ and here: https://www.ssb.no/data-til-forskning/utlan-av-data-til-forskere/variabellister/a-ordningen

[30]Company and firm are used interchangeably in this article.

[31]See more information (in Norwegian) here: https://www.ssb.no/virksomheter-foretak-og-regnskap/artikler-og-publikasjoner/fra-bedrift-til-virksomhet. Company or firm is "foretak" and subunit is "virksomhet".

[32]For instance here: https://e24.no/privatoekonomi/i/0nrOJJ/full-forvirring-rundt-yrkesbil-skatt-har-betalt-90000-kroner-for-mye-i-skatt and here: https://www.skatt.no/2021/10/19/skatteklagenemnda-firmabilen-gav-skattesmell-og-tilleggsskatt/

register, as they are mandated to do, the information in the family and household register will be incomplete.[33]

From the family register we use these variables:

- Person id
- Family id
- Year
- Couple status[34]
- Number of individuals in the family
- Number of children in the family, no matter the age of the children, as long as they are registered to live with their parents
- Number of children in the family under the age of 18

We exclude all individuals under the age of 18 and over the age of 67 (the retirement age in Norway).

B.1.4 Moving register

We use data for who has moved during the period of investigation and create a binary variable for whether an individual has moved or not and year.

B.1.5 Population register

From the population register we get the year of birth and gender.

B.1.6 Employers and employees

We use the monthly digitally reported wage data from employers to the tax administration. The variables that we use are:

- Person id
- Company/firm id
- Gross cash wage (not including the value of fringe benefits)
- Working hours (to find the main employer every month)

[33]See more information about the family register here: https://www.ssb.no/befolkning/barn-familier-og-husholdninger/statistikk/familier-og-husholdninger

[34]More information here: https://www.ssb.no/a/metadata/codelist/datadok/1618382/no

- Occupation code
- NACE code of the firm
- Sector code of the firm

B.1.7 Occupation codes

We use Statistics Norway's occupation codes which are reported by the employer at the same time as the wage. These codes are called STYRK-98. There are also more aggregated occupation codes called STYRK-2008.[35] The converting between the two codes is easily available on the web page of Statistics Norway.[36] The occupation code data probably have some noise as there are no incentives related to reporting this variable correctly.

B.2 Information collected from the data

In this section, we present what we do to extract information from the data.

B.2.1 Company car users

Over the period 2015-2021 there are in total 598,349 observations in the company car reporting data. 19,423 observations are duplicates in terms of all variables in the data, including the taxable amount. We cannot be sure that these are actually duplicates, but since the taxable amount is exactly the same, we assume that they are duplicates and they are removed.

There are 19,094 company cars without a car id. We do not know what type of car the company cars that do not have a car id number is, and they are not part of the analysis. Further 192,003 observations are not found in the vehicle register. This could be cars that are not passenger vehicles. Another explanation is that the car id is wrongly written. Those that are not found in the vehicle register are excluded from the analysis. Cars that are registered for use outside public road (4 car-year observations), van class 2 (1 car-year observation) and veteran car (5 car-year observations) are also excluded from the sample.

Then we have 386,913 observations in total in the company car data. Some of the company cars are used by several employees and some of the employees have several company cars during a year (not necessarily at the same time). There are roughly around 50,000 unique company cars every year. During the whole period of investigation the number of unique cars is 357,299. 86% of the cars have one user during the year and 12% of the cars have

[35]See more information (in Norwegian) here: https://www.ssb.no/klass/klassifikasjoner/145/koder

[36]See converting file here: https://www.ssb.no/klass/klassifikasjoner/145/versjon/683/korrespondanser/426

2 users. 19.3% of the company cars are owned by a private person, while 80.7% is owned by companies, which is both leasing companies and other types of companies.

There are 805 company cars that are marked as scrapped one year or more before the car is reported as a company car. They are still part of the sample, as they are reported and taxed as a company car.

From the company car data we can aggregate information on each person-firm-year. There are 288 person-year missing id on the firm. They are counted when counting number of company car users but are not part of further analysis.

The company cars are valued based on the list price (see Section 2.1).[37] If the value in the company car data is lower than 100 000 NOK for a non-electric car that is 3 years or younger, we assume that the employee do not use the car for the whole year. We divide the amount by 100 000 and get a share of the year that they have the car. For electric vehicles we divide the amount by 60 000 if the year is 2018 or later, and by 50 000 if the year is 2017 or earlier. If the car is older than 3 years, we divide the amount by 75 000.[38] If the amount is higher than what we divide on, the cars are counted as one car the whole year. A more precise way to measure the share of the year a person has a company car is to include the average list price of the company car model.

B.2.2 The number of cars per family per year

We use the vehicle register to count the number of cars per person per year. The vehicle register is the vehicle fleet on December 31 the year in question. We restrict our analysis to passenger cars (cars in vehicle group 101).

We exclude the cars that are scrapped before 2015. Further, we exclude veteran cars, embassy cars, vans, rally cars, cars that are only valid to use outside of public road, and cars that are registered for Svalbard.

The cars that are registered on the owner before or at the end of the year we are observing is counted. The cars that are either

- registered on the owner after the observed year, or
- scrapped before or at the observed year, or
- de-registered after the observed year and after the car is registered on this individual

[37]A non-electric car that costs 636 000 NOK (which is the price in the example in Figure 1) is valued to 159 740 NOK. A non-electric car that costs 340 000 NOK, is valued to 100 540 NOK in 2021. An electric car that costs 636 000 NOK is valued to 108 860 NOK.

[38]For electric vehicles older than 3 years we divide by 45 000 in 2018 and onwards and 37500 in 2017 and earlier.

are not counted.

We limit the possible number of registered cars per person per year to 3 in order to not let outliers with for instance over 100 registered cars influence the average number of cars. Also, it seems plausible that more than 3 cars means that some of the cars are hobby cars (Börjesson & Roberts, 2022).

Then we link the data to the family register and count the total number of cars per couple per year. Also here we limit the number to maximum 3 cars per couple per year. For those that are single, we use the number of cars per person.

B.2.3 Company car occupations

Linking employees and company cars, we count the individuals in each occupation with and without a company car each year. The occupations where 10% or more have a company car that year is defined as a company car occupation.

From this list of occupations, we exclude occupations where it seems likely that the employees decide about the offer of a company car themselves, e.g. top managers. There are two types of occupation codes. In Section 2.3 and Table A-1 we use 4-digit occupation codes, which is more aggregated, while in the analysis we use 7-digit codes, which is more detailed. We also use the aggregated 4-digit code to see who has a top manager position even if the name of the occupation is not CEO, and they are defined as non-company car occupations.

B.2.4 Company car firms

Linking employers and employees and company cars, we define the firms with at least two company car users as company car firms.

B.2.5 Job change

The main employer each month is defined by having the highest number of working hours that month. Job change is defined as:

- the employer in the month n is different than in the month before $n-1$, so firm-id[n] $\neq$ firm-id[n-1], and
- the employer is the same the month after (firm-id[n] = firm-id[n+1])

We only include those that change job *once* during the period of investigation.

Table A-3: Example change of job

Person ID	Month	Employer ID	Job change
1	1	5	0
1	2	7	0
1	3	5	0
1	4	6	1
1	5	6	0
1	6	7	1
1	7	7	0
1	8	7	0

B.2.6 Wage

We take out the outliers on wage. Those with a wage higher than 2 million NOK are excluded from the sample.

B.2.7 The sample when using the Swedish research design

The sample when using the design of Börjesson and Roberts (2022) is adults being employed every year from 2015-2021. In couples, only one adult has to be employed the whole period. Börjesson and Roberts (2022) exclude households with more than 6 cars, and they let the other households have maximum 3 cars. We do not exclude the families with more than 6 cars, but we follow Börjesson and Roberts (2022) in setting a maximum of 3 cars.

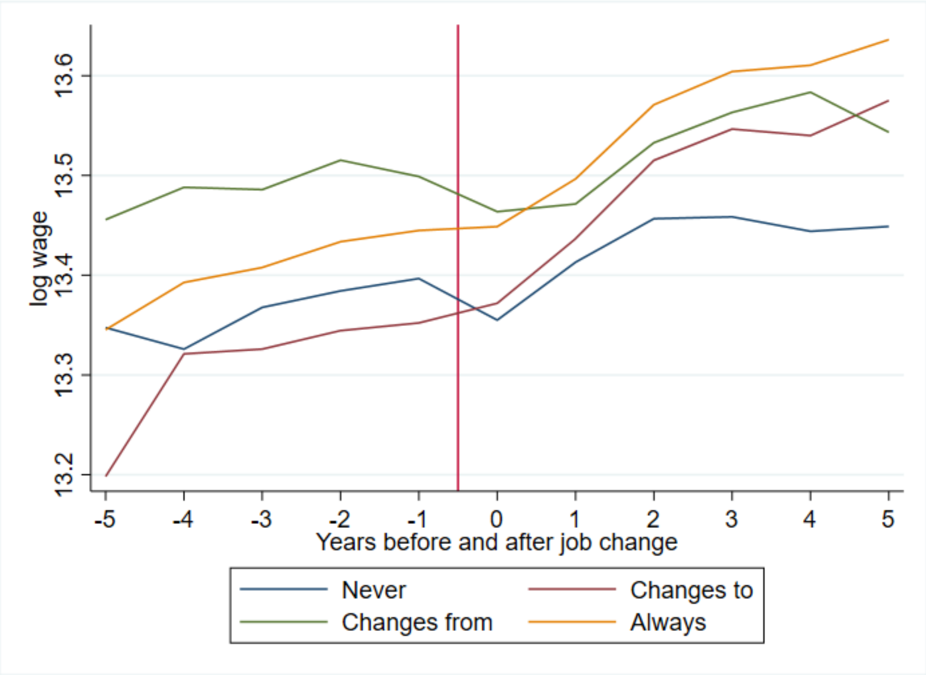
Börjesson and Roberts (2022) define couple households as a married couple or partners with at least one mutual child. We follow the statistical definitions of Statistics Norway for families and households where couples can also be non-married and childless.[39] Those that are not in the family register are defined as single households.

[39]See more information here (in Norwegian): https://www.ssb.no/befolkning/barn-familier-og-husholdninger/statistikk/familier-og-husholdninger

C Details about the empirical strategy

C.1 Raw data

Figure A-3: Raw data: Log wage.



C.2 Balance tests

Figure A-4: Outcome variable: Wage.

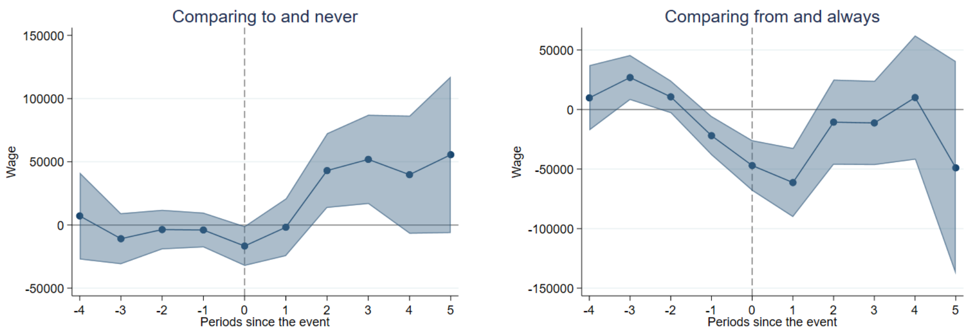


Figure A-5: Outcome variable: The number of children.

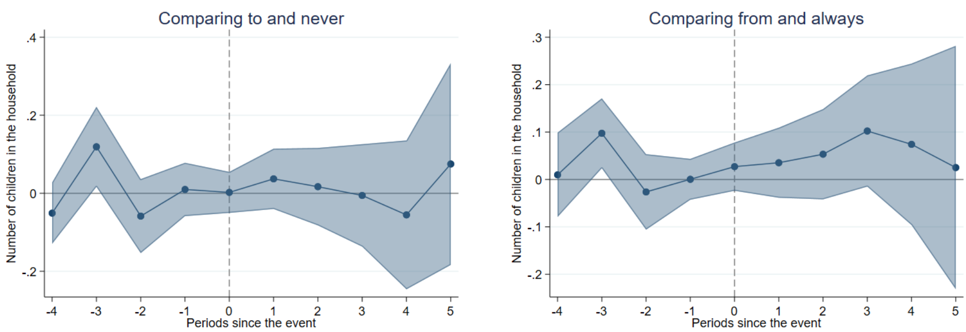


Figure A-6: Outcome variable: The number of children under the age of 18.

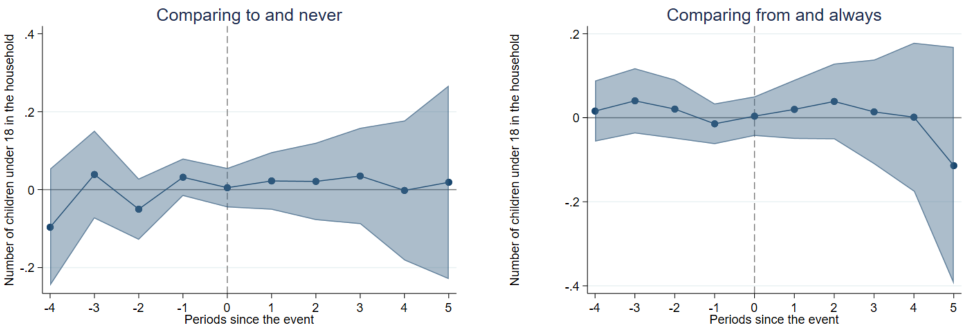


Figure A-7: Outcome variable: The number of persons in the household.

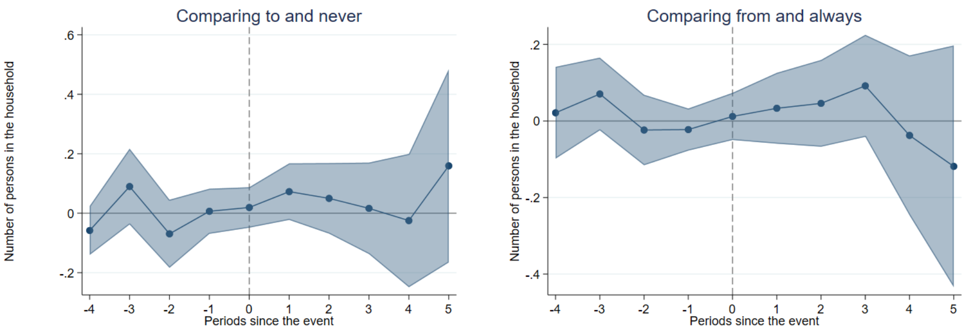


Figure A-8: Outcome variable: Moving (binary).

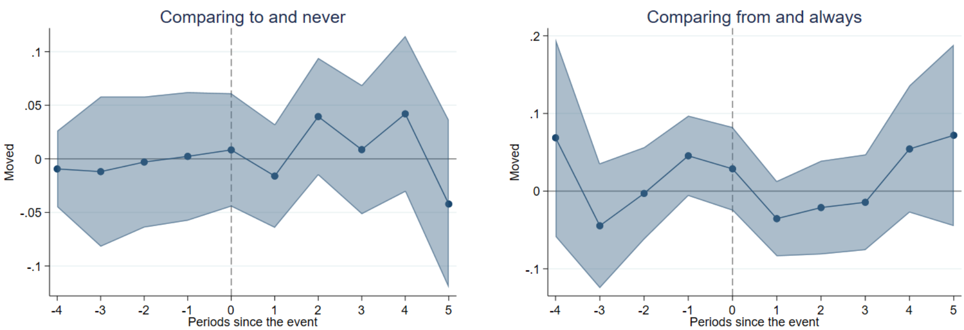
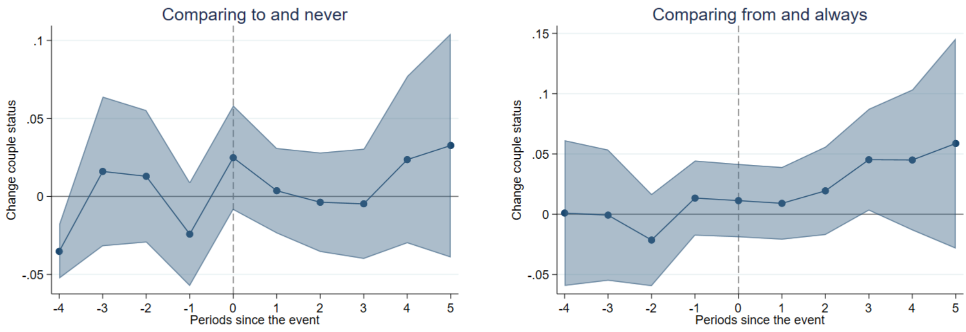
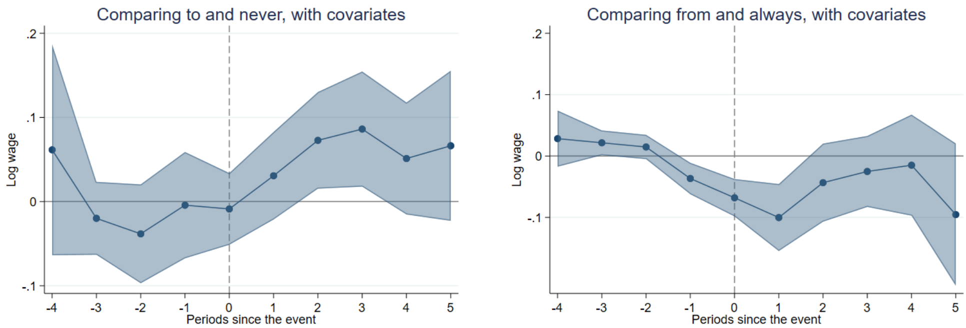


Figure A-9: Outcome variable: Changing couple status (binary).



C.3 Log wage with covariates

Figure A-10: Outcome variable: Log wage. Including covariates



D More results

D.1 With covariates

Figure A-11: The change in the number of cars for those getting access to a company car, including covariates. a) including company cars and b) excluding company cars.

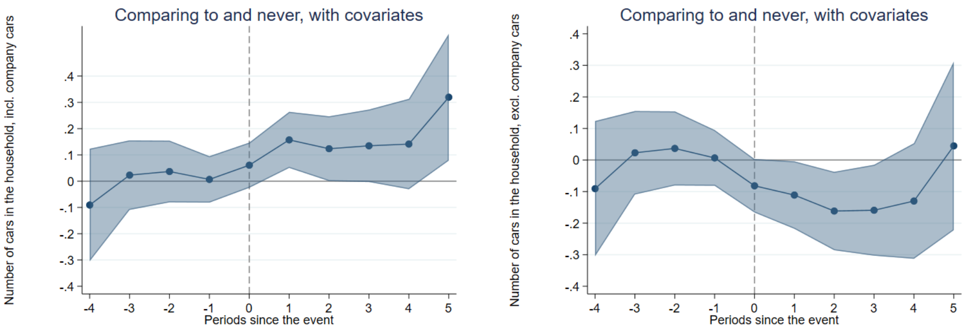
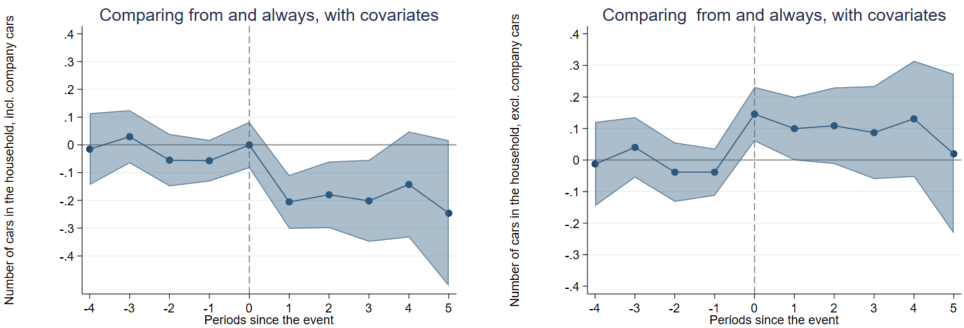


Figure A-12: The change in the number of cars in the household for those losing access to a company car, including covariates. a) including company cars and b) excluding company cars.



D.2 Only looking at those changing job late in the year (from June 1st)

Table A-4: Aggregated effects using the Callaway and Sant'Anna (2021)-estimator for only those changing job from June 1st.

	(1) Getting an offer of a company car	(2) Losing the possibility of a company car
Change in the number of cars in the households, incl. company cars (Figure A-13)	0.157** (0.059)	-0.171** (0.058)
Likelihood of having a car, incl. company cars (Figure A-14)	0.050 (0.026)	-0.047 (0.027)
Change in the number of electric vehicles, incl. company cars (Figure A-15)	0.033 (0.032)	-0.043 (0.035)
Change in the number of non-electric vehicles, incl. company cars (Figure A-16)	0.090 (0.065)	-0.198*** (0.058)
Household fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Number of observations	3,234	6,034
Number of households	462	862

Standard errors are in parenthesis.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Figure A-13: Number of cars, only those changing job late in the year.

Figure A-14: Likelihood of having car, only those changing job late in the year.

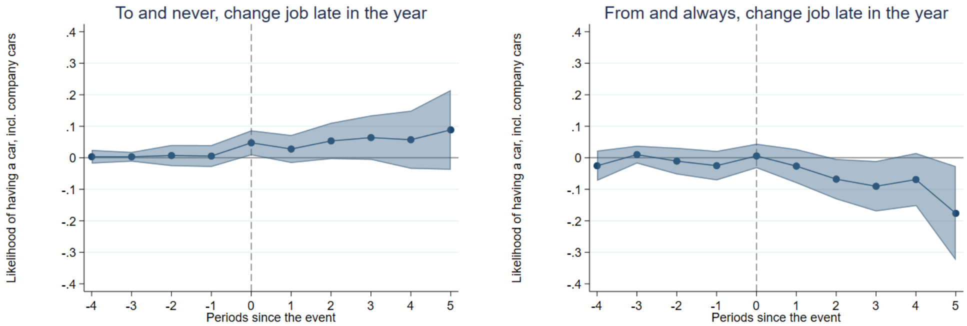


Figure A-15: Number of electric vehicles, only those changing job late in the year.

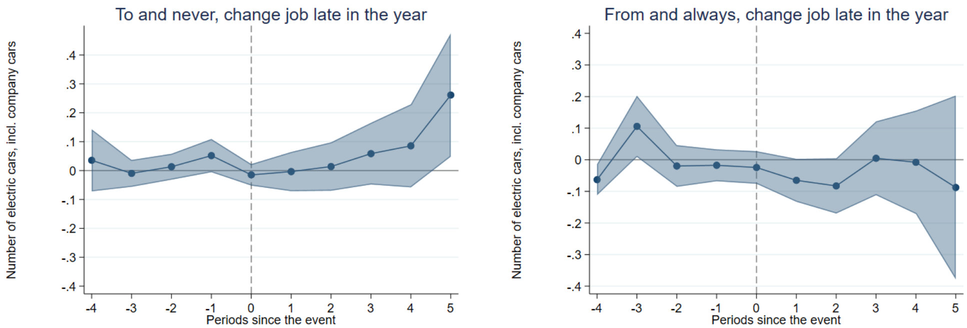
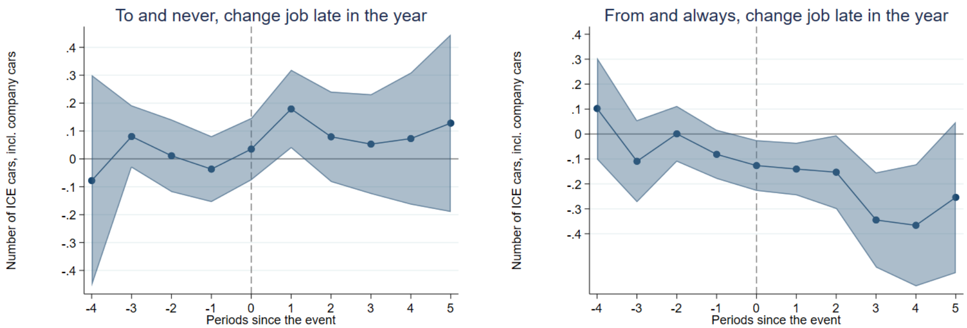


Figure A-16: Number of non-electric vehicles, only those changing job late in the year.



Paper 3: Climate, technology and value: Insights from the first decade with mass-consumption of electric vehicles

Climate, technology and value: Insights from the first decade with mass-consumption of electric vehicles*

Gøril L. Andreassen[†] Jo Thori Lind[‡]

June 13, 2023

Abstract

Adoption of low-carbon technology is key to mitigating climate change. A possible unwanted consequence of fast technological progress is that products get outdated before their technical lifetime is over. We investigate whether the market value of electric vehicles, characterized by rapid technological progress, declines faster over their lifetime than gasoline vehicles, which represent a mature technology. We use novel data from Norway, the market with the highest market shares for electric vehicles in the world. The data are from the largest web platform for secondhand vehicles over the period 2011-2021. Prices of electric vehicles decline faster than gasoline vehicles. This seems to be driven by the electric vehicles with below median driving range. We hypothesize that the large price drop is mainly due to the fast technological improvement of electric vehicles. (*JEL* D12, L60, L62, O33, Q55)

Keywords: Electric vehicles; energy transition; low-carbon technologies; secondhand market; technological progress

*We would like to thank Askill Harkjerr Halse, Svenn Jensen, Bjørn Gjerde Johansen and Maria Nareklishvili and Knut Einar Rosendahl, as well as seminar participants at School of Economics and Business, NMBU, the Institute of Transport Economics and at the TRIPOP workshop for valuable comments. We are grateful to finn.no, Kjell Magne Aalbergsjø in The Norwegian Road Federation (OFV) and Erik Lorentzen and colleagues in the Norwegian Electric Vehicle Association for supplying data and sharing information. Please see disclosure statement online.

[†]Corresponding author. goril.louise.andreassen@nmbu.no, School of Economics and Business, Norwegian University of Life Sciences, PB 5003 NMBU, 1432 Ås, Norway

[‡]j.t.lind@econ.uio.no, Department of Economics, University of Oslo, PB 1095 Blindern, 0317 Oslo, Norway.

1 Introduction

Widespread deployment and continued progress of low-carbon technologies are crucial to reduce greenhouse gas emissions (Barrett, 2009; Dhakal et al., 2022; Pathak et al., 2022; Stock, 2020). The adoption of low-carbon small-scale technologies, such as electric vehicles and solar power, has accelerated the last decade. These technologies have improved fast, both regarding performance and costs (e.g. Pathak et al., 2022). Better and cheaper low-carbon technologies enable more consumers to take part in the energy transition – but also make existing goods obsolete faster than before. We investigate how the market values technology throughout the lifetime when the technology is rapidly improving. These insights are also relevant for other product types where technological progress is high, such as smart mobile phones.

In this paper, we specifically investigate the case of electric vehicles. For electric vehicles, the most important improvement the last decade is the increased driving range, which is due to better and cheaper batteries. This has also allowed production of larger models catering to a larger range of consumers. Gasoline vehicles, on the other hand, is a mature technology. We find the price path of a car over its lifetime by comparing cars of the same model year sold secondhand at different ages. To study the effect of particularly rapid technological progress on market prices, we compare the price path for ten-year-old electric vehicles and gasoline vehicles.

The Norwegian market is the most mature electric vehicle market in the world (IEA, 2022), so this is a good test bed for the future of the market for electric cars worldwide. The market share for battery electric vehicles has been above 10% of new car purchases since 2014 and by October 2022 it is 78%.[1] We use a novel data set from the largest web platform for secondhand vehicles in Norway, finn.no, accounting for close to 90% of the market, over the years 2011-June 2021. At this platform, the electric vehicle share of the market for vehicles that are 10 years or younger has been above 1% since 2013 and is 23% as of June 2021. The time period 2011-2021 covers the years where electric vehicles have been an important part of the Norwegian market.

We find that used electric vehicles decline faster in price than used gasoline vehicles. This finding is robust to various specifications. The difference in the price fall seems to be driven by electric vehicles with driving range below 200 km (close to the median range in our sample). The price pattern of electric cars with the highest driving ranges are more similar to those of gasoline cars.

To understand the difference in the price decline between the two technologies, we first develop a theoretical framework based on the model of Stolyarov (2002) of the resale

[1] As of June 2021 where this analysis stops the market share was 57%.

pattern of durable goods. As electric cars are less mature technology than cars based on combustion engines, technological progress is faster. This reduces the utility of used cars relative to that of a new car, and hence leads to reduced demand and increased supply of secondhand cars. To maintain equilibrium in the market of used cars when the technology is improving, the price of used cars has to decrease. Hence the price of electric vehicles drops faster compared to gasoline vehicles.

The technology shift in the Norwegian car market is a prediction of what may happen in other countries if batteries continue to fall in price and policies promoting electric vehicles and charging infrastructure continue. Other important car markets are less than 10 years behind Norway in the electric vehicle adoption. If batteries continue to decline in price, electric vehicles are predicted to become competitive compared to gasoline vehicles by mid-2020s (Bloomberg, 2020; J.P. Morgan, 2018, 2020).[2]

This paper contributes thematically to three different strands of the literature, namely, technological development, durable goods and the car market. In growth theory there is a literature on how technological progress evolves endogenously as resources are spent on R&D (e.g. Aghion & Howitt, 1998). In addition, there is a literature on the interaction between technological change and environmental policy (e.g. Acemoglu et al., 2012). However, in this paper we take the technological process as exogenously given. Our work relates more closely to the work on vintage capital where technological progress only affects the economy through new capital – and where every vintage of capital is marked by the period in which it was produced (Solow et al., 1966). This also leads to the question of optimal replacement of capital (Rust, 1987). Rosenberg (1976) argues that expectations about future technological improvements are of great importance for the firm's decision to adopt technology now or wait for improved technology.[3] De Groote and Verboven (2019) investigate household's investment decision for solar power, which has had, similiar to electric vehicles, increased quality and decreased prices.

Cars are one of the prime examples of durable goods. Waldman (2003) reviews much of the early literature on durable goods, including theories of optimal durability of goods, the effects of a secondhand market on the new goods market, and information problems in the secondhand market. A study that in many ways is close to ours is the one by Fudenberg and Tirole (1998). They consider a monopolist selling goods in two periods with improvements in quality between the two periods. Their focus, however, is on the behavior of the monopolist selling the new good and taking the secondhand market for given whereas we focus on the secondhand market. In a seminal contribution close to our theoretical approach, Stolyarov (2002) develops a model of the resale pattern of

[2]However, whether battery prices continue to decline the coming years is not sure (Bloomberg, 2021a, 2021b).

[3]This argument is further developed by Balcer and Lippman (1984).

durable goods. Goods are purchased new at a fixed price and the quality of the product deteriorates over time.

There is a vast literature on the demand for cars specifically. A starting point is Akerlof's (1970) seminal theoretical study, which in itself is not very relevant to our study. This study was followed up by Bond (1982), who empirically studied the demand for used pickup trucks (see also Bond (1983)). To study whether bad cars are driving out good ones from the secondhand market, he investigates whether secondhand trucks require more maintenance than otherwise similar trucks bought new. He does not find any difference between first- and secondhand bought trucks.

The newer empirical literature on the demand for automobiles is heavily inspired by the study by Berry et al. (1995). In their study, however, they only consider the static demand for new cars. There is also a literature on the pricing behavior of car manufacturers in the presence of a secondhand market (e.g. J. Chen et al., 2013; Esteban & Shum, 2007). Schiraldi (2011) introduce a dynamic element to this class of models. In his model, consumers decide whether to sell or replace their car in every period, and the supply of new cars is constant over time. Gavazza et al. (2014) provide a model of the household's decision about which cars to buy, hold, and sell in the secondhand market in a framework based on Stolyarov (2002). Gillingham et al. (2022) develop a computationally tractable dynamic equilibrium model of the car market with heterogeneous consumers. Our empirical approach is most closely related to the approach followed by Purohit (1992). He estimates the effect of changes such as major styling changes, downsizing and changes in horsepower, in new cars on the price of used cars and finds that enhanced features of new cars increases the obsolescence effect of used cars. The changes he studies, however, are minor compared to the technological changes electric vehicles have experienced the last decade.

Our paper is also closely related to the literature on the evolution of the price of used durable goods, particularly cars, over time. Wykoff (1970) studies the declining price of selected car models to study the shape of the depreciation function, whereas Porter and Sattler (1999) study trade in secondhand cars in the late 1980's. Not surprisingly, prices of cars are falling over time, but the pattern varies across types of cars. Similar variation is found by Esteban and Shum (2007). Copeland et al. (2011), moreover, document a similar fall in prices for new vehicles.

Schloter (2022) investigates the depreciation rate of electric vehicles compared to gasoline vehicles, and finds that electric vehicles depreciate faster than gasoline vehicles. He draws on web scraped data on prices of nine car makes from multiple countries collected in 2020 and 2021. In comparison we cover the whole used car market on finn.no (which again covers around 90% of the used car market in Norway), while Schloter (2022) ends up only looking at electric vehicles in Norway. Moreover, as we have the whole used car market for ten years in a country that is far ahead on the electric vehicle transition, it gives a more complete picture of the evolution of the market for electric cars although we are limited to a single country. Reassuringly, Schloter (2022) finds the same pattern of prices of electric vehicles decline faster than the price than gasoline vehicles that we find. We also have data on the range of the vehicle and find that the fast price decline of electric vehicles seem to be driven by vehicles with below median range.

The literature on technological progress and improvement of durable goods focusing on other goods than cars is also relevant. Gordon (2009) studies the market for replacement of computer CPUs that improve over time, and Gowrisankaran and Rysman (2012) provides a model of the market for durable goods where the quality of new goods is improving, which resembles the still evolving market for electric cars. However, they do not allow for a secondhand market. Quite similar to our study, Ishihara and Ching (2019) study the market for used video games where newer games are assumed to be better than old games. Their main focus, however, is the effect of the secondhand market on the market for new games. A major difference between automobiles and video games, however, is that users experience satiation from playing a game repeatedly, making games "less durable".

There is also an emerging literature on the demand for electric and "green" cars. Most of this literature, however, suffers from lack of data on observed behavior. Glerum et al. (2014) provides a forecast of future demand for electric vehicles using stated preference survey data. Survey data has also been studied in more sophisticated modelling frameworks (Liu & Cirillo, 2017), and there are studies of specific characteristics such as battery capacity (Danielis et al., 2019). Archsmith et al. (2022) document that the demand for electric vehicles in the US is closely related to environmental preferences, and Holland et al. (2021) build a quantitative model to analyze how different policies affect the transition to electric cars. Muehlegger and Rapson (2022) are one of few studies who use actual transactions. They study the effect of a subsidy of electric vehicles in California. They find quite high price elasticity, and low- and middle-income households benefit the most from the subsidy. Brückmann et al. (2021) survey whether fear of not being able to resell an electric vehicle reduces demand for electric vehicles, and find that consumers expect a higher resale value for electric vehicles than conventional cars.

There is also a literature on provision of incentives to replace polluting cars with newer varieties. Adda and Cooper (2000) present a theoretical model with simulations to study the effect of a subsidy program in France. Li et al. (2020) and Mian and Sufi (2012) provide an analysis of the Cash-for-Clunkers program whereas Guan (2021) analyze the CARS program, both in the US. C.-W. Chen et al. (2021) examine the effect of a subsidy program to fuel-efficient cars in China, while Springel (2021) investigates whether subsidies to electric vehicles or charging stations are most important.

In addition, similar to us, Sallee et al. (2016) use used car prices in their analysis, but investigate whether consumers recognize the value of fuel economy. Also Strittmatter and Lechner (2020) use data similar to us and use it to investigate whether there is a sorting in the secondhand car market based on environmental quality.

Our first contribution is to present empirical results that indicate that the price paths of goods that have a large technological improvement each year is different than for goods that do not have large technological improvements from year to year. Second, we contribute to the state of knowledge on the electric vehicle market. Investigating the price path of electric vehicles during the lifetime with information from the most mature electric vehicle market in the world has not been done before and is relevant since this is a technology that probably will be phased into the car market globally the coming decade. Third, we inform the estimation of the cost of climate policy since valuation of the used low-carbon technology is part of the cost.

The structure of the rest of the paper is as follows. First, we give background information about the car market in Section 2. In Section 3 we present our theoretical framework that we use to make a hypothesis about the cause of the findings. Further, we present the data, descriptive statistics and the empirical strategy in Section 4. In Section 5 we present and discuss the results and in Section 6 we conclude.

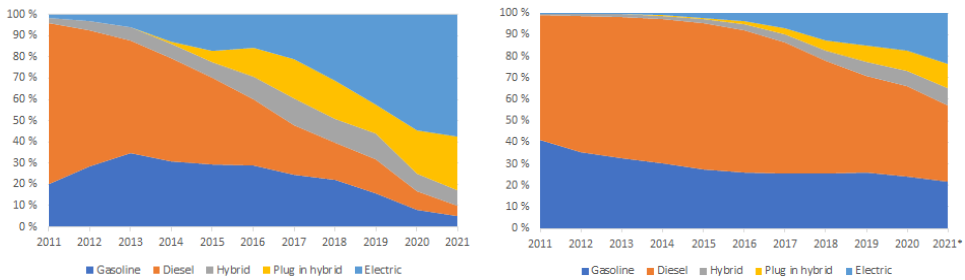
2 Background on the car market

An extraordinary technology shift is expected to happen in the car market. Both the EU and California aim to only sell zero emission passenger cars from 2035 and on wards. A car lasts for 15-20 years. For the car fleet to transition to zero emission vehicles, the market share for zero emission vehicles among the new cars sold need to increase first. A large part of this shift has already happened in the Norwegian car market over the last decade. The share of different types of vehicles sold in Norway from 2011 to 2021 can be seen in Figure 1a. From having 96% market share in 2011, gasoline and diesel vehicles have plummeted to a 10% market share. Electric vehicles have increased from a 1.5% market share in 2011 to 57% by June 2021.[4]

The high sale volumes of new electric vehicles extends into the secondhand vehicle market, but naturally there is some delay. The fuel share of the secondhand vehicle market in

[4]Note that we do not include plug-in hybrids in the electric vehicle category. When we refer to electric vehicles, this is battery electric vehicles. For battery electric and plug-in hybrids the sale share in 2021 (until June) is 80%.

Figure 1: Sale shares by technology for new and second hand cars in the Norwegian market 2011-2021



(a) New cars

(b) Second hand cars

Notes: Data for 2021 covers January to June.

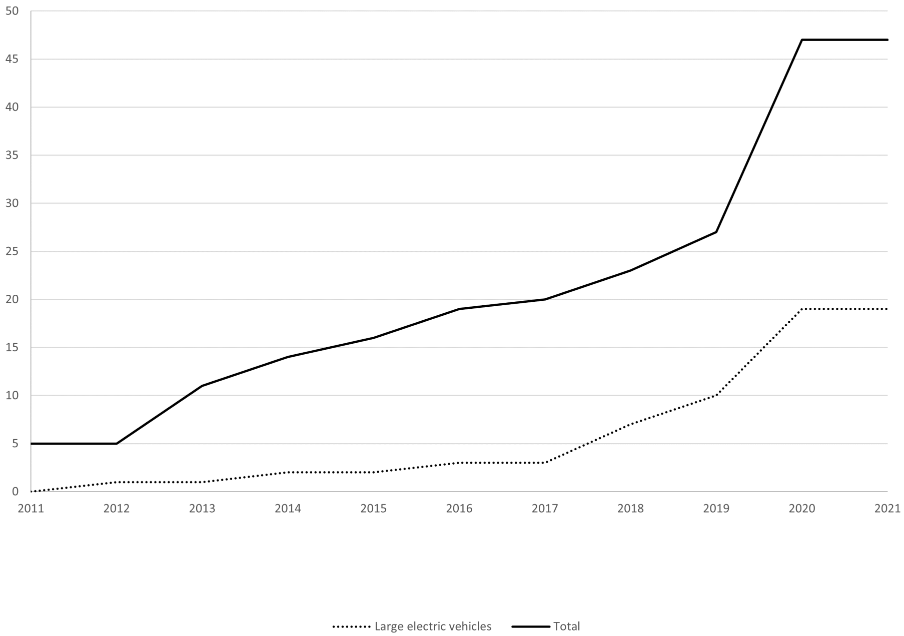
Norway in 2011-2021 can be seen in Figure 1b, where we for each year show the fuel share of all cars that are below 10 years old that are advertised on the web platform finn.no.[5] The share of electric vehicles hits 1% in 2014, and reached 23% by June 2021. The left part of the graph for new vehicles (Figure 1a) from 2011-2017 looks similar to the right part of the graph for used vehicles from 2014-June 2021 (Figure 1b).

The sale shares of electric vehicles in the USA, Korea and Canada in 2021 are equal to the sale shares of new electric vehicles in Norway about ten years ago (IEA, 2022).[6] Globally the sale share of electric vehicles in 2021 is equal to the sale shares in Norway in 2013, while China and Europe are ahead of the USA and have sale shares for electric vehicles in 2021 equal to the sale shares in Norway in 2013-2014 (IEA, 2022). The Netherlands have sale shares for electric vehicles in 2021 that are equal to the Norwegian sale shares in 2017 (IEA, 2022) while Iceland has sale shares for electric vehicles in 2021 that match the Norwegian 2018 numbers (The Norwegian Electric Vehicle Association, 2022b). Thus, these markets are less than 10 years behind Norway in the electric vehicle roll-out.

Driving range has increased considerably since the market of electric vehicles started to grow in the beginning of the 2010s. In addition, comfort of electric vehicles has increased and the variety of vehicle models available has expanded. In Figure 2 we see the number of electric vehicle models available in the Norwegian market until June 2021. The black line is the total number of electric vehicle models available, while the dotted line is the number of large electric vehicle models available. We see that around 50 electric vehicle models are available in the Norwegian car market. As a comparison there are 153 different models available in 2020 for gasoline vehicles. Thus, the electric vehicle market is maturing, but it is not fully mature yet.

[5] We use the term *fuel* also about electric vehicles, all though strictly speaking electricity is not a fuel.
[6] Note again that this is battery electric vehicles, excluding plug-in hybrids.

Figure 2: Number of available electric vehicle models for sale



Notes: Data for 2021 is as by June 2021. Large vehicles are defined as station wagon, SUV, pickup and multipurpose vehicles. Small vehicles are sedan, hatchback, coupe and cabriolet. These are models that are imported by the car manufacturers official seller network. Imported models from other actors are not included here.

3 Theoretical framework

There are several explanations for why prices of cars decline over time. One obvious explanation is depreciation. Our study encompasses this effect, but the main focus is on the effect of technological progress. Gasoline vehicles is a mature technology where we expect technological progress to be slower than for electric cars. To fix ideas on the effect of these two factors, we present a simple version of Stolyarov's (2002) model tailored to the secondhand market for cars. This is a dynamic model with an infinite time-horizon for the consumers. We focus on the steady state of the model, i.e. the situation where the number of buyers and sellers of new and used cars is constant over time.

A car has a characteristic x we refer to as its quality. The market consists of a continuum of consumers each described by a parameter h which indicates their valuation of cars. The parameter h follows a distribution over some interval $\Omega \subseteq \mathbb{R}_+$ with cumulative distribution function F. We assume no holes and no mass points. A consumer with characteristic h has an instantaneous utility over cars of quality x and consumption c

given by

$$U = xh + c, \tag{1}$$

where consumption is the income not spent on car purchases. For simplicity and without loss of generality, utility from other consumption in disregarded in what follows. Consumers have a common discount factor $\beta \in (0, 1)$.

Cars last for two periods. In the first period, they provide a quality x_n. The second period, they deteriorate and provide quality $x_u = \mu x_n$ with $\mu \in (0, 1)$. After two periods, the car provides no further benefit.

3.1 The market for cars without technological progress

Consider first the market for cars that do not have technological progress. This can be seen as conventional cars. The technology in this market is mature, and a new car has the same utility characteristic x_n every period. New cars are sold at some exogenously given price p_n. This could correspond to a small country that acts as a price taker in the global market for cars or a competitive car industry with constant returns to scale. Used cars are traded in the secondhand market at a price p_u.

Assume initially that everybody needs a car. Consumers in the market have three options. They can each period buy a new car and sell it after one period, they can buy a new car and drive it for two periods, or they can every period buy a used car. Let U^N, U^K, and U^O denote the utility of these options. Notice that the K group has no impact on the market for secondhand cars except from being an outside option. The main reason for keeping a car throughout it's lifetime rather than either always buying new or second hand cars may be transaction costs. To avoid having to model transaction costs explicitly, we assume that consumers can commit to a two period strategy. Then consumers with moderately strong preference for new cars will chose the intermediate strategy, which acts as a mixing strategy.

We have

$$U^N = x_n h - p_n + \beta(x_n h - p_n + p_u) \tag{2}$$

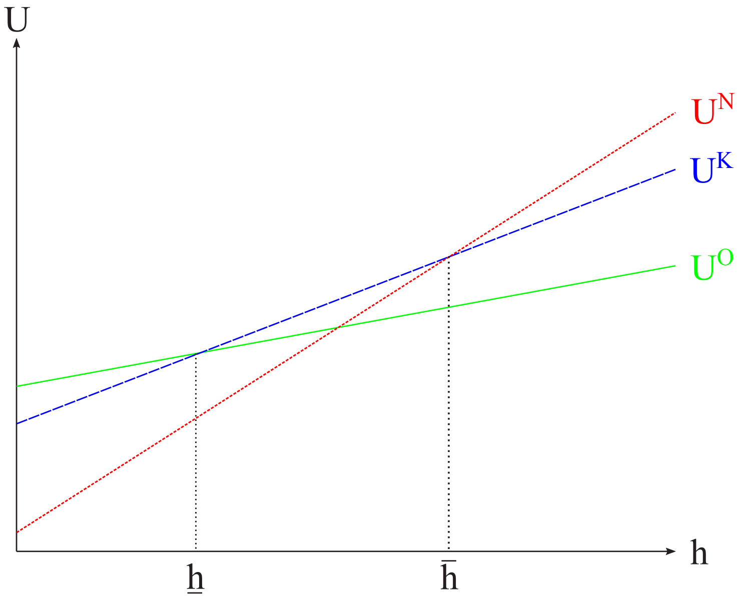
$$U^K = x_n h - p_n + \beta x_u h \tag{3}$$

$$U^O = x_u h - p_u + \beta(x_u h - p_u) \tag{4}$$

The utilities as function of h are illustrated in Figure 3.

Consumers, differentiated though their index h, then choose the option N, K, or O that

Figure 3: Utility of various car ownership strategies by h.



suits their preferences the best. We solve the model by letting consumers make a plan for two periods. The outcome is, however, dynamically consistent so no consumer would like to change her mind in the second period. Whenever the price of secondhand cars is below the price of new cars ($p_u < p_n$), consumer with $h = 0$ prefers O over K and K over N. As the slope of the utility functions is steeper for the latter two, however, consumers with high valuation of car quality (high h) chooses option N, consumers with intermediate h chooses option K, and low valuation consumers choose option O. Specifically, there are levels $\underline{h}$ and $\bar{h}$ so consumers with $h < \underline{h}$ chooses O, consumers with $\underline{h} < h < \bar{h}$ chooses K, and consumers with $h > \bar{h}$ chooses N. The parameters are defined by indifference, so

$$x_u\underline{h} - p_u + \beta(x_u\underline{h} - p_u) = x_n\underline{h} - p_n + \beta x_u\underline{h}$$
$$x_n\bar{h} - p_n + \beta(x_n\bar{h} - p_n + p_u) = x_n\bar{h} - p_n + \beta x_u\bar{h}$$

yielding

$$\underline{h} = \frac{p_n - (1+\beta)p_u}{x_n - x_u}$$
$$\bar{h} = \frac{p_n - p_u}{x_n - x_u}.$$

Equilibrium in the market for secondhand cars requires that p_u is chosen so the number of sellers and buyers of secondhand cars, i.e. the groups N and O, are equal. Using the assumption that the quality of cars deteriorate by a factor μ so $x_u = \mu x_n$, this yields the equilibrium condition

$$F\left(\frac{p_n - (1+\beta)p_u}{(1-\mu)x_n}\right) = 1 - F\left(\frac{p_n - p_u}{(1-\mu)x_n}\right) \tag{5}$$

Implicit differentiation of this expression yields

$$\frac{\partial p_u}{\partial \mu} = \frac{f\left(\underline{h}\right)\underline{h} + f\left(\bar{h}\right)\bar{h}}{(1+\beta)f\left(\underline{h}\right) + f\left(\bar{h}\right)} x_n > 0. \tag{6}$$

Hence, as we should expect, if the quality of a car retained after a period increases, the price of secondhand cars also increases. For the case of electric cars, there is a worry that the battery capacity is declining over time. Usually, batteries will lose one to two percent of their capacity each year (Nichols, 2022). But this depends on how the car is used and charged. There may also be a popular belief that battery degradation is stronger than it actually is. In the model, we can model battery degradation as μ being lower for electric cars than for gasoline cars, and hence having a price that declines faster.

So far in the analysis, we have assumed that all consumers need a car, hence implicitly that the utility of not owning a car is sufficiently low. In many settings, other means of transportation can be a suitable alternative. To include this in the model, we can introduce an outside opportunity of not owning a car yielding a utility level $\underline{U}$. A full analysis of this case can be found in Appendix A.1. This change to the model does not change any qualitative insights from the model, so to maintain simplicity we disregard the presence of an outside opportunity for the rest of the paper.

The solution studied above is a steady state where the price of secondhand cars remains stable. This is a reasonable description of a mature market. However, at the first introduction of cars to the market, there were of course no secondhand car initially. Subsequently the economy converged to an economy where the three groups N, K, and O obtained stable sizes and hence that prices stabilized. We do not think that this dynamic is particularly enlightening to study formally.

3.2 The market for cars with technological progress

Consider now a market for cars with technological progress, i.e. that the utility of a new car is increasing over time. This market can for example be the case of electric cars. The technological progress can be the general comfort of driving the car, but maybe more relevant is the car's driving range and battery capacity. We use this extension to study the market for electric cars and compare the market for secondhand electric and conventional cars. For analytical tractability, we disregard interaction between the two markets.

To account for technological progress, we assume that the utility characteristic x_n of a new car increases by a rate $\gamma > 1$ every period. Seen from a specific period where new cars have quality x_n, next period's new cars have quality γx_n whereas new cars last period were sold with quality $\frac{x_n}{\gamma}$. We still maintain the assumption of a constant price p_n of new cars and study how the price of secondhand cars depend on the rate of technological progress γ.

This implies two changes for the consumers' choice of car ownership option. Consumers always buying new cars (N) face an improved car technology next period, increasing their willingness to sell their used car on the secondhand market. Consumers always buying used cars (O) face an obsolete used car in every period, reducing their utility of the strategy. The new utilities of the three options become

$$\begin{cases} U^N = x_n h - p_n + \beta[\gamma x_n h - p_n + p_u] \\ U^K = x_n h - p_n + \beta\mu x_n h \\ U^O = \dfrac{\mu}{\gamma} x_n h - p_u + \beta(\mu x_n h - p_u). \end{cases} \tag{7}$$

This yields the cut offs

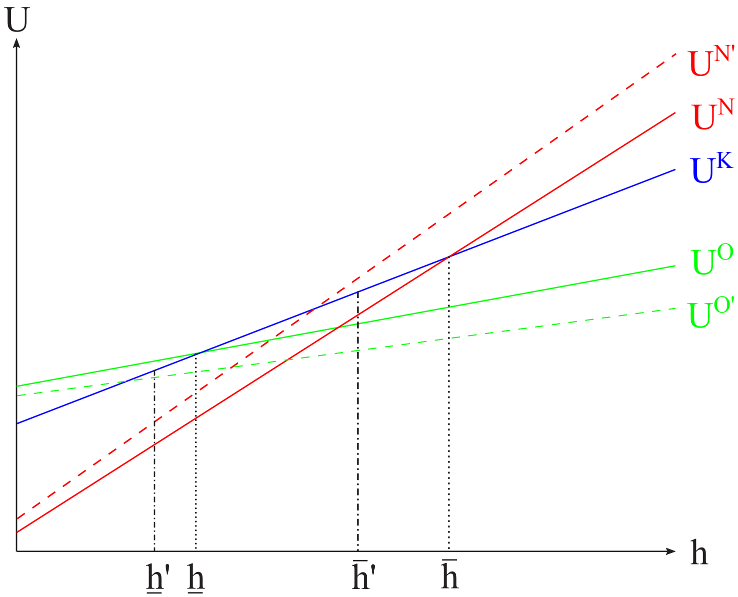
$$\underline{h} = \frac{p_n - (1+\beta)p_u}{\left(1 - \frac{\mu}{\gamma}\right) x_n}$$
$$\bar{h} = \frac{p_n - p_u}{(\gamma - \mu)x_n}$$

and the equilibrium condition becomes

$$F\left(\frac{p_n - (1+\beta)p_u}{\left(1 - \frac{\mu}{\gamma}\right) x_n}\right) = 1 - F\left(\frac{p_n - p_u}{(\gamma - \mu)x_n}\right) \tag{8}$$

An increase in the rate of technological progress initially reduces the utility of the O option and increases the utility of the N option as illustrated in Figure 4. The utility profile of options N and O shifts to $U^{N'}$ and $U^{O'}$. This leads to reductions in both $\underline{h}$ and $\bar{h}$ to levels $\underline{h}'$ and $\bar{h}'$. The first effect leads to reduced demand for secondhand cars, the second effect to increased supply. To maintain equilibrium, the price of used cars has to

Figure 4: The effect of technological progress on the utility of car ownership strategies



Notes: The dashed lines indicate the shift in utility resulting from in increase in the rate of technological progress γ. Subsequent price effects are not shown.

decrease. Specifically, we show in Appendix A.2 that

$$\frac{dp_u}{d\gamma} = -x_0 \frac{f(\underline{h})\underline{h}\frac{\mu}{\gamma} + f(\bar{h})\bar{h}}{f(\underline{h})(1+\beta)(\gamma) + f(\bar{h})} < 0 \tag{9}$$

To see how the speed of technological progress γ affects the size of the secondhand market, we can study $\frac{d\bar{h}}{d\gamma}$. As shown in Appendix A.2, the total effect of increased technological progress on the cut-off for always purchasing a new car can be written as

$$\frac{d\bar{h}}{d\gamma} = -\frac{f(\underline{h})}{(\gamma - \mu)} \times \frac{(1+\beta)\gamma\bar{h} - \frac{\mu}{\gamma}\underline{h}}{f(\underline{h})(1+\beta)\gamma + f(\bar{h})}$$

As $(1+\beta)\gamma\bar{h} > \frac{\mu}{\gamma}\underline{h}$, we get $\frac{d\bar{h}}{d\gamma} < 0$.

The increase in γ increases the utility of new cars and hence tends to reduce $\bar{h}$ as more consumers enter into the N segment. This is the effect illustrated in Figure 4. To maintain equilibrium, the fraction of consumers who always buy used cars (U) increase equivalently, whereas the fraction of consumers who buy new cars and stick with them (K) declines. This is partially offset by a reduction in p_u as it increases the relative price of a new car. This effect, however, is a consequence of the first effect and hence cannot dominate.

This finding is intuitive because the utility of owning a new car increases with technological progress and therefore more people than without technological progress decide to not stick with the car they bought for two periods, but rather decide to buy a new car each period. These are the consumers with quite high values of h, the utility weight on the car's quality.

With the price decline for used cars, consumers who in the market without technological progress would buy a new car in the first period and stick with it for the next, decide to rather buy used cars in both periods. These are the consumers with quite low levels of h. The model therefore predicts larger turnover and a larger second hand market for cars when there is large technological progress.

3.3 Multiple vehicle technologies in the same market

The market we study empirically consists of cars using different fuel types, where our main focus is the difference between electric and gasoline cars. In the model above, we model these as cars where technological progress is still ongoing (immature technologies) and models where technological progress to a larger extent has stagnated (mature technologies). Hence, the consumer has a choice not only between a new and a secondhand car, but also between models where technological progress differs. We do not present a full model of this case but discuss how the preceding framework can be used to understand it.

If the models with technological progress maintain a constant rate of technological improvement, they will eventually completely fill the market at the expense of cars without technological progress. A complete model would have to take this into account, modelling the technological progress as a transition towards a steady state with mature technology that remains at a constant level.

To model that there are consumers preferring both types of cars, we extend the model to the utility function of driving a car with immature technology to

$$U = xh + c + \epsilon,$$

where ϵ, the net utility of the immature technology compared to the mature technology, has a distribution in the population. In general, ϵ can take on any real value indicating either a preference in the direction of mature or immature technologies. This term can be related to technology specific preferences, characteristics such as noise or emission level as well as social image associated with the technology. The utility of driving a car with mature technology remains the same. The prices of new cars of both types are given exogenously. We now find six choice sets for consumers. Consumers can purchase a new car every period and sell it in the secondhand market at the end of the period (N), purchase a used car in the secondhand market every period (O), or purchase a new car every second period and keep it for two periods (K). In all three cases, the consumer can buy a car with mature (m) or immature ($\bar{m}$) technology.

As above, an interesting experiment is to study the effect of increased technological progress γ on the various prices. As for the case with only immature technologies, an increase in γ makes it more attractive to purchase an $\bar{m}$ type car, moving consumers from $K_{\bar{m}}$ to $N_{\bar{m}}$. Second, the increase in γ makes new $\bar{m}$ cars more attractive than new m cars, moving some consumers from N_m to $N_{\bar{m}}$. Both effects increases the supply of secondhand $\bar{m}$ cars. The second effect also reduces the supply of secondhand m cars. To maintain equilibrium in the markets for secondhand cars, we need increased demand of secondhand $\bar{m}$ cars. Hence, the price of secondhand $\bar{m}$ cars goes down.

We should also see an increase in the price of secondhand m cars as their supply is reduced. Hence as long as electric cars undergo more rapid technological progress than gasoline cars, we expect the price of secondhand electric cars to decrease relative the price of secondhand gasoline cars.

4 Data, descriptive statistics and empirical strategy

4.1 Data

In our analysis we use a novel data set from the largest web platform for secondhand vehicles in Norway, finn.no, which accounts for close to 90% of the secondhand car market. This is the first time the data is used for this kind of analysis. Finn.no provided us with the data.

The data cover the period January 2011 to June 20 2021. We start our analysis in 2011 because the Nissan Leaf was introduced to the Norwegian market at the end of this year.[7] Nissan Leaf being the first modern electric five-seat vehicle to be produced for the mass market from a major manufacturer, this corresponds to the start of the mass market for electric cars in Norway.

We analyze passenger vehicles sold as new in 2011 or later. This means that we only have vehicles that are 10 years or younger in our analysis. The total number of observations in the data is 5.5 million, yielding on average 500,000 ads for secondhand vehicles on

[7]Nissan Leaf was first sold to the Japanese and American market in the end of 2010.

finn.no each year. Around 2.9 million cars are older than 10 years and around 1.2 of the 2.6 million that are left have been advertized with less than 3 month in between, and we define them as duplicates and only use the newest ad. Then the total number of observations is 1.4 million. The vehicles that are gasoline or electric vehicles and 10 years or younger are in total around 545,000 observations. The number of vehicles of the different fuels can be seen in Appendix Table A-3.

In addition to the data from the online platform, we have list prices for new vehicles from The Norwegian Road Federation (OFV). The Norwegian Road Federation is a membership organization for car importers, transport companies and other actors within transportation, and have a role as producer of statistics about the car sale in Norway. They also gather price information from the car importers and delivers the official list prices to the tax authorities that use them to calculate wealth tax. The data from The Norwegian Road Federation also categorizes the vehicles into different body style categories.[8]

Further, we have information about the driving range of the electric vehicles, collected from the Norwegian Electric Vehicle Association's website that informs about the different electric vehicle models (The Norwegian Electric Vehicle Association, 2022a).[9] We also have access to a survey of Norwegian electric vehicle owners conducted by the Norwegian Electric Vehicle Association. There is around 15,000 respondents in the survey.[10] Additional details about the data and the variables can be found in Appendix B.

Notice that information on some variables is incomplete. From the platform data, we have the ask prices, but not the price the vehicle is actually sold for as there can be haggling over the prices. However, measurement error in the outcome variable is generally unproblematic as long as this is not a systematic measurement error. Further, we don't know whether a transaction has actually taken place, but for most it probably has.

Each ad is one observation each month. The average time to sell a car on finn.no is less than a month (The Norwegian Electric Vehicle Association, 2021a). We remove duplicate data entries based on a combination of the chassis number, dealer type, effect, engine volume, fuel, main color, make, model, municipality of the seller, transmission wheel drive, year model, the year the vehicle is first registered and number of seats. If the same car is advertized with 3 months or less interval, it is defined as a duplicate. This means that if the same car is advertized two months in a row, only one of the ads

[8] The vehicle body is the main supporting structure of the car (such as windows, doors, engine cover, roof and luggage cover) and defines the shape and the size of the car. The body style can be used to classify the car market into different segments or size classes. However, in Europe there is no official definition of size classes based on objective criteria. See Appendix B.2.3 for more details on this issue.

[9] The standard for measuring driving range is WLTP and if NEDC is the only number available, we reduce the driving range by a factor of 0.65 (J.D. Power, 2020). This is an important number and we do robustness check with a factor of 0.75, based on The Renault Group (2020).

[10] 2021: 15,464 respondents, 2020: 14,170 respondents, 2019: 16,216 respondents.

is part of the analysis. We use the ad that is newest in the analysis, because the price of the newest ad is probably the closest to the deal price.

If the car is advertised with the same price more than three times, even if it is advertized with some time interval it is likely that the car is not sold at all. Therefore, observations that are duplicates and the price is the same for three ads are taken out of the analysis. Note that we have already taken out the observation of the analysis if a car is advertized with less than 3 months in between each ad, no matter if the price is the same or not.

Most cars come in different trims, which are different versions for each models with different equipment level. We do not have consistent data on trim levels of the model that is advertised. As the price of the new vehicle can vary a lot depending on trim, but also e.g. battery capacity, engine size and body style, the price of the new vehicle can have a large interval. We take this into account in one empirical specification by removing models where the relative difference between the maximum and the minimum price of one model exceeds 1.5. This does not change the result much.

4.2 Descriptive statistics

In the analysis we compare electric vehicles and gasoline vehicles. Cars of both fuel types are maximum 10 years old. There are roughly 367,000 gasoline vehicles and 179,000 electric vehicles in the sample, which means that the share of electric vehicles in the sample is around 1/3 and gasoline vehicles around 2/3 (see Table 1). Among the gasoline vehicles, about 2/3 are small and 1/3 is large, while for electric vehicles there are fewer large vehicles available (11% of the sample), which is natural when we recall that the supply of large electric vehicles has been limited up until recently.[11] In 2011 there are 32 times more gasoline vehicles as electric vehicles. By 2016, this number is reduced to 4, while there are more electric vehicles than gasoline vehicles sold used in 2021 (see Table A-4 in Appendix C).

Table 1: Number of vehicles based on size

	Gasoline	Electric	Gasoline	Electric
Total	366 586	178 866	67%	33%
Small	249 307	155 278	68%	87%
Large	112 077	20 131	31%	11%
Not categorized into size classes	5202	3457	1%	2%

Small: Sedan, coupe, cabriolet and hatchback.

Large: SUV, station wagon, multipurpose vehicle and pickup.

[11] Small cars are defined as sedan, hatchback, coupe and cabriolet, while large cars are defined as station wagon, SUV, pickup and multipurpose vehicles. We have done this categorization.

Table 2: The electric vehicle sample

	Number	Share	Mean age
Range below 200 km	100 124	56.0%	3.36
Range [200 km-300 km)	18 989	10.6%	1.45
Range [300- 400 km)	30 618	17.1%	2.32
Range [400- 500 km)	18 231	10.2%	1.09
Range equal to or over 500 km	10 369	5.8%	1.64
Range missing	535	0.3%	3.65

Electric vehicles in the sample are younger than the gasoline vehicles. Average age is 2.7 for electric vehicles, while for gasoline vehicles the average age is 3.5, see more details in Table A-5. The number of secondhand vehicles that are from 2011 or later that are advertised on finn.no every year can be seen in Table A-4 in the Appendix. 56% of the electric vehicle sample has range below 200 km and only 16.2% 400 km or above (Table 2). The mean driving range each year is lower for the used vehicles than the new vehicles, which underlines the fast technological development, see Appendix Table A-6.

The market for gasoline vehicles are more varied then the market for electric vehicles, which is natural when we recall that there are fewer electric models available than gasoline models. The secondhand electric vehicle market is dominated by Nissan Leaf with about 1/5 of the market. In Appendix Table A-8 we see the top ten models in the secondhand market for electric and gasoline vehicles.

4.3 Empirical strategy

A car i is sold new (time $t = 0$) at price P_{i0} which we treat as exogenous. We assume that the resale value follows a process so that at time t it is

$$P_{it} = A_i B_i^t P_{i0}^{\mu} e^{\epsilon_{it}}, \tag{10}$$

where A_i is a car specific characteristic to be detailed below. We assume that secondhand vehicle prices decay exponentially with an annual rate $1 - B_i$. The parameter μ is the pass-through of the new price, and ϵ_{it} is the stochastic error term.

In order to find the annual percentage drop in prices, we take the logarithm of equation (10) which leads us to the following equation where lower case letters denote logs of variables:

$$p_{it} = a_i + \beta_i t + \mu p_{i0} + \epsilon_{it} \tag{11}$$

The key parameter of interest is β_i, the annual percentage decline in prices.[12] As we only observe each vehicle at one point in time (when it is sold in the secondhand market), the specific β_i for each car is not observable. In stead we exploit that vehicles are sold at different ages in the secondhand market and estimate a fuel-specific β_f. The rate is potentially specific within other categories than the fuel, such as the make, the driving range of the electric car, the price category of the new vehicle, the size and the vintage.

The variable a_i is a composite of several characteristics, including range for electric vehicles, mileage, make reputation, fuel and size. We control for these features. First, by including a fuel specific coefficient (γ_f) on log mileage, m_{it}, at the time the vehicle is sold in the secondhand market. Second, we add fixed effects for make (θ_m), size (measured by body style or weight, ζ_s) and fuel times year ($\alpha_{t\times f}$).[13] As the market for electric vehicles are changing each year, it makes sense to have a different control for each fuel each year. For instance is the supply of fast charging stations increasing each year and we control for that with fuel times year fixed effects.

We also control for type of dealer by adding dealer fixed effects (ω_d). There are three different dealer categories: private seller, professional importer of that specific brand and professional car sellers, and there might be selection into what cars are sold from which type of seller.[14] Cars that are similar in age, fuel, make, model and mileage, but are sold by different types of dealers, might be different and we control for this. There is a statistically significant difference between the price fall of the different sellers, as shown in Table A-19 in Appendix D, so we believe it is useful to control for the dealer type.

A vehicle i of make m with fuel type f and size category s sold in year t from a dealer of type d that was new in year n gets a price

$$p_{i,t} = \beta_f t + \alpha_{t\times f} + \theta_m + \zeta_s + \omega_d + \mu p_{i,n} + \gamma_f m_{i,t} + \epsilon_{i,t} \tag{12}$$

The standard errors are clustered on the make (m).

We assume a linear annual percentage fall in prices in the main specification, but we also investigate the price fall with a squared age term. In addition we investigate the secondhand prices non-parametrically in Figure A-2.

If price at time n, $p_{i,n}$, is unknown for some reason, we introduce a dummy for missing variables. This implies simply following the price path downward without information of

[12]As long as β_i is small, we have $\beta \approx ln(1+\beta)$ or $\beta_i = ln(B_i) \approx B_i - 1$.

[13]One challenge is that some car makes only make gasoline cars and some only make electric cars. However, as make fixed effects are additive and the price decline β_f is not make×fuel specific, this does not pose a threat to identification.

[14]The share of vehicles based on seller can be seen in Table A-7.

the initial price. We check whether the results are the same without the dummies (and therefore without the observations without new vehicle price) in Table A-23.

We could also use the price on the same car model as new at the same time as when the used car is sold, rather than when the used car was new. However, the correlation coefficient between the price when the car was new and the price of the new car when the car was sold is above 0.9. Therefore we use the price when the used car is new.

5 Results

In this section we first estimate the effect age has on secondhand prices, both year-by-year price decline and average annual decline. Then we look at range on electric vehicles interacted with age. These are our main findings. In addition we have estimated quantiles instead of the mean for used vehicle prices. Further we have investigated different size categories, new vehicle price percentiles and vintage effects. We also compare electric vehicles with diesel and other fuels, before we turn to other factors affecting the price path. At the end of the chapter we discuss robustness.

5.1 The price fall of electric vehicles compared to gasoline vehicles

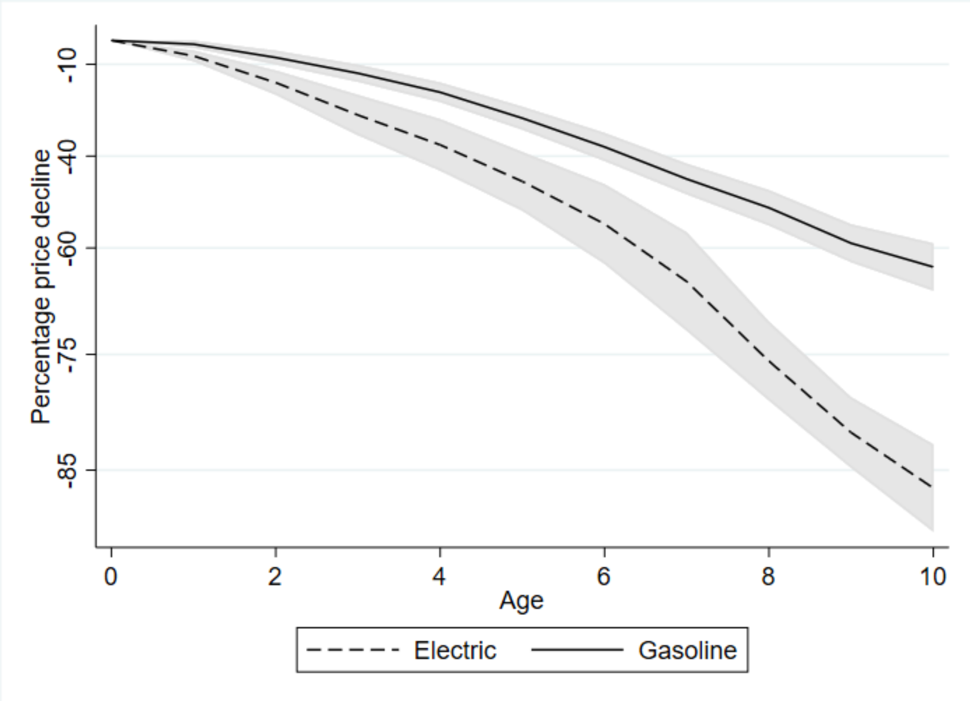
From Figure 5, we see that the overall picture is that while the price of second hand gasoline cars drops by about 60% after 10 years, the price fall for electric cars is even stronger at about 85%. In Table 3, we show that this holds across a range of specifications. Here, different versions of regression equation (12) are shown. Gasoline vehicles is the baseline, and we see that the annual price drop for gasoline vehicles is approximately 10-11%. The price on electric vehicles fall between 4.7-6.4% more than gasoline vehicles, which is 16-17% annually. The difference between gasoline and electric vehicles is statistically significantly at least on a 5% level in all specifications, giving a clear indication that electric cars fall more quickly in price than gasoline cars.

In column (1) we control for year $\times$ fuel fixed effects, which absorb influences of all omitted variables that differ from one year to the next for each fuel type but are constant over all vehicles of the same fuel type in each year. This can for instance be development of fast charging stations or other year specific events for electric vehicles or for gasoline vehicles. In addition, we control for dealer fixed effects in all specifications, except in column (5), where we show the results without dealer fixed effects.

In column (2) we add body style fixed effects to year $\times$ fuel fixed effects.[15] The difference

[15]There are eight different body style categories: sedan, hatchback, coupe, cabriolet, station wagon,

Figure 5: The price path for gasoline and electric vehicles



Notes: The grey areas are 95% confidence intervals. The standard errors are clustered on make. There are 62 clusters. The regression includes year times fuel fixed effects and dealer fixed effects and we control for mileage, vehicle price when new and whether the new vehicle price or mileage is missing.

between gasoline and electric vehicles does not change much compared to column (1).

In column (3) we add make fixed effects to the year × fuel fixed effects. The dummy variables for the makes absorb the influences of all omitted variables that differ from make to make, but are constant over time. The difference between gasoline and electric vehicles reduces by 1.3 percentage points compared to column (1), indicating that the price fall varies between different makes and when only looking at the price fall within each make, the price fall on electric vehicles is lower (but slightly higher for gasoline vehicles). However, the difference in price fall between electric and gasoline vehicles is still statistical significant. We investigate the price fall for specific makes further in Appendix Figure A-6 and in Appendix Section D.1.

In column (4), we take out the vehicles that have a large variation in new vehicle prices. This reduces the sample from around 550,000 to around 340,000. It could be that the

SUV, pickup and multipurpose vehicles, defined by The Norwegian Road Federation (OFV), see Appendix B.2.3.

Table 3: Comparing gasoline and electric vehicles.

	(1)	(2)	(3)	(4)	(5)
Age	-0.105***	-0.103***	-0.109***	-0.112***	-0.111***
	(0.00462)	(0.00433)	(0.00404)	(0.00546)	(0.00444)
Electric × Age	-0.0638***	-0.0632***	-0.0468**	-0.0567***	-0.0584***
	(0.0188)	(0.0193)	(0.0198)	(0.0171)	(0.0194)
Ln new price	1.068***	1.046***	0.998***	1.088***	1.062***
	(0.0242)	(0.0302)	(0.0305)	(0.0290)	(0.0238)
Ln mileage × Gasoline	-0.0770***	-0.0776***	-0.0757***	-0.0608***	-0.0775***
	(0.00773)	(0.00657)	(0.00761)	(0.00542)	(0.00772)
Ln mileage × Electric	0.0170	0.0190	-0.00448	0.0123	0.00939
	(0.0121)	(0.0124)	(0.00855)	(0.0145)	(0.0120)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	545 452	545 452	545 452	336 220	545 452
R^2	0.859	0.861	0.879	0.902	0.857

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but specification (4), where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

models that vary a lot in prices as new also have other characteristics that influence the price decline, so this is not our main specification, but a robustness test. We see that the coefficients do not change a lot and that the difference is still statistically significant.

In column (5), we show the results without controlling for dealer fixed effects. The difference between electric and gasoline vehicles stay in the same magnitude and remain statistically significant.

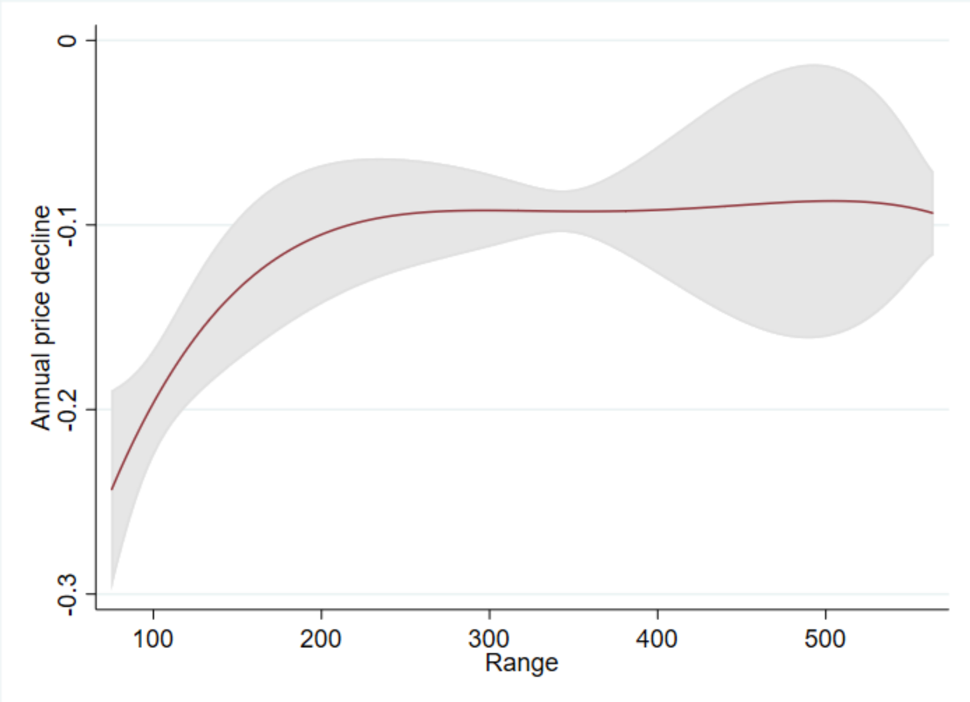
We see that mileage is not an important factor for the price of used gasoline vehicles, and even less important for electric vehicles, when age is taken into account. Each percentage increase in mileage is associated with a price fall of around 0.07% for gasoline vehicles. This might be due to age and mileage being closely correlated (see Appendix Figure A-1). For electric vehicles mileage is not statistically significant in any of the specifications in Table 3, but in some other specifications shown in the appendix. However, the magnitude of the effect is small.

In Figure 5 we show the results from a regression with age dummies interacted with the fuel type. We control for mileage interacted with fuel, new vehicle price, a dummy on those with missing on mileage and new vehicle price, year $\times$ fuel fixed effects and dealer fixed effects. We see that electric vehicles drop faster in price compared to gasoline vehicles. Moreover, the price decline appears to increase over time. The price fall curve seem to be concave and in Table A-9 in Appendix D we investigate whether the concavity is statistically significant by adding an age squared term. The concavity is statistically significant for both technologies, and electric vehicles are statistically significant more concave than gasoline vehicles.

5.2 Range and age

One factor that has increased significantly over the 10 years we look into, is driving range. Range can be seen as a proxy for technological development. We investigate whether the price decline is different for different ranges. Figure 6 shows a version of Equation 12 where the coefficient on age is modelled as a fourth grade polynomial of range. The Figure shows clearly that it is vehicles with range below 200 km that have the largest price decline. The secondhand prices on vehicles with range over approximately 200 km decline at the same level as gasoline vehicles (around 10% annually, see Table 3). However, over half of the electric vehicle sample is vehicles with range below 200 km. The vehicles with range from 200 km and upwards have mean age of 1.74 years, median of 1 year and the highest age is 8 years. We therefore do not have a sample where those with the longer range than 200 km have been in the car market for many years. This is therefore an important question for further investigation when the electric vehicle market has developed further.

Figure 6: The price decline for electric cars with different driving range.



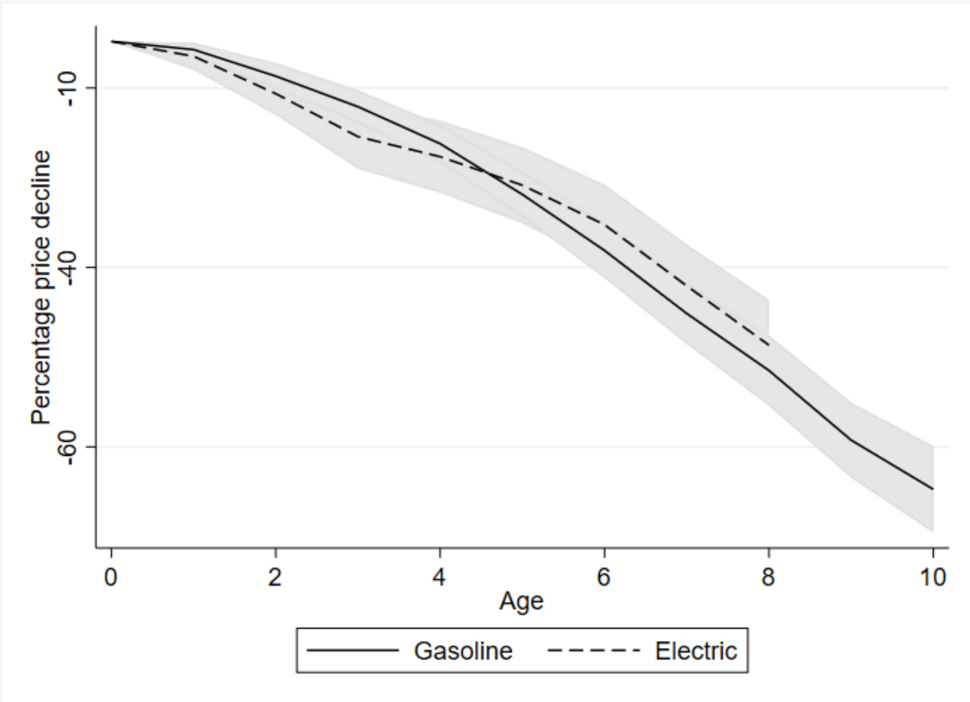
Notes: This is the regression in Equation 12 with a fourth grade polynomial of range interacted with age. Range is WLTP standard. If NEDC is the only available range, we reduce the range by a factor of 0.65 (J.D. Power, 2020). The grey areas are 95% confidence intervals. We start the graph where the sample range start: 76 km range. There are 28 observations with 663 km range. The rest of the sample has a maximum of 564 km. Therefore the graph ends at 564 km. We do a robustness check for the factor converting between NEDC and WLTP and increase it to 0.75. This can be seen in Figure A-3.

In Figure 7 we see that when we take out the electric vehicles with range below 200 km of the analysis, the difference in price decline between gasoline and electric vehicles is no longer present. In Appendix Table A-10 we have the same sample, and the electric vehicles actually decline less in price than gasoline vehicles. However, the comparison between electric and gasoline vehicles might not be of same-sized cars, as electric vehicles with range below 200 km are small cars, while for gasoline vehicles the sample is all sizes.

5.3 Additional findings

We show conditional quantile regression on the 25th, 50th, 75th and 90th percentile in Appendix Table A-11. Instead of estimating the mean of the used vehicles price, as OLS does, quantile regression in this case estimates the median, the 25th, 75th and the 90th

Figure 7: The price path for electric vehicles with range from 200 km and upwards and gasoline vehicles.



Notes: The range is measured with WLTP standard. If NEDC is the only available range, we reduce the range by a factor of 0.65 (J.D. Power, 2020). The grey areas are 95% confidence intervals. The standard errors are clustered on make. There are 59 clusters. The curve for electric vehicles stop at 8 years because there is no older electric vehicles with range from 200 km and more. The regression includes year times fuel fixed effects and dealer fixed effects and we control for mileage, vehicle price when new and whether the new vehicle price or mileage is missing.

percentile of the used vehicle price conditional on age and the other control variables. The quantile regression shows a clear pattern: the least expensive electric vehicles have a larger price decline compared to gasoline vehicles than the most expensive cars. Price and range are highly correlated. The price fall difference between gasoline and electric vehicles is statistically significant for all percentiles we have investigated.

We compare different size categories based on either body style or weight in Appendix Table A-12. Large electric vehicles do not have a statistically significant larger price fall than gasoline vehicles. Depending on how size is defined, it might seem that large electric vehicles have a smaller price decline than large gasoline vehicles. However, this is uncertain as electric vehicle with the same size as a gasoline vehicle weigh more due to the batteries, but it is uncertain exactly how much more.

We investigate whether there are vintage effects. With vintage effects we mean that there are different price decline pattern for the vehicles that are new in the first part of the period (2011-2015) than the vehicles that are new in the second part (2016-2021). The results are shown in Table A-13. The price decline of electric vehicles compared to gasoline vehicles in the first period is around 1 percentage point higher than in the second period (column 1), and within each make the difference between vintages is 1.5 percentage points.

We split the sample into different subgroups in order to investigate whether and how the price decline difference between the two technologies are present in different subgroups. We compare vehicles in different price categories when they were new in Appendix Table A-14.[16] For the vehicles that are priced when new equal to or above the median or equal to or above the 75th percentile the electric vehicles decline less in price than the gasoline vehicles. For vehicles that are below the median in new vehicle price the electric vehicles decline more than gasoline vehicles. This can be due to range, but also other factors. We see in Table A-6 that there is a large difference in range for the cars that are above and below the median.

We also group the sample into different time periods based on when they were new (Appendix Table A-15), when they were sold (Appendix Table A-16) and different age groups (Appendix Table A-17). The difference in price fall between gasoline and electric vehicles is statistically significant for all subgroups, except for those new in 2014-2016 and those sold in 2018-2021.

5.4 Diesel and other fuels

We compare electric vehicles with gasoline vehicles which is a mature technology. Diesel vehicles could also be included in the analysis, but the price path of diesel vehicles will not just represent vehicle technology that are mature, but a vehicle technology that policymakers want to phase out, to a larger degree than gasoline vehicles. Diesel cars had a large advantage from the Norwegian car tax system in 2007-2011, and the diesel share of the new car market was above 70% during this period. From 2012 the car tax system was changed in order to reduce the diesel share. Because other things than being a mature technology is important for the price path of diesel vehicles, they are not in the main analysis.

We present the results for diesel vehicles and the other fuels in Table A-18 in Appendix D. This shows that electric vehicles fall more in price than all other fuel types, including diesel vehicles. However, the difference in price drop between diesel and electric vehicles

[16] We have calculated the statistics for new vehicle price weighted by the vehicles of all fuel types that are advertized on finn.no. The statistics is not differentiated by fuel.

is only statistically significant in some specifications.

5.5 Other factors affecting the price path

5.5.1 Battery degradation

Degraded batteries or a worry of degraded batteries may be a reason for the price fall on electric vehicles. Degradation of batteries was a concern when the modern electric vehicles market had just started, but anecdotal evidence in the media and correspondence with experts in the sector point in the direction that rapid degradation, rendering batteries useless, is not a large problem (Kelleher Environmental, 2019).[17] However, this is a question that warrants further investigation.

The warranty that are given by the car manufacturers can give some indication of the life length of batteries. Nissan has a warranty of 8 years for the vehicles sold in 2016 and onward,[18] guaranteeing the batteries are 75% of its original state. From 2014 Tesla has a warranty that the battery maintain 70% of its original state for 8 years or a kilometer stand of 160,000-240,000 km depending on the model. Hyundai Ioniq guarantees 8 years/200,000 km. This indicates that the car sellers are confident about the battery lifetime.

Even though the batteries last long, a 25-30% degradation of the batteries might be enough to reduce the price of the vehicle, especially if the range is already quite low. Whether this is the case cannot be found with the data from finn.no. To investigate the battery question further, we have looked into a survey among Norwegian electric vehicle owners conducted by the Norwegian Electric Vehicle Association.[19] For the years 2019-2021 they were asked whether the battery capacity in their car has become considerably lower since it was new.[20] Notice that the survey does not provide a clear definition of the term "considerably lower". Still it gives an indication of the state of the battery. Respondents answer on a 1-5 Likert scale range, and the higher the score the better experience do the consumer have with the battery.

In Figure 8 we see the share of respondents who experience that the battery capacity is considerably lower since the car was new (answering 1 or 2 on the survey question). When the car is between 0-3 years the share is around or below 10%. Between 4 and 6 years the share is lower than 30%. Between 7 and 8 years-old the share is between 20 and

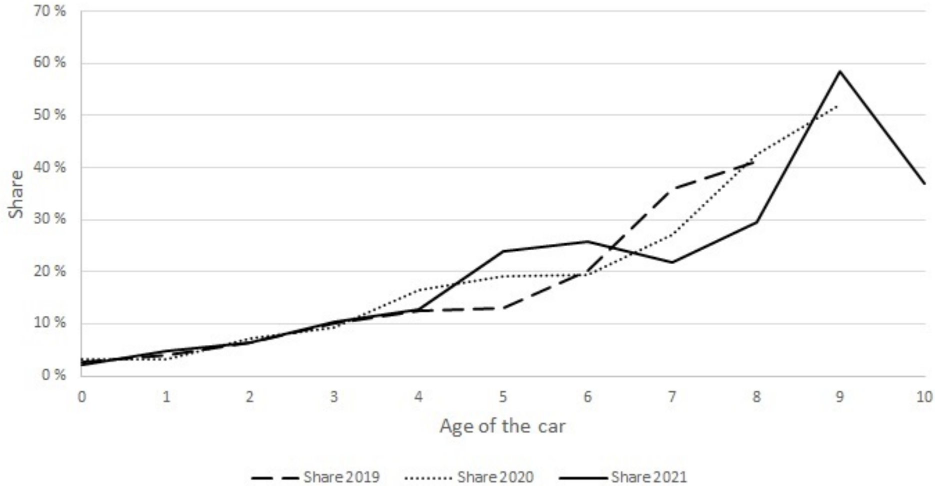
[17] Email correspondence with researchers at NTNU and SINTEF and phone conversation with a representative from a car recycle company (Bilgjenvinning AS), which has 45% of the car recycling market.

[18] 5 years for the Leafs between 2011 and 2015

[19] We have not looked into whether those that answer the survey are representative of electric vehicle owners in Norway.

[20] They were also asked the question in 2018, but in that round of the survey they don't report the year the car was new so we do not know the age of the car.

Figure 8: Reported battery degradation by vehicle age



Notes: The figure shows the fraction of respondents who report that they experience that the battery has degraded (score 1 or 2 out of 5) since the car was new.

45%. The 9 year-olds have shares between 50 and 60% and 10 year-olds down to 37%. However, the sample size is low for the 9 and 10 year-olds (below 100 for each year).

The mean score for 5 year-old electric vehicles is 3.4 in 2021, 3.5 in 2020 and 3.8 in 2019, which means that the mean score has gone down from 2019 to 2021. This can be seen in Figure A-5 in Appendix D. The mean score for 8 year-old electric vehicles is 3.3 in 2021 and 2.9 in 2019 and 2020, which means that the mean score has gone up from 2019 to 2021. For nine year old cars the score is lower with 2.5 in 2021 and 2.8 in 2020, but again: the sample size is low.

From this information we cannot exclude the possibility that some of the price fall for electric vehicles is due to some degradation of the batteries, but the information does not indicate that degradation of the batteries drives the whole price fall on electric vehicles. However, we can not be conclusive on this matter. Another important point is that cars with short range has to be charged more often than cars with longer range. Therefore, as charging reduces the quality of the battery, the cars with short range might have more degraded batteries and as the battery technology improves, battery degradation might also reduce.

5.5.2 Maintenance cost

Gasoline vehicles typically have higher maintenance cost when they are older. Besides the battery degradation, this is not the case for electric vehicles, though.[21] Therefore, without technological change and battery degradation, electric vehicles should have a *higher* price on the secondhand car than gasoline vehicles if the two technologies are otherwise equal.

5.5.3 Supply side constraints

There have been – and still are – supply side constrains on electric vehicles, both that the models that fit the preferences of different consumers are not available and that there are waiting lists on popular electric vehicles. The number of individuals on the waiting list that actually end up buying the car when given the possibility is not public information. The waiting lists might also be part of a marketing strategy, as simply raising the price on the car would seem to be a more straightforward approach. We don't know if and how the supply side constrains affect the secondhand car market, but we can assume that it had a positive effect on the price in the secondhand electric car market. Hyundai Kona, for instance, has been advertised with higher price on finn.no than the price on the new vehicle, but we do not know whether the vehicle is sold for this price. If waiting lists have influenced the used car market, the effect is probably that the price fall on electric vehicles is lower than without the waiting lists. This means that without supply side constraints the price fall on electric vehicles would probably be higher, especially on large electric vehicles.

5.6 Robustness

We check whether the main results hold under other specifications than in Table 3. The difference in price fall between gasoline and electric vehicles is statistically significant in all robustness checks, except with absolute values instead of log values when we include make fixed effects. We use all variables available, such as transmission, wheel drive and main color. In addition, instead of using the price when the vehicle was new as control, we use the new car price the year the vehicle was sold used. Especially for electric vehicles the price of new vehicles might change in a non-linear way because of new models entering the market and reducing prices on existing models (The Norwegian Electric Vehicle Association, 2021b). The price fall difference when we do not control for dealer fixed effects and at the same time control for new vehicle price when the vehicle was sold is very high (Table A-20, column 5), indicating that the private sale of electric vehicles and gasoline vehicles is different. We also test whether the main results hold

[21] See for instance Green Cars (2021).

when we drop the observations that are 0 years old when they are sold on finn.no. We also take out the dummies on those that miss the control variables new vehicle price and mileage (which result in a smaller sample). In addition we do the regression with absolute values, instead of log values. We also show the results when clustering the standard errors differently, both with make × fuel and make × the year the vehicle is new. The standard errors are as expected somewhat smaller with more clusters, but the statistical significance stay at the same level. The robustness checks are reassuring for the main result. See more details in Appendix E.

6 Conclusion

In this article we have investigated whether the price of electric vehicles decline faster than the price of gasoline vehicles. We have found empirical evidence that they do, but only those with range below 200 km. Our hypothesis is that the faster price fall on electric vehicles compared to gasoline vehicles is mostly due to faster technological development. As the adoption of electric vehicles is increasing, this is relevant information for more consumers in more markets. The valuation of electric vehicles that are ten years or younger in 2021 is a snapshot that might change as the improvements of the technology of electric vehicles flattens out. Comparing the results of this analysis with an analysis that is done 2-10 years later will be interesting. It will especially be interesting to see how the price path of the electric vehicles with longer range than 200 km develops. As the electric vehicles with range from 200 km and upwards is still young, we need to wait some more years to get the full picture of the price path of electric vehicles with longer range. Further, the price path of other technologies with rapid improvements would be interesting to investigate.

Our findings do not directly answer whether buying an electric vehicle is an economic sensible choice. Even if electric vehicles with less range than 200 km have fallen more in price the last decade than gasoline vehicles, there are other factors than value loss that influence the total cost of ownership of a vehicle. Electric vehicles have lower maintenance cost and lower fuel cost compared to vehicles with internal combustion engine. The batteries can be reused for other purposes and the car can be recycled (Kelleher Environmental, 2019). In addition, electric vehicles are subsidized in many countries, making new technology cheaper for consumers (IEA, 2021).

The maturity of a technology might depend on the adoption rates in combination with other factors (Pathak et al., 2022, p. TS-128-129). Therefore the findings of our paper should not be used as an argument for delaying the deployment of new low-carbon technologies. Rather, the findings may be used to inform about the cost of implementing climate policies. The value of the secondhand products matters for the total cost of ownership of the good, which again matters for the cost of climate policy. The Norwegian government, for instance, has a goal that "the purchase of zero-emission cars should be more economically favourable than the purchase of conventional cars" (Meld. St. 33, 2016-2017). When comparing whether it is favourable to buy an electric vehicle compared to a gasoline vehicle, it is important to take into account also the difference in the value of the used car, not just the price of the new car. This point can be transferred to other low-carbon technologies with fast technological progress. At the same time, many actors are working on finding new business models for batteries that are no longer in use in a car (see for instance Evyon (2022)). This indicates that even if products with fast technological development deteriorates faster, they are not without value.

This paper is an investigation into how the price path of different technologies develops over the life-time of the car. We have looked into some heterogeneities related to range, price and size. It could be interesting to investigate further which factors influence the vehicle price and the price fall, for instance using causal forest approaches.

References

Acemoglu, D., Aghion, P., Bursztyn, L., & Hemous, D. (2012). The environment and directed technical change. *American Economic Review*, *102*(1), 131–66.

Adda, J., & Cooper, R. (2000). Balladurette and Juppette: A Discrete Analysis of Scrapping Subsidies. *Journal of Political Economy*, *108*(4), 778–806.

Aghion, P., & Howitt, P. W. (1998). *Endogenous growth theory.* MIT press.

Akerlof, G. A. (1970). The market for "lemons": Quality uncertainty and the market mechanism. *The Quarterly Journal of Economics*, *84*(3), 488–500.

Archsmith, J., Muehlegger, E., & Rapson, D. S. (2022). Future Paths of Electric Vehicle Adoption in the United States: Predictable Determinants, Obstacles, and Opportunities. *Environmental and Energy Policy and the Economy*, *3*(1), 71–110.

Balcer, Y., & Lippman, S. A. (1984). Technological expectations and adoption of improved technology. *Journal of Economic Theory*, *34*(2), 292–318.

Barrett, S. (2009). The coming global climate-technology revolution. *Journal of Economic Perspectives*, *23*(2), 53–75.

Berry, S., Levinsohn, J., & Pakes, A. (1995). Automobile prices in market equilibrium. *Econometrica*, 841–890.

Bloomberg. (2020). *Batteries for electric cars speed toward a tipping point.* https://www.bloomberg.com/news/articles/2020-12-16/electric-cars-are-about-to-be-as-cheap-as-gas-powered-models

Bloomberg. (2021a). *Battery price declines slow down in latest pricing survey*. https://www.bloomberg.com/news/articles/2021-11-30/battery-price-declines-slow-down-in-latest-pricing-survey

Bloomberg. (2021b). *EV battery prices risk reversing downward trend as metals surge*. https://www.bloomberg.com/news/newsletters/2021-09-14/ev-battery-prices-risk-reversing-downward-trend-as-metals-surge

Bond, E. W. (1982). A direct test of the "Lemons" model: The market for used pickup trucks. *The American Economic Review*, *72*(4), 836–840.

Bond, E. W. (1983). Trade in used equipment with heterogeneous firms. *Journal of Political Economy*, *91*(4), 688–705.

Brückmann, G., Wicki, M., & Bernauer, T. (2021). Is resale anxiety an obstacle to electric vehicle adoption? results from a survey experiment in switzerland. *Environmental Research Letters*, *16*(12), 124027.

Chen, C.-W., Hu, W.-M., & Knittel, C. R. (2021). Subsidizing Fuel-Efficient Cars: Evidence from China's Automobile Industry. *American Economic Journal: Economic Policy*, *13*(4), 152–84.

Chen, J., Esteban, S., & Shum, M. (2013). When do secondary markets harm firms? *American Economic Review*, *103*(7), 2911–34.

Commission of the European Communities. (1999). Case No COMP/M.1406 - HYUNDAI / KIA. https://ec.europa.eu/competition/mergers/cases/decisions/m1406_en.pdf

Copeland, A., Dunn, W., & Hall, G. (2011). Inventories and the automobile market. *The RAND Journal of Economics*, *42*(1), 121–149.

Danielis, R., Scorrano, M., Giansoldati, M., & Rotaris, L. (2019). *A meta-analysis of the importance of the driving range in consumers' preference studies for battery electric vehicles* (Working Papers 19_2), SIET Società Italiana di Economia dei Trasporti e della Logistica.

De Groote, O., & Verboven, F. (2019). Subsidies and time discounting in new technology adoption: Evidence from solar photovoltaic systems. *American Economic Review*, *109*(6), 2137–72.

Dhakal, S., Minx, J., F.L. Toth, A. A.-A., Meza, M. F., Hubacek, K., Jonckheere, I., Kim, Y.-G., Nemet, G., Pachauri, S., Tan, X., & Wiedmann, T. (2022). Emissions Trends and Drivers. In P. Shukla, J. Skea, R. Slade, A. A. Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, & J. Malley (Eds.), *IPCC, 2022: Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK; New York, NY, USA.

Esteban, S., & Shum, M. (2007). Durable-goods oligopoly with secondary markets: The case of automobiles. *The RAND Journal of Economics*, *38*(2), 332–354.

Evyon. (2022). Planet-friendly battery energy storage systems. https://www.evyon.com/

Fudenberg, D., & Tirole, J. (1998). Upgrades, tradeins, and buybacks. *The RAND Journal of Economics*, 235–258.

fueleconomy.gov. (n.d.). Frequently Asked Questions. https://www.fueleconomy.gov/feg/info.shtml%5C#sizeclasses

Gavazza, A., Lizzeri, A., & Roketskiy, N. (2014). A quantitative analysis of the used-car market. *American Economic Review*, *104*(11), 3668–3700.

Gillingham, K., Iskhakov, F., Munk-Nielsen, A., Rust, J. P., & Schjerning, B. (2022). Equilibrium trade in automobiles. *Journal of Political Economy*.

Glerum, A., Stankovikj, L., Thémans, M., & Bierlaire, M. (2014). Forecasting the demand for electric vehicles: Accounting for attitudes and perceptions. *Transportation Science*, *48*(4), 483–499.

Gordon, B. R. (2009). A dynamic model of consumer replacement cycles in the PC processor industry. *Marketing Science*, *28*(5), 846–867.

Gowrisankaran, G., & Rysman, M. (2012). Dynamics of consumer demand for new durable goods. *Journal of Political Economy*, *120*(6), 1173–1219.

Green Cars. (2021). Cost to maintain an electric car. https://www.greencars.com/post/what-does-it-cost-to-maintain-an-electric-car

Guan, J. (2021). Automobile Replacement and Government Subsidy: An Analysis of the CARS Program. *Available at SSRN 3873076*.

Holland, S. P., Mansur, E. T., & Yates, A. J. (2021). The electric vehicle transition and the economics of banning gasoline vehicles. *American Economic Journal: Economic Policy*, *13*(3), 316–44.

IEA. (2021). *Global EV Outlook 2021*. https://www.iea.org/reports/global-ev-outlook-2021

IEA. (2022). *Global EV Outlook 2022*. https://www.iea.org/reports/global-ev-outlook-2022

IIHS and HLDI. (2020). HLDI automobile size and class definitions. https://www.iihs.org/media/b19c7e8c-54ea-4a35-a3bb-3a05fa2a5c16/g5MZTA/Ratings/Protocols/current/hdi-auto-size-class.pdf

Ishihara, M., & Ching, A. T. (2019). Dynamic demand for new and used durable goods without physical depreciation: The case of Japanese video games. *Marketing Science*, *38*(3), 392–416.

J.D. Power. (2020). Electric Vehicle Range Testing: Understanding NEDC vs. WLTP vs. EPA. https://www.jdpower.com/Cars/Shopping-Guides/electric-vehicle-range-testing-understanding-nedc-vs-wltp-vs-epa

J.P. Morgan. (2018). *Driving into 2025: The future of electric vehicles*. https://www.jpmorgan.com/insights/research/electric-vehicles

J.P. Morgan. (2020). The future is electric. https://www.jpmorgan.com/insights/research/future-is-electric

Kelleher Environmental. (2019). *Research study on reuse and recycling of batteries employed in electric vehicles: The technical, environmental, economic, energy and cost implications of reusing and recycling ev batteries.*

Li, S., Liu, Y., & Wei, C. (2020). *The cost of greening stimulus: A dynamic discrete choice analysis of vehicle scrappage programs*, Mimeo, GWU.

Liu, Y., & Cirillo, C. (2017). A generalized dynamic discrete choice model for green vehicle adoption. *Transportation research procedia*, *23*, 868–886.

Meld. St. 33. (2016-2017). *National Transport Plan 2018–2029. Report to the Storting (white paper) English Summary.*

Mian, A., & Sufi, A. (2012). The effects of fiscal stimulus: Evidence from the 2009 cash for clunkers program. *The Quarterly Journal of Economics*, *127*(3), 1107–1142.

Muehlegger, E., & Rapson, D. S. (2022). Subsidizing low-and middle-income adoption of electric vehicles: Quasi-experimental evidence from california. *Journal of Public Economics*, *216*, 104752.

National Highway Traffic Safety Administration. (n.d.). Frequently Asked Questions. https://www.nhtsa.gov/ratings

Nichols, D. (2022). *Battery degradation and how to prevent it*. https://www.greencars.com/greencars-101/battery-degradation-and-how-to-prevent-it

Pathak, M., Slade, R., Shukla, P., Skea, J., Pichs-Madruga, R., & Ürge-Vorsatz, D. (2022). Technical Summary. In P. Shukla, J. Skea, R. Slade, A. A. Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, & J. Malley (Eds.), *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*. Cambridge University Press, Cambridge, UK; New York, NY, USA.

Porter, R. H., & Sattler, P. (1999). *Patterns of trade in the market for used durables: Theory and evidence* (No. 7149), NBER Working Paper.

Purohit, D. (1992). Exploring the relationship between the markets for new and used durable goods: The case of automobiles. *Marketing Science*, *11*(2), 154–167.

Rosenberg, N. (1976). On technological expectations. *The Economic Journal*, *86*(343), 523–535.

Rust, J. (1987). Optimal replacement of GMC bus engines: An empirical model of Harold Zurcher. *Econometrica*, 999–1033.

Sallee, J. M., West, S. E., & Fan, W. (2016). Do consumers recognize the value of fuel economy? Evidence from used car prices and gasoline price fluctuations. *Journal of Public Economics*, *135*, 61–73.

Schiraldi, P. (2011). Automobile replacement: A dynamic structural approach. *The RAND journal of economics*, *42*(2), 266–291.

Schloter, L. (2022). Empirical analysis of the depreciation of electric vehicles compared to gasoline vehicles. *Transport Policy*, *126*, 268–279.

Solow, R. M., Tobin, J., von Weizsäcker, C. C., & Yaari, M. (1966). Neoclassical Growth with Fixed Factor Proportions. *Review of Economic Studies*, *33*(2), 79–115.

Springel, K. (2021). Network externality and subsidy structure in two-sided markets: Evidence from electric vehicle incentives. *American Economic Journal: Economic Policy*.

Stock, J. H. (2020). Climate change, climate policy, and economic growth. *NBER Macroeconomics Annual*, *34*(1), 399–419.

Stolyarov, D. (2002). Turnover of used durables in a stationary equilibrium: Are older goods traded more? *Journal of Political Economy*, *110*(6), 1390–1413.

Strittmatter, A., & Lechner, M. (2020). Sorting in the used-car market after the Volkswagen emission scandal. *Journal of Environmental Economics and Management*, *101*, 102305.

The Norwegian Electric Vehicle Association. (2021a). Bruktbil-bonanza: Nå topper elbilene blant to år gamle biler. https://elbil.no/na-topper-elbilene-blant-to-ar-gamle-biler/

The Norwegian Electric Vehicle Association. (2021b). Prisene presses: Nå kan du gjøre et elbil-kupp. https://elbil.no/prisene-presses-na-kan-du-gjore-et-elbil-kupp/

The Norwegian Electric Vehicle Association. (2022a). The electric vehicle selector. https://elbilvelgeren.elbil.no/

The Norwegian Electric Vehicle Association. (2022b). Nybilsalget 2021: Nå selges det flere elbiler enn dieselbiler i Europa. https://elbil.no/na-selges-det-flere-elbiler-enn-dieselbiler-i-europa/

The Norwegian Tax Administration. (n.d.). Calculating the one-off registration tax for plug-in hybrids. https://www.skatteetaten.no/en/person/duties/cars-and-other-vehicles/importing/which-duties-do-you-have-to-pay/one-off-registration-tax/what-is-the-one-off-registration-tax/calculating-the-one-off-registration-tax-for-plug-in-hybrids/

The Renault Group. (2020). The wltp: A standard that car drivers can understand. https://www.renaultgroup.com/en/news-on-air/news/the-wltp-a-standard-that-car-drivers-can-understand/

Waldman, M. (2003). Durable goods theory for real world markets. *Journal of Economic Perspectives*, *17*(1), 131–154.

Wykoff, F. C. (1970). Capital depreciation in the postwar period: Automobiles. *The Review of Economics and Statistics*, 168–172.

Appendix

A The effect of technological progress

A.1 Opting out of car ownership

In the main analysis we assume that all consumers need a car, hence implicitly that the utility of not owning a car is sufficiently low. In many settings, other means of transportation can be a suitable alternative. To include this in the model, we can introduce an outside opportunity of not owning a car yielding a utility level $\underset{\sim}{U}$. This alternative is most relevant for consumers with a low car preference parameter h. Hence this alternative is chosen for consumers with $U^O < \underset{\sim}{U}$. This yields a new cut-off level $\underset{\sim}{h}$ defined by

$$x_u\underset{\sim}{h} - p_u + \beta(x_u\underset{\sim}{h} - p_u) = \underset{\sim}{U} \Rightarrow \underset{\sim}{h} = \frac{\underset{\sim}{U}}{(1+\beta)x_u} + \frac{p_u}{x_u}$$

As the number in the N and O groups still have to be equally sized in equilibrium, this yields a new equilibrium condition

$$F\left(\frac{p_n - (1+\beta)p_u}{(1-\mu)x_n}\right) - F\left(\frac{\underset{\sim}{U}}{(1+\beta)x_u} + \frac{p_u}{x_u}\right) = 1 - F\left(\frac{p_n - p_u}{(1-\mu)x_n}\right)$$

This change to the model does not change any qualitative insights from the model, so to maintain simplicity we disregard the presence of an outside opportunity for the rest of the paper.

A.2 Proof of theoretical results

To see the effect of technological progress on the market, we can differentiate equation (8) to get

$$f(\underline{h})\left[-\frac{1+\beta}{\left(1-\frac{\mu}{\gamma}\right)x_n}dp_1 - \frac{[p_n-(1+\beta)p_u]\frac{\mu x_n}{(\gamma)^2}}{\left[\left(1-\frac{\mu}{\gamma}\right)x_n\right]^2}d\gamma\right]$$
$$= -f(\bar{h})\left[-\frac{1}{(\gamma-\mu)x_n}dp_1 - \frac{(p_n-p_u)x_n}{[(\gamma-\mu)x_n]^2}d\gamma\right] \quad (13)$$

where the left hand side are the demand effects and the right hand side the supply effects. Solving, we find

$$\frac{dp_1}{d\gamma} = -x_0 \frac{f(\underline{h})\underline{h}\frac{\frac{\mu}{(1+\gamma)^2}}{1-\frac{\mu}{\gamma}} + f(\bar{h})\bar{h}\frac{1}{(\gamma-\mu)}}{f(\underline{h})\frac{1+\beta}{1-\frac{\mu}{\gamma}} + f(\bar{h})\frac{1}{\gamma-\mu}} \tag{14}$$

$$= -x_0 \frac{f(\underline{h})\underline{h}\frac{\mu}{\gamma} + f(\bar{h})\bar{h}}{f(\underline{h})(1+\beta)(\gamma) + f(\bar{h})} < 0 \tag{15}$$

Moreover, we have

$$\frac{d\bar{h}}{d\gamma} = -\frac{(p_n - p_u)x_n}{(\gamma-\mu)^2 x_n^2} - \frac{1}{(\gamma-\mu)x_n}\frac{dp_u}{d\gamma}$$

Using equation (8), we find

$$\frac{d\bar{h}}{d\gamma} = -\frac{1}{(\gamma-\mu)}\left(\bar{h} - \frac{f(\underline{h})\underline{h}\frac{\mu}{\gamma} + f(\bar{h})\bar{h}}{f(\underline{h})(1+\beta)\gamma + f(\bar{h})}\right)$$

$$= -\frac{f(\underline{h})}{(\gamma-\mu)} \times \frac{(1+\beta)\gamma\bar{h} - \frac{\mu}{\gamma}\underline{h}}{f(\underline{h})(1+\beta)\gamma + f(\bar{h})}$$

As $(1+\beta)\gamma\bar{h} > \frac{\mu}{\gamma}\underline{h}$, we then get $\frac{d\bar{h}}{d\gamma} < 0$.

B Data

In this Appendix, we present details of the data we use in our analysis.

B.1 Variables from finn.no

The data from finn.no forms the basis of our analysis. It includes a hashed vehicle id number, chassis number, the listed secondhand price of the vehicle the seller wants, the year the vehicle is first registered, year model, fuel type, mileage, make and model, number of seats, municipality of the seller, dealer type, engine effect, engine volume, transmission, wheel drive, main color, as well as the month and year of an ad on finn.no.

We will now go through the variables that we use in the analysis.

B.1.1 Vehicle id number

Each vehicle has an id number which is unique and encrypted to keep the data anonymous. We combine this variable with the chassis number, dealer type, effect, engine volume, fuel, main color, make, model, municipality of the seller, transmission wheel drive, year model, the year the vehicle is first registered and number of seats to check whether a vehicle has been advertised for more than a month (and therefore becomes a duplicate observation) and to a lower price.

B.1.2 Vehicle age

To find the age of a vehicle, we can use two variables to tell us the year the vehicle was new: The year model and the year the vehicle was first registered. The year model in itself is an imprecise term. Some manufacturers start selling year model t early in year $t-1$, and some maintain the year on the model until they change the model.

However, year of first registration can also be wrong. Although our data ends in 2021, there are observations with year of first registration date after 2021. There are also numerous observations with year of first registration before 1940. Although some of these may be antique cars, some are clear mistakes. There are for instance multiple Nissan Leaf presumably registered before 1940, which is unreasonable as the model entered the market after 2010.

Our solution is to use the lowest of the year of first registration and the model year whenever both are present. Moreover, we assume that vehicles first registered before 1940 is a mistake, and in this case we use the year model unless the year of first registration and year model is the same year, we keep the year of first registration.

As we have data on the year the vehicle is advertised on finn.no, we find the age of the vehicle by subtracting the year the vehicle is advertised with the year the vehicle is new.

B.1.3 Fuel type

The data from finn.no has data on fuel type. However, there may be mistakes by the seller, for instance claiming that a vehicle is a gasoline vehicle when it is a hybrid gasoline vehicle or stating that it is an electric vehicle when it is a hybrid or plug-in hybrid. When there is only one observation of a vehicle model one year that is electric, the electric model is not listed by OFV, and we do not recognize the model name as an electric vehicle (there are so few electric vehicle models that it is possible to know most of them), we take them out of the analysis, because it is likely that they are erroneously classified as electric vehicles. This is the case of 41 observations.

Gasoline vehicles that are not found on the OFV list are treated differently, see more elaboration on this in Section B.2.1.

The finn data do not distinguish between plug-in hybrid and hybrid. To distinguish between the two, we also use data from OFV. If a vehicle is listed as gasoline-hybrid in the finn data and plug-in gasoline hybrid or a gasoline vehicle in the OFV data, we code it as a plug-in gasoline hybrid. If a vehicle is listed as hybrid in the finn data and hybrid *and* plug-in hybrid in the OFV data, we do not change it. As most of our analyses compare electric and gasoline vehicles this coding scheme has a minor impact on our results. In Table A-18, however, we compare all fuel types.

B.1.4 The price of the secondhand vehicle

We only have the price the seller lists on the finn platform, not the price the vehicle is actually sold at. There can be case where buyer and seller agree on a lower price than the listed one.

Moreover, the price is without re-registration fee which varies through the period of investigation and for different vehicles, depending on age and fuel.

B.1.5 Mileage

We use mileage as a control variable because this is a variable that probably affect the price of the vehicle. Finn has rounded the number to the nearest thousand in order to anonymize the data. Observations where mileage is missing are controlled for with a dummy variable. See Table A-2 to see the number of missing on mileage.

B.1.6 Number of seats

This variable is used to distinguish between passenger vehicles and utility vehicles with the same model name.

B.1.7 Municipality of the seller

We use the municipality of the seller as one of the variables to detect duplicates.

B.2 Variables from OFV

The Norwegian Road Federation (OFV) data are merged into the finn data set by fuel, model, make and the year the vehicle is new. The variables from OFV that we use are the price on the new vehicle and body style category.

The data from OFV are combined with the data from finn.no matching on the following variables: make, model, fuel and the year the vehicle is new.

B.2.1 Price on the new vehicle

Norwegian Road Federation (OFV) collects prices on new vehicles from all importers that are formally linked to the producer. The price list of June every year is used to find the price on the new vehicle. When not found in the June list, we use the November list or the December list. If not found on either June, November or December list, the vehicle is marked as missing price on the new vehicle (see below for more information on the reason for the vehicle missing on the price list). See Table A-2 to see the number of missing on new vehicle price.

There are many different equipment level within the same model and the information from finn.no do not tell us which equipment level each vehicle has. Some equipment levels within a model are a lot more expensive than the others. Therefore, we take the median price of the make, model, fuel and year. For robustness check we take out those models where the ratio between the maximum price and the minimum price is above 1.5. This can be seen in Table 3, column 4.

Body style category should also be one of the variables that the median price is based on, but since finn.no do not have this variable, we can not merge on this variable. Some models are more than one type of category. For instance Ford Focus can be bought as a hatchback or station wagon. Mercedes-Benz A-class is either sedan or hatchback. Mercedes-Benz C-class is either sedan or station wagon. Then the median price is the median of all the models in the two types of vehicles body style categories.

Notice that the new prices we use are listed new prices. Actual prices of new cars could be lower due to e.g. haggling, rebates or campaigns.

Those observations with make or model "others" or "N/A" and fuel "N/A" when the model can be both electric and conventional vehicle are not merged and therefore lack the price on the new vehicle.

Some observations on finn.no are not found on the OFV list of new vehicle prices. There are four main explanations: 1) privately imported new vehicles from the factory, i.e. not through the importer that is related to the producer, 2) models from earlier years, 3) import of used vehicles, and 4) mistakes in the OFV list or at finn.no, for instance the advertiser is not aware that the vehicle is a hybrid and list it as a gasoline vehicle.

An example of explanation 1) is Fiat 500 Plug-in Hybrid which was produced for the American market. Fiat decided not to sell these vehicles in Europe, but some were imported through channels that were not related to the producer's importer network.

The price on the new vehicle in category 2) is difficult to know. We can find the price on the model in earlier years, but the price probably changes from year to year.

For category 1), the price on finn.no is strictly speaking the price of the new vehicle in the Norwegian market if the car is 0 years-old. All vehicles that are not part of the OFV list get a dummy and the dummy is controlled for in the regression in Table 3. We also have the same specifications as in Table 3 without a dummy on those missing new vehicle price and that can be seen in Table A-23.

B.2.2 OFV listed fuel type

In the beginning of the period of investigation there were some models that were flexible fuel vehicles (cars that are able to use both gasoline and ethanol). OFV have them on their list, but as the market for these vehicles never took off in Norway, finn.no do not distinguish between gasoline vehicles and flexible fuel vehicles. We define all flexible fuel vehicles in OFV data as gasoline vehicles.

B.2.3 Size categories

There is no clear definition of different size categories. The EU Commission lists different segments in the car market, but also state that "the exact market definition was left open"(Commission of the European Communities, 1999, p.2).

In the USA the Environmental Protection Agency (EPA) has different size classes based on body style combined with passenger and cargo volume (fueleconomy.gov, n.d.). In contrast, the National Highway Traffic Safety Administration (NHTSA) in the USA categorize by class and weight (National Highway Traffic Safety Administration, n.d.). A third option in the USA is by The Insurance Institute for Highway Safety (IIHS) and The Highway Loss Data Institute (HLDS) which both are organizations funded by auto insurers and insurance associations. They use a combination of weight and length times width (IIHS and HLDI, 2020).

Body style Most models have different variants. Some models are in two different body style categories. For instance, Volkswagen Golf can be both a hatchback or a station wagon. However, for electric vehicles the different variants of a model are mostly in the same body style categories. For gasoline there are several models that can be both a hatchback and a station wagon. We categorize them based on which body style categories there are most model variants of.

We use the body style categories that The Norwegian Road Federation (OFV) categorize different models into.[22] We have translated their definition.

"*Cabriolet* are cars with roofs that can be opened or removed, either by folding it into the body style, or being completely removed. Roadsters should have body style category cabriolet.

Hatchbacks are cars with a large tailgate/rear door that include the rear window. The rear edge of the rear window ends where the body ends, without any horizontal surface/trunk lid. The hedge on the hatchback may have different inclination. The trunk is relatively small compared to the total volume of the car. The station wagon has larger volume, while the body shape may otherwise be quite similar.

Coupes are cars that have prioritized appearance at the expense of space and practical considerations. They are characterized by what most people will perceive as "elegant lines". Often, the coupes are lower with a flatter rear window than ordinary hatchbacks and sedans, which the space, especially from the front seats and backwards, suffers underneath. The tailgate is hinged under the rear window. Coupes can have 2 and 4 doors.

Pickups are cars with an open loading plane behind a cab. The cab can contain several rows of seats.

Sedan are cars with preferably 4 doors and separate trunk and marked trunk lid that are hinged under/behind the rear window.

Station wagon are cars with full height backwards to the tailgate. The tailgate can be somewhat sloping and the trunk is open towards the cabin. They are characterized by large trunk in relation to the total volume of the car.

[22]Personal email communication with Kjell Magne Aalbergsjø in OFV, 11.02.22.

Multipurpose car are cars that are designed for maximum interior space utilization and flexibility. The body style shape is similar to that of the station wagon or hatchback, but the multipurpose cars are usually higher than these, albeit with normal ground clearance. They have a minimum of 5 seats in addition to luggage space."

SUV is not defined by OFV.

Weight

Weight can be used as a proxy for size. We take the median of the different trims of the same model. As electric vehicles are heavier than gasoline vehicles due to the batteries, we use the gasoline vehicles as the basis to find the cutoff between large and small vehicles. We use the 75th percentile of the weight for all gasoline vehicles in the sample as the cutoff. This is 1382.5 kg. How much more an electric vehicle weigh due to the batteries is difficult to know, but the tax authorities use 15% extra weight for plug-in hybrids from 1st of January 2022 and before that they used 23% (The Norwegian Tax Administration, n.d.). We therefore add 10%, 20% and 30% to the electric vehicle weight when distinguishing between large and small vehicles based on weight in Table A-12.

B.3 Variables from other sources

B.3.1 Range

Range is taken from the webpage of the Norwegian Electric Vehicle Association (The Norwegian Electric Vehicle Association, 2022a). When the same model the same year has different range alternatives, we construct the median of the range. The range we use is the WLTP, which is the new standard. If the old standard, NEDC, is the only available, we reduce the driving range by a factor of 0.65 (J.D. Power, 2020). Some models are for sale with different year models with different range at the same time and therefore we do not know for sure the range of the car the year the vehicle is new. We use the median range of the year model the year the vehicle is new.

B.4 Sample selection

Vehicles that are new in 2011 or after is part of the analysis. We therefore do not include the observations for vehicles that are new earlier than 2011. See Table A-1 for an overview of the number of observations that are not part of the analysis.

In order to not let outliers influence the result, we analyze vehicles with a secondhand price range between 10 000 NOK and 2 million NOK, see Table A-1 for the number of observations. In addition, we take out Think and Buddy cars as these can not be characterized as modern vehicles. Observations where the recorded vehicle age is negative

Table A-1: Observations not part of the analysis

	Number of observations
Ads on finn.no 2011- June 20th 2021	5 546 617
Advertized more than one time with less than 3 months in between	1 187 042
Older than 2011	2 903 240
Price over 2 mill NOK	9 330
Price under 10 000 NOK	1 746
Age -1 or less	5 732
Age missing	45
Advertised more than three times without changing the price	7 494
Utility vehicles	2 275
Missing information, such as model name	2 231
Wrong fuel (see Section B.1.3 for explanation)	42
Think	116
Buddy	20
Hydrogen vehicles	80
Gas vehicles	171
Total number of observations (all fuels, except hydrogen and gas)	1 427 053
Total number of observations, electric and gasoline	545 452

Table A-2: Number of observations with some of the variables missing

	Number of observations
Total	545 452
Missing new vehicle price	8 659
Missing body style	8 659
Missing mileage	21 400
Missing range (and electric vehicle)	535

at the time of transaction are also removed.

C Descriptive data

Table A-3: Number of vehicles based on fuel

Number of vehicles		Share
Gasoline vehicles	366 586	26%
Electric vehicles	178 866	13%
Hybrid vehicles	80 276	6%
Plug-in hybrid vehicles	82 676	6%
Diesel vehicles	718 649	50%
Total	1 427 053	

Table A-4: Number of vehicles that are new in 2011 or later advertised each year.

Year sold	Gasoline	Electric
	Number of vehicles	
2011	1 752	55
2012	6 316	217
2013	13 067	1 068
2014	21 178	2 241
2015	28 693	5 040
2016	37 510	8 979
2017	50 050	17 242
2018	54 201	30 077
2019	62 131	39 553
2020	61 338	43 300
2021	30 350	31 094

Table A-5: Number of vehicles based on how old they when they are for sale

	Number of vehicles	
Age	Electric	Gasoline
0	25 605	25 727
1	37 174	52 811
2	30 559	57 074
3	30 242	72 089
4	22 743	54 427
5	14 873	36 822
6	9 401	26 582
7	4 751	19 566
8	2 313	12 783
9	929	6 697
10	276	2008
Mean age	2.65	3.45
Mean age for vehicles that are 5 years or younger	2.20	2.62

Table A-6: The mean range in the year the vehicles are new and sold in the secondhand market. The median refers to the price of the vehicle as new.

Year	Mean range new	Mean range sold	Mean range sold over the median	Mean range sold below the median
2011	114	108	–	108
2012	122	115	–	115
2013	176	134	300	121
2014	169	161	300	124
2015	165	175	304	129
2016	199	175	323	133
2017	261	187	346	149
2018	289	201	383	173
2019	384	241	430	195
2020	396	275	484	211
2021	403	296	444	234
For all years	240		416	190

We have calculated the statistics for new vehicle price weighted by the vehicles that are on finn.no.
The 50th percentile is 362 000 NOK.
In 2011 and 2012 there are no electric vehicles with price as new equal to or over the median.
Over median includes those equal to the median.

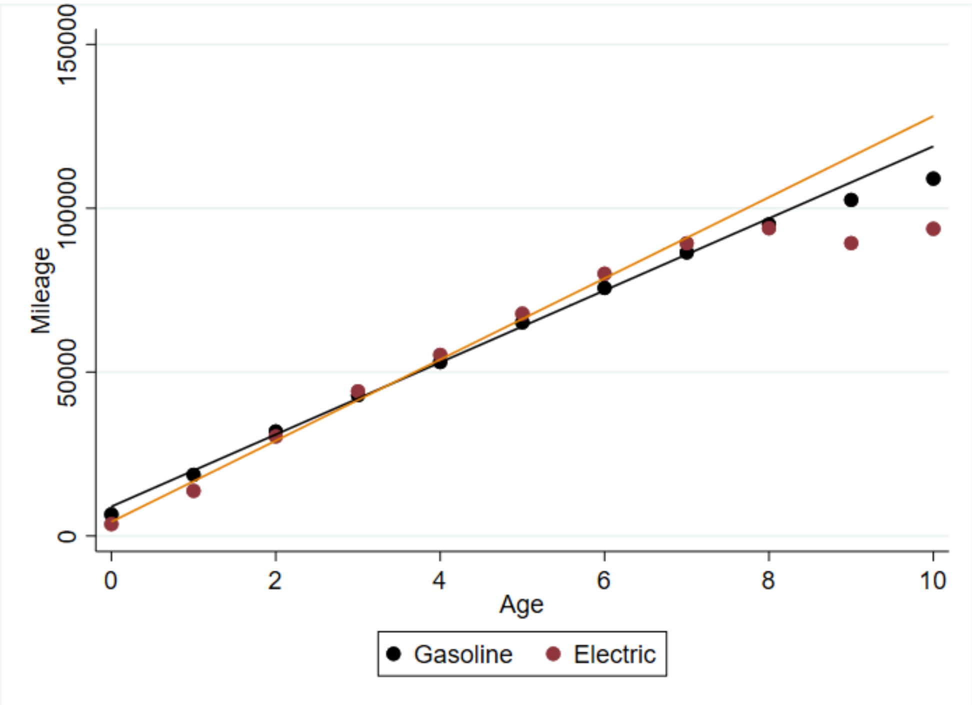
Table A-7: Share of vehicles based on seller.

	Share of vehicles	
	Electric	Gasoline
Private seller	41%	21%
Professional seller of the same make	25%	59%
Other professional seller	33%	20%

Table A-8: Top 10 secondhand models

	Electric secondhand		Gasoline secondhand	
	Model	Share	Model	Share
1	Nissan Leaf (Hatchback)	23%	VW Golf (Hatchback)	7%
2	VW E-golf (Hatchback)	15%	VW Polo (Hatchback)	3%
3	Tesla Model S (Hatchback)	11%	Ford Focus (Hatchback/Station wagon)	3%
4	BMW i3 (Hatchback)	9%	Ford Fiesta (Hatchback)	3%
5	Kia E-soul (Hatchback)	6%	Audi A3 (Hatchback)	3%
6	VW E-up! (Hatchback)	4%	Mercedes A-klasse (Hatchback/Sedan)	2%
7	Tesla Model X (SUV)	3%	Toyota Avensis (Sedan/Station wagon)	2%
8	Renault Zoe (Hatchback)	3%	Skoda Octavia (Station wagon)	2%
9	Hyundai Ioniq (Hatchback)	3%	Toyota Yaris (Hatchback)	2%
10	Hyundai Kona (SUV)	2%	Audi A1 (Hatchback)	2%

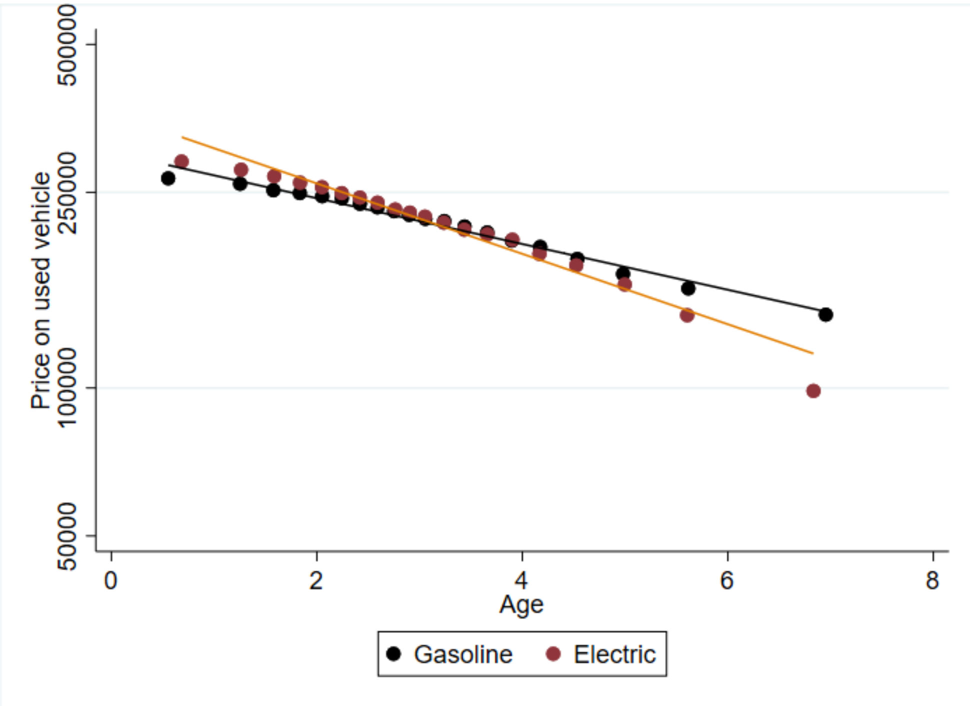
Figure A-1: Binned scatterplot of the relationship between mileage and age.



D More detailed results

The relationship between vehicle age and secondhand price is illustrated in Figure A-2. As expected, the price is declining in age. We also see that this decline is clearly stronger for electric vehicles than for gasoline cars.

Figure A-2: Secondhand vehicle prices by age and fuel type



Notes: Each point represent an equal number of observations. Results control for mileage, the log price of the new car and dummies for missing variables. The y axis is on a logarithmic scale.

Table A-9: Table 3 with age squared.

	(1)	(2)	(3)	(4)	(5)
Age	-0.0339***	-0.0316***	-0.0408***	-0.0352***	-0.0400***
	(0.00673)	(0.00669)	(0.00659)	(0.00840)	(0.00650)
Age squared	-0.00774***	-0.00780***	-0.00742***	-0.00831***	-0.00775***
	(0.000537)	(0.000550)	(0.000544)	(0.000649)	(0.000559)
Electric × Age	-0.0240	-0.0216	0.00289	0.00373	-0.0126
	(0.0221)	(0.0215)	(0.0170)	(0.0211)	(0.0220)
Electric × Age squared	-0.00587**	-0.00610***	-0.00706***	-0.00839***	-0.00666***
	(0.00223)	(0.00222)	(0.00164)	(0.00177)	(0.00220)
Ln new price	1.080***	1.058***	1.013***	1.106***	1.074***
	(0.0245)	(0.0300)	(0.0317)	(0.0309)	(0.0243)
Ln mileage × Gasoline	-0.100***	-0.102***	-0.0983***	-0.0869***	-0.101***
	(0.00700)	(0.00586)	(0.00683)	(0.00450)	(0.00698)
Ln mileage × Electric	-0.0201	-0.0189	-0.0443***	-0.0340**	-0.0292**
	(0.0137)	(0.0138)	(0.00649)	(0.0135)	(0.0136)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	545 452	545 452	545 452	336 220	545 452
R^2	0.865	0.866	0.884	0.911	0.862

Dependent variable is log of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but in (4) where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Table A-10: Table 3 without the electric vehicles with range below 200 km.

	(1)	(2)	(3)	(4)	(5)
Age	-0.105***	-0.104***	-0.107***	-0.111***	-0.112***
	(0.00465)	(0.00436)	(0.00345)	(0.00551)	(0.00441)
Electric × Age	0.0291***	0.0413***	0.0342***	0.0354***	0.0365***
	(0.00756)	(0.00839)	(0.00585)	(0.00793)	(0.00765)
Ln new price	1.058***	1.009***	1.039***	1.087***	1.052***
	(0.0209)	(0.0256)	(0.0238)	(0.0225)	(0.0219)
Ln mileage × Gasoline	-0.0741***	-0.0743***	-0.0753***	-0.0606***	-0.0748***
	(0.00752)	(0.00603)	(0.00689)	(0.00541)	(0.00754)
Ln mileage × Electric	-0.0390***	-0.0412***	-0.0361***	-0.0262***	-0.0472***
	(0.00987)	(0.0100)	(0.00773)	(0.00587)	(0.00906)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer category fixed effects	Y	Y	Y	Y	N
Body style category fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	444 793	444 793	444 793	239 401	444 793
R^2	0.871	0.875	0.884	0.918	0.868

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 59 clusters in all but specification (4), where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

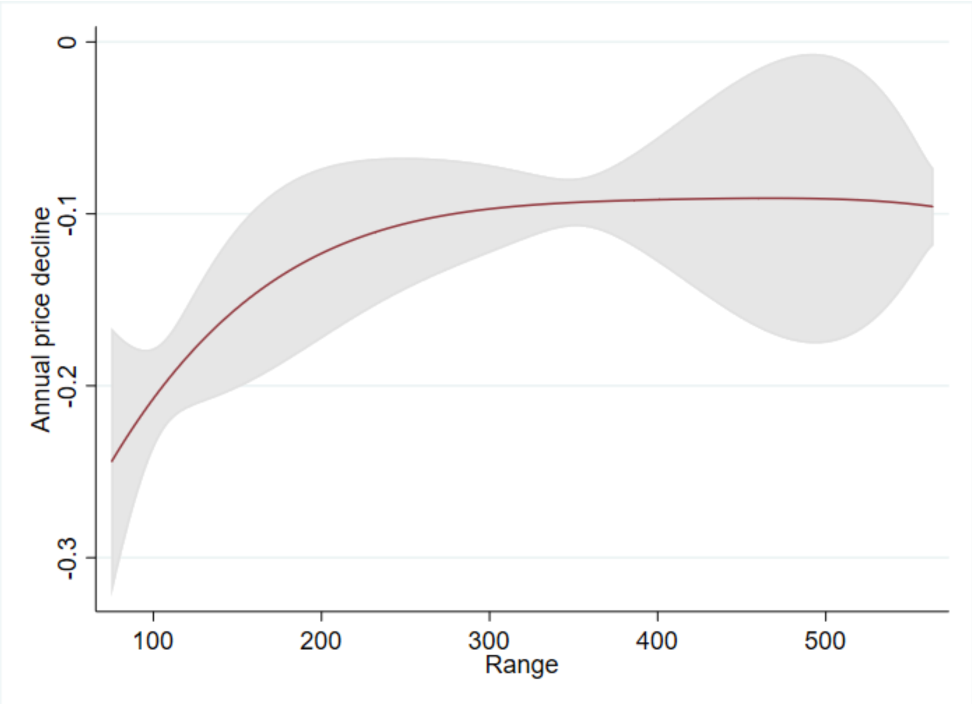


Figure A-3: The price decline for electric cars with different driving range, using 0.75 instead of 0.65 as converting rate between the range standard NEDC and WLTP.

Table A-11: Quantile regression

	(1) 25th percentile	(2) Median	(3) 75th percentile	(4) 90th percentile
Age	-0.111***	-0.104***	-0.0950***	-0.0936***
	(0.000355)	(0.000297)	(0.000318)	(0.000428)
Electric × Age	-0.0634***	-0.0433***	-0.0262***	-0.0163***
	(0.000634)	(0.000580)	(0.000517)	(0.000610)
Ln new price	1.038***	1.065***	1.095***	1.116***
	(0.000945)	(0.000790)	(0.000805)	(0.00108)
Ln mileage × Gasoline	-0.0688***	-0.0636***	-0.0641***	-0.0650***
	(0.000635)	(0.000520)	(0.000563)	(0.000850)
Ln mileage × Electric	0.0130***	0.00260***	-0.0100***	-0.0214***
	(0.000785)	(0.000661)	(0.000674)	(0.000809)
Year × fuel fixed effects	Y	Y	Y	Y
Dealer category fixed effects	Y	Y	Y	Y
Observations	545 452	545 452	545 452	545 452

Dependent variable is ln of the secondhand price.
Standard errors are robust, in parentheses.
Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.
We use a dummy on those observations that have missing new vehicle price and mileage.

Table A-12: Different size categories based on either body style or weight.

	(1) Body style	(2) Weight 20% added	(3) Weight 10% added	(4) Weight 30% added
Age	-0.107***	-0.111***	-0.110***	-0.111***
	(0.00444)	(0.00422)	(0.00407)	(0.00422)
Electric × Age	-0.0578***	-0.0568***	-0.0592***	-0.0572***
	(0.0192)	(0.0170)	(0.0206)	(0.0168)
Large vehicles × Age	0.00450	0.00890	0.00832	0.00889
	(0.00381)	(0.00484)	(0.00493)	(0.00483)
Electric × Large vehicles × Age	0.0181	0.0525***	0.0127	0.0562***
	(0.0168)	(0.0129)	(0.0231)	(0.0136)
Ln new price	1.065***	1.037***	1.061***	1.037***
	(0.0252)	(0.0248)	(0.0227)	(0.0262)
Ln mileage × Gasoline	-0.0771***	-0.0734***	-0.0740***	-0.0734***
	(0.00669)	(0.00729)	(0.00725)	(0.00727)
Ln mileage × Electric	0.00867	-0.00483	0.00675	-0.00458
	(0.0108)	(0.00934)	(0.00956)	(0.0100)
Year × fuel fixed effects	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y
Body style fixed effects	Y	Y	Y	Y
Observations	545 452	545 452	545 452	545 452
R^2	0.871	0.872	0.870	0.872

The cutoff between small and large vehicles based on weight is the 75th percentile for weight for gasoline vehicles. See Appendix B.2.3 for more information.
Weight added means how much more weight is added to the electric vehicles to be in the same category as gasoline vehicles.
Due to battery weight, electric vehicles have added 20% to the cutoff in column 2, 10% added in column 3 and 30% added in column 4.
Dependent variable is ln of the secondhand price.
Standard errors clustered on make, in parentheses. There are 62 clusters.
Small gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.
Large vehicles are defined as station wagon, SUV, pick-up and multi-purpose cars.
Small vehicles are sedan, hatchback, coupe and cabriolet.
We use a dummy on those observations that have missing new vehicle price and mileage.

Table A-13: Investigating vintage effects.

	(1)	(2)
Age	-0.0694***	-0.0749***
	(0.00471)	(0.00509)
Electric × Age	-0.0445***	-0.0295***
	(0.0130)	(0.0105)
Early × Age	-0.0265***	-0.0230***
	(0.00587)	(0.00558)
Early × Electric × Age	-0.0363**	-0.0382***
	(0.0142)	(0.0126)
Ln new price	1.062***	1.011***
	(0.0202)	(0.0299)
Ln mileage × Gasoline	-0.0785***	-0.0784***
	(0.00629)	(0.00602)
Ln mileage × Electric	-0.0224**	-0.0371***
	(0.0105)	(0.00490)
Year × fuel fixed effects	Y	Y
Dealer fixed effects	Y	Y
Make fixed effects	N	Y
Observations	460 146	460 146
R^2	0.857	0.876

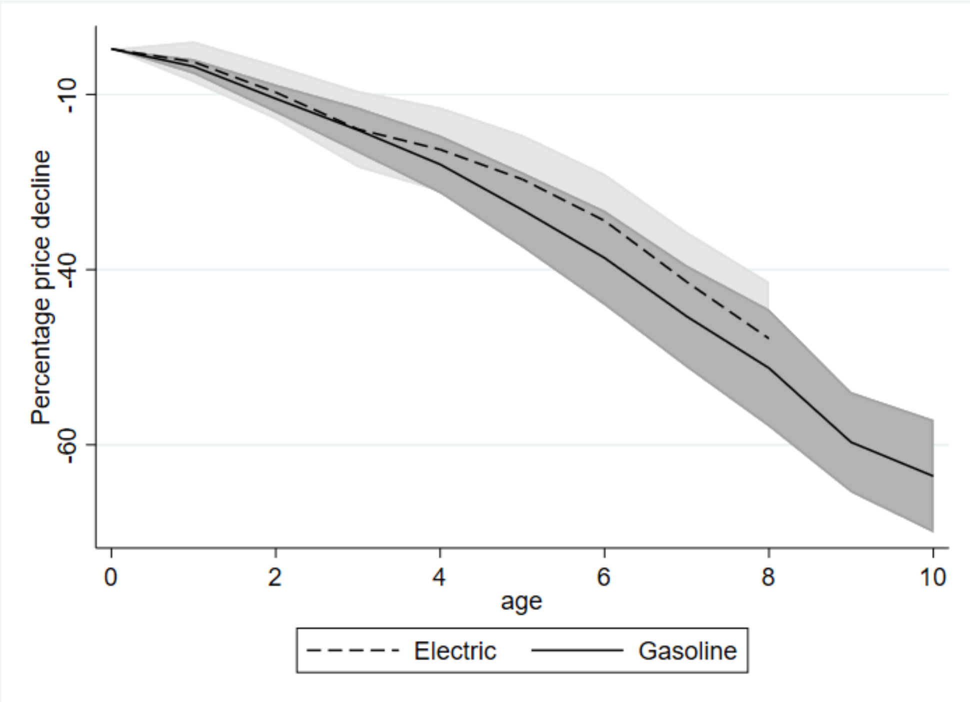
Baseline is gasoline vehicles from 2016-2021. Early refers to the vehicles from 2011-2015.
Only the vehicles that are 5 years or younger are included to make it comparable between time periods.
Dependent variable is ln of the secondhand price.
Standard errors clustered on make, in parentheses. There are 61 clusters.
Year fixed effects are based on the year the vehicle is sold/advertised.
We use a dummy on the observations that have missing mileage and those that have missing new car price.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-14: Different price categories.

	(1) Over p75	(2) Over p50	(3) Below p50	(4) Below p25
Age	-0.103***	-0.1000***	-0.108***	-0.104***
	(0.0126)	(0.00956)	(0.00470)	(0.00592)
Electric × Age	0.0406***	0.0245**	-0.0636***	-0.0767***
	(0.0138)	(0.0107)	(0.0182)	(0.0171)
Ln new price	1.000***	0.961***	1.116***	1.197***
	(0.0407)	(0.0408)	(0.0311)	(0.0483)
Ln mileage × Gasoline	-0.0835***	-0.0709***	-0.0786***	-0.0891***
	(0.0105)	(0.00895)	(0.00734)	(0.00457)
Ln mileage × Electric	-0.0625***	-0.0476***	0.000393	-0.0165
	(0.00742)	(0.00888)	(0.0121)	(0.0124)
Year × fuel fixed effects	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y
Observations	80 045	142 580	394 213	249 364
R^2	0.781	0.812	0.817	0.812

Dependent variable is ln of the secondhand price.
Standard errors clustered on make × fuel, in parentheses.
There are 39 clusters in (1), 54 clusters in (2), 50 clusters in (3) and 44 clusters in (4).
Gasoline vehicles are the baseline. Year times fuel fixed effects are based on the year
the vehicle is sold/advertised.
p25, p50 and p75 refers to the statistics of the new vehicle price for the vehicles
of all fuel types that are advertised on finn.no.
The 75th percentile is 461 275 NOK, the 50th percentile is 359 900 NOK and
the 25th percentile is 275 600 NOK.
73% of the electric vehicles that are over the median is Tesla.
79% of the electric vehicles that are over the 75th percentile is Tesla.
Those that have missing new vehicle price is not part of this analysis (6921 observations).
We use a dummy on those observations that have missing mileage.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure A-4: The price path of electric vs gasoline vehicles, both with price of the new vehicle over the median.



The grey area is the 95% confidence interval. The standard errors are clustered on make $\times$ fuel.

Table A-15: The cars grouped into when they where new.

	(1) New in 2011-2013	(2) New in 2014-2016	(3) New in 2017-2021
Age	-0.127***	-0.0814***	-0.0585***
	(0.00765)	(0.00825)	(0.00827)
Electric × Age	-0.212***	-0.0392	-0.0308*
	(0.0780)	(0.0382)	(0.0163)
Ln new price	1.078***	1.107***	1.039***
	(0.0368)	(0.0322)	(0.0261)
Ln mileage × Gasoline	-0.105***	-0.0905***	-0.0800***
	(0.00598)	(0.00958)	(0.00970)
Ln mileage × Electric	0.00542	-0.0200	-0.0402***
	(0.0637)	(0.0187)	(0.00385)
Year× fuel fixed effects	Y	Y	Y
Dealer fixed effects	Y	Y	Y
Observations	183 165	213 809	148 478
R^2	0.847	0.840	0.861

Dependent variable is ln of the secondhand price.
Standard errors clustered on make, in parentheses.
There are 54 clusters in (1), 53 clusters in (2) and 50 clusters in (3).
Gasoline vehicles are the baseline.
Year fixed effects are based on the year the vehicle is sold/advertised.
We use a dummy on those observations that have missing mileage and those that have missing new car price.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-16: Comparing 0-3-year-old used vehicles sold in different time periods.

	(1) Sold in 2011-2013	(2) Sold in 2014-2017	(3) Sold in 2018-2021
Age	-0.0839***	-0.0801***	-0.0688***
	(0.00914)	(0.00619)	(0.00689)
Electric × Age	-0.105***	-0.0742***	-0.0251
	(0.0226)	(0.0241)	(0.0134)
Ln new price	0.980***	1.063***	1.038***
	(0.0226)	(0.0311)	(0.0195)
Ln mileage × Gasoline	-0.0403***	-0.0666***	-0.0847***
	(0.00323)	(0.00696)	(0.00935)
Ln mileage × Electric	-0.0114	0.00312	-0.0393***
	(0.0128)	(0.0217)	(0.00540)
Year × fuel fixed effects	Y	Y	Y
Dealer fixed effects	Y	Y	Y
Observations	22 475	129 214	179 592
R^2	0.825	0.854	0.858

Dependent variable is ln of the secondhand price.
Standard errors clustered on make, in parentheses.
There are 45 clusters in (1), 54 clusters in (2) and 53 clusters in (3).
Gasoline vehicles are the baseline.
Year × fuel fixed effects are based on the year the vehicle is sold/advertised.
We use a dummy on those observations that have missing mileage
and those that have missing new car price.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-17: Comparing different age groups.

	(1) Age 0-3	(2) Age 4-6	(3) Age 7-10
Age	-0.0766***	-0.112***	-0.145***
	(0.00438)	(0.00584)	(0.00883)
Electric × Age	-0.0341**	-0.0697***	-0.204***
	(0.0138)	(0.0258)	(0.0540)
Ln new price	1.046***	1.117***	1.179***
	(0.0136)	(0.0397)	(0.0454)
Ln mileage × Gasoline	-0.0700***	-0.153***	-0.292***
	(0.00616)	(0.0118)	(0.0173)
Ln mileage × Electric	-0.0258***	-0.0102	-0.0718
	(0.00685)	(0.0490)	(0.0992)
Year × fuel fixed effects	Y	Y	Y
Dealer fixed effects	Y	Y	Y
Observations	331 281	164 848	49 323
R^2	0.857	0.814	0.813

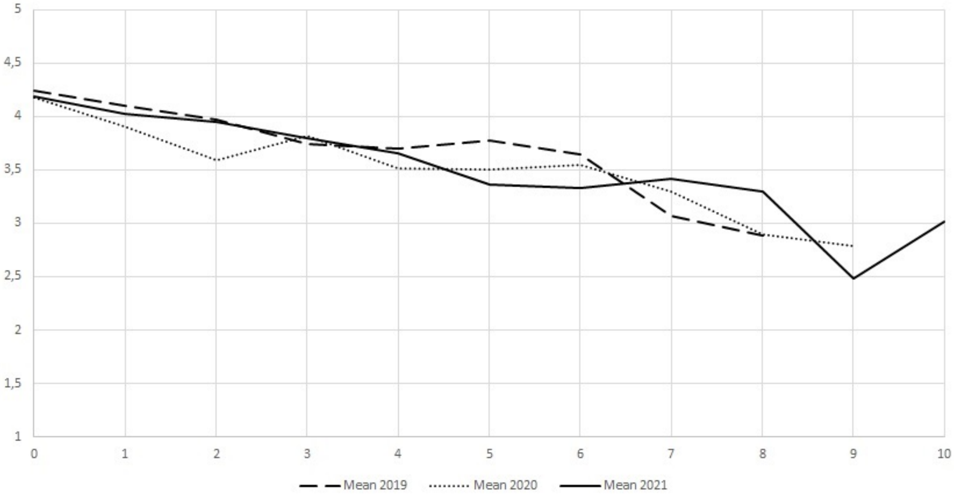
Dependent variable is ln of the secondhand price.
Standard errors clustered on make, in parentheses.
There are 61 clusters in (1), 54 clusters in (2) and 53 clusters in (3).
Gasoline vehicles are the baseline.
Year × fuel fixed effects are based on the year the vehicle is sold/advertised.
We use a dummy on those observations that have missing mileage
and those that have missing new car price.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-18: Table 3 with all fuels and electric vehicles as the baseline.

	(1)	(2)	(3)	(4)	(5)
Age	-0.166***	-0.165***	-0.156***	-0.168***	-0.168***
	(0.0188)	(0.0191)	(0.0198)	(0.0170)	(0.0197)
Gasoline × Age	0.0630***	0.0629***	0.0497**	0.0567***	0.0571***
	(0.0188)	(0.0191)	(0.0195)	(0.0171)	(0.0196)
Hybrid × Age	0.0843***	0.0861***	0.0714***	0.0864***	0.0796***
	(0.0196)	(0.0201)	(0.0206)	(0.0188)	(0.0200)
Diesel × Age	0.0305*	0.0296	0.0210	0.0400**	0.0273
	(0.0175)	(0.0178)	(0.0190)	(0.0150)	(0.0183)
Plug-in hybrid × Age	0.0767***	0.0755***	0.0580***	0.0832***	0.0720***
	(0.0200)	(0.0184)	(0.0216)	(0.0170)	(0.0209)
Ln new price	1.091***	1.056***	1.025***	1.092***	1.082***
	(0.0246)	(0.0270)	(0.0378)	(0.0320)	(0.0247)
Ln mileage × Electric	0.0142	0.0180	-0.00352	0.0117	0.00670
	(0.0120)	(0.0125)	(0.00915)	(0.0145)	(0.0119)
Ln mileage × Gasoline	-0.0779***	-0.0772***	-0.0780***	-0.0610***	-0.0786***
	(0.00832)	(0.00746)	(0.00845)	(0.00559)	(0.00829)
Ln mileage × Hybrid	-0.109***	-0.112***	-0.107***	-0.108***	-0.111***
	(0.0147)	(0.0144)	(0.0144)	(0.0157)	(0.0145)
Ln mileage × Diesel	-0.0973***	-0.0934***	-0.0989***	-0.0735***	-0.105***
	(0.0126)	(0.0122)	(0.0133)	(0.00919)	(0.0129)
Ln mileage × Plug-in hybrid	-0.0608***	-0.0598***	-0.0524***	-0.0608***	-0.0629***
	(0.0103)	(0.0120)	(0.00849)	(0.0108)	(0.0103)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer category fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	1 427 053	1 427 053	1 427 053	768 179	1 427 053
R^2	0.847	0.851	0.860	0.895	0.844

Dependent variable is ln of the secondhand price.
Standard errors are clustered on make, in parentheses.
There are 66 clusters in all specifications except in (4) where there are 49 clusters.
Year fixed effects are based on the year the vehicle is sold/advertised.
Electric vehicles are the baseline.
We use a dummy on those observations that have missing mileage and those that have missing new car price.
Hydrogen and gas vehicles are not part of this as there are few observations.

Figure A-5: Mean of the answers to the question about whether the battery has degraded since the car was new.



Notes: The higher the better experience of the battery from 1-5.

D.1 Makes

There is a large difference in the average price fall between the different makes, which can be seen in Figure A-6. This can be due to different vintage or age of the cars, since electric Nissan entered the market in 2011, while electric Jaguar entered the market in 2018, but there can also be other reasons. There is a pattern where makes with large price fall have small cars with four seats (Smart, Fiat, Mitsubishi, Peugeot, Citroën).[23] Further, the majority of Ford's and Renault's models cannot fast charge, and the price fall of these cars is also above average of electric vehicles.[24]

The majority of the used cars sold from Tesla, Opel, Jaguar, Audi and Polestar have range above 400 km, and these makes have less than 10% price fall. Polestar has a price increase. Hyundai, which has a price fall in the same magnitude as Opel, has a model with range above 400 km (Hyundai Kona with range 449 km), but the sample also include Hyundai Ioniq which has 180 km[25]-311 km.

We also make this plot controlling for when the new vehicle price when the car was sold, instead of when the car was new, in Appendix Figure A-7. This changes the estimate for some of the makes, for instance Tesla.

We compare the price path of some specific models and makes. The most sold second-hand electric model, Nissan Leaf, compared to the most sold secondhand gasoline model, Volkswagen Golf, (see Table A-8) can be seen in Figure A-8.

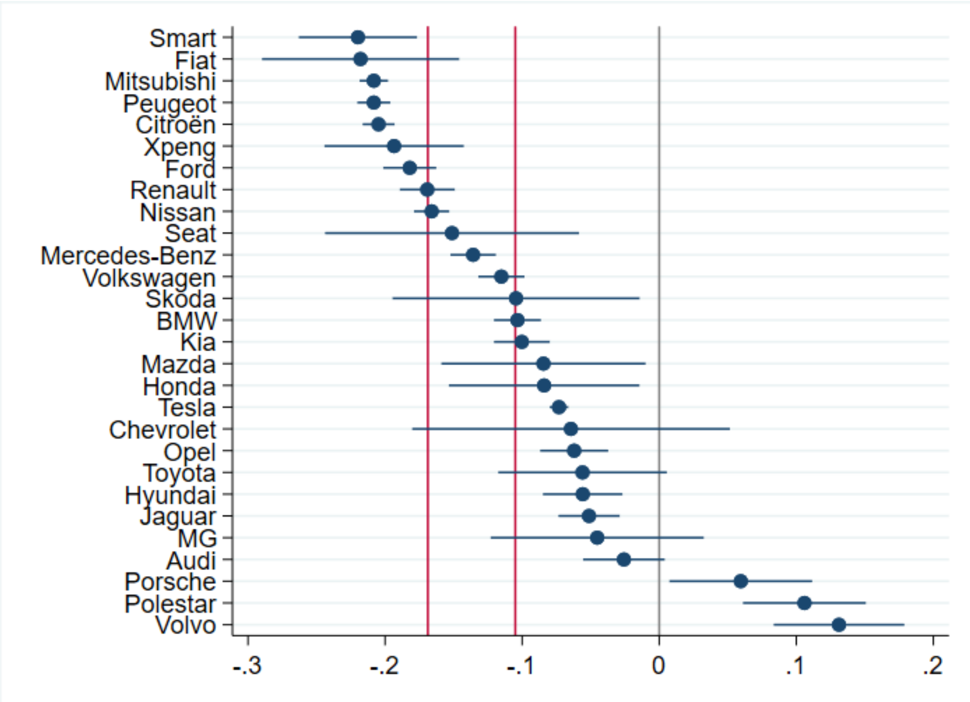
In Figure A-9 we compare gasoline vehicles where the new car price more than the median price of new vehicles with Tesla in the same price range. We see that Tesla fall less in price than gasoline vehicles.

[23] The exception is BMW which has a price fall close to the average for gasoline vehicles.

[24] Mercedes-Benz B-class can also not fast charge, but the price fall of this make is close to the average of electric vehicles. Toyota have not until recently supplied full electric vehicles and the Toyotas that is part of this sample is 147 RAV4 that was new during the years 2012-2015.

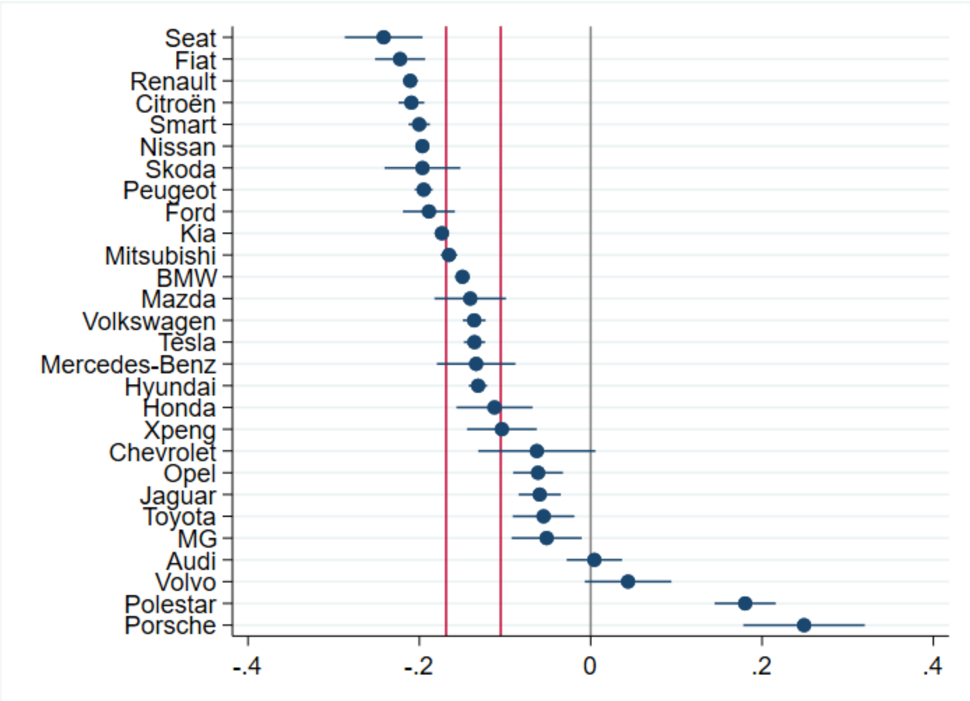
[25] The range is converted from NEDC range, see the Appendix B.3.1 for explanation.

Figure A-6: The average price fall for electric vehicles of different makes.



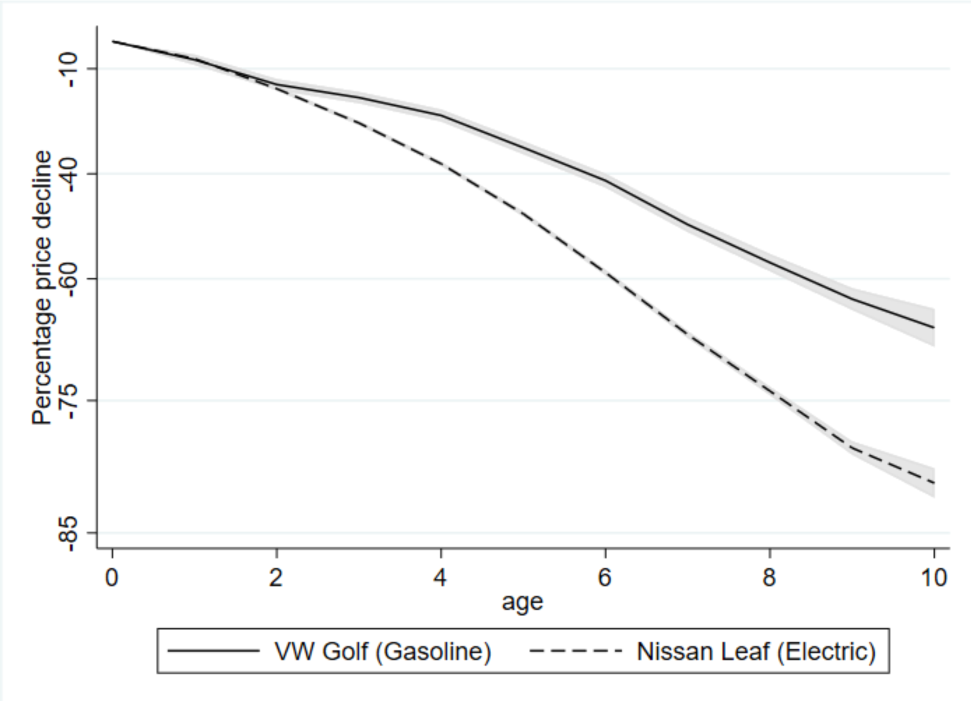
Notes: The red lines mark the average price fall for electric vehicles (-0.173) and the average price fall for gasoline vehicles (-0.106), based on the result in column 1 in Table 3. The grey line mark 0.

Figure A-7: Price fall for different makes controlling for the price of the new model when the car was sold, not when the car was new.



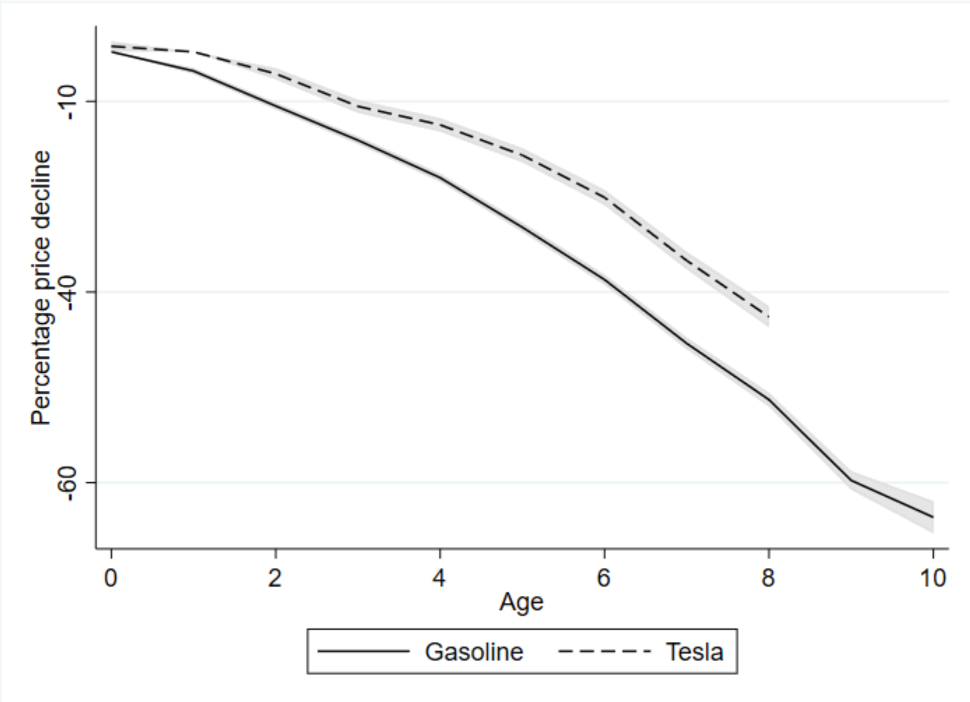
Notes: The red lines mark the average price fall for electric vehicles (-0.173) and the average price fall for gasoline vehicles (-0.106), based on the result in column 1 in Table 3. The grey line mark 0.

Figure A-8: Price path of the most sold used electric vehicle Nissan Leaf, compared to the most sold used gasoline vehicle, Volkswagen Golf.



The grey area is the 95% confidence interval. The standard errors are robust.

Figure A-9: The price path of Tesla vs gasoline vehicles.



Notes: The grey area is the 95% confidence interval. Here we compare the Teslas and gasoline vehicles that both have new vehicle price over the median. The standard errors are robust.

E Robustness

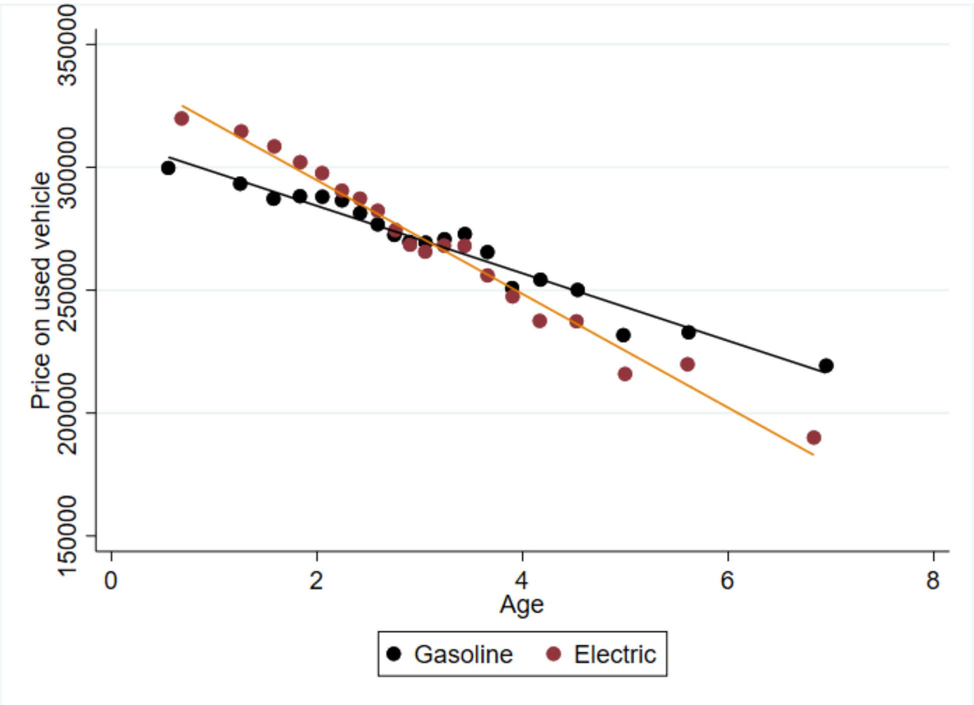


Figure A-10: Binned scatter plot of the data with prices in absolute values.

Table A-19: Controlling for many variables.

	(1)
Age	-0.110***
	(0.00288)
Electric × Age	-0.0413**
	(0.0179)
Ln new price	0.158***
	(0.0394)
Ln mileage × Gasoline	-0.0747***
	(0.00467)
Ln mileage × Electric	-0.0326***
	(0.00513)
Dealer category: Private seller	-0.103***
	(0.00780)
Dealer category: Professional car seller (not the make's own)	-0.0509***
	(0.00955)
Engine effect	0.00000891
	(0.0000207)
Number of seats	-0.000133
	(0.000690)
Year × fuel fixed effects	Y
Body style fixed effects	Y
Make fixed effects	Y
Model fixed effects	Y
Transmission fixed effects	Y
Wheel drive fixed effects	Y
Color fixed effects	Y
Observations	545 452
R^2	0.926

Dependent variable is ln of the secondhand price.
Gasoline vehicles are the baseline.
Among dealer categories are the make's professional car sellers baseline.
Year fixed effects are based on the year the vehicle is sold/advertised.
Standard errors clustered on make, in parentheses.
There are 62 clusters.
We use a dummy on those observations that have missing mileage
and those that have missing new car price.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-20: Table 3 with new vehicle price the year the vehicle is sold, not the year the vehicle is new.

	(1)	(2)	(3)	(4)	(5)
Age	-0.134***	-0.132***	-0.137***	-0.144***	-0.155***
	(0.00505)	(0.00478)	(0.00477)	(0.00632)	(0.00955)
Electric × Age	-0.0466***	-0.0464***	-0.0331***	-0.0367***	-0.139***
	(0.0121)	(0.0126)	(0.0107)	(0.0125)	(0.0349)
Ln new price when sold	1.059***	1.016***	0.903***	1.068***	0.0211***
	(0.0166)	(0.0219)	(0.0222)	(0.0175)	(0.00771)
Ln mileage × Gasoline	-0.0651***	-0.0627***	-0.0631***	-0.0387***	-0.0197
	(0.00788)	(0.00682)	(0.00818)	(0.00666)	(0.0168)
Ln mileage × Electric	-0.0332***	-0.0263***	-0.0351***	-0.0305***	0.154
	(0.00613)	(0.00632)	(0.00496)	(0.00621)	(0.107)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	545 452	545 452	545 452	336 220	545 452
R^2	0.791	0.793	0.823	0.817	0.364

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but in (4) where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-21: Table 3 with new vehicle price and fuel interacted.

	(1)	(2)	(3)	(4)	(5)
Age	-0.105***	-0.103***	-0.108***	-0.112***	-0.110***
	(0.00467)	(0.00441)	(0.00404)	(0.00544)	(0.00445)
Electric × Age	-0.0550**	-0.0550**	-0.0512**	-0.0565***	-0.0554***
	(0.0209)	(0.0219)	(0.0198)	(0.0188)	(0.0172)
Ln new price × Gasoline	1.065***	1.039***	1.022***	1.087***	1.062***
	(0.0245)	(0.0272)	(0.0289)	(0.0265)	(0.0253)
Ln new price × Electric	1.089***	1.058***	0.893***	1.090***	1.066***
	(0.0337)	(0.0445)	(0.0485)	(0.0760)	(0.0323)
Ln mileage × Gasoline	-0.0744***	-0.0751***	-0.0747***	-0.0608***	-0.0766***
	(0.00741)	(0.00620)	(0.00708)	(0.00542)	(0.00752)
Ln mileage × Electric	0.00734	0.0106	-0.00611	0.0122	0.00573
	(0.0105)	(0.0112)	(0.00845)	(0.0134)	(0.0102)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	452 743	452 743	452 743	283 785	452 743
R^2	0.867	0.868	0.882	0.899	0.862

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but specification (4), where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Table A-22: Table 3 without those with age=0.

	(1)	(2)	(3)	(4)	(5)
Age	-0.104***	-0.102***	-0.108***	-0.111***	-0.111***
	(0.00473)	(0.00433)	(0.00417)	(0.00555)	(0.00458)
Electric X Age	-0.0693***	-0.0690***	-0.0509**	-0.0621***	-0.0638***
	(0.0192)	(0.0197)	(0.0207)	(0.0171)	(0.0199)
Ln new price	1.077***	1.054***	1.003***	1.101***	1.071***
	(0.0256)	(0.0313)	(0.0331)	(0.0318)	(0.0255)
Ln mileage X Gasoline	-0.0978***	-0.0994***	-0.0953***	-0.0807***	-0.0982***
	(0.00838)	(0.00695)	(0.00806)	(0.00555)	(0.00843)
Ln mileage X Electric	0.00815	0.0104	-0.0192**	-0.000644	-0.00100
	(0.0143)	(0.0147)	(0.00880)	(0.0162)	(0.0142)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	494 120	494 120	494 120	299 668	494 120
R^2	0.853	0.855	0.875	0.897	0.850

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but in (4) where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-23: Table 3 without dummy on those that have missing new vehicle price and mileage, meaning that the sample is smaller.

	(1)	(2)	(3)	(4)	(5)
Age	-0.109***	-0.107***	-0.111***	-0.112***	-0.116***
	(0.00457)	(0.00421)	(0.00403)	(0.00547)	(0.00441)
Electric × Age	-0.0545***	-0.0540**	-0.0426**	-0.0579***	-0.0488**
	(0.0197)	(0.0203)	(0.0204)	(0.0173)	(0.0204)
Ln new price	1.071***	1.044***	1.015***	1.090***	1.064***
	(0.0232)	(0.0292)	(0.0277)	(0.0298)	(0.0230)
Ln mileage × Gasoline	-0.0709***	-0.0716***	-0.0720***	-0.0615***	-0.0714***
	(0.00738)	(0.00594)	(0.00726)	(0.00547)	(0.00734)
Ln mileage × Electric	0.0107	0.0133	-0.00473	0.0132	0.00284
	(0.0113)	(0.0118)	(0.00927)	(0.0145)	(0.0113)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	515 705	515 705	515 705	318 478	515 705
R^2	0.882	0.883	0.890	0.900	0.879

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses. There are 44 clusters in all but column 4, where there are 43 clusters.

The sample is smaller by 23 861 observations.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

Table A-24: Table 3 with absolute values instead of ln values.

	(1)	(2)	(3)	(4)	(5)
Age	-22873.2***	-21477.6***	-25096.0***	-22383.1***	-22986.3***
	(3829.1)	(3518.7)	(3397.9)	(3342.8)	(3716.2)
Electric × Age	-11624.2**	-11498.8***	-2585.1	-7842.4*	-11515.0**
	(4659.1)	(4113.2)	(4397.0)	(4038.9)	(4638.1)
New car price	0.728***	0.703***	0.613***	0.715***	0.729***
	(0.0414)	(0.0407)	(0.0217)	(0.0453)	(0.0410)
Mileage × Gasoline	-0.745***	-0.784***	-0.659***	-0.643***	-0.744***
	(0.135)	(0.111)	(0.109)	(0.0984)	(0.138)
Mileage × Electric	-0.0817	-0.0427	-0.568***	-0.198	-0.0929
	(0.133)	(0.130)	(0.165)	(0.149)	(0.134)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	545 452	545 452	545 452	336 220	545 452
R^2	0.786	0.790	0.835	0.869	0.786

Dependent variable is log of the secondhand price.

Standard errors clustered on make, in parentheses. There are 62 clusters in all but in (4) where there are 44 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-25: Table 3 with clusters based on make × fuel.

	(1)	(2)	(3)	(4)	(5)
Age	-0.105***	-0.103***	-0.109***	-0.112***	-0.111***
	(0.00452)	(0.00421)	(0.00371)	(0.00536)	(0.00441)
Electric × Age	-0.0638***	-0.0632***	-0.0468**	-0.0567***	-0.0584***
	(0.0195)	(0.0199)	(0.0194)	(0.0182)	(0.0202)
Ln new price	1.068***	1.046***	0.998***	1.088***	1.062***
	(0.0232)	(0.0287)	(0.0268)	(0.0267)	(0.0229)
Ln mileage × Gasoline	-0.0770***	-0.0776***	-0.0757***	-0.0608***	-0.0775***
	(0.00780)	(0.00668)	(0.00717)	(0.00545)	(0.00779)
Ln mileage × Electric	0.0170	0.0190	-0.00448	0.0123	0.00939
	(0.0126)	(0.0129)	(0.00798)	(0.0145)	(0.0127)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	545 452	545 452	545 452	336 220	545 452
R^2	0.859	0.861	0.879	0.902	0.857

Dependent variable is ln of the secondhand price.

Standard errors clustered on make, in parentheses.

There are 90 clusters in all but specification (4), where there are 68 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A-26: Table 3 with clusters based on make × year the vehicle is new.

	(1)	(2)	(3)	(4)	(5)
Age	-0.105***	-0.103***	-0.109***	-0.112***	-0.111***
	(0.00333)	(0.00321)	(0.00295)	(0.00396)	(0.00337)
Electric × Age	-0.0638***	-0.0632***	-0.0468***	-0.0567***	-0.0584***
	(0.0120)	(0.0122)	(0.0111)	(0.0122)	(0.0121)
Ln new price	1.068***	1.046***	0.998***	1.088***	1.062***
	(0.0163)	(0.0228)	(0.0167)	(0.0217)	(0.0163)
Ln mileage × Gasoline	-0.0770***	-0.0776***	-0.0757***	-0.0608***	-0.0775***
	(0.00389)	(0.00356)	(0.00360)	(0.00364)	(0.00390)
Ln mileage × Electric	0.0170	0.0190	-0.00448	0.0123	0.00939
	(0.0115)	(0.0114)	(0.00698)	(0.0117)	(0.0114)
Year × fuel fixed effects	Y	Y	Y	Y	Y
Dealer fixed effects	Y	Y	Y	Y	N
Body style fixed effects	N	Y	N	N	N
Make fixed effects	N	N	Y	N	N
Taken out those with large variation in new vehicle price and those without new vehicle price	N	N	N	Y	N
Observations	545 452	545 452	545 452	336 220	545 452
R^2	0.859	0.861	0.879	0.902	0.857

Dependent variable is ln of the secondhand price.

Standard errors clustered on make × the year the vehicle is new, in parentheses.

There are 482 clusters in all but specification (4), where there are 332 clusters.

Gasoline vehicles are the baseline. Year fixed effects are based on the year the vehicle is sold/advertised.

We use a dummy on those observations that have missing mileage and those that have missing new car price.

Paper 4: One or two non-fossil technologies in the decarbonized transport sector

Resource and Energy Economics 69 (2022) 101314

Contents lists available at ScienceDirect

Resource and Energy Economics

journal homepage: www.elsevier.com/locate/ree

One or two non-fossil technologies in the decarbonized transport sector?

Gøril L. Andreassen[a,*], Knut Einar Rosendahl[a]

[a] School of Economics and Business, Norwegian University of Life Sciences, Handelshøyskolen Postboks 5003 NMBU, 1432 Ås, Norway

ARTICLE INFO

Article history:
Received 10 September 2021
Received in revised form 7 March 2022
Accepted 19 May 2022
Available online 27 May 2022

JEL classification:
L62
Q42
Q54
Q58
R48

Keywords:
Indirect network effects
Decarbonization
Climate policy
Electric vehicles
Hydrogen vehicles
Technology

ABSTRACT

What factors determine whether policymakers should promote one or more technologies in a decarbonized road transport sector, and what policies should governments choose? We investigate these questions theoretically and numerically through a static, partial equilibrium model for the road transport market. We find that one important factor is how close substitutes the two vehicle technologies are. Further, the number of vehicles of one technology depends on the number of vehicles of the other technology, both in the market and in the first-best solution. The first-best policy involves a subsidy of the markup on charging and filling, where the markup is higher the more utility increases with the number of stations. However, as there are several possible market equilibria, additional policies may be needed to avoid an unwanted lock-in.

1. Introduction

Limiting global warming to well below 2 °C and aiming at 1.5 °C, in line with the Paris agreement, requires rapid and far-reaching transitions in all sectors, including the transport sector (IPCC, 2018). The EU has an objective of net-zero emissions by 2050, and the average share of non-fossil-fueled cars in their 2050 scenarios is 96 % (European Commission, 2018). Many countries, including China, Great Britain, France and Norway, have decided to stop the sales of gasoline and diesel cars some time between 2025 and 2040 (Burch and Gilchrist, 2018). Policies in some of the most climate-ambitious regions in the world, such as the EU and California, promote both fast charging stations for electric vehicles and hydrogen stations (European Commission, 2016; European Commission, 2018; CARB, 2022). However, there is limited scientific knowledge about whether it is optimal with one or more technologies in a decarbonized road transport market, and what policies governments should choose.

* Corresponding author.
E-mail addresses: goril.louise.andreassen@nmbu.no (G.L. Andreassen), knut.einar.rosendahl@nmbu.no (K.E. Rosendahl).

https://doi.org/10.1016/j.reseneeco.2022.101314
0928-7655/

On the one hand, having more than one technology in the transport sector gives the consumer more variety in which type of vehicle to choose. For instance, electric vehicles are more energy-efficient and thus cheaper to use than hydrogen vehicles, whereas hydrogen vehicles can refuel faster than batteries can be charged. The benefit of product differentiation therefore points in the direction of more technologies. This is especially the case when we think of the whole road transport sector, not just passenger cars, and interpret 'consumers' as all road transport users, including commercial and public agents using trucks, buses etc.

On the other hand, there are indirect network effects between vehicles (base good) and stations (complementary good). The utility of a vehicle owner increases the more stations there are with the same technology. Thus, the indirect network effects in the transport sector point in the direction of only one technology, as the size of each network is likely to be smaller if there are several incompatible vehicle technologies. How to balance the trade-off between the indirect network effects and the benefit of product differentiation? This article investigates what factors determine whether one or more technologies are optimal in a decarbonized road transport market, what the market outcome will be, and what policies governments should choose.

We analyze these questions theoretically and numerically through a static, partial equilibrium model. We find that the market outcome for one particular technology depends crucially on the number of vehicles of the other technology as well as how close substitutes the two vehicle technologies are. Furthermore, we show that critical mass may be needed to pass an unstable equilibrium. This means that if one technology has gotten a head, the other technology might not be able to enter into the market, even if it is optimal to have two technologies.

The numerical results, based on a calibration to the Norwegian road transport sector, indicate that a combination of the two technologies is optimal, even when they are quite close substitutes. The welfare of having two technologies decreases the closer substitutes the two technologies are, and if they are sufficiently close substitutes, welfare is highest with only one technology.

Dynamic investigations of the transition phase are important, and for instance Greaker and Midttømme (2016) and Zhou and Li (2018) find that there can be excess inertia in the transition from fossil-fueled to non-fossil-fueled vehicles. Zhou and Li (2018) show that there can be multiple equilibria with one technology, while this paper considers multiple equilibria with two technologies and investigates how the two technologies influence each other.

We model the station market as monopolistic competition between stations of the same technology. We find analytically that the first-best policy is simply a subsidy of the monopoly markup on charging/filling, i.e., the use of the *complementary* good (stations), which leads to the price of using this good being equal to the marginal cost. Obviously, the subsidy should only be applied to a vehicle technology if it is optimal from a welfare perspective to use this technology. In addition comes Pigouvian taxes reflecting any environmental costs. That is, subsidizing investments in stations or vehicles is not needed if charging/filling is subsidized, despite the indirect network effects.[1] Spence (1976) finds that with monopolistic competition, there can either be too many or too few products (cf. also (Dixit and Stiglitz, 1977), depending in particular on the substitutability of the products (here: stations). Although there is a love-of-variety effect with differentiated products, there is also a "business-stealing effect" that works in the opposite direction (Mankiw and Whinston, 1986). Moreover, the subsidy of *using* the product (i.e., charging/filling) increases demand and hence profits, indirectly increasing the number of stations.[2] Still, since we use a particular (but common) functional form, our result should be interpreted with some caution.

In our model, the monopoly markup increases with the consumers' utility from more stations. The higher the utility of more stations, the bigger the network effect, and hence the higher is the first-best subsidy. This result, that is, the preference for variety in the complementary good being important for determining the size of the network effect, is in line with Church et al. (2008). In addition, due to the possibility of an unstable equilibria, a temporary stimulus may be needed to reach the stable equilibrium and avoid an unwanted lock-in.

In contrast to network effects that are directly linked to the primary product, *indirect* network effects mean that the utility of the consumer increases through increased supply of the complementary good such as stations (Greaker and Midttømme, 2016). In a review article about network effects, Katz and Shapiro (1994), p.105–106) state that for *direct* network effects there are at least two important features. First, it is a "tendency of one system to pull away from its rivals in popularity once it has gained an initial edge." Second, "[c]onsumer heterogeneity and product differentiation tend to limit tipping and sustain multiple networks."[3] It is not trivial that results for direct network effects carries over to indirect network effects (Clements, 2004; Meunier and Ponssard, 2020), but we find exactly the same in a model with *indirect* network effects. Thus, our first contribution is to establish that the conclusion in Katz and Shapiro (1994) for competing products and direct network effects carries over to indirect network effects.

Most previous research on indirect network effects assume from the outset that there is either one or two network, without analyzing whether it is optimal with one or two. Greaker and Midttømme (2016) and Greaker and Heggedal (2010) investigate whether there are excess inertia or lock-in in the transition to a clean network good and per assumption divide the market between one clean and one dirty network good. Conrad (2006) investigates the choices of quality and pricing policies when the market consists of either one or two network goods, but does not characterize when the market outcome will be one or two technologies.

[1] Greaker (2021) finds that it is optimal to subsidize both the monopoly markup on charging and the charging station itself. However, as explained below, he transforms his model into one with *direct* network effects.

[2] Meunier and Ponssard (2020) find that it is optimal with a subsidy only to the station itself and not charging, but in their model price of charging is equal to marginal costs and charging per vehicle is exogenous.

[3] Katz and Shapiro (1994) build on the findings in e.g., Katz and Shapiro (1985), Farrell and Saloner (1986a) and Farrell and Saloner (1986b).

Meunier and Ponssard (2020) analyze the indirect network effects related to zero emission vehicles and stations in a static partial equilibrium model somewhat similar to ours. However, they consider only one technology, a competitive station market and fixed fuel use per vehicle, but instead assume Cournot competition and scale effects in the vehicle market. Like our paper, Meunier and Ponssard (2020) find multiple equilibria and the possibility of lock-in.

Greaker (2021) also applies a partial equilibrium model somewhat similar to ours, focusing on different charging standards (but otherwise identical electric vehicles). However, he makes a crucial assumption about the relationship between two important model parameters that turns the model into having direct instead of indirect network effects.

Among the few papers on the interaction between vehicle fleet and their network of stations, only Greaker (2021) and Meunier and Ponssard (2020) analyze first-best policies, as far as we know. While Meunier and Ponssard (2020) assume that quantity of fuel per vehicle is fixed, Greaker (2021) assumes that the total number of vehicles is fixed. In our paper, both quantities of charging/filling per vehicle and the total market size of vehicles are endogenous, which makes the analysis richer and is a contribution to the literature on network effects. To our knowledge this is the first model of indirect network effects with two competing, incompatible goods where the division of the market between the goods *and* the total size of the market are endogenous. The latter feature is particularly important in the context of our policy question, namely whether governments should support one or two technologies in a fully decarbonized road transport sector, as the answer to this partly depends on the total size of the market.

There is also an empirical literature that compares a subsidy to charging stations with a subsidy to electric cars (Springel, 2021; Li et al., 2017; Li et al., 2021). All three papers find that subsidies to stations leads to more electric cars than if cars are subsidized, assuming the same total subsidy payment. Springel (2021) also find that this holds only in the early development of the market as the returns to subsidizing charging stations are diminishing.

The rest of the paper is organized as follows. In the next section, we present the model, characterize the market solution, and analyze the possibility of zero, one or two market equilibria. Then, in Section 3 we derive the first-best solution, compare it with the market outcome, and derive the first-best policy. Further, in Section 4 we calibrate the model, and perform a variety of simulations, before we conclude and discuss limitations in the final section.

2. Modeling the road transport market

2.1. The model

2.1.1. Assumptions in the model

We develop a static, partial equilibrium model of the road transport market. Two imperfect substitutes (vehicles) that are part of two incompatible networks (stations) are modeled, and we will refer to the two vehicle technologies as electric and hydrogen. The insights from our analysis easily carries over to a situation with three or more technologies.[4] The analytical model is quite general, and may be applied also in other sectors than the road transport market. As the model is static, we do not analyze the transition phase, and also disregard other important externalities such as related to technological progress and knowledge generation (see e.g., Arthur (1989) and Acemoglu et al. (2012).

In our model, there are two types of economic agents; a representative consumer (representing both consumers and firms) that buy and use vehicles, and firms that supply the network of stations. Both types of agents are assumed to maximize their surplus. Using a representative consumer approach, where this consumer represents all types of road transport, the consumer will likely have a large number of vehicles, possibly of both technologies. Heterogeneous preferences for the two technologies are captured through modeling them as imperfect substitutes in the representative consumer's utility function. The indirect network effect is modeled through the utility of the consumer being dependent on how many stations there are. However, the representative consumer treats the number of stations as exogenous, and hence does not take into account that increased number of vehicles leads to increased number of stations. Therefore, the representative consumer does not internalize the indirect network effects.

We do not model the market for vehicles, but rather assume exogenous vehicle prices. This is in line with Springel (2021) where supply of vehicles is assumed to be perfectly elastic. This is reasonable for a country that is mostly importing vehicles, but is also valid if vehicle production takes place in a competitive market with constant returns to scale (CRTS). Both Greaker (2021) and Meunier and Ponssard (2020) assume instead Cournot competition in the vehicle market, with respectively CRTS and economies of scale in production. Hence, they both find that the first-best policy includes subsidies to vehicles.

We assume that there is only one vehicle model of each technology. This means that we disregard the fact that there are different segments of the vehicle market, and that there are different varieties and sizes of each type of vehicle, as we want to focus on the choice between two technologies.[5] Note that when we refer to demand for vehicles, we do *not* refer to sales in a given period but to the number of vehicles in a long-run equilibrium (i.e., the stock of vehicles).

Station owners decide which technology to choose; building hydrogen stations or fast charging stations. We assume monopolistic competition in the station market (for each technology). Although two stations of the same type supply the same

[4] This also means that gasoline vehicles can be part of the market analyzed. However, if we take the gasoline vehicle stock as of today as the starting point, the market is large and the network of stations are fully developed. Meunier and Ponssard (2020) show that the indirect network effect is less important for larger markets.

[5] This also means that we assume that all vehicles of the same technology can charge/fill at the same stations, which is different from Greaker (2021) who focuses specifically on different charging standards. At least for hydrogen it seems to be the case that trucks and cars can fill on the same stations (E24, 2019a).

energy input, they are spatially differentiated and can therefore charge different prices without losing all customers. Monopolistic competition for the complementary good is also assumed in the seminal paper on indirect network effects by Chou and Shy (1990). Due to free entry in monopolistic competition, the station market is characterized by zero profits in equilibrium. It then follows that if the number of vehicles with technology i changes, the number of stations adjusts such that capacity utilization stays constant.

Although our focus is on non-fossil vehicle technologies, we allow for potential environmental costs related to driving these vehicles, either directly or upstream when producing the energy carrier (electricity/hydrogen). This cost is proxied by the amount of charging/filling and we add a possibility of a Pigouvian tax on charging/filling, so that the economic agent internalizes the environmental costs.

2.1.2. Consumer's utility of vehicles

The utility of the representative consumer is assumed to depend on two additively separable vehicle-related benefits. In addition, it depends linearly on the composite good y. The first of the vehicle-related benefits is the benefit of the vehicles themselves (x_i), where utility is quadratic in vehicle demand with decreasing marginal utility. Moreover, the marginal utility of vehicles of technology i depends negatively on the number of vehicles of the other technology $-i$. The second vehicle-related benefits are the benefits of charging/filling, which depend on the number of stations (M_i) and charging/filling per station (q_{ij}),[6] where j denotes the individual stations (which are likely to be spread out geographically). The utility of the representative consumer is:

$$u(y, \boldsymbol{x_i}, \boldsymbol{q_{ij}}) = y + \sum_{i=1}^{2} a_i x_i - 1/2(b_1 x_1^2 + 2\phi x_1 x_2 + b_2 x_2^2) + \sum_{i=1}^{2}\left(x_i \kappa_i \left(\sum_{j=1}^{M_i} q_{ij}^{\rho_i}\right)^{\frac{\beta_i}{\rho_i}}\right) \tag{1}$$

where a_i is the utility of the first vehicle, b_i is determining the price sensitivity of demand for vehicles, ϕ the substitutability between the vehicle technologies, κ_i the utility of charging/filling and therefore affects the magnitude of the indirect network effect, ρ_i the utility from more stations (i.e. to what extent the stations can substitute each other), and β_i the indirect utility from more stations via total number of charges/fillings per vehicle.

The consumer maximizes its utility constrained by a binding budget constraint:

$$I = y + \sum_{i=1}^{2}\left(p_i(1-u_i)x_i + x_i \sum_{j=1}^{M_i}(\omega_{ij}(1-s_i)q_{ij})\right) \tag{2}$$

where I is exogenous income for the representative consumer, $_{pi}$ is the exogenous (periodical) price of vehicle i, u_i is a potential subsidy of the vehicle, ω_{ij} is the seller price of charging/filling at station ij, and s_i is a potential ad valorem subsidy of charging/filling vehicle i. We assume that any environmental tax t_i is paid upstream by the station as a tax proportional to charging/filling.[7]

In order to get a tractable analytical solution, we assume that stations of a certain technology i are symmetric, meaning that they have the same costs and face the same demand structure (the latter is already implicitly assumed in (1)). It then follows that in equilibrium we will have $q_{ij} \equiv q_i$.

When combining eqs. (1) and (2), we then get:

$$\begin{aligned} u(\boldsymbol{x_i}, \boldsymbol{q_i}) \;=\; & I - \sum_{i=1}^{2}(p_i(1-u_i)x_i + x_i M_i \omega_i (1-s_i) q_i) + \sum_{i=1}^{2} a_i x_i \\ & - 1/2(b_1 x_1^2 + 2\phi x_1 x_2 + b_2 x_2^2) \\ & + \sum_{i=1}^{2}\left(x_i \kappa_i M_i^{\frac{\beta_i}{\rho_i}} q_i^{\beta_i}\right) \end{aligned} \tag{3}$$

We assume that the gross utility from charging is strictly concave in the total number of charging/filling per vehicle ($M_i q_i$), which implies that $\beta_i < \rho_i/(1+\rho_i)$. The representative consumer optimizes its utility with respect to the number of electric vehicles, hydrogen vehicles, charging and filling (for a given number of stations). We assume interior solution for the variables we optimize, but the equations hold whether or not the other technology is used. By differentiating equation (3) with respect to q_i (strictly speaking with respect to q_{ij}) and x_i and setting equal to zero, we find the following expressions for charging/filling and vehicles.[8].

[6] This second part of the utility function is taken from Greaker (2021), which again is based on Belleflamme and Peitz (2015) and Chou and Shy (1990).

[7] The results would be the same if the tax is paid directly by the vehicle owner, even though we assume monopolistic competition in the station market.

[8] The first expression implies that the price elasticity of demand for charging/filling is $\frac{-1}{1-\beta_i}$. When $\beta_i > 0$, it means that the price elasticity (absolute value) is larger than 1, which is a quite high elasticity. Most studies on long-run price elasticity of demand for gasoline is between 0.5 and 1, see for instance (Labandeira et al., 2017) and (Yatchew and No, 2001).

$$q_i = M_i^{-\frac{\rho_i-\beta_i}{\rho_i(1-\beta_i)}}\left(\frac{\kappa_i\beta_i}{\omega_i(1-s_i)}\right)^{\frac{1}{1-\beta_i}} \tag{4}$$

$$x_i = \frac{1}{b_i}\left(a_i - \phi x_{-i} - p_i(1-u_i) + M_i^{\frac{\beta_i(1-\rho_i)}{\rho_i(1-\beta_i)}}(\omega_i(1-s_i))^{\frac{-\beta_i}{1-\beta_i}}\kappa_i^{\frac{1}{1-\beta_i}}\beta_i^{\frac{\beta_i}{1-\beta_i}}(1-\beta_i)\right) \tag{5}$$

where we have inserted for q_i from eq. (4) when deriving eq. (5). Note that x_i depends on M_i and x_{-i}. As the price of charging/filling (ω_i) increases with the tax (see Subsection 2.1.3), we notice that the optimal q_i is lower the higher is the environmental tax.

2.1.3. The station network

Each station owner maximizes profit $x_i(\omega_{ij} - \psi_{ij} - t_i)q_{ij}$ with respect to ω_{ij}, taking into account that q_{ij} depends on ω_{ij}, where $\psi_{ij} \equiv \psi_i$ is the unit cost of charging/filling. It is straightforward to show that the optimal price for the station owner then is $\omega_{ij} \equiv \omega_i = (\psi_i + t_i)/\rho_i$, so that the monopoly markup is $\frac{1}{\rho_i}$.[9] If the government wants to correct the market failure of monopoly pricing, it could subsidize the monopoly markup, including the markup of the tax. There is a fixed cost f_i of setting up a station. We allow for a government ad valorem subsidy σ_i to investments in stations, so that the station owner only pays $f_i(1-\sigma_i)$. In equilibrium, due to free entry we assume that each station owner earns zero profit, meaning that total fixed and variable costs must equal total payments for charging/filling from the representative consumer:

$$f_i(1-\sigma_i) = x_i(\omega_i - \psi_i - t_i)q_i \tag{6}$$

We then insert for the consumer's optimal charging/filling q_i in (4) into (6), and reorganize to get the following expression for M_i:

$$M_i = x_i^{\frac{\rho_i(1-\beta_i)}{\rho_i-\beta_i}}(f_i(1-\sigma_i))^{\frac{-\rho_i(1-\beta_i)}{\rho_i-\beta_i}}(\psi_i+t_i)^{\frac{-\rho_i\beta_i}{\rho_i-\beta_i}}(\kappa_i\beta_i)^{\frac{\rho_i}{\rho_i-\beta_i}}\left(\frac{1-\rho_i}{\rho_i}\right)^{\frac{\rho_i(1-\beta_i)}{\rho_i-\beta_i}}\left(\frac{1-s_i}{\rho_i}\right)^{\frac{-\rho_i}{\rho_i-\beta_i}} \tag{7}$$

We see that the number of stations of technology i increases with the number of vehicles with technology i, and also with the two types of subsidies σ_i and s_i, whereas higher fixed (f_i) and variable (ψ_i) costs and higher environmental tax (t_i) reduce the number of stations. In general, it is not possible to express x_i and M_i on reduced form.

2.2. The existence and the number of equilibria

In the previous subsection, we assumed that a market equilibrium exists for technology i, and derived conditions that must hold in equilibrium. In this subsection we examine under what conditions an equilibrium exists, and whether there can be multiple equilibria. In order to do that, we examine the interaction between the number of vehicles (x_i) and the number of stations (M_i) for a given technology. Eq. (5) expresses the consumer's demand for vehicles x_i as a function of M_i and x_{-i}, while eq. (7) determines the number of stations M_i as a function of x_i. An equilibrium requires that these two equations are simultaneously fulfilled for each technology in use.

Eq. (5) can be expressed as follows, where we also allow for the case where technology i is not in use:

$$x_i = \max[0; g(M_i, x_{-i})] = \max[0; A_i(x_{-i}) + B_i M_i^{\zeta_i}] \tag{8}$$

where

$$A_i(x_{-i}) = \frac{1}{b_i}(a_i - \phi x_{-i} - p_i(1-u_i))$$

$$B_i = \frac{1}{b_i}\left(\left(\frac{\psi_i+t_i}{\rho_i}(1-s_i)\right)^{\frac{-\beta_i}{1-\beta_i}}\kappa_i^{\frac{1}{1-\beta_i}}\beta_i^{\frac{\beta_i}{1-\beta_i}}(1-\beta_i)\right) > 0$$

$$\zeta_i = \frac{\beta_i(1-\rho_i)}{\rho_i(1-\beta_i)} > 0$$

Whereas B_i is strictly positive, A_i can be either positive or negative, depending in particular on the value of x_{-i} and ϕ.

Eq. (7) can be inverted as follows:

[9] The utility function implies that the elasticity of substitution for charging/filling between the differentiated stations is $\frac{-1}{1-\rho_i}$, implying a markup of $\frac{1}{\rho_i}$. This only holds when M_i is large. When e.g. $M_i = 1$, the markup is higher and equal to $\frac{1}{\beta_i}$, but then it is no longer monopolistic competition but monopoly.

$$x_i = h(M_i) = C_i M_i^{\gamma_i} \tag{9}$$

where

$$C_i = f_i(1-\sigma_i)(\psi_i + t_i)^{\frac{\rho_i\beta_i}{\rho_i(1-\beta_i)}}\left(\frac{1-s_i}{\rho_i\kappa_i\beta_i}\right)^{\frac{1}{1-\beta_i}}\left(\frac{\rho_i}{1-\rho_i}\right) > 0$$

$$\gamma_i = \frac{\rho_i - \beta_i}{\rho_i(1-\beta_i)} > 0$$

In the following discussion, we will first consider possible equilibria for one type of technology, for an exogenously given number of vehicles of the other type (x_{-i}). Subsequently, we will consider possible equilibria for both technologies simultaneously.

2.2.1. One technology: Three different cases

We first notice that both ζ_i and γ_i are strictly between 0 and 1, which means that both $g(M_i, x_{-i})$ and $h(M_i)$ are strictly increasing and concave in M_i. Because of the functional forms, eqs. (5) and (7) can be jointly satisfied for either zero, one or two values of $M_i > 0$, that is, there are either zero, one or two possible equilibria with strictly positive number of stations and vehicles (for a given level of x_{-i}). Which of the two functions that has the highest value as M_i goes to infinity is important and depends on the exponents ζ_i and γ_i. From our concavity assumption in Section 2.1.2 ($\beta_i < \rho_i/(1+\rho_i)$) it follows that $\zeta_i < \gamma_i$ at least if $\rho_i \geq 0.5$,[10] and in the following we will assume $\zeta_i < \gamma_i$.[11] This implies that the equilibrium with the highest level of M_i and x_i is a stable equilibrium (denoted M_i^S and x_i^S), while if there are two possible equilibria (with $M_i > 0$), then the other equilibrium is unstable (denoted M_i^U and x_i^U).[12]

The number of equilibria depends especially on $A_i(x_{-i})$. It is straightforward to see that we have one (and only one) equilibrium if $A_i(x_{-i}) > 0$, and we refer to this as case I. As explained above, the equilibrium in case I is stable. If $A_i(x_{-i}) < 0$, we have either two or zero positive equilibria, and we refer to these cases as case II and case III, respectively.[13] All three cases are illustrated in Fig. 1.

From the expression of $A_i(x_{-i})$ in eq. (8), we find the following results:

- If the number of vehicles of the other type is below a certain threshold, i.e., $x_{-i} < \frac{1}{\phi}(a_i - p_i(1-u_i))$, there is one unique stable and strictly positive equilibrium for technology i. The threshold can be positive or negative, depending on the utility of the first vehicle irrespective of charging/filling (a_i) relative to the price (net of subsidies). If the threshold is negative, there cannot be one unique equilibrium. If positive, the threshold is higher the lower is the substitutability between the two technologies (ϕ).
- If the number of vehicles of the other type is above the same threshold, there is either zero or two equilibria for technology i. In the latter case, the equilibrium with highest values of x_i and M_i is stable, while the other is unstable (cf. discussion above).

A positive $A_i(x_{-i})$, i.e., case I, seems more likely for electric than for hydrogen vehicles. Electric vehicles can to some degree be charged at home, while hydrogen vehicles cannot be filled without access to a hydrogen station. Therefore, we would expect the utility of the first vehicle (a_i), when there are no stations, to be higher for electric vehicles than for hydrogen vehicles. In addition, as electric vehicles have gotten a head on hydrogen vehicles in many countries, x_{-i} is typically highest for hydrogen vehicles.

Whether we are in case II or III when $A_i(x_{-i}) < 0$, depends on whether $h(M_i)$ is always above $g(M_i, x_{-i})$ (case III), or whether $g(M_i, x_{-i})$ is above $h(M_i)$ for some interval (M_i^U, M_i^S).

From eqs. (5) and (7) we can derive the following results:

- If $x_{-i} < \frac{1}{\phi}\left(a_i - p_i(1-u_i) + b\left(B_i M_i^{\zeta_i} - C_i M_i^{\gamma_i}\right)\right)$ for at least one M_i, then we are in case II with one stable and one unstable equilibrium for technology i. The lower is the substitutability between the two technologies (ϕ), the more likely it is that we are in case II.
- If the inequality above does not hold for any M_i, we are in case III with no positive equilibria for technology i.

Case II with one stable and one unstable equilibrium is of special interest. In this case, one cannot expect the market to move towards the stable equilibrium by itself if x_i and M_i start at low levels, i.e., lower than in the unstable equilibrium. Then the (representative) consumer may consider that there are too few stations, and scale down its number of vehicles, while the

[10] In our numerical analysis, we assume $\rho_1 = 0.6$ and $\rho_2 = 0.65$, see Section B.1.8 and B.2.4 in Appendix B.

[11] Note that $\zeta_i < \gamma_i$ implies $\beta_i < \frac{\rho_i}{2-\rho_i}$. Greaker (2021) in fact assumes $\beta_i = \frac{\rho_i}{2-\rho_i}$, which turns his model into a model with direct network effects.

[12] When $\zeta_i < \gamma_i$, then $h(M_i)$ exceeds $g(M_i, x_{-i})$ for all $M_i > M_i^S$ (with no positive equilibria, $M_i^S = 0$). This implies that if we are in a situation with M_i and x_i larger than (M_i^S, x_i^S), then M_i and x_i will move towards (M_i^S, x_i^S) (on the other hand, $\zeta_i > \gamma_i$ would imply the opposite, which seems highly unlikely). If two positive equilibria are possible, then M_i and x_i will move towards zero if starting below (M_i^U, x_i^U).

[13] If $A = 0$, there is either 0 or 1 strictly positive equilibrium, and thus we consider the former case as case III and the latter case as case I.

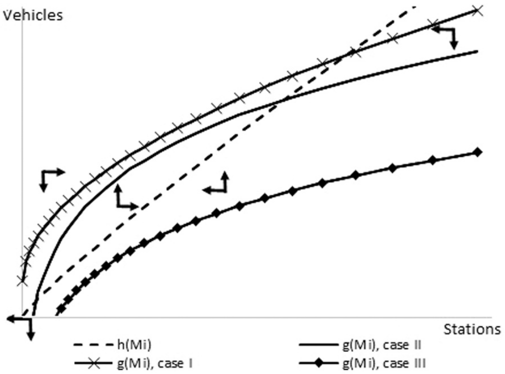


Figure 1. The three cases illustrated. The arrows apply to case II.

station owners may face negative profits and prefer to contract. Hence, we could see a negative tatonnement process going towards zero vehicles and zero stations.[14] This is also illustrated in Fig. 1, with arrows showing in which direction x_i and M_i move when the market is not in equilibrium. x_i will decrease (increase) whenever we start above (below) the g-curve, while M_i will decrease (increase) whenever we start to the left (right) of the h-curve. We see that if we start between the two curves to the left of the leftmost (unstable) equilibrium, market forces will move the market towards the origin with no vehicles and stations. On the other hand, if we initially are beyond the unstable equilibrium, $(M_i, x_i) > (M_i^U, x_i^U)$, we may see a positive tatonnement process moving towards the stable equilibrium (at least if we are between the two curves).

2.2.2. Two technologies simultaneously

From the discussion in the previous subsection, we know that both the likelihood of a positive equilibrium and the numbers of vehicles (x_i) and stations (M_i) in a stable equilibrium decrease with the number of vehicles of the other technology (x_{-i}). We can formulate this as response functions $x_i^S = X_i^S(x_{-i})$, where X_i^S is decreasing in x_{-i} up to the thresholds defined for case I and II above. For a potential unstable equilibrium for technology i (in case II) we have similar response functions $x_i^U = X_i^U(x_{-i})$, where X_i^U is increasing in x_{-i}. This is illustrated as response curves for the two technologies in Fig. 2, where the decreasing parts of the curves reflect $X_i^S(x_{-i})$, while the increasing parts reflect $X_i^U(x_{-i})$. The Fig. is inspired by Fig. 2 in Katz and Shapiro (1985). Where the curves intersect, we have an equilibrium for both technologies simultaneously. There are five possible equilibria in the Figure, where two of them are unstable (i.e., where one of the response curves are increasing). The three stable equilibria include one where both technologies are used, and two equilibria where only one is used (in which case x_{-i} is above the threshold defined for technology i in the previous subsection).

Although our model is static, the stability features of the various equilibria give some indication of where the market will move when not being in an equilibrium initially. If we are in a situation between the two unstable equilibria, the market will most likely move towards the stable equilibrium with two technologies. On the other hand, if we initially are between one of the equilibria with only one technology and the closest unstable equilibrium, the market will most likely move towards the former equilibrium.[15] Thus, if one technology has gotten a head start, it can be more and more difficult for the other technology to enter the market.

To sum up, for some model parameters we may have a situation where the three following stable equilibria are all feasible: (i) There are only electric vehicles, (ii) there are only hydrogen vehicles, and (iii) there are both electric and hydrogen vehicles. Which equilibrium that evolves will be path dependent, but a formal analysis of this is beyond the scope of our static analysis. We will however return to this issue in relation to the numerical analysis in Section 4. Another question is which of the equilibria that is best from a welfare perspective, something we discuss analytically in Section 3 and also in the numerical analysis in Section 4.

2.3. Effects of policy

Because of the network effects and monopolistic pricing of charging/filling, policy makers may want to implement subsidies to building of stations (σ_i), and/or to charging/filling (s_i), and/or to vehicles (u_i), in addition to a (Pigouvian) environmental tax

[14] See Meunier and Ponssard (2020), Greaker and Heggedal (2010) and Zhou and Li (2018) for a similar discussion of stable and unstable equilibria.

[15] In Fig. 2 there are five possible equilibria. This is not always the case, and depends on the parameters. For some parameter values there may be only one intersection with strictly positive levels of x_1 and x_2. In our numerical model below, there are five possible equilibria, see Fig. 3.

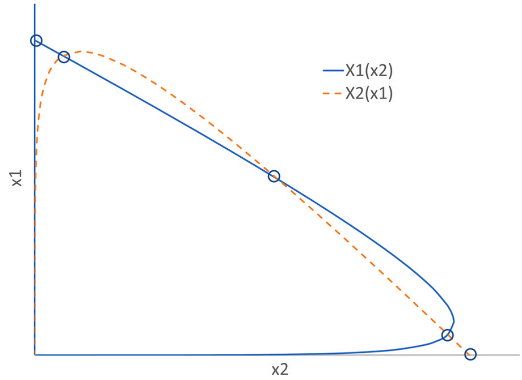


Figure 2. Simultaneous equilibrium for both technologies. The small circles denote the five possible equilibria.

on charging/filling (t_i). In the next section we examine first-best policies, but first we consider the effects of subsidies and taxes on the likelihood of a market equilibrium and the size of x_i and M_i in a stable equilibrium.

First, notice that subsidies to purchase of vehicles can affect whether $A_i(x_{-i}) > 0$, and hence whether or not we are in case I. On the other hand, the subsidies to stations and charging/filling and the environmental tax do not enter in $A_i(x_{-i})$ and thus do not affect whether or not we are in case I. If $A_i(x_{-i}) < 0$, the subsidies and the tax may all affect whether there will be two or zero equilibria (case II or III). The higher the subsidies and the lower the tax, the more likely we are in case II.[16]

Both in case I and II, the subsidies and the tax affect the equilibrium outcome, i.e., the size of x_i and M_i. An increase in one of the subsidies or decrease in the tax either decreases $h_i(M_i)$ or increases $g_i(M_i, x_{-i})$ or both. Thus, in both cases I and II, the higher are the subsidies and the lower is the tax, the higher is (M_i^S, x_i^S) and the lower is (M_i^U, x_i^U) (in case II). Hence, the subsidies may also make it easier to move beyond an unstable equilibrium, i.e., helping the market to move towards the stable equilibrium, while the tax has the opposite effect.

3. Welfare effects

In the previous Section, we derived conditions that must hold in a market equilibrium, examined under what conditions an equilibrium exists, and whether there can be multiple equilibria. In this Section we search for the socially optimal (global first-best) solution, and compare this with the market solution without and with policy. We will also consider locally optimal solutions, that is, solutions that are locally optimal for one or both technologies, but not necessarily the globally optimal solution. Next, we discuss whether the market will provide the optimal number of technologies.

3.1. Welfare maximization problem: First-best solution

The social planner maximizes welfare.[17].

$$\begin{aligned} W \;=\; & I + \sum_{i=1}^{2} a_i x_i - 1/2(b_1 x_1^2 + 2\phi x_1 x_2 + b_2 x_2^2) - \sum_{i=1}^{2} p_i x_i \\ & + \sum_{i=1}^{2} \left(x_i \kappa_i M_i^{\frac{\beta_i}{\rho_i}} q_i^{\beta_i} \right) \\ & - \sum_{i=1}^{2} (x_i M_i \psi_i q_i + f_i M_i) - \sum_{i=1}^{2} \tau_i q_i M_i x_i \end{aligned} \tag{10}$$

where the second and third terms are the gross utility of vehicles, the fourth term includes the costs of buying these vehicles (e.g., from abroad), the fifth term is the utility from charging/filling, the sixth and the seventh terms include the total costs of charging/filling, and the eighth term is the environmental cost (τ_i) related to driving vehicles.

[16] u_i enters positively in A_i, σ_i enters negatively in C_i, s_i enters negatively in C_i and positively in B_i, whereas t_i enters positively in C_i.

[17] The social welfare function is assumed to be utilitarian, meaning that it is the unweighted sum of consumer surplus, producer surplus and net government revenues, or equivalently the gross utility of the representative consumer minus the total vehicle-related costs.

In general, the globally optimal solution can include either both or just one of the two technologies (we disregard the possibility of zero technologies). If it is optimal from a welfare perspective to use a technology, the first order conditions must hold for this technology. These are (after some rearranging):

$$q_i^{*}=M_i^{-\frac{\rho_i-\beta_i}{\rho_i(1-\beta_i)}}\left(\frac{\kappa_i\beta_i}{\psi_i+\tau_i}\right)^{\frac{1}{1-\beta_i}} \tag{11}$$

$$x_i^{*}=\frac{1}{b_i}\left(a_i-\phi x_{-i}-p_i+M_i^{\frac{\beta_i(1-\rho_i)}{\rho_i(1-\beta_i)}}(\psi_i+\tau_i)^{\frac{-\beta_i}{1-\beta_i}}\kappa_i^{\frac{1}{1-\beta_i}}\beta_i^{\frac{\beta_i}{1-\beta_i}}(1-\beta_i)\right) \tag{12}$$

$$M_i^{*}=x_i^{\frac{\rho_i(1-\beta_i)}{\rho_i-\beta_i}}f_i^{\frac{-\rho_i(1-\beta_i)}{\rho_i-\beta_i}}(\psi_i+\tau_i)^{\frac{-\rho_i\beta_i}{\rho_i-\beta_i}}(\kappa_i\beta_i)^{\frac{\rho_i}{\rho_i-\beta_i}}\left(\frac{1-\rho_i}{\rho_i}\right)^{\frac{\rho_i(1-\beta_i)}{\rho_i-\beta_i}} \tag{13}$$

where the asterisk denotes the global first-best solution.

Note that these expressions are necessary conditions for an interior solution, but not sufficient conditions for the global first-best solution. We see the similarities with eqs. (5) and (7) (or (8)-(9)) in Section 2, indicating the possibility of multiple sets of solutions to equations (11)-(13). Indeed, the discussion of Figs. 1 and 2 carries over to here, where stable equilibria in the market correspond to global or local welfare maxima whereas unstable equilibria correspond to saddle points (cf. the corresponding discussion in Meunier and Ponssard (2020).[18]

Next, we would like to know if it is optimal with one or two technologies. This is difficult to conclude in general, but for the two extreme cases $\phi = 0$ (the technologies are not substitutes) and $\phi = b_1 = b_2$ (the technologies are perfect substitutes) we can conclude as follows (see proof in Appendix A):

- If the two technologies are symmetric and not substitutes ($\phi = 0$), then it is optimal to use both technologies.
- If the two technologies are symmetric and perfect substitutes ($\phi = b_1 = b_2$), then it is optimal to use only one technology.

If ϕ is between 0 and b, either one or two technologies may be optimal and this is an empirical question. Therefore, we return to this issue in the numerical analysis in Section 4.

Next, we want to compare the first-best solution with the market outcome, starting with the case without any subsidies, which we term business-as-usual (BAU).

3.2. Market solution without policy (BAU)

The market solution without any subsidies (BAU) means that we have $s_i = 0$, $\sigma_i = 0$, $u_i = 0$ and $t_i = 0$. We can then derive the following expressions for an interior solution for technology i based on eqs. (4), (5) and (7):

$$q_i^{BAU}=M_i^{-\frac{\rho_i-\beta_i}{\rho_i(1-\beta_i)}}\left(\frac{\kappa_i\beta_i}{\psi_i/\rho_i}\right)^{\frac{1}{1-\beta_i}} \tag{14}$$

$$x_i^{BAU}=\frac{1}{b_i}\left(a_i-\phi x_{-i}-p_i+M_i^{\frac{\beta_i(1-\rho_i)}{\rho_i(1-\beta_i)}}\left(\frac{\psi_i}{\rho_i}\right)^{\frac{-\beta_i}{1-\beta_i}}\kappa_i^{\frac{1}{1-\beta_i}}\beta_i^{\frac{\beta_i}{1-\beta_i}}(1-\beta_i)\right) \tag{15}$$

$$M_i^{BAU}=x_i^{\frac{\rho_i(1-\beta_i)}{\rho_i-\beta_i}}f_i^{\frac{-\rho_i(1-\beta_i)}{\rho_i-\beta_i}}\psi_i^{\frac{-\rho_i\beta_i}{\rho_i-\beta_i}}(\kappa_i\beta_i)^{\frac{\rho_i}{\rho_i-\beta_i}}\left(\frac{1-\rho_i}{\rho_i}\right)^{\frac{\rho_i(1-\beta_i)}{\rho_i-\beta_i}}\rho_i^{\frac{\rho_i}{\rho_i-\beta_i}} \tag{16}$$

How does the BAU outcome for technology i compare with the first-best solution (given interior solution)? This depends crucially on the size of the potential environmental costs of driving vehicle of technology i. Obviously, if τ_i is sufficiently large, there will be too much use of each vehicle and consequently also too many vehicles and stations of technology i.

On the other hand, if there are no environmental costs of using the vehicles ($\tau_i = 0$), there will be too little use of each vehicle due to the monopoly pricing of charging/filling. This is seen by comparing (14) with (11), where ρ_i makes q_i^{BAU} smaller than q_i^{*} (for a given level of M_i).

[18] Of course, the levels of x_i and M_i may differ, depending in particular on the subsidies and taxes imposed in the market.

Comparing next (15) with (12) and (16) with (13), still assuming $\tau_i = 0$, we see that x_i^{BAU} is smaller than x_i^* (for given levels of M_i and x_{-i}) and M_i^{BAU} is smaller than M_i^* (for a given x_i). Thus, in the case without any environmental costs of driving vehicle with technology i, there will be too few vehicles and stations of this type.[19]

An interesting special case is when $\psi_i + \tau_i = \frac{\psi_i}{\rho_i}$. Then (11) and (14) becomes equal, that is, the consumer is facing the total (private and social) unit cost of charging/filling. In other words, the environmental externality and the monopoly pricing cancel each other (for a given level of M_i). Further, we see that (12) and (15) also become equal (for given M_i), whereas (13) and (16) are not. For a given number of vehicles x_i, we find that M_i^{BAU} has an additional factor between zero and one, which goes towards one as ρ approaches one.[20] This means that the number of stations is too low in BAU in this special case. The reason is that station owners earn too little profits even if the number of vehicles and the level of charging/filling is optimal. As the number of vehicles is an increasing function of the number of stations, the number of vehicles also becomes too low in BAU in this special case.

To summarize, if the two technologies are symmetric and both are in use in both BAU and the first-best solution, and the environmental costs of technology i are sufficiently small ($\tau_i < \psi_i \frac{1-\rho_i}{\rho_i}$), we have: $M_i^{BAU} < M_i^*$, $q_i^{BAU} M_i^{BAU} < q_i^* M_i^*$ and $x_i^{BAU} < x_i^*$. The same holds of course if the environmental externality is higher but already internalized somehow in the BAU solution.

3.3. First-best policy

Can the first-best solution be implemented in the market, through an appropriate set of subsidies and taxes? To examine this, we compare eqs. (11)-(13) with eqs. (4), (5) and (7).

First, comparing (11) with (4), we see that the optimal level of charging/filling can be realized by combining a Pigouvian tax ($t_i = \tau_i$) with a subsidy rate s_i equal to $1 - \rho_i$, i.e., correcting for the monopoly markup. In the same manner, we notice that by inserting $s_i = 1 - \rho_i$ and $t_i = \tau_i$ into (5), this equation becomes identical to (12) as long as $u_i = 0$. Finally, doing the same in equation (7), we get the same expression as in (13) after some rearranging if and only if $\sigma_i = 0$.

Hence, the first-best solution can be implemented simply by implementing a Pigouvian environmental tax and correcting for the monopoly pricing in the charging and filling stations - then there is no need for a subsidy to building the stations or purchase of vehicles. We summarize this finding in the following proposition:

Proposition 1. Consider a market with two potential transport technologies as described above, and assume that the market develops towards a stable equilibrium with the optimal number of technologies. Then the first-best solution can be realized in the market through a Pigouvian tax ($t_i = \tau_i$) and subsidizing charging/filling at the rate $s_i = 1 - \rho_i$, and no subsidies to stations or vehicles. The subsidy should only be implemented for technology i if the first-best solution includes the use of this technology. The number of vehicles, stations and total charging/filling is higher in the first-best solution than in the BAU solution if $\tau_i < \psi_i \frac{1-\rho_i}{\rho_i}$ or the environmental externality is already internalized.

It may seem a bit surprising that there is no need for subsidies to stations or vehicles as long as the monopoly pricing is corrected, given the indirect network effect. As pointed to in the introduction, monopolistic competition can in general lead to too many or too few products (here: stations). Moreover, the subsidy to the *use* of the stations increases profits for station owners and hence indirectly stimulates the number of stations. Still, the finding in Proposition 1 should be interpreted with some caution as it hinges on the chosen functional forms.

If we are in case I with $A_i(x_{-i}) > 0$, there is only one market equilibrium, which is stable. In this case, the market is likely to move towards this equilibrium, and the policy described in Proposition 1 should be sufficient. Note, however, that $A_i(x_{-i})$ is decreasing with x_{-i}, so that we may move from case I to case II to case III for technology i as x_{-i} increases.

If we are not in case I, things are more complicated. First, we noticed in Subsection 2.3 that the likelihood of the existence of an equilibrium increases with the subsidies (if $A_i(x_{-i}) < 0$), and that the size of an unstable equilibrium decreases with the subsidies (and vice versa for the tax). Thus, it may be the case that no market equilibrium exists without any policy, while it exists with the first-best policy (or vice versa if the environmental externality is large). Moreover, if a stable market equilibrium exists even without policies, it may be less difficult to reach this equilibrium with first-best policy since the unstable equilibrium (i.e., the threshold to pass) is then characterized by lower levels of vehicles and stations (unless the environmental externality is large).

Hence, even if we do not observe any market developing for one of the technologies, it might be optimal to use this technology, too. This can also be the case even if the first-best policies described in Proposition 1 are in place. Thus, the market may need additional policies initially to reach the stable and first-best equilibrium. It may be challenging for policy makers, however, to know whether or not it is optimal with an additional technology.

[19] At least this is the case with symmetric vehicle technologies or with only one technology in use. With asymmetric vehicle technologies, we cannot rule out the case that the number of vehicle is highest in the BAU solution for one of the vehicle technologies. In the symmetric case, the lower level of M_i implies higher level of q_i, i.e., charging/filling at each station, so we cannot say whether q_i is higher or lower in the BAU solution. However, the total amount of charging/filling per vehicle ($q_i M_i$) is unambiguously lower in the BAU solution, due to both lower level of M_i and the monopoly pricing.

[20] Remember that the higher ρ_i, the less important is the network effect.

It is difficult to formulate analytical conditions for whether it is optimal with one or two technologies. For this purpose, we rely on numerical simulations, cf. Section 4. But first we briefly consider second-best policies, that is, when the first-best policies are not available.[21]

3.4. Second-best policy

It may be politically difficult to subsidize the markup on charging/filling, e.g., because it may be expensive for the government, and subsidies to investments in stations and vehicles are more common. What is the optimal level of σ_i and/or u_i in this case (i.e., if $s_i = 0$ but still $t_i = \tau_i$)?

As noted in Subsection 2.3, a higher s_i decreases $h_i(M_i)$ and increases $g_i(M_i, x_{-i})$, whereas a higher σ_i only decreases $h_i(M_i)$. Thus, as σ_i increases, we move to the right along the $g_i(M_i, x_{-i})$ curve in Fig. 1, while the first-best solution (with $s_i > 0$) lies above the $g_i(M_i, x_{-i})$ curve. Hence, a second-best policy with only subsidies to stations will likely lead to more stations per vehicle than in the first-best solution, and there will be a trade-off between too many stations or too few vehicles. If also subsidies to vehicles are used, it is possible to obtain the optimal number of both M_i and x_i.[22] However, the level of charging/filling will be suboptimal as the consumer will have to pay the full price. It is difficult to derive an expression for the second-best investment subsidy, and also to know whether it should be differentiated across technologies. Instead we come back to this in the numerical analysis.

4. Numerical analysis

4.1. Calibration

We calibrate the model based on data and future projections for the Norwegian vehicle market, considering electric ($i = 1$) and hydrogen ($i = 2$) vehicles. Norway has a very large share of electric vehicles compared to most other countries, with more than 60 % of new sales of cars in 2021. The calibration of a future equilibrium is obviously uncertain, as this is currently an emerging market. The uncertainty is both related to how the technologies and the market structure will develop the next years, as well as the consumers' utility from owning and using (i.e., charging/filling) the two types of vehicles (cf. the sensitivity analysis in Appendix E). A reasonable calibration is anyway useful in order to gain more insight into how different cost and utility parameters may affect the market outcome as well as the importance of policies.

We assume initially that there are no environmental costs from these two decarbonized vehicle technologies. Although there may be some upstream emissions in producing electricity and hydrogen, the Norwegian electricity production is almost 100 % renewable.[23] Still, we consider the effects of possible environmental costs in the sensitivity analysis.

It seems most natural to consider the calibrated equilibrium as the first-best solution, as the transition towards a decarbonized transport market in Norway is highly driven by government policies.[24] Moreover, we first assume that there are only electric vehicles in first-best equilibrium, as electric vehicles are much more prevalent today than hydrogen vehicles. Subsequently, we introduce hydrogen vehicles into the numerical model. We use the term *constrained* first-best equilibrium when we impose that the solution is optimal for one technology (with the other technology being absent or exogenous). Details about assumptions, sources and numbers are found in Appendix B.

In the calibrated constrained first-best equilibrium with only electric vehicles there are (by construction) 3.6 million electric vehicles (x_1 = 3.585 mill), almost 5000 charging stations (M_1 = 4, 975), and charging per vehicle per station is $q_1 = 0.014$, see Table 1 below. Moreover, we are in case I, i.e., with only one equilibrium, with $A_1 = 0$ (cf. footnote 13).

Calibration of the hydrogen network and vehicles is even more uncertain, and to some degree we apply the same parameters as for electric vehicles. Specifically, we assume that b_i, β_i and $_{pi}$ are the same for the two technologies. However, as hydrogen vehicles are more dependent on the network than electric vehicles, we assume $a_2 = 0.5a_1$ and $\kappa_2 > \kappa_1$ (cf. equation (1)). To make the two networks comparable, we require in the calibration that the level of x_2 in the constrained first-best equilibrium with only hydrogen vehicles is the same as that of x_1 (with only electric vehicles). See Table 1 and Appendix B for details.[25]

In Appendix C we present the results of the road transport market with only electric vehicles (Section C.1) and a hypothetical market with only hydrogen vehicles (Section C.2). Now we turn to the interaction between the two technologies.

[21] Whether governments should regulate or subsidize is also a question. If the government chooses to regulate the price on charging to marginal cost, the station owners will not earn money to cover the investments to stations, and the government will need to subsidize station building along with price regulation. We investigate subsidies to stations in Subsection 3.4.

[22] σ_i can be adjusted so that $h(M_i)$ passes through the optimal levels of x_i and M_i, and u_i can be adjusted so that $g(M_i, x_{-i})$ also passes through these levels, cf. eqs. (8) and (9).

[23] Norway trades electricity with neighboring countries, so increased use of electricity may lead to higher emissions abroad. However, the electricity sector in Europe is gradually being decarbonized, and is also regulated by the EU Emissions Trading System, which are further arguments for disregarding environmental costs of using electric vehicles. Hydrogen can be produced from either electricity (green if coming from renewables) or natural gas with or without carbon capture and storage (respectively gray and blue). Both green and blue hydrogen can be approximately carbon-free.

[24] For instance, the Norwegian Parliament has decided that from 2025 sales of new cars will only be non-fossil vehicles (The Norwegian Parliament (Stortinget), 2017)

[25] The model is solved using GAMS. The model code and data to replicate simulation results are readily available upon request.

Table 1
Numerical results with close substitutes. x_i is in million vehicles, M_i is in 1000 stations, q_i is in number of charges/fillings per year per vehicle per station, W is in billion NOK welfare. Local first-best is with only one technology.

	x_1	M_1	q_1	q_1M1	x_2	M_2	q_2	q_2M_2	x_1+x_2	W
Global first-best	2.278	3.049	0.023	0.070	1.768	1.912	0.039	0.075	4.046	38.032
Local first-best	3.585	4.975	0.014	0.070	–	–	–	–	–	37.328
Local first-best	–	–	–	–	3.585	4.054	0.019	0.077	–	33.915
BAU	3.209	2.394	0.016	0.038	0	0	0	0	3.209	35.101
Second-best I	2.342	3.062	0.013	0.040	1.390	1.741	0.027	0.047	3.732	36.398
Second-best II	2.309	3.050	0.013	0.040	1.655	1.763	0.026	0.046	3.964	36.593
First-best with τ_i	2.548	3.389	0.018	0.060	1.334	1.385	0.043	0.060	3.882	35.836
BAU with $t_i=\tau_i$	3.158	2.317	0.014	0.032	0	0	0	0	3.158	33.982

4.2. Interactions between the technologies

In this Subsection we investigate the response curves for the two technologies (cf. the discussion in Subsection 2.2 and Fig. 2) in a context where the first-best policy has been implemented for both technologies.[26] The response curves are displayed in Fig. 3. The solid curve shows the response curve of hydrogen vehicles with the number of electric vehicles as exogenous, while the dotted curve shows the response curve of electric vehicles with the number of hydrogen vehicles as exogenous. Possible equilibria (for both technologies simultaneously) are found where the response curves intersect, and we return to this below.

First, it is interesting to consider the response curves individually, that is, consider the other technology as exogenous. As discussed in Subsection 2.2.1, the higher the number of vehicles of the other technology (x_{-i}), the more likely is it that no equilibrium exists for technology i. However, this also depends on how close substitutes they are, represented by the parameter ϕ. The higher is ϕ, the lower is the likelihood of equilibria for technology i (for a given number of x_{-i}). Here we assume that the technologies are close substitutes (denoted case A), which we define as $\phi=2b_i/3$ (b_i is assumed equal for the two technologies, cf. Appendix B). Remember from Subsection 3.1 that if the technologies are symmetric and $\phi=b$, then it is optimal with only one technology, while it is optimal to use both if $\phi=0$.

When considering both technologies simultaneously, we see from Fig. 3 that there are five possible equilibria. Three of them are stable (denoted 1, 3 and 5), while two are unstable (2 and 4). Equilibria 1 and 5, with only electric and hydrogen vehicles, respectively, correspond to the locally first-best equilibria shown in Figs. 5 and 6 in Appendix C. Equilibrium 3 is the only stable equilibrium with two technologies. This equilibrium, which is the globally first-best outcome, is also illustrated in Fig. 7 in Appendix C. If the number of hydrogen (electric) vehicles is lower than in the unstable equilibrium 2 (4), hydrogen (electric) vehicles will not reach critical mass and move towards zero and equilibrium 1 (5). If the number of vehicles is higher, it will instead move towards equilibrium 3. We see from Fig. 3 that electric vehicles need a lower number of vehicles before the unstable equilibrium is passed compared to hydrogen vehicles.

This shows that when the two technologies are close substitutes, it may be difficult to reach the first-best solution for the hydrogen network and vehicles if the number of electric vehicles is already considerable. Assume e.g., that first-best subsidies to charging have been put in place, and that electric vehicles have been established in the market with a large number of vehicles. Then the hydrogen network will not be established even if first-best subsidies to filling is also implemented. Note however that we do not model this dynamic process explicitly.

The results of the globally first-best solution (equilibrium 3 in Fig. 3), where both vehicle technologies are used, and the locally first-best outcomes with only one technology (equilibria 1 and 5 in Fig. 3) can been seen in Table 1 in Section 4.4.

Annual welfare in the road transport sector increases by 704 million NOK (+2 %) when there are two technologies (equilibrium 3 in Fig. 3 compared to the case with only electric vehicles, and by 4.1 billion NOK (+12 %) compared to the case with only hydrogen vehicles. Thus, the importance of having two instead of one vehicle technology is quite moderate when they are close substitutes.

4.3. Comparing first-best and BAU

We now compare the global first-best solution with the corresponding BAU outcome, again when the technologies are close substitutes. When charging/filling is no longer subsidized in BAU and the technologies are close substitutes, there is no feasible market equilibrium with both technologies in use. This means that the two response curves in Fig. 3 do not cross. We cannot know for certain whether the market will choose electric or hydrogen vehicles. However, when we compare with the global first-best solution from Section 4.2, we will assume that the market chooses the equilibrium with the highest welfare, which is the one with electric vehicles.

The total number of vehicles are reduced by 21 % in BAU compared to the global first-best outcome. The number of electric vehicles increases by 41 % in BAU since this technology is now alone in the market. Charging per vehicle per station decreases by

[26] As explained in Proposition 1, the subsidy should not be provided to a technology which is not used in the global first-best solution.

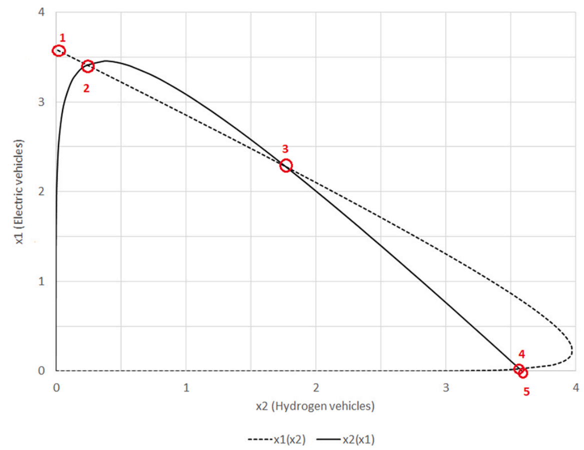


Figure 3. Graph showing how the number of hydrogen (electric) vehicles depends on the number of electric (hydrogen) vehicles. Five equilibria are shown, where three are stable (1, 3 and 5) and two unstable (2 and 4).

30 % when charging is no longer subsidized in the BAU outcome. Therefore, even if the number of electric vehicles increases, the number of charging stations decreases by 21 %. The reduction in annual welfare in the road transport market in BAU compared to first-best is 8 % (2.9 billion NOK). In contrast, when the technologies are distant substitutes, there are two technologies in the market also in BAU (cf. Appendix C).

4.4. Second-best solutions

For various reasons, the first-best policy may not be feasible or desired by the government. First, subsidizing investments in stations and purchase of vehicles may be easier to implement and administer than subsidizing charging/filling. Second, public expenditures may be higher when subsidizing charging/filling, in which case it may be more desirable to subsidize stations and/or vehicles. This is indicated by subsidies to stations and vehicles being more widespread than subsidies to charging/filling in the world today (IEA, 2019).

Ideally, constraints on public expenditures should be incorporated into the welfare function somehow (e.g., as the cost of public funds). In this subsection, we instead investigate two kinds of second-best policies. The first is to give an investment subsidy to the stations, and we refer to this as second-best I. The second is a combination of a subsidy to stations and to vehicles, and we refer to this as second-best II. Welfare in second-best II will be at least as high as in second-best I. We focus on close substitutes here, and leave distant substitutes to Appendix C. The main results are shown in Table 1.

4.4.1. Second-best I (subsidy to stations)

We see from Table 1 that when the two technologies are close substitutes, subsidizing stations instead of charging/filling leads to almost the same number of charging stations as in the first-best solution, and about 20 % fewer filling stations. However, charging per electric vehicle (q_1M_1) is reduced by 43 %, and is only slightly higher than in the BAU outcome, while filling per hydrogen vehicle (q_2M_2) is reduced by 37 % compared to the first-best solution. The second-best subsidy rates to fast charging and hydrogen stations are respectively 42 % and 47%.

The total number of vehicles is reduced by 8 % compared to the first-best solution and is 16 % higher than the BAU outcome, see Table 1. The market share for electric vehicles is now 63 % compared to 56 % in the first-best outcome, as the number of electric vehicles increases slightly whereas the number of hydrogen vehicles drops by 21 %. Thus, when the technologies are close substitutes, the electric vehicles are taking over some of the market from hydrogen vehicles in the second best I solution, but not as much as in the BAU outcome (when it is 100 %).

Annual welfare from road transport in the second-best I solution is 1.6 billion NOK lower than in the first-best outcome, but 1.3 billion NOK higher than in BAU, see Table 1. Thus, the second-best I policy is an improvement over BAU, but still falls short of the first-best welfare level.

4.4.2. Second-best II (subsidies to stations and vehicles)

When vehicles may be subsidized in addition to stations, we get closer to the first-best solution. That is, the number of hydrogen vehicles increases compared to the second-best I outcome, while the number of electric vehicles is actually somewhat lower when they are subsidized (second-best II) compared to when they are not (second-best I), see Table 1. The total size of the vehicle market is only 2 % lower than in the first-best outcome. The number of stations and charging/filling per vehicle change only marginally in second-best II compared to second-best I, see Table 1. The second-best subsidy rates to fast charging and filling stations are now respectively 43 % and 37 %, while the subsidy rates to purchasing electric and hydrogen vehicles are respectively 2.3 % and 3.8 %.

Annual welfare from road transport in the second-best II solution is 1.4 billion NOK lower than in the first-best outcome, but 1.5 billion NOK higher than in BAU, see Table 1. Thus, the additional gains of subsidizing vehicles in addition to stations are merely 200 million NOK.

4.4.3. Public expenditures

Public expenditures are more than twice as high in the first-best outcome compared to the second-best I outcome (annual subsidy payments of 8.6 versus 3.7 billion NOK), see Table 14 in Appendix C. Combining subsidies to both stations and vehicles (second-best II) has almost the same public expenditures as in first-best (8.3 billion NOK). As a comparison, total annual welfare in the road transport market is 38 billion NOK in the first-best scenario (with close substitutes), see Table 1. Thus, if we had added costs of collecting public funds to the welfare expression, the second-best I policy might have outperformed the first-best policy.[27]

Public expenditures are lower if only electric vehicles are available than in the case with two technologies, both in the first- and second-best solutions, because then the government do not have to subsidize two station networks, either through subsidizing charging/filling or stations. Public expenditures with only electric vehicles are 6.3 and 2.8 billion NOK in the first-best and second-best I solutions, respectively, see Fig. 14 in Appendix C.[28]

The effects on public expenditures show that in addition to the tradeoff for the consumer between network size and product differentiation, there is also a tradeoff for the government between welfare and government budget.

4.5. When is only one technology optimal? The role of substitutability

Fig. 4 shows the (global or local) first-best and second-best policies with either one or two technologies for different values of the substitutability, ϕ. When $\phi = b_i = 6.8$, the technologies are perfect substitutes. The figure confirms what we noticed above, that is, the welfare gains from using both technologies are much higher when the two technologies are distant substitutes. The figure further shows that when ϕ exceeds 4.7, using only electric vehicles is welfare-superior compared to using both technologies. When ϕ is between 4.7 and 5, implementing the first-best policy proposed in Proposition 1*but for both technologies* can in fact lead to a market equilibrium with both technologies in use, even if welfare is higher when only using electric vehicles. When ϕ is higher than 5, only one technology can sustain in the market with first-best policy.

We also compare the welfare level with second-best I policy when there are two technologies and when there is one technology, see Fig. 4. The results are not very different from with first-best policy, but the threshold value of (ϕ) increases slightly, meaning that with second-best I policy, it is slightly more favorable with two technologies.

4.6. Environmental cost ($t_i = \tau_i$)

Up to now we have disregarded any environmental costs in our numerical analysis. We next investigate the effects of implementing a Pigouvian tax set equal to the environmental unit costs. We set the cost of upstream CO2 emissions from one charge to 5 NOK (see details in B.1.13) and from one hydrogen filling to 13.5 NOK (see details in B.2.7), both corresponding to 100 km drive. One might also include the costs of emissions from particulate matter when driving, but these costs vary considerably between urban and rural areas and are therefore difficult to estimate.[29]

In Table 1 we see the first-best solution with $t_i = \tau_i$ included and also the outcome when only the environmental tax is introduced (“BAU with $t_i = \tau_i$”). Since hydrogen vehicles have higher environmental costs than electric vehicles, the number of hydrogen vehicles is reduced in the new first-best solution. The reduction of hydrogen vehicles gives electric vehicles an advantage and thus the number of electric vehicles increases when environmental costs are included, but the total number of vehicles is naturally reduced.

In BAU with Pigouvian tax the market equilibrium has only one technology, electric vehicles, as in the original BAU without environmental tax, but the number of vehicles and stations and charging per vehicle are naturally lower. The welfare is however lowest when the environmental cost is internalized, but not the network effect (BAU with $t_i = \tau_i$ compared to BAU in Table 1). This illustrates that correcting only one market failure but not all may in fact lead to lower welfare.

5. Discussion and conclusion

Whether there should be one or more technologies in a decarbonized road transport sector is an important policy question for the coming years. Our goal has been to provide insight into this question. We have demonstrated, both theoretically and

[27] If the technologies are distant substitutes, public expenditures will be higher because there will be more vehicles, charging per vehicle and stations, but also welfare will be higher. See more details in Appendix C.

[28] With only hydrogen vehicles, public expenditures are 9.7 and 4.0 billion NOK in the first-best and second-best I solutions, Table 14 in Appendix C.

[29] There are also other external costs related to driving such as congestion, accidents, noise and making neighborhoods less safe, but these are not included here.

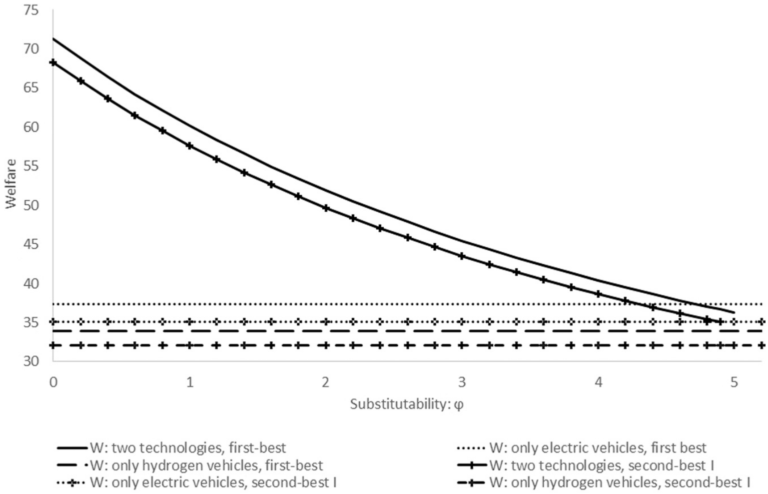


Figure 4. Graph showing how the welfare of having two technologies reduces the closer substitutes the two technologies become, measured by the size of ϕ. Close substitutes are defined as $\phi = 2b_i/3 = 4.545$, and distant substitutes as $\phi = b_i/3 = 2.272$, where $b_i = 6.8$. It is not feasible with two technologies in the market when $\phi > 5$ (hence the line stops there).

numerically, that a decisive factor is the substitutability between the vehicle technologies. Further, the market outcome for one vehicle technology depends crucially on the number of vehicles of the other technology, and critical mass may be needed to pass an unstable equilibrium. This means that if one technology has gotten a head, the other technology might not be able to get into the market, even if it is optimal to have two technologies.

Further, we have shown that with our assumptions and specifications the first-best solution can be realized in the market by combining Pigouvian taxation of any environmental costs with subsidizing (only) charging/filling. The subsidy should only be provided to a technology if it is optimal from a welfare perspective to use this technology. However, our conclusion depends on the functional form and should be interpreted with caution. Due to the possibility of unstable equilibria, the market may need additional policies initially to reach the stable and optimal equilibrium.

The numerical results in the context of the Norwegian road transport sector indicate that a combination of the two technologies, even when they are quite close substitutes, is optimal. The welfare gains going from one to two technologies are much larger if the technologies are distant than if they are close substitutes. If they are much closer substitutes, however, it is possible that both technologies are realized in the market (with the first-best subsidy implemented), even though it is optimal with only one technology. We have also found that a second-best policy of subsidizing stations instead of charging/filling implies less than half the public cost, and takes us quite close to the first-best solution.

The results in our study should be interpreted with caution, however, as they are derived from a quite stylized model with several uncertain parameters. Calibration of the model is highly uncertain as this is currently an emerging market. The uncertainty is both related to how the technology and the market structure will develop the next years, and the consumers' utility from owning and using the two types of vehicles. Even if first-best policies were to be implemented, it is difficult to identify the optimal subsidy rate due to the uncertainty about the crucial parameter ρ_i. It is therefore difficult to know whether a first-best policy actually has been implemented.

We have identified one particularly important factor for whether one or more technologies are optimal, that is, how close substitutes the vehicle technologies are. How the substitutability between the technologies will develop is difficult to predict, and it depends among other things on how the technological development of batteries evolves, both when it comes to range and charging time. In addition, the substitutability will likely vary across different segments of the vehicle market. For some segments of the transport market such as long distance heavy trucks the substitutability is low at the moment and may also stay low, but this is uncertain. Due to the importance of substitutability, it will be vital to study this factor more closely, also in other markets where network effects and product differentiation are central.

As mentioned above, the number of vehicles of the other technology can be important for whether a new technology will get into a market. Hence, it might be difficult to identify whether a situation with first-best policies in place but only one technology observed in the market, means that it is in fact optimal with only one technology, or whether instead it is optimal with two technologies but the new technology is struggling to pass the unstable equilibrium.

We have assumed exogenous vehicle prices, in line with Springel (2021), while Meunier and Ponssard (2020) and Greaker (2021) assume Cournot competition (Meunier and Ponssard, 2020) assume increasing returns to scale). The exogenous vehicle price assumption might be too simplistic. For instance, if there are capacity constraints in the production of vehicles, subsidies to vehicles might not be fully passed on to consumers. On the other hand, if the vehicle producers decide to cross-subsidize their electric or hydrogen vehicles when more stations become available, subsidies to stations or charging/filling might influence the price of vehicles. The relation between the market structure and the indirect network effect of the vehicle market deserves more investigation. Further, if we had included knowledge externalities in the vehicle market as the technology is developed, it might be optimal to subsidize vehicles for that reason.

Last but not least, our model is static, and hence cannot be used to analyze the dynamic transition from a fossil-based to a non-fossil-based road transport market. The results from a static model may not be valid in a dynamic setting, especially as transitional costs may be important for the overall welfare assessment. That is, we cannot rule out the possibility that the optimal solution within our static framework is not optimal when accounting for the transition period. Thus, extending our model to a dynamic model could be valuable. Potential government interventions in order to reduce the cost and increase the performance of the technologies through technological development are also disregarded in our analysis, and could be included in a dynamic analysis.

CRediT authorship contribution statement

Gøril L. Andreassen: Conceptualization, Writing-original draft, Methodology, Software, Formal analysis. **Knut Einar Rosendahl:** Writing-review & editing, Supervision, Methodology, Software, Formal analysis.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declarations of interest

none.

Acknowledgments

We would like to thank Mads Greaker for valuable input and discussions, and the editor and two anonymous reviewers for valuable comments.

Appendix A. Analytical proofs

A.1. Proof of result in Subsection 3.1

In Subsection 3.1 the following conclusions are stated:

1. If the two technologies are symmetric and not substitutes ($\phi = 0$), then it is optimal to use both technologies.
2. If the two technologies are symmetric and perfect substitutes ($\phi = b_1 = b_2$), then it is optimal to use only one technology.

Proof.

1. If $\phi = 0$, then there is no connection between the two technologies in (10), that is, the welfare expression can be separated into two independent expressions. It then follows that if it is optimal to use technology i, then it is also optimal to use technology $-i$ (given that they are symmetric). Since we have disregarded the possibility of using no technologies, the conclusion follows.
2. If ($\phi = b_1 = b_2$), notice first that the second, third and fourth terms in (10) are all functions of the sum of vehicles (i.e., distribution between technologies does not matter anymore). Assume first that it is optimal with two technologies. Since they are symmetric, they will have the same numbers of x_i, M_i and q_i. Consider an outcome with only one technology and the same total number of vehicles and stations and same number of charging/filling per vehicle (which means that q_i is halved). All terms in (10) except the fifth are then unchanged. The fifth term increases by the factor $2^{(\beta/\rho - \beta)} > 1$. This shows that it is possible to choose an outcome with one technology that gives higher welfare than the optimal solution when using two technologies.

$\square$.

B. Calibration of numerical model

B.1. Calibration of the electric vehicle market

We calibrate the model against the Norwegian road transport market, using both current data and future projections.[30] As mentioned in the main text, we consider the calibrated equilibrium as the local first-best solution.

B.1.1. The number of vehicles (x_1)

Norwegian Environment Agency (2015) analyzes different packages of measures for 2030, and uses a reference level for total number of vehicles in Norway in 2030 (p. 149–150). This number is 3 585 000 vehicles and includes cars, light commercial vehicles, trucks and buses. As electric vehicles are much more prevalent today than hydrogen vehicles, we initially calibrate our model so that in the first-best equilibrium the number of electric vehicles is identical to the projected number for the whole vehicle stock (and assume no hydrogen vehicles).[31]

B.1.2. The number of charges per vehicle per station (q_1)

According to Figenbaum (2019) the average charging in 2017 lasted for 20.3 minutes. We use this number and assume 20 % utilization of the charging stations. This means 14.2 charges per charging point per day.[32] We also assume that there will be 10 charging points on average per charging station.[33] We can then calculate the total number of charges per year per station, and by dividing by the number of vehicles we derive the number of charges per vehicle per station in our calibrated equilibrium ($q_1 = 0.014$).

B.1.3. The price of one charge (ω_1)

At some stations in Norway customers pay for charging per minute. At other stations customers pay per minute and kWh. In the calibration we have used the prices of the provider of fast charging stations that has the highest market share, Fortum Charge & Drive. The price is 3.10 NOK per minute (Norwegian Electric Vehicle Association, 2019). As the average charge in 2017 lasted for 20.3 min (see above), this implies 62.93 NOK per charge, which is the value we use for ω_1 in our calibration. The prices for fast charging might change in the future, but we choose to use current prices.[34]

B.1.4. The fixed annual cost of a charging station (f_1)

We assume that one charging point costs 800 000 NOK, everything included.[35] With 10 charging points per charging station (see above), and an interest rate of 10 % and 10 years lifetime, the fixed annual cost of a charging station is 1.3 million NOK.

B.1.5. The unit cost of each charge (ψ_1)

We use eq. (6) and the numbers derived above (for f_1, q_1, x_1 and ω_1) to determine ψ_1, which then becomes 37.79 NOK. According to Sales & Product Manager Snorre Sletvold at Fortum Charge & Drive, the unit cost is 3–3.5 NOK/kWh (excl. VAT). If we use the energy that an average charge gave in 2017 (9.6 kWh), this means that the unit cost of one charge is 36–42 NOK. Thus, a value of $\psi_1 = 37.79$ seems realistic. In the future there will be more energy per charge, but then probably the price will change as well.

B.1.6. The number of charging stations (M_1)

We assume that the number of charging stations per vehicle is the same as the number of Tesla cars per Tesla charging station in Norway in 2019, which were 721.[36] Combining this with the number of vehicles, we get 4975 fast charging stations in our calibrated first-best equilibrium.

B.1.7. The price of the vehicle (p_1)

In our model, there is just one type of electric (and hydrogen) vehicle, which should represent everything from small electric vehicles to large trucks. Hence, it is natural to think of the price per vehicle as a rough average of all these. For this purpose, we

---

[30] In Norway there are over 337 000 electric vehicles and electric cars constitutes 12 % of the total car park (Norwegian Electric Vehicle Association, 2021a, 2021b), which gives some data into the calibration.

[31] Obviously, it will not be 3.6 million electric vehicles in Norway in 2030, but we are interested in a long-run equilibrium with only non-fossil vehicles. It will take more years to reach that equilibrium.

[32] According to Sales & Product Manager Snorre Sletvold at Fortum Charge & Drive they need 10–12 charges per day in order to not loose money.

[33] On average, Tesla currently has 13 charging points per charging station in Norway, while the other fast charging network for other electric vehicle models has 2.24 charging points per charging station, according to Nobil (2019).

[34] How much can a vehicle drive on one charge? According to Figenbaum (2019), the average charge in 2017 gave 9.6 kWh energy. Given larger batteries, it is reasonable to assume that the energy delivered to each vehicle per minute of charging will increase. If energy per charging is 2.5 times higher than today, while charging lasts the same amount of time, one charge will take the vehicle 100 km, assuming that vehicles spend 2.5 kWh per 10 km (Norwegian Electric Vehicle Association, 2017).

[35] This is somewhat higher than for instance Fortum Charge & Drive's fixed cost of 50 kW stations which is 600–650 000 NOK, but with higher effect, the costs might increase somewhat.

[36] Note that this is vehicles per charging station, not per charging point.

use the price of the cheapest trim of Tesla Model Y in June 2019, which is 450 320 NOK (OFV, 2019). This price is exempted from VAT as electric vehicles are exempted from VAT in Norway. Further, we assume an interest rate of 5 % and a vehicle lifetime of 15 years. This gives an annual price of 43 385 NOK. Adding VAT would increase the price by 25 %. On the other hand, battery costs are projected to fall. Hence, we stick to this price in our model, but consider this as the price incl. VAT.

B.1.8. The degree the stations with the same technology can substitute each other (ρ_1)

The size of ρ_1 follows from the relationship $\rho_1 = \frac{\psi_1}{\omega_1} = 0.6$.

B.1.9. The indirect utility from more stations (β_1)

The size of β_1 is highly uncertain, except that we have required $\beta_i < \frac{\rho_i}{2-\rho_i}$. A positive β_1 implies that the elasticity of demand for charging is below − 1 (when keeping the number of stations fixed), and the higher β_1 the more elastic demand. Therefore, we believe that β_1 should not be too high. In lack of good guidelines to determine the value of β_1, we simply assume that $\beta_1 = 0.1$. In the robustness section we discuss the results of changing the values for β_i.

B.1.10. The utility from the charging network (κ_1)

Before calibrating the utility, we normalize x_i to million vehicles, M_i to 1000 stations, and normalize prices and costs so that utility and welfare is measured in billion NOK.[37] Based on the values of parameters and variables determined above, we can calibrate κ_1 based on eq. (4), giving $\kappa_1 = 32$.

B.1.11. The utility of the first vehicle (a_1)

It is difficult to know the size of a_1 and we simply set it equal to p_1 so that $A_1(x_2) = 0$ when there are no hydrogen vehicles ($x_2 = 0$). We consider alternative values of a_i in the sensitivity analysis.

B.1.12. The parameter that determines the price sensitivity of demand (b_1)

Finally, based on eq. (5) and the other values already determined, we derive $b_1 = 6.8$.[38]

B.1.13. Environmental cost of electric vehicles ($\tau_1 = t_1$)

In subsection B.1.3 with the footnote 34 we see that we assume that one future charge is 24 kWh per charge. According to Agency (2021), the average kg emissions per kWh in Europe is 0.231 CO2. We therefore have 5.5 kg CO2 per unit of charging. With prices in the EU ETS of 90 Euro per ton CO2 and 1 Euro= 10 NOK, we have around 5 NOK per charge.

B.1.14. The substitutability between hydrogen and electric vehicles (ϕ)

With no hydrogen vehicles in the calibrated equilibrium, the value of ϕ is irrelevant. However, for subsequent simulations we investigate two cases for ϕ. Case A: the technologies are close substitutes and ϕ_A is equal to 4.53, i.e., $\frac{2b_i}{3}$. Case B: the technologies are distant substitutes and ϕ_B is equal to 2.27, i.e., $\frac{b_i}{3}$.

B.2. Calibration of the hydrogen vehicle market

The parameter values for the hydrogen vehicle market is even more uncertain than for the electric vehicle market. Where we don't have reasons to believe that they are different, we assume the same values for hydrogen as for electric vehicles in the calibration. These are the following: .

- $b_1 = b_2$
- $\beta_1 = \beta_2$
- $p_1 = p_2$

We will however vary some of these (and other) parameter values in the sensitivity analysis. For the fixed and operating costs of hydrogen stations, we use specific data and information to derive cost estimates for these stations. From this information we calculate ρ_2. For the remaining utility parameters (a_2 and κ_2) we initially choose numbers so that a first-best equilibrium with only hydrogen vehicles would give the same numbers of vehicles as in the electric vehicle first-best equilibrium calibrated above.

[37] The price of vehicles is measured in 1000 NOK, while the cost of stations is measured in million NOK.

[38] To get a better understanding of what the calibration implies for the utility of electric vehicles, it is useful to compute the gross contribution to utility of respectively owning a vehicle and charging a vehicle (i.e., before subtracting the costs of buying and charging). That is, the second and third parts of the utility function in eq. (3). With the calibrated values, the second part (utility of owning) amounts to 112 billion NOK, while the third part (utility of charging at stations) amounts to 97 billion (this corresponds to about 22,000 NOK per capita and 19,000 NOK per capita, i.e., 2200 Euro and 1900 Euro, respectively per year). This means that the utility of owning the electric vehicle is approximately as important as the utility of charging via the fast charging network.

B.2.1. The fixed annual cost of a hydrogen station (f_2)

Hydrogen can be produced using electricity and water in an electrolyzer, which can be done on-site. The fixed cost of a hydrogen station that is currently build is in the range 17–25 million NOK (Enova, 2019). These costs are assumed to fall, but by how much is uncertain. Assuming a cost of 15 million NOK, 10 % interest rate and 10 years lifetime, the annual fixed cost becomes 2.44 million NOK.

B.2.2. The unit cost of one hydrogen filling lasting for 100 km (ψ_2)

The hydrogen vehicle Toyota Mirai can drive approximately 100 km per kg of hydrogen (US Department of Energy, 2019). Producing 1 kg of hydrogen uses approximately 50 kWh of electricity, and about 15 kWh more for compression and cooling, according to information from the hydrogen company NEL.[39] Future electricity prices are uncertain, and we assume 0.8 NOK per kWh (about 80 Euro per MWh), including grid tariffs. Adding VAT (25 %), we derive $\psi_2 = 65$ NOK per 100 km of driving.

B.2.3. The price of one filling lasting for 100 km (ω_2)

The price of hydrogen on hydrogen stations in Norway has been 90 NOK/kg incl. VAT, but this is below the total unit cost at the moment. One hydrogen station owner has notified that the price will increase to around 100 NOK/kg (E24, 2019b). This price might change in the future, but we choose $\omega_2 = 100$.

B.2.4. The degree the stations with the same technology can substitute each other (ρ_2)

The size of ρ_2 follows from the relationship $\rho_2 = \frac{\psi_2}{\omega_2} = 0.65$. Thus, ρ_2 is slightly higher than ρ_1.

B.2.5. The utility of the first vehicle (a_2)

It seems reasonable to assume that the utility of the first hydrogen vehicle is lower than the utility of the first electric vehicle because the hydrogen vehicle can not be filled at home and is therefore more dependent on the station network, similar to the gasoline and diesel vehicle technology. We therefore assume that $a_2 < a_1$ and set $a_2 = 0.5 * p = 21.7$.

B.2.6. The utility of the station network (κ_2)

As hydrogen vehicles are more dependent on the station network than electric vehicles, it is reasonable to assume $\kappa_2 > \kappa_1$. We calibrate κ_2 so that $x_2 = x_1$ in the first-best scenario when there are only hydrogen vehicles in the market, implying $\kappa_2 = 61$.

With this set of parameters, a first-best equilibrium with only hydrogen vehicles would give $x_2 = 3.585$, $M_2 = 4.054$ and $q_2 = 0.019$.

B.2.7. Environmental cost of hydrogen ($\tau_2 = t_2$)

In subsection B.2.2 we see that we assume that one filling uses 65 kWh. According to Agency (2021), the average kg emissions per kWh in Europe is 0.231 CO2. We therefore have 15 kg CO2 per unit of filling. With prices in the EU ETS of 90 Euro per ton CO2 and 1 Euro= 10 NOK, we have around 13.5 NOK per filling.

C. Numerical analysis – Additional results

C.1. The road transport market with only one technology (Electric vehicles)

The local first-best outcome with only electric vehicles is constructed in the calibration and is illustrated in Fig. 5. We see that the $h(M_i)$ curve is almost linear, meaning that the number of stations responds almost proportionally to the number of vehicles. The $g(M_i)$ curve, however, is highly concave, with the number of vehicles initially rising rapidly with the number of stations, but then almost leveling off when there are a few hundred stations. The first-best equilibrium is found where these two curves intersect (cf. the numbers mentioned in Subsection 4.1).

We compare this local first-best (calibrated) equilibrium with the corresponding BAU outcome, that is, when there are no policies (and still no hydrogen vehicles). Also in the BAU scenario we are in case I (one equilibrium). Remember that according to Proposition 1, the first-best solution can be realized in the market via a subsidy to charging equal to $s = 1 - \rho$, so going from first-best to BAU simply means to remove this subsidy (as there are no environmental costs in this point in the analysis).

Not surprisingly, in the BAU solution there is less charging per vehicle, as charging is no longer subsidized. Total charging per vehicle ($q_1 M_1$) drops by 47 %, while the number of stations drops by 52 % (see Fig. 5). Thus, charging per station per vehicle (q_1) increases slightly, from 0.014 to 0.016. More expensive charging and fewer stations reduce the demand for electric vehicles, but only by 10 %. Annual welfare in the road transport market (i.e., all terms except the first in eq. (10)) declines by 6 %, from 37.3 to 35.1 billion NOK.

[39] Personal communication with VP Investor Relations & Corporate Communication, Bjørn Simonsen, 19th of December 2019.

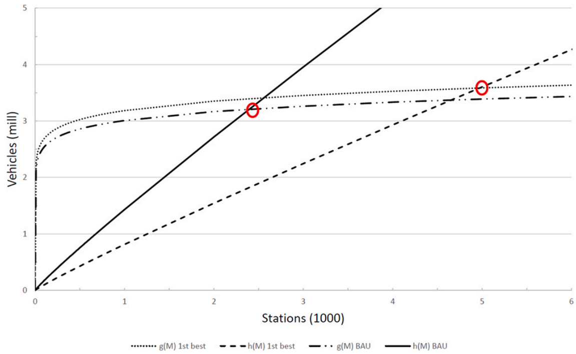


Figure 5. First-best and BAU equilibrium with only electric vehicles in the market.

C.2. The road transport market with only hydrogen technology

We consider here a hypothetical market with only hydrogen vehicles. In the first-best equilibrium, the number of vehicles is (by construction) $x_2 = 3.585$ million. There are somewhat fewer stations, but more filling per station, than in the case with electric vehicles only: $M_2 = 4,054$ and $q_2 = 0.019$. We are in case II with two equilibria, see Fig. 6. Demand for hydrogen vehicles shows more responsiveness to the number of stations than does electric vehicles, at least when there are more than a few hundred stations. The unstable equilibrium is very small, meaning very low levels of hydrogen vehicles (x_2) and hydrogen stations (M_2) need to be passed in order for the market to reach the first-best equilibrium (with subsidies to filling in place).

In the first-best solution, total welfare when there is only hydrogen vehicles is 3.4 billion NOK lower than in the case with only electric vehicles (in BAU, the difference is 4.3 billion NOK). This is due to the higher costs of hydrogen stations and hydrogen filling, and the lower utility of the first hydrogen vehicle (the prices of hydrogen and electric vehicles are assumed to be equal).

When comparing the first-best solution with the BAU outcome, we find that also for hydrogen vehicles total filling is reduced substantially when filling is no longer subsidized. Even though the subsidy rate to hydrogen filling is lower than to charging ($\rho_2 > \rho_1$), total filling per vehicle is reduced by 69 % (compared to 47 % for electric vehicles). This is a result of both the number of stations (− 50 %) and the filling per station per vehicle (− 37 %) being reduced. More expensive filling and fewer filling stations reduce the demand for hydrogen vehicles by 16 %. Welfare in the road transport market is reduced by 9 %. Also in BAU the unstable equilibrium is very small and is therefore not too difficult to pass.

C.3. The technologies being close substitutes

Fig. 7 shows the global first-best solution when the two technologies are *close* substitutes (i.e., equilibrium 3 in Fig. 3). The number of electric vehicles is reduced by 36 % compared to when they are alone in the market (equilibrium 1 in Fig. 3), while hydrogen vehicles are reduced by 51 % compared to when they are alone (equilibrium 5 in Fig. 3). There are more vehicles in

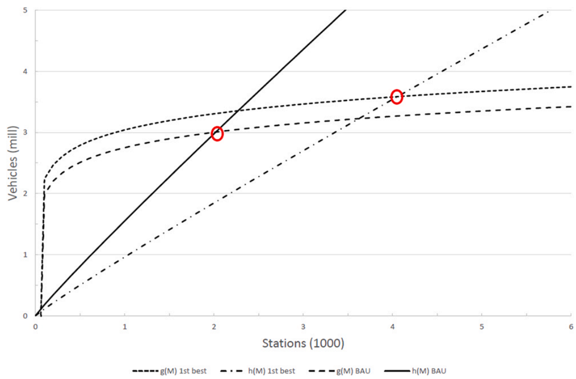


Figure 6. First-best and BAU equilibrium with only hydrogen vehicles in the market.

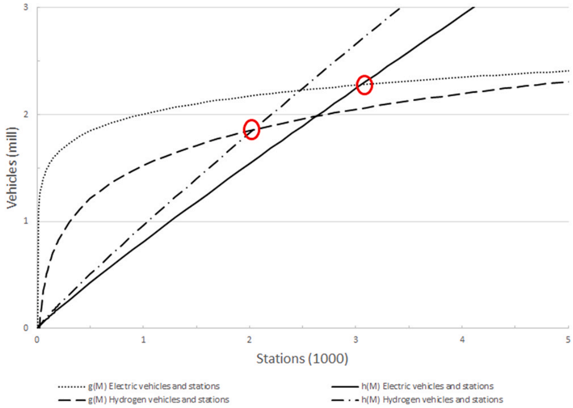


Figure 7. Graph showing the first-best equilibrium for both electric and hydrogen vehicles and station when the technologies are close substitutes.

total with two technologies than with only one technology. The market share of electric vehicles in this case is 56 %. The number of charging and filling stations decrease by respectively 39 % and 53 % when going from one to two technologies. Charging/filling per vehicle does not change much, while charging/filling per station per vehicle increases.

Electric vehicles move from being in case I to being in case II when there are two technologies in the market. However, as the unstable equilibrium is very low, it is hardly visible in Fig. 7. If the number of hydrogen vehicles were to increase first, the electric vehicles might need critical mass in order to overcome the unstable equilibrium, or else electric vehicles may not get a foothold in the market. Hydrogen vehicles stay in case II when there are two technologies in the market.

Fig. 8 compare the first-best, the second-best I and the BAU solution for the electric vehicle and station market, while Fig. 9 shows the second-best I solution together with the first-best solution for the hydrogen vehicle and station market, both when the two technologies are close substitutes.

C.4. The technologies being distant substitutes

In this section we present analysis similar to those presented in section 4, but with the technologies being distant substitutes.

C.4.1. The global first-best solution

When the two technologies are *distant* substitute, the numbers of electric and hydrogen vehicles are reduced by less than when they are close substitutes. Thus, there are more vehicles in total when the products are distant substitutes. The total number of vehicles in the first-best solution increases by 45 % compared to when there is only one technology, compared to 29 % when they are close substitutes. This is as expected – the size of the market increases when there is more variety to choose

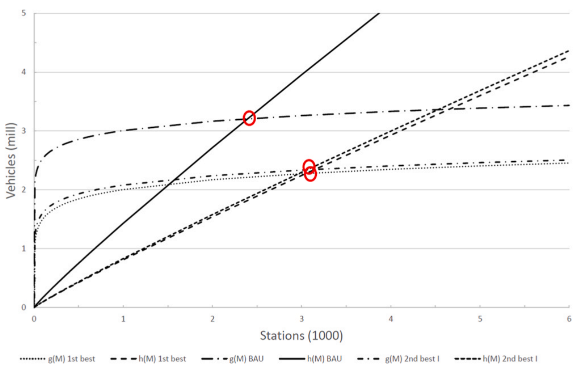


Figure 8. Graph comparing the first-best, the second-best I and the BAU solution for the electric vehicle and station market when the two technologies are close substitutes. The BAU solution is the one with the highest number of vehicles, while the difference between the first-best and the second-best I solution is small.

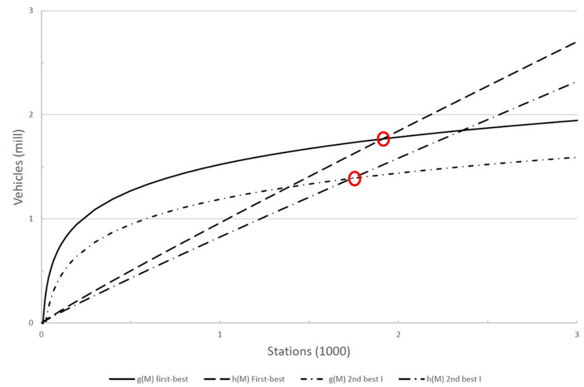


Figure 9. Graph showing the second-best I solution compared to the first-best outcome for the hydrogen vehicle and station market when the two technologies are close substitutes. In the BAU outcome there are no hydrogen vehicles.

from. The market share of electric vehicles is now 51 %, thus an almost equal split of the market. The number of stations decrease less when the technologies are distant substitutes, as the number of vehicles is also less reduced. Charging/filling per vehicle still does not change much, while charging/filling per station per vehicle increase less than when they are close substitutes.

Similar to when the technologies are close substitutes, electric vehicles move from being in case I to being in case II, while hydrogen vehicles stay in case II. Thus, even when the technologies are distant substitutes, there is a risk that electric vehicles might not get a foothold into the market if there are many hydrogen vehicles already.

The annual welfare in the road transport sector increases by 12.7 billion NOK (+34 %) compared to the case with only electric vehicles, and by 16.1 billion NOK (+47 %) compared to the case with only hydrogen vehicles. Thus, when the technologies are distant substitutes, there is a substantial welfare gain from having two instead of one technology.

C.4.2. Comparing first-best and BAU

When the technologies are distant substitutes, the market shares only change slightly in BAU compared to the first-best outcome. The market share of electric vehicles increases from 51 % in the first-best solution to 55 % in the BAU outcome. The number of electric vehicles falls by 7 %, while the number of hydrogen vehicles falls by 21 %. Thus, the total number of vehicles drops by 14 %.

Charging/filling per vehicle is reduced by 41–47 %. The number of hydrogen stations decreases by 53 %, while the number of fast charging stations declines by 51 %. Hence, charging and filling per vehicle per station increases somewhat. The percentage reduction in annual welfare is the same as when they are close substitutes, i.e., 8 %.

C.4.3. Second-best solutions

Second-best I (subsidy to stations): When the two technologies are distant substitutes, the number of electric vehicles in the second-best I solution is quite close to both first-best and BAU, see Fig. 10. The number of hydrogen vehicles is almost 300 lower than in first-best and 200 higher than in BAU. The total number of vehicles is reduced by 8 % compared to first-best, but 7 % higher than in BAU. The second-best subsidy rates to fast charging and filling stations are respectively $\sigma_1 = 0.44$ and $\sigma_2 = 0.43$, i.e., very close the subsidy rates when they are close substitutes.

As we can see from Fig. 10, the number of fast charging stations is almost the same as in first-best, and much bigger than in BAU (almost 1700 stations more). The same applies for hydrogen stations. This reflects that in the second-best I scenario the stations are subsidized, and therefore the numbers of stations are close to the optimal number. In contrast, charging/filling per vehicle is reduced by 36–47 %, as charging/filling is no longer subsidized. The annual welfare from the road transport in the second-best I solution is reduced by 2.1 billion NOK compared to the first-best outcome, and is 1.7 billion NOK higher than in the BAU outcome. Hence, also in this case we see that the second-best I policy is a clear improvement over BAU, but still somewhat far from first-best.

Second-best II (subsidies to stations and vehicles): When also the vehicles may be subsidized, the number of vehicles in the second-best II solution is even closer to the first-best solution than in the second-best I solution. The total number of vehicles is now only 2 % lower than in the first-best outcome. The results for the numbers of stations and charging/filling per vehicle are approximately the same as in the second-best I-solution. The second-best subsidy rates to fast charging and filling stations are now respectively $\sigma_1 = 0.43$ and $\sigma_2 = 0.37$, while the subsidy rates to purchasing electric and hydrogen vehicles are respectively $u_1 = 0.023$ and $u_2 = 0.038$, which is identical to the vehicle subsidy when they are close substitutes.

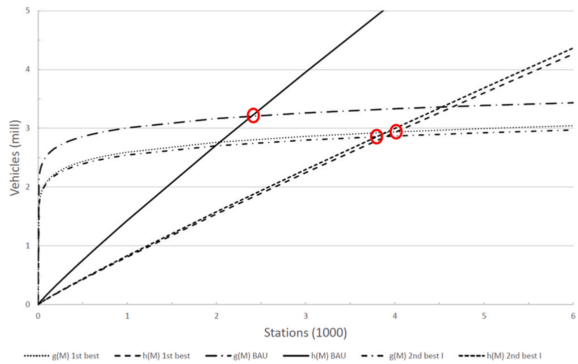


Figure 10. Graph showing how close the second-best I solution for the electric vehicle and station market is to the first-best solution when the two technologies are distant substitutes.

The annual welfare from the road transport in the second-best II solution is reduced by 1.9 billion NOK compared to the first-best outcome, and is 1.9 billion NOK higher than in BAU. Thus, also in this case the additional gains of subsidizing vehicles in addition to stations is somewhat limited.

Public expenditures: Also when the technologies are close substitutes, the public expenditures are more than twice as high in the first-best outcome compared to the second-best I outcome. Total expenditures for the government are higher when the technologies are distant substitutes, as the total market is larger. The subsidy payment in the first-best solution is 11.6 billion NOK, while in second-best I it is 4.8 billion NOK, and in second-best II it is 11.1 billion NOK.

D. Detailed results from the numerical analysis

Figuers 11, 12, 13, 14.

Only electric vehicles														
	First-best	BAU	Second-best I	Second-best II	Diff BAU vs. first-best	Percentage diff BAU vs. first-best	Diff second-best I vs. first-best	Percentage diff second-best I vs. first-best	Diff second-best I vs. BAU	Percentage diff second-best I vs. BAU	Diff second-best II vs. first-best	Percentage diff second best II vs. first-best	Diff second-best II vs. BAU	Percentage diff second best II vs. BAU
x1	3.585	3.209	3.379	3.530	-0.376	-10%	-0.206	-6%	0.170	5%	-0.055	-2%	0.321	10%
M1	4.975	2.394	4.812	4.823	-2.581	-52%	-0,163	-3%	2.418	101%	-0.152	-3%	2.429	101%
q1	0.014	0.016	0.008	0.008	0.002	14%	-0.006	-43%	-0.008	-50%	-0.006	-43%	-0.008	-50%
M1q1	0.070	0.038	0.038	0.039	-0.031	-45%	-0.031	-45%	0.000	1%	-0.031	-45%	0.000	1%
W	37.328	35.101	36.110	36.187	-2.227	-6%	-1.219	-3%	1.009	3%	-1.142	-3%	1.086	3%
s1	0.4	0	0	0	--	--	--	--	--	--	--	--	--	--
σ1	0	0	0.448	0.425	--	--	--	--	--	--	--	--	--	--
u1	0	0	0	0.024	--	--	--	--	--	--	--	--	--	--
Only hydrogen vehicles														
	First-best	BAU	Second-best I	Second-best II	Diff BAU vs. first-best	Percentage diff BAU vs. first-best	Diff second-best I vs. first-best	Percentage diff second-best I vs. first-best	Diff second-best I vs. BAU	Percentage diff second-best I vs. BAU	Diff second-best II vs. first-best	Percentage diff second best II vs. first-best	Diff second-best II vs. BAU	Percentage diff second best II vs. BAU
x2	3.585	3.006	3.254	3.506	-0.579	-16%	-0.331	-9%	0.248	8%	-0.079	-2%	0.500	17%
M2	4.054	2.020	3.905	3.918	-2.034	-50%	-0.149	-4%	1.885	93%	-0.136	-3%	1.898	94%
q2	0.019	0.012	0.012	0.012	-0.007	-37%	-0.007	-37%	0	0%	-0.007	-37%	0	0%
M2q2	0.077	0.024	0.047	0.047	-0.053	-69%	-0.030	-39%	0.023	93%	-0.030	-39%	0.023	94%
W	33.915	30.789	32.122	64.672	-3.126	-9%	-1.793	-5%	1.333	4%	30.757	91%	33.883	110%
s2	0.35	0	0	0	--	--	--	--	--	--	--	--	--	--
σ2	0	0	0.417	0.374	--	--	--	--	--	--	--	--	--	--
u2	0	0	0	0.039	--	--	--	--	--	--	--	--	--	--

Figure 11. Results from the numerical analysis for only electric vehicles in the market and for only hydrogen vehicles. x_i is in million, M_i is in 1000, q_i is in number of charges/fillings per year per vehicle per station, W is in billion NOK.

Two technologies. Close substitutes. Phi= 4,545														
	First-best	BAU	Second-best I	Second-best II	Diff BAU vs. first-best	Percentage diff BAU vs. first-best	Diff second best I vs. first-best	Percentage diff second best I vs. first-best	Diff second-best I vs. BAU	Percentage diff second-best I vs. BAU	Diff second best II vs. first-best	Percentage diff second best II vs. first-best	Diff second best II vs. BAU	Percentage diff second best II vs. BAU
x1	2.278	3.209	2.342	2.309	0.931	41%	0.064	3%	-0.867	-27%	0.031	1%	-0.900	-28%
x2	1.768	0	1.390	1.655	-1.768	-100%	-0.378	-21%	1.390	--	-0.113	-6%	1.655	--
x1+x2	4.046	3.209	3.732	3.964	-0.837	-21%	-0.314	-8%	0.523	16%	-0.082	-2%	0.755	24%
M1	3.049	2.394	3.062	3.050	-0.655	-21%	0.013	0%	0.668	28%	0.001	0%	0.656	27%
M2	1.912	0	1.741	1.763	-1.912	-100%	-0.171	-9%	1.741	--	-0.149	-8%	1.763	--
q1	0.023	0.016	0.013	0.013	-0.007	-30%	-0.010	-43%	-0.003	-19%	-0.010	-43%	-0.003	-19%
q2	0.039	0	0.027	0.026	-0.039	-100%	-0.012	-31%	0.027	--	-0.013	-33%	0.026	--
q1M1	0.070	0.038	0.040	0.040	-0,032	-45%	-0.030	-43%	0.002	4%	-0.030	-43%	0.001	4%
q2M2	0.075	0	0.047	0.046	-0.075	-100%	-0.028	-37%	0.047	--	-0.029	-39%	0.046	--
W	38.032	35.100	36.398	36.593	-2.932	-8%	-1.634	-4%	1.298	4%	-1.439	-4%	1.493	4%
s1	0.4	0	0	0	--	--	--	--	--	--	--	--	--	--
s2	0.35	0	0	0	--	--	--	--	--	--	--	--	--	--
σ1	0	0	0.419	0.425	--	--	--	--	--	--	--	--	--	--
σ2	0	0	0.468	0.374	--	--	--	--	--	--	--	--	--	--
u1	0	0	0	0.023	--	--	--	--	--	--	--	--	--	--
u2	0	0	0	0.038	--	--	--	--	--	--	--	--	--	--

Figure 12. Results from the numerical analysis for the two network technologies when they are close substitutes. x_i is in million, M_i is in 1000, q_i is in number of charges/fillings per year per vehicle per station, W is in billion NOK.

Two technologies. Distant substitutes. Phi= 2.272														
	First-best	BAU	Second-best I	Second-best II	Diff BAU vs. first-best	Percentage diff BAU vs. first-best	Diff second best I vs. first-best	Percentage diff second best I vs. first-best	Diff second-best I vs. BAU	Percentage diff second-best I vs. BAU	Diff second best II vs. first-best	Percentage diff second best II vs. first-best	Diff second best II vs. BAU	Percentage diff second best II vs. BAU
x1	2.646	2.465	2.544	2.616	-0.181	-7%	-0.102	-4%	0.079	3%	-0.030	-1%	0.151	6%
x2	2.560	2.032	2.268	2.490	-0.528	-21%	-0.292	-11%	0.236	12%	-0.070	-3%	0.458	23%
x1+x2	5.206	4.497	4.812	5.106	-0.709	-14%	-0.394	-8%	0.315	7%	-0.010	-2%	0.609	14%
M1	3.584	1.800	3.486	3.490	-1.784	-50%	-0.098	-3%	1.686	94%	-0.094	-3%	1.690	94%
M2	2.833	1.332	2.711	2.722	-1.501	-53%	-0.122	-4%	1.379	104%	-0.111	-4%	1.390	104%
q1	0.020	0.021	0.011	0.011	0.001	5%	-0.009	-45%	-0.010	-48%	-0.009	-45%	-0.010	-48%
q2	0.027	0.034	0.018	0.018	0.007	26%	-0.009	-33%	-0.016	-47%	-0.009	-33%	-0.016	-47%
q1M1	0.072	0.038	0.038	0.038	-0.034	-47%	-0.033	-47%	0.001	1%	-0.033	-46%	0.001	2%
q2M2	0.076	0.045	0.049	0.049	-0.031	-41%	-0.028	-36%	0.004	8%	-0.027	-36%	0.004	8%
W	50.004	46.160	47.858	48.078	-3.844	-8%	-2.146	-4%	1.698	4%	-1.926	-4%	1.918	4%
s1	0.4	0	0	0	--	--	--	--			--	--	--	--
s2	0.5	0	0	0	--	--	--	--			--	--	--	--
σ1	0	0	0.440	0.425	--	--	--	--			--	--	--	--
σ2	0	0	0.428	0.374	--	--	--	--			--	--	--	--
u1	0	0	0	0.023	--	--	--	--			--	--	--	--
u2	0	0	0	0.038	--	--	--	--			--	--	--	--

Figure 13. Results from the numerical analysis for the two network technologies when they are distant substitutes. x_i is in million, M_i is in 1000, q_i is in number of charges/fillings per year per vehicle per station, W is in billion NOK.

Costs first best	Costs second best I	Costs second best II
Two technologies. Close substitutes. Phi= 4,545		
8.6	3.7	8.3
Two technologies. Distant substitutes. Phi= 2,272		
11.6	4.8	11.3
Only electric vehicles		
6.3	2.8	6.3
Only hydrogen vehicles		
9.7	4.0	9.5

Figure 14. Results from the numerical analysis of the public costs. Numbers in billion NOK.

Sensitivity analysis

phi=4,545	Parameter	New values	x1, first-best	x2, first-best	M1, first-best	M2, first-best	W, first-best	W, BAU	Delta W
Result base-case	--	--	2.278	1.768	3.049	1.912	38.032	35.100	2.932
Increase by 100%	f1	2.603926	1.675	2.275	1.035	2.499	35.737	34.087	1.650
Reduce by 50%	f1	0.650982	3.038	1.051	8.795	1.099	41.339	39.587	1.752
Increase by 100%	f2	4.88236	3.585	0	4.975	0	37.328	35.101	2.227
Reduce by 50%	f2	1.22059	1.477	2.795	1.909	6.500	42.388	38.839	3.549
Increase by 100%	p	86.77	0	0	0	0	0		
Reduce by 50%	p	21.692	4.050	4.128	5.675	4.710	171.094	165.247	5.847
Increase by 100%	kappa1	63.51196	8.851	0	30.325	0	227.544	213.970	13.574
Reduce by 50%	kappa1	15.87799	0	3.585	0	4.054	33.915	5.758	28.157
Increase by 100%	kappa2	122.57	0	13.524	0	37.747	531.249	35.101	496.148
Reduce by 50%	kappa2	30.643	3.585	0	4.975	0	37.328	35.101	2.227
Increase by 100%	b	13.634	1.275	1.128	1.629	1.184	21.261	19.579	1.682
Reduce by 50%	b. NB. Here phi=2.272	-3.409	4.217	4.570	5.929	5.247	89.161	81.944	7.217
Increase by 100%	a1	86.77	10.263	0	15.490	0	338.861	332.354	6.507
Reduce by 50%	a1	21.692	0	3.585	0	4.054	33.915	30.789	3.126
Increase by 100%	a2	43.384	0	7.066	0	8.342	149.815	143.962	5.853
Reduce by 50%	a2	10.846	3.585	0	4.975	0	37.328	35.101	2.227
Increase by 100%	psi1	75.58	1.382	2.512	1.636	2.777	34.897	31.784	3.113
Reduce by 50%	psi1	18.895	3.924	0	5.960	0	44.724	42.056	2.668
Increase by 100%	psi2	130	3.585	0	4.975	0	37.328	35.101	2.227
Reduce by 50%	psi2	32.5	0	4.242	0	5.262	48.487	44.247	4.24
	rho	0.9	2.125	1.539	0.433	0.326	36.974	36.871	0.103
	rho	0.7	2.082	1.774	1.695	1.497	36.433	34.716	1.717
	rho	0.45	0	6.339	0	22.888	81.089	43.388	37.701
	rho	0.3	0	32.444	0	836.839	1545.047	0.166	1544.881
	beta	0.4	395.214	0	362770	0	59180.272	923.618	58256.654
	beta	0.3	5.168	0	39.873	0	39.113	22.815	16.298
	beta	0.2	3.557	0	11017	0	28.771	5.271	23.500
	beta	0.05	1.731	3.057	1.196	1.788	60.186	58.513	1.673

Figure 15. Results from the sensitivity analysis. x_i is in million, M_i is in 1000, q_i is in number of charges/fillings per year per vehicle per station and W is in billion NOK.

E. Sensitivity analysis

As mentioned before, many of the parameters are highly uncertain. Thus, we have performed a number of sensitivity analysis, increasing and reducing one and one parameter value, keeping other parameters unchanged. Overall, the results are quite intuitive, and a detailed overview of the sensitivity results are shown below. Further, we find that the results are especially sensitive to the values of a_i, κ_i, ρ_i and β_i, and thus we focus on those parameters here, and the case with close substitutes.

First, when we increase a_1 (a_2) by 100 %, the first-best solution has only electric (hydrogen) vehicles. Likewise, when we decrease a_1 (a_2) by 50 %, the first-best solution has only hydrogen (electric) vehicles. Second, when κ_i changes, the numbers of vehicles and stations change in a predictable way, but the numbers are highly sensitive to the value of κ_i. When we increase κ_1 (κ_2) by 100 %, the first-best solution has only electric (hydrogen) vehicles. Likewise, when we decrease κ_1 (κ_2) by 50 %, the first-best solution has only hydrogen (electric) vehicles. Hence, whether there should be one or two technologies depends highly on both the direct utility of the two vehicle technologies, and the utility derived through charging/filling.

Further, the higher ρ_i, the fewer stations in the first-best solution, and the less difference between the first-best and the BAU outcome. This is intuitive since ρ_i measures the utility of more stations. If ρ_i is lower, the network effect becomes more important, and at some point it is optimal with only one technology and many stations, as the network effect dominates the benefit of having access to different types of vehicles. In our simulations, the optimal choice is then to have only hydrogen vehicles, as the benefit of these vehicles increases more with the number of stations than electric vehicles do.[40]

The numbers of vehicles and stations are also highly sensitive to the value of β_i, which determines the indirect utility from more stations via the total number of charging per vehicle. The higher β_i, the more the utility increases from more charges/fillings per vehicle (for a given number of stations). The sensitivity analysis suggests that a higher β_i increases the number of stations, and for sufficiently high β_i it is optimal with only electric vehicles. In this case it is not the importance of the network size that increases, as opposed to when ρ_i is reduced, which explains why we get only electric vehicles in the former case while only hydrogen vehicles in the latter case. A higher β_i also increases the welfare difference between the optimal and BAU solutions Fig. 15.

References

Acemoglu, D., Aghion, P., Bursztyn, L., Hemous, D., 2012. The environment and directed technical change. Am. Econ. Rev. 102 (1) 131–66.
Agency, E.E. , 2021. Greenhouse gas emission intensity of electricity generation in europe. ⟨https://www.eea.europa.eu/ims/greenhouse-gas-emission-intensity-of-1⟩.
Arthur, W.B., 1989. Competing technologies, increasing returns, and lock-in by historical events. Econ. J. 99 (394), 116–131.
Belleflamme, P., Peitz, M., 2015. Industrial Organization: Markets and Strategies. Cambridge University Press.
Burch, I., Gilchrist, J. , 2018. Survey of global activity to phase out internal combustion engine vehicles. ⟨https://climateprotection.org/wp-content/uploads/2018/10/Survey-on-Global-Activities-to-Phase-Out-ICE-Vehicles-FINAL-Oct-3–2018.pdf⟩.
CARB, 2022. Zero-Emission Vehicle Program. ⟨https://ww2.arb.ca.gov/our-work/programs/zero-emission-vehicle-program/about⟩.
Chou, C.-f., Shy, O., 1990. Network effects without network externalities. Int. J. Ind. Organ. 8 (2), 259–270.
Church, J., Gandal, N., Krause, D., 2008. Indirect network effects and adoption externalities. Rev. Netw. Econ. 7 (3), 337–358.
Clements, M.T., 2004. Direct and indirect network effects: are they equivalent? Int. J. Ind. Organ. 22 (5), 633–645.
Conrad, K., 2006. Price competition and product differentiation when goods have network effects. Ger. Econ. Rev. 7 (3), 339–361.
Dixit, A.K., Stiglitz, J.E., 1977. Monopolistic competition and optimum product diversity. Am. Econ. Rev. 67 (3), 297–308.
E24 (2019a). Hydrogenselskapet Nel: Et nasjonalt basisnett for hydrogen kan koste kun to milliarder kroner. ⟨https://e24.no/naeringsliv/i/QogavR/hydrogenselskapet-nel-etnasjonalt-basisnett-for-hydrogen-kan-koste-kun-to-milliarder-kroner⟩.
E24. (2019b). Venter på klarsignal for hydrogenstasjon: - Vi sitter hydrogenfast alle sammen. ⟨https://e24.no/energi/i/jdXMjL/venter-paa-klarsignal-for-hydrogenstasjon-visitter-hydrogenfast-alle-sammen⟩.
Enova, 2019. Enova project list hydrogen. ⟨https://www.enova.no/om-enova/om-organisasjonen/prosjektliste-2012–2018/?Sektor=Transport&Program=Hydrogeninfrastruktur⟩.
European Commission, 2016. A European Strategy for Low-Emission Mobility. [COM(2016) 501 final]. ⟨https://eur-lex.europa.eu/resource.html?uri=cellar:e44d3c21–531e-11e6–89bd-01aa75ed71a1.0002.02/DOC_1&format=PDF⟩.
European Commission, 2018. In-depth analysis in support of the commission communication com(2018) 773. A Clean Planet for all. ⟨https://ec.europa.eu/clima/system/files/2018–11/com_2018_733_analysis_in_support_en.pdf⟩.
Farrell, J., Saloner, G., 1986a. Installed base and compatibility: innovation, product preannouncements, and predation. Am. Econ. Rev. 940–955.
Farrell, J., Saloner, G., 1986b. Standardization and variety. Econ. Lett. 20 (1), 71–74.
Figenbaum, E. , 2019. Charging into the future: Analysis of fast charger usage. [TØI Report 1682/2019].
Greaker, M., 2021. Optimal regulatory policies for charging of electric vehicles. Transp. Res. Part D: Transp. Environ. 97, 102922.
Greaker, M., Heggedal, T.-R., 2010. Lock-in and the transition to hydrogen cars: should governments intervene? BE J. Econ. Anal. Policy 10, 1.
Greaker, M., Midttømme, K., 2016. Network effects and environmental externalities: do clean technologies suffer from excess inertia? J. Public Econ. 143, 27–38.
IEA, 2019. Global EV Outlook 2019. Scaling-up the transition to electric mobility.
IPCC, 2018. Global warming of 1. 5°C. Summary for Policymakers.World Meteorological Organization, Geneva, Switzerland.
Katz, M.L., Shapiro, C., 1985. Network externalities, competition, and compatibility. Am. Econ. Rev. 75 (3), 424–440.
Katz, M.L., Shapiro, C., 1994. Systems competition and network effects. J. Econ. Perspect. 8 (2), 93–115.
Labandeira, X., Labeaga, J.M., López-Otero, X., 2017. A meta-analysis on the price elasticity of energy demand. Energy Policy 102, 549–568.
Li, S., Tong, L., Xing, J., Zhou, Y., 2017. The market for electric vehicles: indirect network effects and policy design. J. Assoc. Environ. Resour. Econ. 4 (1), 89–133.
Li, S., Zhu, X., Ma, Y., Zhang, F., Zhou, H., 2021. The role of government in the market for electric vehicles: evidence from china. J. Policy Anal. Manag.
Mankiw, N.G., Whinston, M.D., 1986. Free entry and social inefficiency. RAND J. Econ. 17 (1), 48–58.
Meunier, G., Ponssard, J.-P., 2020. Optimal policy and network effects for the deployment of zero emission vehicles. Eur. Econ. Rev., 103449.
Nobil, 2019. Nobil database.[Recieved info per email, 16.12.19].

[40] This result hinges of course on the calibration of our model, where the calibration for hydrogen vehicles is especially uncertain.

Norwegian Electric Vehicle Association, 2017. How much you can save on driving electric vehicle.⟨https://elbil.no/sa-mye-kan-du-spare-pa-a-kjore-elbil/⟩.
Norwegian Electric Vehicle Association, 2019. Prices fast charging. ⟨https://elbil.no/elbilstatistikk/ladestasjoner/⟩.
Norwegian Electric Vehicle Association. (2021a). Statistics of electric vehicles. [Updated per 31.12.2020]. ⟨https://elbil.no/elbilstatistikk/⟩.
Norwegian Electric Vehicle Association. (2021b). Statistics of electric vehicles. [Updated per 31.12.2020]. ⟨https://elbil.no/elbilstatistikk/elbilbestand/⟩.
Norwegian Environment Agency, 2015. Klimatiltak og utslippsbaner mot 2030. Kunnskapsgrunnlag for lavutslippsutvikling. [Report M-386]. ⟨https://tema.miljodirektoratet.no/Documents/publikasjoner/M386/M386.pdf⟩.
OFV, 2019. OFV list prices.[Recieved per email 26.08.2019].
Spence, M., 1976. Product selection, fixed costs, and monopolistic competition. Rev. Econ. Stud. 43, 217–236.
Springel, K., 2021. Network externality and subsidy structure in two-sided markets: evidence from electric vehicle incentives. Am. Econ. J.: Econ. Policy.
The Norwegian Parliament (Stortinget) 2017. Innstilling fra transport- og kommunikasjon-skomiteen om nasjonal transportplan 2018–2029.⟨https://www.stortinget.no/no/Saker-og-publikasjoner/Publikasjoner/Innstillinger/Stortinget/2016–2017/inns-201617–460s/⟩.
US Department of Energy, 2019. Compare Fuel Cell Vehicles. [The official U.S. government source for fuel economy information]. ⟨https://www.fueleconomy.gov/feg/fcv_sbs.shtml⟩.
Yatchew, A., No, J.A., 2001. Household gasoline demand in Canada. Econometrica 69 (6), 1697–1709.
Zhou, Y., Li, S., 2018. Technology adoption and critical mass: the case of the US electric vehicle market. J. Ind. Econ. 66 (2), 423–480.

Gøril L. Andreassen

Gøril L. Andreassen was born in Røyken, Norway in 1981. She is a researcher in Economic Analysis at the Institute of Transport Economics (TØI) from August 2023.

She holds a Master of Philosophy in Economics (2018) and a Bachelor of Arts (2011) from the University of Oslo, Norway. She has also taken courses in mathematics and material technology at the University of Oslo (2012), as well as a course about politics and policy in the 21st century China at the University in Beijing (2012).

From 2002-2016 she worked in the environmental NGOs ZERO, Nature and Youth and the Rainforest Foundation Norway. In ZERO she was head of the transport department, in addition to other roles. She was a member of the advisory board of the government agency Transnova, member of the hydrogen council and member of the council for electrification of the road transport.

Andreassen has also worked part time in Multiconsult as a consultant (2017). In May 2022-February 2023 she was Board of director in the green investment company Saga Pure.

Andreassen has taught different courses during her time as a PhD candidate: Climate Economics, Mathematics, Environmental Economics, Microeconomics and Economics of Sustainability. She has also been external examiner at the University of Oslo and at OsloMet.

Professor Knut Einar Rosendahl was Gøril's main supervisor.

E-mail: gla@toi.no

School of Economics and Business
Norwegian University of Life Sciences (NMBU)
P.O Box 5003
N-1432 Ås, Norway

Telephone: +47 6496 5700
e-mail*: hh@nmbu.no*
http:/www.nmbu.no/hh

ISSN: 1894-6402
ISBN: 978-82-575-2086-1

ISBN: 978-82-575-2086-1
ISSN: 1894-6402

Norwegian University
of Life Sciences

Postboks 5003
NO-1432 Ås, Norway
+47 67 23 00 00
www.nmbu.no

118562 / ANDVORDGRAFISK.NO