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Policies for electrification of the car fleet in the short and long run – subsidizing electric vehicles or subsidizing charging stations?[1]

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Abstract

Abatement can be performed by measures that have an impact on present emissions, but no lasting effect, and by long-lived infrastructure investments. We study the optimal combination of short and long-lived options for reducing greenhouse gas (GHG) emissions, by specifying abatement cost functions depending on abatement from these two options. Electrification of the transport sector is used as an example. A transition from internal combustion engines vehicles (ICEVs) to electric vehicles (EVs) can be incentivized by both subsidies on purchases of EVs and increased density of fast chargers. Subsidizing the purchase of EVs only leads to emissions reductions in the next few years (static option), whereas investment in infrastructure also will reduce abatement costs in several years to come (dynamic option). We find that the present marginal abatement cost of the dynamic alternative exceeds the costs of static abatement in optimum, thus the dynamic option may be profitable even if it is more expensive. A higher expected abatement cost in later periods most likely makes it even more profitable to use the dynamic policy instrument. This framework is used for a numerical study on electrification of the transport sector in Norway. The numerical simulations confirm the results of the theory model. Flexibility in the domestic target over time and the presence of an international permit market affect the combination of static and dynamic abatement. This stresses the importance of early and time consistent plans for international regulations of GHG emissions.

Keywords: Emissions permit market; infrastructure investments; electric vehicles.

JEL classifications: C63, H21, Q54, R42.

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1 Introduction

The long-term goal in the Paris agreement from 2015 is to keep global warming well below two degrees Celsius, and preferably down to 1.5 degrees. In order to comply with this target, many countries and regions have implemented short- and long-term goals for their emissions. For instance, the EU aims to reduce greenhouse gas (GHG) emissions by at least 55% below 1990 levels by 2030, while for 2050, the aim is to become carbon neutral.[6]

The transition to a low carbon society requires investments in new clean production capital. Some of the abatement investments may have long-lasting effect on emissions and abatement costs, while others may have significant effects on present emissions, but they last for a shorter time period. Examples of long-lasting investments are building or extending a public transport system, carbon capture and storage facilities, and infrastructure for charging stations for electric vehicles. Infrastructure investments may have low or modest impact on immediate emissions so that emissions reductions are initially costly. However, once the investments are made, future abatement may become cheaper. For instance, present investments in charging stations for electric vehicles may have low impacts on present emissions, but may be vital for the costs of a decarbonized transport sector in the future (Sierzchula, 2014). Postponing investments in infrastructure may lead to high demand for infrastructure over a short time-period in the future. With significant adjustment costs (convex per period investment costs), postponing investments may become a costly policy in the end. As argued by Vogt-Schilb et.al (2018), starting with expensive options may make sense when reducing emissions requires investments in long-lived goods, which takes time to deploy. Policy options that work in a similar way is investing in solar panels or battery production that may reduce costs in the future due to learning by doing (Wigley et al., 1996; Kverndokk and Rosendahl, 2007; Gillingham and Stock, 2018).

In this paper, we study the optimal combination of short- and long-lived abatement options for reducing emissions through electrification of the transport sector. Abatement costs are typically specified as functions of the level of abatement, for instance to find the marginal abatement cost curves, see, e.g., McKitrik (1999). One contribution of this paper is to specify abatement costs as functions of abatement from static and dynamic abatement separately. Our definition of static abatement is that they do not affect the costs of future emissions

[6] https://www.consilium.europa.eu/en/policies/eu-plan-for-a-green-transition/ (accessed 1.2.2022).

reductions, while dynamic abatement will affect future costs of meeting emissions targets. With our specification, we can compare the marginal abatement costs for the two options and over time.

A third option for meeting abatement obligations is international trade in emissions reduction (permit trade). Permit trading has been implemented in several regions in the world such as EU's Emissions Trading System (EU ETS), where companies in the countries that are part of the EU ETS decide to what degree they want to reduce their emissions versus buying emission permits. The EU ETS does not cover emissions from the transport sector apart from emissions from aviation operating between member states. However, EU's Effort Sharing Regulation opens for emissions trading also for non-ETS sectors, and there is also some flexibility to access allowances from the EU ETS for some member states.[7] An emissions trading regime can also be designed to allow for various degrees of intertemporal flexibility in abatement.[8]

In general, for most countries it will not be cost effective to meet the emissions targets by permit purchases only, even in the presence of a well-functioning permit market, as it is cost effective to implement domestic abatement options with lower marginal cost than the present permit price. Furthermore, a nation can also set restrictions on how many permits their companies can buy, either explicitly or by imposing a sufficiently high domestic carbon price, so that a certain share of emissions reductions has to be taken at home.[9]

Based on the discussion above, a nation or a large company then faces the following options to meet its climate goals; reduce emissions by short-lived options, buy emissions permits in the international market, and/or make infrastructure investments that also makes it cheaper to meet future emissions targets. These choices are studied in this paper, where we focus on how the choices depend on different assumptions about the flexibility in emissions targets over time and flexibility in emissions across countries through permit markets.

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[7] https://ec.europa.eu/clima/policies/effort/regulation_en (accessed 29.1.2022).

[8] For instance, in EU ETS, banking permits to be used in a future time period is allowed, whereas borrowing from future commitments is not allowed.

[9] Several countries have targets for their own emissions, for instance documented in their Climate Action Laws. Germany is one of these countries having annual emission budgets for different sectors. Another example is that Norway's Government elected in the fall 2021, has announced that they want to take the emission reductions for 2030 at home, even if Norway is fully acceded to EUs ambitious climate rules and regulations through a bilateral agreement, and can use the flexible mechanisms available.

We first set up a simple model to analyze the implications of the emissions targets and permit market on the profitability of investments in long-lived infrastructure (dynamic abatement) compared to short-term options (static abatement). An abatement cost function is specified as a function of the emissions levels following from the two abatement options respectively. To simplify the presentation, we stick to a two-period analytical model. Without any restrictions on banking and borrowing, in which case the permit price is the same in the two periods (in present value), a higher price gives an incentive for more abatement of both types.[10] However, with no intertemporal flexibility, the prices are in general no longer equal across periods. We show that a higher future permit price likely favors the dynamic abatement option over the static option today.

We next calibrate and simulate a numerical model for Norwegian abatement policies, where we use electrification of the car fleet in Norway as an example. Norway is the world leader in supporting the transition from internal combustion engines vehicles (ICEVs) to electric vehicles (EVs). In 2021, more than 60 % of the new private cars in Norway were EVs[11], and this share is expected to increase in the coming years. Still, it takes time until the *stock* of EVs exceed that of ICEV. The electrification of the car fleet is encouraged by the government through several types of subsidies and privileges (exemption from VAT and excise tax on cars, free parking, free charging, exemption from tolls, right to use the bus lanes). Furthermore, investments in fast charging stations outside the big cities are subsidized. It has been argued that electrification of the transport sector is an expensive way of reducing current GHG emissions (van Vliet et al. 2011; Bjertnæs, 2013; Holtsmark and Skontoft, 2014; Bye et al., 2021). On the other hand, it takes time to build a charging infrastructure and replace the car fleet, and a large body of literature points to the significance of charging infrastructure for EV adoption (Sierzchula et al., 2014; Zang et al., 2016; Mersky et al., 2016; Yu et al., 2016; Li et al., 2017; Figenbaum, 2018). Thus, large investments in EV infrastructure today may pay off in the future if emissions targets become tighter (Thiel et al., 2010). In our model, we distinguish between the lifetime of the two types of EV support, where investments in infrastructure (distribution grid) for fast charges have a significantly longer lifetime than an EV (NVE, 2019). Thus, subsidizing EVs to replace ICEVs is the static

[10] Identical present value permit prices over time will also hold if there is a non-binding constraint on borrowing, no constraints on banking, and the emitters have perfect foresight, see Hagem and Westskog (2008).

[11] https://ofv.no/bilsalget/bilsalget-i-desember-2021 (accessed 29.1.2022).

option, whereas long-lived investment in grids and fast charging stations is the dynamic option.[12]

Norway is a part of the EU ETS and cooperates with the EU on emissions reductions in the non-ETS sectors, which also include road transport. At present, there are emissions targets for these sectors for 2030 (annual emissions allocations-AEAs), and we assume that the emission targets get tighter over time. According to the Effort Sharing Regulation, Member States can trade allocations with other Member States. Hence, a permit market for AEAs may emerge in the future. Such a market will have implications for policies to reduce domestic emissions. Based on the literature on future permit prices for the non-ETS sectors, we discuss under what conditions the present EV policy in Norway can be considered as a cost-effective climate policy, and discuss the optimal combination of EV purchase subsidies, public support of investments in fast charging stations and trade in emissions permits.

The numerical simulations confirm and extend the simple theory model. We incorporate *charging anxiety* which is the fear that one will be trapped in queues due to limited charging infrastructure. In a thinly populated country with large distances and cold temperatures in wintertime, *range anxiety*, the fear that battery will be empty between charging stations, affects consumer decisions.[13] Both these anxieties have important implications for the results, as the first anxiety increases in the number of EVs whereas both fall in the number of charging stations.

Flexibility in the domestic target over time affects the combination of static and dynamic abatement. As we show below, with intertemporal flexibility but no permit market, it will be optimal to increase abatement in the first period, but relatively less efficient to invest in the dynamic abatement option compared to no intertemporal flexibility. With a permit market, the choices will largely depend on the permit prices. Early and time consistent plans for international regulation of GHG emissions will therefore be important for making optimal electrification plans for the transport sector.

[12] In Norway, the average lifetime of an ICEV is 18 years (see https://www.ssb.no/transport-og-reiseliv/artikler-og-publikasjoner/100-000-el-biler). However, the lifetime of EVs may be shorter than the lifetime of ICEVs due to the duration of batteries. There are also indications that the second hand price of EVs falls faster than the second hand price of ICEVs due to expectations of shorter lifetime (Andreassen and Lind, 2022).

[13] Batteries will typically perform worse with longer charging times, less capacity and more power leakage in subzero temperatures. This is an obvious concern in large parts of Norway.

2 A two-period abatement model

Assume that a country has signed an agreement that puts restrictions on its GHG emissions in period 1 (e.g., 2020-2030) and period 2 (e.g., 2030-2050), implying that emissions must be reduced by a certain amount from a given business as usual (BAU) level. Emissions reductions (abatement) follow from replacing fossil-based consumption by consumption derived from a non-emitting energy sources (e.g., by replacing ICEVs with EVs). The replacement of fossil-based consumption is induced through two types of measures; static policy instrument and dynamic policy instrument. The static policy instrument is direct support to purchase and use of the non-emitting consumption capital (e.g., by subsidizing use and purchase of EVs), whereas the dynamic policy instrument is long-lived investments in infrastructure which reduces the user cost of the non-emitting consumption capital (e.g., by investing in charging infrastructure, pipelines for storing captured carbon, wind mills etc.). Thus, total abatement level at time *t*, a_t, is the sum of abatement due to the static policy instrument, a_{ts}, and the dynamic policy instrument, a_{td}.

Investments in long lasting infrastructure in period 1 affect the abatement costs also in the second period. Thus, the costs of abatement in period 1 and 2 are given by

(1) $$C_1 = C_1(a_{1s}, a_{1d})$$

(2) $$C_2 = C_2(a_{2s}, a_{2d}, a_{1d})$$

where the per period cost of abatement is increasing in both types of emissions reductions within each period, but abatement following from investment in infrastructure in period 1 decreases the abatement cost in period 2. By omitting "*a*" in the subscript, these assumptions can be written:

(3) $$C'_{1_{1s}} > 0,\ C'_{1_{1d}} > 0,\ C'_{2_{2s}} > 0, C'_{2_{2d}} > 0, \text{ and } C'_{2_{1d}} < 0.$$

Abatement costs are assumed to be convex in a_{ts} and a_{td}, respectively:

(4) $$C''_{1_{1s,1s}} > 0,\ C''_{1_{1d,1d}} > 0, C''_{2_{2s,2s}} > 0, C''_{2_{2d,2d}} > 0, \text{ and } C''_{2_{1d,1d}} > 0.$$

In addition, we take into account the limited ability for an economy to switch from low to high level of infrastructure over a short time period, by assuming convex investments cost, see Vogt-Schilb et.al (2018). In our model setup, this means that the cost of reducing emissions through increased stock of infrastructure in period 2 is lower the higher abatement following from infrastructure in period 1:

(5) $C''_{2_{2d,1d}} < 0$.

2.1 No Permit trade

In the absence of permit trading, and with **no intertemporal flexibility** (no banking or borrowing) the country must ensure that the sum of abatement in each period equals the sum of abatement obligations in each period, $\bar{a}_t$:

(6) $a_{ts} + a_{td} = \bar{a}_t \quad t = 1, 2$

This leads to the following optimization problem where we have omitted discounting for simplicity:

(7) $\min TC(a_{1s}, a_{1d}, a_{2s}, a_{2d}) = \min \{C_1(a_{1s}, a_{1d}) + C_2(a_{2s}, a_{2d}, a_{1d})\}$

subject to the constraints in (6). We can then form the Lagrangian

(8) $L = C_1(a_{1s}, a_{1d}) + C_2(a_{2s}, a_{2d}, a_{1d}) + \lambda_1(\bar{a}_1 - a_{1s} - a_{1d}) + \lambda_2(\bar{a}_2 - a_{2s} - a_{2d})$

where λ_t is the shadow cost of the emissions constraint in period *t*. This gives the following first order conditions:

(9) $$\begin{aligned} C'_{1_{1s}} &= C'_{1_{1d}} + C'_{2_{1d}} = \lambda_1 \\ C'_{2_{2s}} &= C'_{2_{2d}} = \lambda_2 \end{aligned}$$

In the case of **full intertemporal flexibility**, abatement over both periods equal the sum of targets over both periods, where $\bar{a}_1 + \bar{a}_2 = \bar{a}$

The abatement constraint is thus given by:

(10) $a_{1s} + a_{1d} + a_{2s} + a_{2d} = \bar{a}$

The first order conditions are then:

(11) $C'_{1_{1s}} = C'_{1_{1d}} + C'_{2_{1d}} = C'_{2_{2s}} = C'_{2_{2d}} = \lambda$

where λ is the shadow cost of the emissions constraint given by (10).

As $C'_{2_{1d}} < 0$, equations (9) and (11) give the following Proposition:

Proposition 1: *If the emissions constraints are binding, cost-effective climate policy implies that the marginal abatement costs of dynamic policies exceed the marginal costs of static policies in period 1.*

This confirms the conclusion in Vogt-Schilb et al. (2018) that it may be optimal to start with an expensive abatement option even if there are cheaper options available.

2.2 Permit trade

Next, we consider the case where there is an international market for emissions permit as part of the agreement. We assume that the country is sufficiently small to be a price-taker in this market, where P_t denotes the permit price in period *t*. In the case of no intertemporal flexibility, the country must ensure that abatement in each period plus permit purchase (d_t) equal the initial abatement obligation for each period $\bar{a}_t$:[14]

(12) $$d_t = \bar{a}_t - a_{ts} - a_{td} \quad t = 1,2$$

In the following, this is called **spatial flexibility**. This leads to the following optimization problem:

(13) $$\min TC(a_{1s}, a_{1d}, a_{2s}, a_{2d}) = \min\left\{C_1(a_{1s}, a_{1d}) + C_2(a_{2s}, a_{2d}, a_{1d})\right\}$$

subject to (12). We can then form the objective function

(14) $$L = C_1(a_{1s}, a_{1d}) + C_2(a_{2s}, a_{2d}, a_{1d}) + P_1(\bar{a}_1 - a_{1s} - a_{1d}) + P_2(\bar{a}_2 - a_{2s} - a_{2d}),$$

This gives the following first order conditions:

(15) $$\begin{aligned} C'_{1_{1s}} &= C'_{1_{1d}} + C'_{2_{1d}} = P_1 \\ C'_{2_{2s}} &= C'_{2_{2d}} = P_2 \end{aligned}$$

This result echoes Proposition 1.

As the dynamic abatement option lasts over both periods, the permit price in one of the periods has an impact on the optimal abatement policy also in the other period. The impact depends on the sign (and the magnitude) of the cross derivatives $C''_{t_{ts,td}}$, which express the

[14] In addition, the country may set restrictions on maximum permit purchase within each period, denoted Q_t, where $d_t \leq Q_t$. If $Q_t = 0$, all abatement must be taken at home, while for $Q_t > 0$, a certain amount of abatement has to be taken at home. In the simulations below, we only consider cases where there are no constraint or where all emissions have to be taken at home ($Q_t = 0$).

increase in marginal cost of one abatement option of an increase in the other abatement option.

***Proposition 2**: For $C''_{t_{ts,td}}$ = 0, an increase in the permit price in one period increases the optimal level of the dynamic abatement option in the other period, but has no impact on the static abatement option in the other period* $(\frac{da_{1s}}{dP_2}=\frac{da_{2s}}{dP_1}=0, \quad \frac{da_{1d}}{dP_2}>0, \frac{da_{2d}}{dP_1}>0)$.

For $C''_{t_{ts,td}}$ < 0, an increase in the permit price in one period increases the optimal level of both types of abatement in the other period $(\frac{da_{1s}}{dP_2}>0, \quad \frac{da_{1d}}{dP_2}>0, \quad \frac{da_{2s}}{dP_1}>0, \quad \frac{da_{2d}}{dP_1}>0)$.

For $C''_{t_{ts,td}}$ > 0, an increase in the permit price in one period can increase or decrease the optimal level of abatements in the other period depending on whether the value exceeds the value of the direct second order derivative. The impact on the two types of abatement will have opposite sign.

***Proof:** See Appendix A.*

Proposition 2 states that it is not obvious how a future price increase of carbon affects dynamic abatement today. However, we know that if an increase in one abatement option decreases the marginal cost of the other, a rise in the price of carbon in the next period increases both dynamic and static abatement today. If dynamic abatement does not affect the cost of static abatement, only dynamic abatement will increase if the cost of carbon in the next period increases.

To get a better understanding of the effects, we can make assumptions based on the second order condition. For the necessary second order conditions of (14) to be satisfied, the absolute values of the cross derivatives cannot be too large relative to the second order derivatives; specifically we must have that $C''_{1_{1s1s}}\left(C''_{1_{1d1d}}+C''_{2_{1d1d}}\right)-\left(C''_{1_{1s1d}}\right)^2>0$ and $C''_{2_{2d,2d}}C''_{2_{2s,2s}}-C''^2_{2_{2s,2d}}>0$.[15] This means that we cannot have that the absolute value of the cross

[15] Let **A** be the Hessian of (14), see Appendix A. In order for necessary conditions for a local minimum to be satisfied, all principal minors must have non-negative determinants. $C''_{1_{1s1s}}\left(C''_{1_{1d1d}}+C''_{2_{1d1d}}\right)-\left(C''_{1_{1s1d}}\right)^2$ is the determinant of the principal minor when the two last rows/columns have been removed. $C''_{2_{2d,2d}}C''_{2_{2s,2s}}-C''^2_{2_{2s,2d}}$ is the determinant of the principal minor when the two first rows/columns have been removed.

derivatives exceed the second order direct derivatives for both abatement options.[16] In the following we assume that both of the direct second order derivatives exceed the absolute value of the cross derivatives in both periods.

***Proposition 3*:** *Given* $C''_{t_{ti,ti}} > \left| C''_{t_{td,ts}} \right|, i = d, s$, *we find that:*

For $C''_{t_{ts,td}}$ *> 0, an increase in the permit price in one period increases the optimal level of the dynamic abatement options and decreases the optimal level of the static abatement option in the other period (* $\frac{da_{1s}}{dP_2} < 0, \frac{da_{2s}}{dP_1} < 0, \quad \frac{da_{1d}}{dP_2} > 0, \frac{da_{2d}}{dP_1} > 0$ *).*

For $C''_{t_{ts,td}}$ *< 0, an increase in the permit price in one period gives a larger impact on the dynamic abatement option than on the static abatement option in the other period (* $0 < \frac{da_{1s}}{dP_2} < \frac{da_{1d}}{dP_2}, \ 0 < \frac{da_{2s}}{dP_1} < \frac{da_{2d}}{dP_1}$ *).*

Proof of proposition 3: *See Appendix A.*

Hence, we can conclude that if the absolute level of the cross derivatives is not too large relative to the second order derivatives, an increase in the future permit price makes it more profitable to invest in the dynamic abatement option, relative to the static abatement option, today.[17]

We now turn to the case of **full intertemporal flexibility** where the permit market is efficient (intertemporal and spatial flexibility) and competitive. Here, both borrowing ($a_{1s} + a_{1d} + d_1 < \bar{a}_1$) and banking ($a_{1s} + a_{1d} + d_1 > \bar{a}_1$) of permits from the first period to the second are allowed. This is specified as $\bar{a}_1 + \bar{a}_2 = \bar{a}$, which gives:

(16) $$a_{1s} + a_{1d} + a_{2s} + a_{2d} + d_1 + d_2 = \bar{a}$$

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[16] Note that if $C''_{t_{ts,td}}$ = 0, the second order condition is fulfilled.

[17] In the numerical illustration of our model, see Section 3, we consider a model where increasing abatement of one type decreases the marginal cost of the other ($C''_{t_{ts,td}}$ *< 0).*

It is straightforward to show that the permit prices must be equal in the two periods, i.e., $P_1 = P_2 = P$, This implies that emitters are indifferent about when to sell/buy permits, so (16) can be simplified to:

$$(17) \qquad a_{1s} + a_{1d} + a_{2s} + a_{2d} + d = \bar{a} \,,$$

where d denotes the total permit purchases over the two periods. The total costs then become:

$$(18) \quad TC(a_{1s}, a_{1d}, a_{2s}, a_{2d}) = C_1(a_{1s}, a_{1d}) + C_2(a_{2s}, a_{2d}, a_{1d}) + P\left(\bar{a} - a_{1s} + a_{1d} + a_{2s} + a_{2d}\right),$$

and minimizing these costs yields the following first order conditions:

$$(19) \qquad C'_{1_{1s}} = C'_{1_{1d}} + C'_{2_{1d}} = C'_{2_{2s}} = C'_{2_{2d}} = P$$

Thus, independent of flexibility, we see that Proposition 1 still holds, i.e., $C'_{1_{1s}} < C'_{1_{1d}}$ in optimum.

3 An application of the model - electrification of the car fleet

We now derive how abatement policies to induce electrification of the car fleet can be represented by the model above.

3.1 The market equilibrium

The social cost of electrifying the car fleet consists of four main elements. First, there is a cost difference between cars running on fossil fuels (ICEVs) and EVs. Second, there is a disutility associated with EVs compared to ICEVs related to the need for charging the EV batteries, which brings about both “range anxiety” and “charging anxiety” (Hidrue et al., 2011). The former is due to the limited range for the batteries, and the concern for not reaching the charging station (e.g., on long trips) before the battery is empty. Charging anxiety is related to the concern for long queues in front of the fast chargers. Range anxiety is higher the fewer charging stations in total (and the geographical distribution), whereas charging anxiety is higher the more EVs there are per charging station. Both these types of social costs can be reduced by increased density of fast charger stations (Zhang et al., 2016 and Sierzchula, 2014). The third main cost is the investment in new infrastructure.[18]

[18] The benefit of reduced CO_2 emissions is not included in our analysis as the emission target in exogenous and the benefits from emissions reduction vis-à-vis BAU will therefore be constant across policies. However, in the scenarios with international permit trading, emissions reductions are valued by the permit price.

For simplicity, we present at two-period model as in the stylized model above, t = 1,2. Furthermore, we assume a given driving distance per car and a given number of cars, $\bar{E}_t$, in each period. Abatement is achieved by an increase in the share of electric cars, μ_t, where $0 \leq \mu_t \leq 1$. Consumers driving a car can choose between an ICEV and an EV.

The total utility from driving for all consumers driving EVs at a certain time period t (i.e., $\mu_i \bar{E}_i$) is specified in the following way, where foot script e means EV:

(20)
$$U_{e,t}\left(\mu_t, s_t, K_t\right) = \alpha\mu_t\bar{E}_t - \frac{\beta}{2}\left(\mu_t\bar{E}_t\right)^2 - A_1\left(\frac{\mu_t\bar{E}_t}{G_t}\right)\mu_t\bar{E}_t - A_2\left(\frac{\mu_t\bar{E}_t}{K_t}\right)\mu_t\bar{E}_t - \frac{C}{K_t}\mu_t\bar{E}_t - \left(q_e - s_t\right)\mu_t\bar{E}_t$$

The two first terms reflect that consumers are heterogeneous in their preferences for driving an EV, i.e., the additional utility by adding a new EV driver is falling in the number of EVs ($\alpha > 0$ and $\beta > 0$).[19] Further, the disutility related to EV charging is represented by the next three terms. For charging anxiety, we distinguish between driving in urban and rural areas. $A_1\left(\frac{\mu_t\bar{E}_t}{G_t}\right)$ represents the charging anxiety per driver in urban areas, while $A_2\left(\frac{\mu_t\bar{E}_t}{K_t}\right)$ is the charging anxiety in rural areas, where $A_1 > 0, A_2 > 0$. The charging anxiety per EV user is increasing in the number of EVs, but falling in the number of charging stations, where G_t is the number of charging stations in urban areas, and K_t is the number of charging stations in rural areas. We distinguish between the two geographic locations assuming that it is privately profitable to build charging stations in urban areas, while not in rural areas without subsidies. Further, $\frac{C}{K_t}\mu_t\bar{E}_t$ is the range anxiety, which is falling in the number of charging stations in rural areas ($C > 0$). To simplify the analysis, we assume that anxiety is identical across consumers, and thus only consider heterogeneity among consumers via the two first terms in (20). Finally, q_e is the annual cost of driving an EV, which is assumed constant over time, and s is the annual subsidy to an EV driver.

[19] There may be several reasons why some people are more in favor of an EV than others, such as environmental values, social norms, identity, interest in new technology, practical issues etc., see the literature survey in Kverndokk et al. (2020).

From (20) we can find that the marginal consumer has the following utility from driving an EV:[20]

(21) $$u_{e,t}\left(\mu_t \bar{E}_t\right) = \alpha - \beta\mu_t \bar{E}_t - A_1\left(\frac{\mu_t \bar{E}_t}{G_t}\right) - A_2\left(\frac{\mu_t \bar{E}_t}{K_t}\right) - \frac{C}{K_t} - \left(q_e - s_t\right)$$

The amount of capital in rural areas (fast chargers) in period 1 and 2 respectively, is given by

(22) $$\begin{aligned} K_1 &= I_1 + (1-\delta_0)K_0, \\ K_2 &= I_2 + \left(1-\delta_1\right)K_1 \end{aligned},$$

where δ_t is the depreciation of capital in each period, I_t is investment and K_0 is exogenously given by history.[21]

As mentioned above, G_t is the infrastructure capital that would be available in the absence of public investment, i.e., commercially profitable investments in fast chargers in urban areas. We assume that more EVs increase the profitability of investing in charging stations, and thus lead to more stations in urban areas. In addition, more charging stations reduce the disutility of driving an EV, and therefore increase the incentives to buy an EV (equation (20)). This is an example of indirect network effect, which has been studied in the literature when it comes to infrastructure investments, and in particular investments in charging stations, see e.g., Greaker and Midttømme (2016).

Following Meunier and Ponssard (2020) [22], we assume that the number of charging stations is proportional to the number of EVs, that is:

(23) $$G_t = B\mu_t \bar{E}_t, \;\; B > 0,$$

where G is increasing in the number of EVs on the road. Note that by inserting this equation in (20), the charging anxiety per EV driver in urban areas becomes constant ($\frac{A_1}{B}$) and the coordination problem from an indirect network effect will also disappear.

[20] This is derived by differentiating (20) with respect to $\mu_i \bar{E}_i$, but taking into account that the parentheses in the third and fourth terms are exogenous to the individual driver.

[21] Note that in the simulations below, the time periods are not equal as we study the years 2020, 2030 and 2050. Thus, the depreciation rates in equation (22) will differ.

[22] See their equation (12).

In rural areas, investment in charging stations does not respond to more EVs in a similar manner. Unless the regulator increases the investments in *K*, for instance by providing subsidies to commercial investors, more EVs will not lead to more stations in rural areas, only to an increasing charging anxiety for each EV.

The total utility of driving ICEVs at a certain time period *t* (i.e., $(1-\mu_t)\bar{E}_t$) is specified as follows, where foot script *f* means ICEV:

$$U_{f,t}(\mu_t) = \left(\Pi_f - q_f\right)(1-\mu_t)\bar{E}_t. \tag{24}$$

Here, $\Pi_f > 0$ is a fixed utility term, while q_f is the annual cost of driving an ICEV, which is also assumed constant. Thus, the only heterogeneity among consumers is the preference for driving an EV, i.e., when switching car from an ICEV to an EV.

Each EV driver takes the number of EVs and charging stations as given. By assuming that the utility of the last consumer buying an EV is equal to its utility of driving an ICEV, we find by using (21), (23) and (24):

$$\alpha - \beta\mu_t\bar{E}_t - \frac{A_1}{B} - \frac{A_2}{K_t}\mu_t\bar{E}_t - \frac{C}{K_t} - q_e + s_t = \Pi_f - q_f \tag{25}$$

Thus, in the market equilibrium, it follows that the share of drivers that chooses an EV is (assuming interior solution):

$$\mu_t(s_t, K_t) = \frac{\alpha - \frac{A_1}{B} - \frac{C}{K_t} - \left(q_e - s_t - q_f\right) - \Pi_f}{\left(\beta + \frac{A_2}{K_t}\right)\bar{E}_t}. \tag{26}$$

The government can influence the decision of the drivers by implementing transport policies. In our model, it has two policy instruments; reducing the user cost of EVs through subsidies s_t and investing in fast chargers K_t. Thus, the value of μ_t depends on s_t and K_t, with the share of EVs increasing in both policy instruments.

Note that $\lim_{K_t \to 0} \mu_t(s_t, K_t) = -C / A_2\bar{E}_t$, which implies that unless K_t is above a critical value, no individual will choose an EV, i.e., $\mu_t(0,0)=0$.[23] This critical value is given by:

[23] Note that in our specification, the marginal driver of an EV drives in both urban and rural areas, see (21). We do not distinguish between people living in urban and rural areas. An alternative would be to distinguish between

$$(27) \qquad K^{crit}(s) = \frac{C}{(\alpha + s - q_e + q_f - \Pi_f) - A_1/B}$$

Clearly, K^{crit} can only be non-negative if the denominator is positive which may give a lower bound on *s*.

We can decompose the emissions reductions that follow from s_t and K_t in the following manner.[24] Let σ be an emissions coefficient, i.e., CO_2 emissions from driving an ICEV in the given time period, while there are no CO_2 emissions from driving an EV. Total abatement in period *t* can then be specified as follows:

$$(28) \qquad \begin{aligned} a_t &= \sigma\left[\mu_t(s_t,K_t)\bar{E}_t - \mu(0,0)\bar{E}_t\right] \\ &= \underbrace{\sigma\left[\mu_t(0,K_t)\bar{E}_t - \mu(0,0)\bar{E}_t\right]}_{a_{td}\text{ =Abatement induced by }K_t} + \underbrace{\sigma\left[\mu_t(s_t,K_t)\bar{E}_t - \mu_t(0,K_t)\bar{E}_t\right]}_{a_{ts}\text{ =Abatement induced by }s_t} \end{aligned}$$

The last line in this equation separates the effect of subsidies and infrastructure investment, where we first single out abatement induced by K_t and then additional abatement induced by s_t (given the size of K_t). We can write out this line in the following way:

$$(29) \qquad \sigma\left[\mu_t(0,K_t)\bar{E}_t - \mu_t(0,0)\bar{E}_t\right] = a_{td}$$

$$(30) \qquad \sigma\left[\mu_t(s_t,K_t)\bar{E}_t - \mu_t(0,K_t)\bar{E}_t\right] = a_{ts}$$

$$(31) \qquad a_{td} + a_{ts} = a_t$$

Here a_{te} is the dynamic abatement created by the infrastructure and a_{tf} is the additional static abatement from the subsidy, see Section 2 above. Together with the equations of motion in (22), equations (29)-(31) give us 8 equations in 12 variables; $a_{td}, a_{ts}, a_t, s_t, K_t, I_t$, where t = 1,2. Thus, to determine the system, we need to set the policy instruments K_t and s_t, which we assume are determined optimally by the government. We can solve (29) and (30) with respect to K_t and s_t This yields:

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different geographical areas and allow consumers to have more than one car. In that case it could be optimal to have an EV even if the critical value of *K* is not reached (equation (27)). However, this would complicate the analysis without affecting the main findings.

[24] Note that we define emissions reductions (and abatement) relative to the situation with no subsidy and no charging station (in which case there are no EVs), and not relative to a scenario without emissions constraint. In the numerical simulations, the number of charging stations and EVs are both strictly positive even in the case without emissions constraint.

(32) $$K_t\left(a_{td}\right)=\frac{C+\frac{a_{td}}{\sigma}A_2}{\alpha-\Pi_f-q_e+q_f-\frac{A_1}{B}-\frac{a_{td}}{\sigma}\beta}$$

(33) $$s\left(a_{td},a_{ts}\right)=\frac{\frac{a_{ts}}{\sigma}\left(\beta C+A_2\left(\left(\alpha-q_e+q_f-\Pi_f\right)-\frac{A_1}{B}\right)\right)}{C+\frac{a_{td}}{\sigma}A_2}$$

Note that as expected $K_t(a_{td})$ is an increasing function in a_{td}. We also see that $K_t(a_{td})$ is lower the cheaper it is to drive an EV (q_e) or the more expensive it is to drive an ICEV (q_f). The reason is that this increases the benefits of driving an EV, and the need for investments as an instrument to increase EVs is therefore lower.

From (31) and $\mu_t\left(0,0\right)=0$ it follows that the fraction of cars, optimally chosen by the representative consumer, can be expressed as a function of the two types of abatements:

(34) $$\hat{\mu}_t\left(a_{td},a_{ts}\right)=\mu_t\left(s_t\left(a_{td},a_{ts}\right),K_t\left(a_{td}\right)\right)=\frac{a_{td}+a_{ts}}{\sigma\bar{E}}$$

We can now define the utility of the EV owners as functions of abatement efforts:

(35) $$V_{e,t}\left(a_{td},a_{ts}\right)=U_{e,t}\left(\mu_t\left(s_t\left(a_{td},a_{ts}\right),K_t\left(a_{td}\right)\right),s_t\left(a_{td},a_{ts}\right),K_t\left(a_{td}\right)\right)$$

3.2 The Government's decision problem

The governmental decision problem is to decide the values of a_{td} and a_{ts} that minimize social cost, taken into account the abatement targets and permit trade restrictions. We define the consumer's cost as the loss in welfare (eq. (20) and (24)) of the transport policy. As derived above, the fraction of EVs can be expressed as a function of the two types of abatement, and therefore, the welfare of the representative consumer is a function of a_{td} and a_{ts} . In addition, the government must also consider the cost of investing in K_t. If we denote the cost of I_t by $\kappa_t\left(I_t\right)$, we can write the social cost of abatement in each period by:[25]

[25] Note also that the investment cost functions can be written as functions of abatement in the following way, $I_1\left(a_{1d}\right)=K\left(a_{1d}\right)-\left(1-\delta_1\right)K_0$ and $I_2\left(a_{1d},a_{2d}\right)=K\left(a_{2d}\right)-\left(1-\delta_2\right)K\left(a_{1d}\right)$.

(36)
$$\begin{aligned} C_1\left(a_{1s},a_{1d}\right) &= -V_{e,1}\left(a_{1d},a_{1s}\right)-\left(\Pi_f-q_f\right)\left(1-\hat{\mu}_1\left(a_{1d},a_{1s}\right)\right)\bar{E}_1 \\ &\quad +s\left(a_{1d},a_{1s}\right)\hat{\mu}_1\left(a_{1d},a_{1s}\right)\bar{E}_1+\kappa\left(I_1\left(a_{1d}\right)\right) \\ C_2\left(a_{2s},a_{2d},a_{1d}\right) &= -V_{e,2}\left(a_{2d},a_{2s}\right)-\left(\Pi_f-q_f\right)\left(1-\hat{\mu}_2\left(a_{2d},a_{2s}\right)\right)\bar{E}_2 \\ &\quad +s\left(a_{2d},a_{2s}\right)\hat{\mu}_2\left(a_{2d},a_{2s}\right)\bar{E}_2+\kappa\left(I_2\left(a_{1d},a_{2d}\right)\right) \end{aligned}$$

Note that we have added the payments of s_t from the government to EV drivers into the cost functions in (36). The subsidy should not be included in the social cost as it is only an internal domestic transfer. However, since s_t is included in the utility of the EV owners ($V_{e,t}\left(a_{td},a_{ts}\right)$), it must be counterbalanced by government payments.

For simplicity, we have omitted the social cost of public funds. The government's intertemporal cost function may then be written as:

(37)
$$TC=\theta_1 C_1\left(a_{1s},a_{1d}\right)+\theta_2 C_2\left(a_{2s},a_{2d},a_{1d}\right)$$

where θ_1 and θ_2 are discount factors for period 1 and 2, respectively, which is necessitated by our simulations bundling several years into one period. As assumed in Section 2, eq (5), the cost of reducing emissions through increased stock of infrastructure in period 2 is lower the higher abatement following from infrastructure in period 1. This can be seen by differentiating $C_2\left(a_{2s},a_{2d},a_{1d}\right)$ in (36) with respect to a_{1d} and a_{2d}.:

(38)
$$\begin{aligned} C''_{2_{2d,1d}} &= \frac{\partial^2\kappa\left(I_2\left(a_{1d},a_{2d}\right)\right)}{\partial a_{2d}\partial a_{1d}} \\ &= \frac{\partial^2}{\partial a_{2d}\partial a_{1d}}\kappa\left(K\left(a_{2d}\right)-\left(1-\delta_2\right)K\left(a_{1d}\right)\right) \\ &= -\left(1-\delta\right)K'\left(a_{2d}\right)K'\left(a_{1d}\right)\kappa''\left(I_2\right)<0 \end{aligned}$$

The first equality in (38) follows from $\kappa\left(I_2\left(a_{1d},a_{2d}\right)\right)$ being the only term in $C_2\left(a_{2s},a_{2d},a_{1d}\right)$ that contains both a_{1e} and a_{2e} and is therefore the only term with non-zero crossderivative. As discussed in Section 2, the conditions for optimal abatement policies depend on the flexibility of the emissions targets across periods (intertemporal flexibility) and the international permit trade options (spatial flexibility). The first order conditions under the various flexibility scenarios can be expressed in the same way as in (9), (11), (15) and (19).

An increase in the number of fast charger, K_t, reduces both charging and range anxiety, and thus increases the consumers' utility of shifting from ICEV to EV, which again decreases the level of the subsidy to induce more EVs. This means that $C''_{t_{ts,td}} < 0$ in our model specification.

3.3 Calibration of the model

The model is calibrated to data for Norway with 2020 as the base year. We further consider the periods 2020-2030 and 2030-2050, but assume that all variables are identical each year within in each period, except for the investments in charging station, which occur in the first year within each period. For ease of reference, all parameters are summarized in Appendix C.

The total number of private cars in 2018 is according to Statistics Norway (2019) about 2,750,000, with a share of electric vehicles equal to 7.1%. Predictions for the number of private cars and private transport for the next decades vary (see, e.g., Madslien et al., 2014; KPMG, 2018), but based on these and the current trends, such as car sharing and self-driving cars, it may be reasonable to assume that the total number of private cars will not increase significantly. We have therefore set the total number to 2,900,000 across both periods.

The capital stock in the model is defined as the number of fast charges or supercharges for electric vehicles. 94% of the owners of electric vehicles in Norway charge their cars at home (Figenbaum, 2018). However, fast chargers are important for long distance driving, and the investments in chargers the last few years have mainly been fast chargers in the traffic corridors between cities. In addition, fast chargers in cities may be important for those living in flats without access to home charging. Figenbaum (2018) points to investments in fast chargers as a main instrument to reduce distance anxiety. According to Elbilforeningen (2019), there were 1,852 fast chargers in Norway per 30 June 2019. The Government subsidizes fast chargers outside the main cities through the governmental body ENOVA. The subsidy is 40% of the cost. We assume that there are 2000 fast chargers in Norway in the year 2020, where 50 %, i.e., 1,000, is the number of commercial fast chargers (G) not receiving subsidies, while the rest (K) have received governmental subsidies. The parameter B in the equation for G, i.e., (23), is calibrated based om 2020-values.

Fast chargers consist of several components with different lifetimes. The lifetime of the charger itself is about 10-15 years (Schroeder and Trabe, 2012). However, the cost of the charger is only about 25% of the total costs.[26] Physical facilitation is required such as casting

[26] Erik Figenbaum, personal communication.

and burial of cables, in addition to power connection. These components have longer lifetimes. For road projects as well as power connections, the lifetime is set to 40 years (Statens vegvesen, 2018; NVE, 2019). We therefore choose a lifetime of fast chargers of 40 years, using linear depreciation. We have not set an explicit lifetime of EVs, but we assume that it is possible to set the share of EVs optimal in each period. Alternatively, this can be interpreted as a lifetime of EVs equal to 10 years.

The costs of fast chargers vary. Schroeder and Trabe (2012) report numbers for Germany. For all chargers, the numbers vary between €1000 and €125,000, where the highest number is for public superchargers. Figenbaum (2018, also personal communication) reports prices for fast chargers from NOK 400.000 (€ 40,000) and higher, and that the fast chargers that have received governmental support cost between NOK 500,000 and 700,000 (€50,000 and €70,000). Based on this, we set the price of fast chargers to €60,000 and the subsidy to €24,000 (40%). In the model, the investment cost is assumed quadratic, i.e., $\eta(I) = \eta I^2$, where η is calibrated based on values in 2020.

The costs of driving a car are taken from Smarte Penger (2019). Based on a set of assumptions,[27] the annual cost of an EV and an ICEV vehicle is set to €8,600 and € 10,900 respectively. These numbers include taxes and subsidies. The subsidy rate is taken from Kverndokk et al. (2020), who calculate the subsidy to electric vehicles to be 20%. Thus, the cost of driving an electric vehicle without subsidies is set to €10,300. Further, the tax rate on ICEVs is set to 40% based on Kverndokk et al. (2020).

CO_2 emissions per year from ICEVs is set to 2.2 ton, and held constant in the analysis. This calculation is based on a driving distance of 16,000 kilometers per year, and emissions of 140g CO_2 per kilometer. This is a little bit lower than the numbers calculated for 2016 from Statistics Norway (2018), which is 153g per kilometer. However, the CO_2 emissions from driving an average car have fallen over the last few years.

Further, we set the discount rate to 4% annually.[28]

[27] E.g., the retail price is NOK 400,000 (€40,000), annual driving distance is 16,000 kilometers, and the car is sold after three years.

[28] The recommendation in the Ministry of Finance (2012) for public projects with normal risk and a horizon of less than 40 years is to use a discount rate equal to 4 per cent. They assume a risk-free interest rate of 2.5 per cent and a risk adjustment of 1.5 per cent.

It is hard to find estimates from the literature to calibrate the rest of the parameters (*α, β, A_1, A_2, C, Π_f*), and we need to make some assumptions. We assume that the marginal charging anxiety is the same in rural and urban areas, and that the total (urban plus rural) marginal charging anxiety is the same as the marginal range anxiety. As the total number of vehicles is exogenous, we can scale the model so that $\Pi_f = q_f$. We further assume that in absence of range and charging anxiety, 90% of the population would choose an EV instead of driving an ICEV. Thus, there would still be preferences for ICEVs in this case even if the costs of driving are cheaper for EVs, due to heterogeneity of preferences for cars beyond costs. Finally, we assume that the present (base year) subsidy is too low to compensate for range and charging anxiety. For simplicity, we assume that the subsidy should be doubled to outweigh these anxieties. However, as several of these assumptions are a bit ad hoc, we do sensitivity analyses.

The model is a two-period model, and investments made for the period 2031-2050 will have lower value than investments made for the period 2020-2030, since the benefits of the investments after 2050 do not count. Thus, to adjust for this, we have included a factor that scale down the investment costs based on the remaining lifetime of the investments from 2051 onwards. The longer the remaining lifetime, the lower is this factor. Appendix B gives the calculations of these factors at the different times of investment.

3.4 Permit market assumptions

We will explore how the possibilities for emissions trade across countries affect the optimal distribution of the two types of abatement policies. For this task, we will need estimates of the future prices of tradable emissions. EU aims to cut emissions by 55% by 2030 (compared to 1990) and to be carbon neutral by 2050.[29] However, at present (February 2022), EU has not specified the new emissions target for sectors not covered by the EU-ETS (non-ETS); the Effort Sharing Regulation. In addition to EU Member States, Iceland and Norway have agreed to implement the Effort Sharing Regulation, which translates this commitment into binding annual GHG emission. Norway's present target is to reduce non-ETS emissions by 45% in 2030 compared to 2005, but the new EU target will likely mean that Norway has to reduce non-ETS emissions with more than 50%. Non-ETS includes land and sea transport as well as agriculture, buildings and waste. However, we restrict the analyses to emissions from passenger cars in our numerical analysis, and assume that these emissions will have to drop in

[29] 2030 Climate Target Plan | Climate Action (europa.eu) (accessed 21.9.2021).

line with total non-ETS emissions in Norway. As Norwegian emissions from passenger cars fell by 18% from 2005 to 2019,[30] and by assuming a new target of 55% in 2030, emissions then have to fall by 45% from 2020 to 2030. For simplicity, we set this target to 50%. Further, in 2050, we assume that the whole car fleet has to be electric. As we do simulations over periods of ten years (2020-2030) and 20 years (2030-2050), we set the targets equal to the average between the start year and the final year in the period. Thus, annual targets are implemented as 25% reduction from 2020 to 2030, and 75% reduction from 2030 to 2050.[31]

The Effort Sharing Regulation allows for some flexibility in terms of banking and borrowing across time periods, and limited flexibility in terms of access to credits from the land use sectors and EU-ETS allowances. Member States can also buy and sell allowances from and to other Member States. In the following, we refer to this potential trade in allowances across countries as the non-ETS permit market. Although permit trade is an option, there is yet no permit market, and it remains to be seen whether a permit market will emerge. Also, the Norwegian Government has signaled that permit trade will only be used if it is "strictly necessary".[32]

The literature investigating the potential price path for non-ETS permits is scarce, and obviously, price estimates will be highly uncertain. The permit market price, if a permit market emerge, will not only depend on the abatement costs in the non-ETS sectors, but also on the use of the flexible mechanisms of the Effort Sharing Regulation, and the use of other policy instruments and legislations for achieving other energy and environmental targets (e.g., renewable shares and energy efficiency), see Aune and Golombek (2021) and EC (2018).

Bye et al. (2019) construct marginal abatement costs under EU's Effort Sharing Regulation based on a multi sector CGE model. For estimating the permit market price in 2030, they have as a starting point two reference scenarios for projected 2030 emissions of CO_2 in EU (with current policies), EC (2016) and EU (2017), and they consider various options for flexibility mechanism and abatement also for non-CO_2 GHG. They pick out two key scenarios, one which leads to a 2030 permit price of 64 Euro per ton CO_2, and another

[30] Klimagassutslipp fra veitrafikk (miljodirektoratet.no) (accessed 21.09.2021).

[31] The emissions in 2020 are equal to $\sigma(1-\mu_0)\bar{E}$, while emissions in 2030 should be $0.75\cdot\sigma(1-\mu_0)\bar{E}$. Setting $0.75\cdot\sigma(1-\mu_0)\bar{E}=\sigma(1-\mu_{2030})\bar{E}$, i.e., $0.75\cdot(1-\mu_0)=(1-\mu_{2030})$, we calculate that μ over the period 2020-2030 should be about 0.3. In a similar way, μ over the period 2030-2050 should be about 0.77.

[32] Granavolden-plattformen - regjeringen.no (accessed 21.09.2021).

(the highest cost scenario) which gives a permit price of 158 Euro per ton CO_2. The permit price in the low-cost scenario of Bye et al. (2019) is in line with the permit price of 70 Euro in the uniform tax scenario in Vielle (2020) and the prices of Euro 60 and Euro 91 based on macro-economic modelling of cost efficient abatement in Capros et al. (2014).[33] We will use the price scenarios from Bye et al. (2019) for 2030 in our numerical model.

Bye et al. (2019) do not present any figures for 2050, but they report that the marginal abatement cost curve is convex. For 2050 with carbon neutrality in Europe, we choose to operate with marginal abatement costs (permit prices) 2.5 times as high as the 2030 prices in our numerical illustration. This is in line with Capros et al. (2014). Thus, in the low permit price scenario, the permit price in 2030 is €64 and €160 in 2050. In the high permit price scenario, the permit price is €158 in 2030 and €395 in 2050.

4 Numerical results – the case for Norway

We now turn to scenarios for electrification of passenger cars in Norway, given the emissions targets as explained in the previous section. We denote the first period (2020-2030) 2030 and the second period (2030-2050) 2050. As the second period starts ten years after the beginning of the first period, second period welfare is discounted by ten years in order to compute the net present value (NPV) of total welfare. To capture the uncertainty about flexibility in non-ETS across periods and across countries, we consider five scenarios (S1-S5), where the sum of emissions targets over both periods are identical across the scenarios. These scenarios are compared to a benchmark scenario without emissions caps (S0):

S0. No emissions caps

S1. Emissions targets in each period without permit trade.

S2. Full intertemporal flexibility without permit trade.

S3. Emissions targets in each period and permit trade (spatial flexibility). Permit price set to €64 in 2030 and €160 in 2050.

S3b. Same as scenario S3 (spatial flexibility), but with higher permit prices. Permit price set to €158 in 2030 and €395 in 2050.

[33] Bye et al. (2019) use 2011-prices, whereas Vielle (2020) and Capros et al. (2014) use 2017-prices and 2005-prices, respectively.

S4. Full intertemporal flexibility and permit trade (spatial flexibility). Permit price set to €229 in 2030 and €342 in 2050 (this gives constant NPV price, equal to the a weighted average of the permit prices in S3b).

The results are summarized in Table 1. From the table we see that a general result is that the subsidy should be lower and the investments in charging stations should be higher than in the initial situation in all scenarios. More EVs increase charging anxiety, while more charging stations reduce anxiety ceteris paribus. This might indicate that charging and range anxiety have not been taken fully into account in the present governmental decision-making.

In the scenario with no emissions caps (S0), no new abatement policies are implemented, but there are still significantly higher shares of electric cars in the two periods (26.4% and 33.3%, respectively) than in 2020 (7.1%). The optimal number of subsidized charging stations (*K*) increases eightfold as compared to 2020, i.e., (see the Table 1). These results should be interpreted with caution, however, as they follow to a large degree from the calibration, and the implicit assumption that the current level of stations and EVs are far too low. In absence of emissions targets, the optimal subsidy is negative as more EVs mean more charging anxiety (negative externality), but we only consider non-negative subsidies in our analysis.[34] Building more charging stations, on the other hand, reduces both charging and range anxiety.

Imposing constraints on emissions over the two periods involves social costs, i.e., defined as a fall in social welfare, see Table 1 (all welfare values are shown as NPV). Without any flexibility (S1), welfare decreases by more than 800 million Euro in period 1 and almost 6 billion in period 2 (when social welfare turns from positive to negative). Note, however, that environmental welfare gains from lower GHG emissions are not included in our analysis, so we cannot assess from these results whether the emissions cap involves a welfare gain or loss. We are instead interested in comparing the different policy scenarios, i.e., scenarios S1-S4.

Looking more closely at scenario S1, where the emissions cap must be met without any spatial or intertemporal flexibility, the share of EVs increases moderately in period 1 and substantially in period 2. This follows from the much stronger emissions cap in the last period. Note that the emissions constraint in period 1 is in fact not binding – the share of EVs

[34] If we allow for negative subsidies, the optimal subsidies in periods 1 and 2 are -162 and -180, respectively, and the shares of EVs drop to respectively 22% and 27%. The number of charging stations then *increases* by 7-10%.

is 35% and thus exceeds the target of 30%. The reason is that it is optimal to invest in many charging stations already in period 1, which increases the demand for EVs even without any subsidy (note that the subsidy in period 1 is zero). The number of subsidized charging stations increases by around 50% in period 1 and doubles in period 2 (compared to scenario S0). The large number of stations makes it more tempting for car owners to buy an EV as the charging and range anxieties diminish substantially. In the second period it is optimal to implement a subsidy to EV owners (but only one third of the initial subsidy).

Next, we consider the effects of allowing for intertemporal flexibility (scenario S2). That is, total emissions in the two periods cannot exceed the sum of emissions in the two periods in scenario S1, but the temporal distribution of emissions is chosen optimally. We see from Table 1 that it is optimal to decrease emissions further in Period 1 compared to scenario S1, that is, increasing the share of EVs (from 35% to 45%), to allow for less emissions reductions in Period 2 (reducing the share of EVs from 77% to 70%). Welfare drops in Period 1, but the sum of NPV welfare increases by around one billion Euro. A higher share of EVs in the first period requires a positive subsidy also in this period, whereas the subsidy is slightly reduced in the second period. The number of charging stations increases by around 20% in Period 1 compared to S1, but it is only marginally reduced in Period 2, reflecting that there are diminishing returns from new stations. Hence, the optimal number of stations is less sensitive to the number of EVs the higher is the EV share. The reason is that the marginal benefits of more stations (with respect to reducing anxieties) drop quite substantially as the number of stations increases, see e.g. equation (20).

With spatial instead of intertemporal flexibility (comparing S3 with S1), the impacts obviously depend highly on the assumed permit price. With the low price (scenario S3), there are only small changes in Period 1 (some purchase of permits), while in Period 2 it is optimal to buy a huge amount of permits, relaxing the domestic emissions constraint and reducing the number of EVs from 77% to 44%. The EV subsidy and the number of stations also drop accordingly. Total welfare improves by around 3 billion Euro compared to scenario S1 with no flexibility.

If permit prices are about 150% higher (scenario S3b), it is optimal to sell rather than buy permits in Period 1, while still buy in Period 2, although significantly less than in S3. Compared with S3, it is optimal to increase the share of EVs in both periods. A positive EV subsidy is now required in both periods, and it is substantially larger in Period 2, compared with S3. There are still welfare gains from permit trade (vis-a-vis scenario S1 with no flexibility), but less than in scenario S3.[35] Both scenario 3 and 3b show that the emission price has a significant impact on the electrification of the car fleet.

Finally, we consider the scenario (S4) with full flexibility (spatial and intertemporal), where the permit price is initially much higher than in the other scenarios and rises with the assumed discount rate of 4%, so that the weighted permit price is the same as in scenario 3b. Compared with 3b, it is optimal to reduce emissions much more in the first period, realized via a very high EV subsidy and building of more stations. The reason is that the permit price is so high that it will be optimal to sell permits and the need for abatement is therefore larger. Emissions are also reduced more in period 2 (compared with scenario 3b) even though the permit price in this period is lower. The additional buildup of stations in period 1 makes it more beneficial to stimulate the use of EVs by subsidies also in period 2. Total welfare is reduced less in this scenario than in any of the other scenarios with emissions constraint (S1-S4).

Scenario	Period	Share of EVs (μ)	Number of stations (1000 K)	EV subsidy (€/year)	Total welfare (bill. €)	a_{td} million tons/year	a_{ts} million tons/year	$\frac{a_{td}}{a_{td}+a_{ts}}$
Initial situation	*2020*	*7%*	*1.0*	*1700*	*NA*	NA	NA	NA
S0	2030	26%	8.2	0	1.1	1.69	0.00	1
	2050	33%	11.3	0	2.6	2.13	0.00	1
S1	2030	35%	12.2	0	0.3	2.22	0.00	1
	2050	77%	22.2	565	-3.3	2.96	1.93	0.61
S2	2030	45%	14.7	128	-1.1	2.46	0.38	0.86
	2050	70%	22.0	436	-0.9	2.96	1.48	0.67
S3	2030	33%	11.0	0	0.7	2.09	0	1
	2050	44%	16.2	64	-0.65	2.59	0.20	0.93

[35] As seen in Table 1, welfare in Period 1 actually drops (marginally) when permit trade is allowed in scenario S3b (vis-a-vis scenario S1 with no flexibility). The reason is that the higher number of stations in Period 1 also benefits Period 2 (while the investment costs fall on Period 1).

S3b	2030	40%	14.1	55	0.3	2.41	0.16	0.93
	2050	71%	22.0	462	-2.7	2.9	1.58	0.65
S4[36]	2030	52%	16.4	236	2.9	2.61	0.73	0.78
	2050	85%	24.9	653	-4.2	3.09	2.30	0.57

Table 1. Outcomes of different scenarios

Table 1 also shows the levels of a_{td} and a_{ts}, i.e., the levels of abatement through respectively investing in charging stations (dynamic abatement policy) and EV subsidies (static abatement policy). We see that variations in a_{td} and a_{ts} correspond to variations in number of stations (*K*) and EV subsidy. We use these results to test the propositions in Section 2.

Proposition 1 states that if the emissions constraint for period 2 is binding, cost-effective climate policy implies that the marginal abatement cost of dynamic policies exceeds the marginal cost of static policies in period 1. This is the case independent of flexibility in reaching the climate target. We test this proposition for the scenarios S2, S3b and S4. Note that we cannot test this in the scenarios where a_{1s} =0 as we do not have interior solutions in these cases (i.e., scenarios S1 and S3). We find that the marginal costs of a_{1d} are 2-3 times higher than the marginal costs of a_{1s}, thus confirming Proposition 1.

Proposition 2 states that when there are constraints on banking and borrowing in the permit market, an increase in the permit price in one period makes it profitable to increase both static and dynamic abatement in the other period if the cross derivative ($C''_{t_{ts,td}} < 0$) is negative, which is the case in our numerical model. Further, Proposition 3 states that under certain conditions, dynamic abatement increases more than static abatement (when the permit price increases in another period). Scenarios S3 and S3b cover the cases with these constraints, and Figure 1 illustrates the case with an increase of the permit price in Period 1. The figure shows the permit price in Period 1 along the horizontal axis, and the optimal abatement and permit demand as a function of this price (with the Period 2 permit price being fixed at 395 Euro/ton).

[36] When the price of emission quotas increase with the discount rate and quotas are bankable, one is indifferent between buying and selling at the different points in time so whether costs/income is allocated to period 1 or 2 does not matter for total social welfare. Here the cost of quota purchases, 5.46 billion € is allocated to period 1.

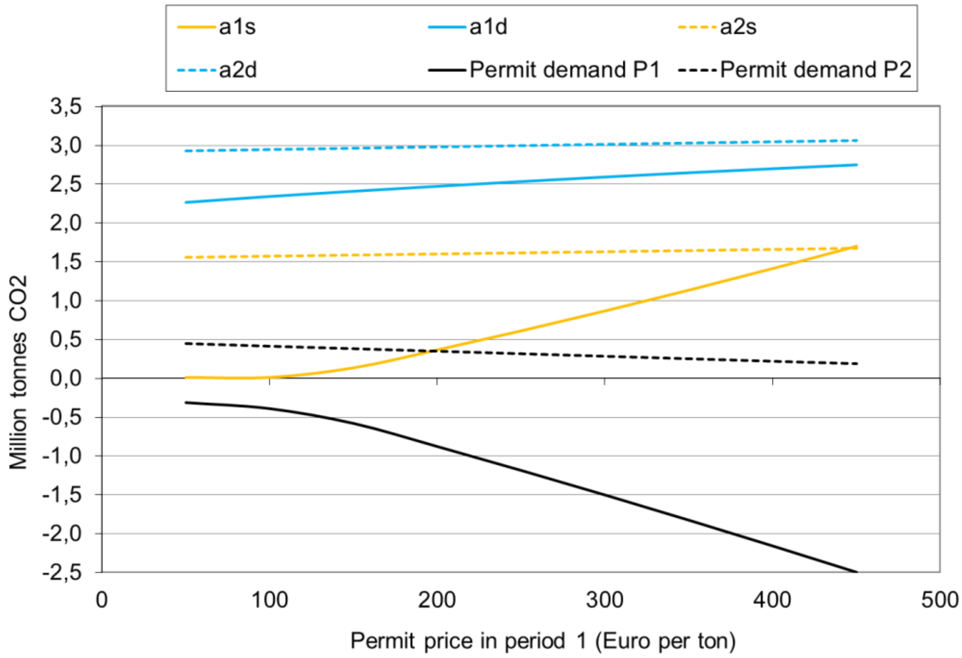

Figure 1: Effects of an increase in the permit price in Period 1 on the two abatement options and permit demand in a permit market with restrictions on banking and borrowing (spatial flexibility).

We see from Figure 1 that permit sales in the first period increase as expected (permit demand becomes more negative). Furthermore, both static (a_{1s}) and dynamic (a_{1d}) abatement in Period 1 increase with the permit price. The sum of additional abatement equals the additional permit sales. As seen from the figure, static abatement increases much more than dynamic abatement in the first period. This is because of the diminishing returns to stations, as explained above. We also notice that both static (a_{2s}) and dynamic (a_{2d}) abatement in Period 2 also increase, although only slightly, with higher permit price in Period 1, thus confirming Proposition 2. The reason is that the additional charging stations built in Period 1 are also to some degree in operation in Period 2, which makes it less costly to comply with the emissions target in the second period. Although hardly visible in the figure, dynamic abatement in Period 2 increases slightly more than static abatement, confirming Proposition 3. As a consequence of somewhat more abatement in Period 2, permit demand in this period declines as the permit price in Period 1 increases.

We now turn to the effects of an increase of the permit price in Period 2, see Figure 2.

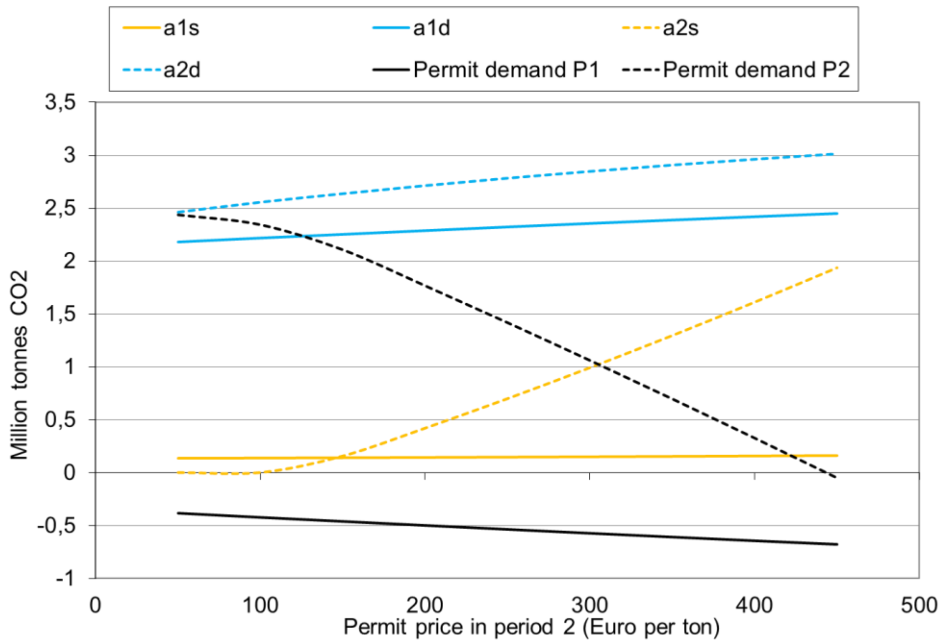

Figure 2: Effects of an increase in the permit price in Period 2 on the two abatement options and permit demand in a permit market with restrictions on banking and borrowing (spatial flexibility).

Not surprisingly, permit demand in Period 2 drops substantially as the permit price in that period increases, whereas both static (a_{2s}) and dynamic (a_{2d}) abatement in Period 2 increase to comply with the emissions target in that period. Again we see that static abatement increases much more than dynamic abatement. This is partly because of the diminishing returns to stations, but also because more stations are being built in Period 1 and these are only partially depreciated in the following period. That is, even though the permit price in Period 1 is unchanged, and there is no intertemporal flexibility, it is optimal to build more stations in Period 1 as the future permit price increases (increasing a_{1d} in Figure 2). The explanation is the convex investment costs of building stations, which makes it cost-effective to smooth investments over time.[37] More charging stations in Period 1 further increases the optimal level of EVs in the first period, thus increasing both static (a_{1s}) and dynamic (a_{1d}) abatement, again in accordance with Proposition 2. The increase in static abatement is much smaller than the increase in dynamic abatement in period 1 though, consistent with Proposition 3. With more abatement in Period 1, permit sales in this period are accordingly increased when the permit price in Period 2 increases. To conclude, the numerical results

[37] Due to partial depreciation and discounting it is optimal to build a majority of stations in the second period when there are more EVs (because of the stricter emissions target), see the figure.

confirm our results from the analytical model in Section 2; the larger the increase in the permit price in the second period, the more profitable to invest in long lasting infrastructure today, relative to short-lived policies.

We can also illustrate demand for permits when there is intertemporal flexibility as in scenario S4. Recall that with efficient markets, the government is indifferent between different purchasing dates, as the price of a permit will increase at a rate equal to the discount rate. Without loss, we can therefore assume that all permit sales/purchases have been done in Period 1. Permit demand and policy instruments have been plotted in Figure 3 as a function of the generic permit price.

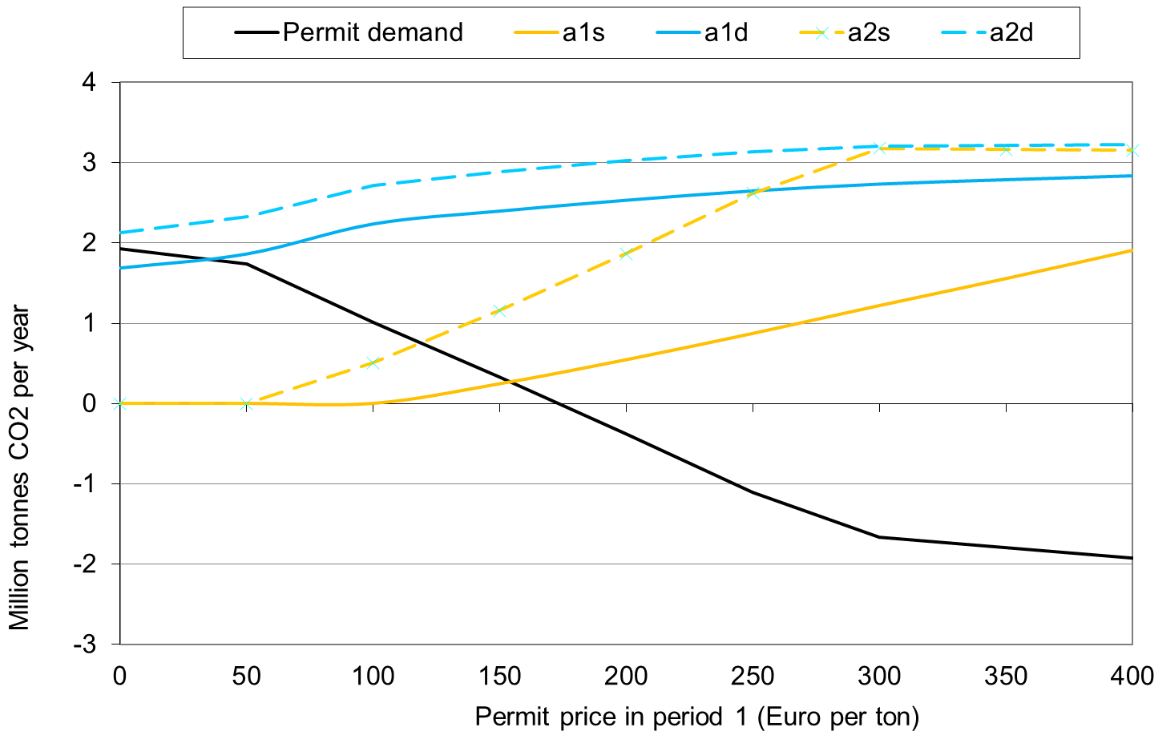

Figure 3: Effects of an increase in the permit price on the two abatement options and permit demand in a permit market with intertemporal flexibility.

As Figure 3 shows, abatement increases and permit purchase turns into permit sales as the permit price increases. As in Figure 2, static abatement increases much more than dynamic abatement (the exception being at low permit prices when the optimal EV subsidy is zero).

4.1 Sensitivity analyses

As indicated in Section 3, the parameters of the model are uncertain, and we had to make several assumptions in the calibration of the model. Thus, we have performed a number of sensitivity analyses, focusing on the most uncertain and important parameters. In reporting the results of these analysis, we mainly focus on the size of respectively static (a_{is}) and dynamic (a_{id}) abatement in the two periods in Scenario 3b, that is, with spatial but not intertemporal flexibility. The results are shown in Table 2.

We see from the table that the results are quite robust to changes in most of the exogenous variables. However, the results are sensitive to two main changes, that is, the user costs of EVs in period 2, and the total anxiety. If the user costs of EVs in period 2 fall by 25%, more abatement should be done by the static alternative than the dynamic alternative in period 2. We know from equation (32) that a lower user costs for EV reduces the optimal number of chargers, and therefore, dynamic abatement, and from equation (33) that lower dynamic abatement increases the subsidy rate. Thus, static abatement will increase.

Further, if the total anxiety is reduced, we find that more abatement should be taken by the static alternative than the dynamic alternative in both periods. The reason is that we do not have to make so large investments to reduce anxiety, and the negative impact of subsidies for anxiety is smaller.

	a_{1d} Mtons/ year	a_{1s} Mtons/ year	$\frac{a_{1d}}{a_{1d}+a_{1s}}$	a_{2d} Mtons/ year	a_{2s} Mtons/ year	$\frac{a_{2d}}{a_{2d}+a_{2s}}$
Benchmark[a]	*2.41*	0.16	0.94	*2.95*	*1.58*	0.65
Faster depreciation of stations (20 years)	2.28	0.15	0.94	2.81	1.47	0.66
50% lower investment costs (κ = 12) for stations in Period 2	2.82	0.23	0.92	3.29	1.89	0.64
30% more cars in Period 2	2.51	0.17	0.94	3.11	2.09	0.60
25% lower user costs of EVs in Period 2	1.86	0.13	0.93	1.32	5.06	0.21
Total charging anxiety = 2 · Total range anxiety	1.28	0.15	0.90	1.73	1.26	0.58
Total range anxiety = 2 · Total charging anxiety	3.83	0.30	0.93	4.38	2.00	0.69
Total anxiety = 1.5 · Total EV subsidy	0.87	1.20	0.42	1.70	4.61	0.27
Total anxiety = 4 · Total EV subsidy	3.44	0	1	3.67	0.20	0.95

50% of car owners buy EV when no anxiety	1.88	0	1	2.04	0.42	0.83
100% of car owners buy EV when no anxiety	2.62	0.14	0.95	3.23	1.68	0.66

Table 2. Sensitivity results for Scenario 3b.

[a] In the benchmark model, depreciation of stations is 40 years, total charging anxiety is assumed to equal total range anxiety, total anxiety is assumed to equal twice the total EV subsidies, and 90% of car owners would buy EV if there were no anxiety. See Section 3.3 for details.

5 Conclusions

Policy makers and owners of large companies face many options to reduce GHG emissions. Some of these options are static in the way that they do not affect the costs of future emissions reductions. Examples of this is buying permits in the international permit market or reducing consumption of fossil fuel based goods. Other options are dynamic in the sense that they will affect future costs of meeting emissions targets. Such options may be infrastructure investments that for instance makes it possible to use other fuel types or reduce emission intensive consumption activities.

This paper studies the choice of policy instruments to reduce GHG emissions with different restrictions in flexible instruments such as permit trading. Independent on flexibility, we find that cost-effective climate policy implies that the marginal abatement cost of the dynamic alternative may exceed the costs of static abatement, such as the permit price. Thus, expensive abatement investments today are justified if the benefits last over several time periods. However, introducing restrictions on flexibility, so that permit prices across periods are not equal, have impacts on the choice of policy instrument. A higher expected price in later periods can make it more profitable to use the dynamic policy instrument, while the opposite may be the result for a higher permit price today.

The framework is used for a numerical study on electrification of the cars in Norway, where infrastructure investments such as building charging stations across the country, makes it expensive to reduce emissions in the transport sector from electrification today, but will reduce costs in later periods.

Our numerical simulations show that it can be cost-effective to invest in charging stations today at a marginal abatement cost of two – three times higher than the marginal abatement cost of subsidizing EVs. Thus, starting with the most expensive abatement option may make sense if it has impacts on abatement costs in years to come.

The flexibility in how to reach the abatement targets has a large impact on the choice of the two abatement options. In our numerical model, the option of intertemporal flexibility, but no international permit trading, implied that it was cost-efficient to increase the share of abatement implemented in the first period relative to the second period. That would also imply that it became less efficient to invest in the dynamic abatement option relative to the static abatement option today (period 1), compared to when there is no intertemporal flexibility.

The international permit market may also influence the domestic transition from petrol-based fuel to electricity in the transport sector. Higher future permit price makes it relatively more efficient to invest in the dynamic abatement relative to the static option today, although the impact is quite small. Within the same period, we find that static abatement increases much more than the dynamic abatement when the permit price increases. The reason is diminishing return from new stations, that is, the marginal benefits of more stations drop quite significantly as the number of stations increases.

The results show that the options available to reach long-term emissions target have a large impact on the optimal policy choices of the Government. Large infrastructure investments may be more profitable under some regimes than other. This stresses the importance of early and time consistent plans for regulations of international GHG emissions.

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Appendix A: Finding the abatements as functions of prices under restrictions in the permit market

By total differentiating (15), we find:

A*da=dP, where

$$\mathbf{A}=\begin{pmatrix} C''_{1_{1s1s}} & C''_{1_{1s1d}} & 0 & 0 \\ C''_{1_{1s1d}} & C''_{1_{1d1d}}+C''_{2_{1d1d}} & 0 & C''_{2_{1d2d}} \\ 0 & 0 & C''_{2_{2s2s}} & C''_{2_{2s2d}} \\ 0 & C''_{2_{2d1d}} & C''_{2_{2s2d}} & C''_{2_{2d2d}} \end{pmatrix}, \mathbf{da}=\begin{pmatrix} da_{1s} \\ da_{1d} \\ da_{2s} \\ da_{2d} \end{pmatrix},\ \mathbf{dP}=\begin{pmatrix} dP_1 \\ dP_1 \\ dP_2 \\ dP_2 \end{pmatrix}$$

Solving the system of equations gives:

$$da_{1s}=\frac{\left(C''_{1_{1s,1d}}-C''_{2_{1d,1d}}-C''_{1_{1d,1d}}\right)\left(C''^2_{2_{2s,2d}}-C''_{2_{2d,2d}}C''_{2_{2s,2s}}\right)-C''^2_{2_{1d,2d}}C''_{2_{2s,2s}}}{|\mathbf{A}|}dP_1,$$

$$+\frac{C''_{1_{1s,1d}}C''_{2_{1d2d}}\left(C''_{2_{2s,2s}}-C''_{2_{2s,2d}}\right)}{|\mathbf{A}|}dP_2,$$

$$da_{1d}=\frac{\left(C''_{1_{1s,1d}}-C''_{1_{1s,1s}}\right)\left(C''^2_{2_{2s,2d}}-C''_{2_{2d,2d}}C''_{2_{2s,2s}}\right)}{|\mathbf{A}|}dP_1-\frac{C''_{1_{1s1s}}C''_{2_{1d,2d}}\left(C''_{2_{2s,2s}}-C''_{2_{2s,2d}}\right)}{|\mathbf{A}|}dP_2,$$

$$da_{2s}=\frac{\left(C''_{1_{1s,1s}}-C''_{1_{1s,1d}}\right)C''_{2_{1d,2d}}C''_{2_{2s,2d}}}{|\mathbf{A}|}dP_1$$

$$-\frac{\left(C''_{2_{2d,2d}}-C''_{2_{2s,2d}}\right)C''^2_{1_{1s,1d}}-C''_{1_{1s,1s}}\left(C''^2_{2_{1d,2d}}+\left(C''_{1_{1d,1d}}+C''_{2_{1d,1d}}\right)\left(C''_{2_{2s,2d}}-C''_{2_{2d,2d}}\right)\right)}{|\mathbf{A}|}dP_2,$$

$$da_{2d}=\frac{\left(C''_{1_{1s,1d}}-C''_{1_{1s,1s}}\right)C''_{2_{1d,2d}}C''_{2_{2s,2s}}}{|\mathbf{A}|}dP_1-\frac{\left(C''^2_{1_{1s,1d}}-C''_{1_{1s,1s}}\left(C''_{1_{1d,1d}}+C''_{2_{1d,1d}}\right)\right)\left(C''_{2_{2s,2s}}-C''_{2_{2s,2d}}\right)}{|\mathbf{A}|}dP_2, \tag{39}$$

where |**A**| = Det(**A**) = $\left[C''^2_{1_{1s,1d}}-C''_{1_{1s,1s}}\left(C''_{1_{1d,1d}}+C''_{2_{1d,1d}}\right)\right]\left(C''^2_{2_{2s2d}}-C''_{2_{2d,2d}}C''_{2_{2s,2s}}\right)-C''_{1_{1s,1s}}C''_{2_{2s,2s}}C''^2_{2_{1d,2d}}$. It follows from the assumptions about the second order conditions for the optimization problem that |**A**| >0.

As stated in footnote 15, the terms $\left(C''^{2}_{1_{1s,1d}} - C''_{1_{1s,1s}}\left(C''_{1_{1d,1d}} + C''_{2_{1d,1d}}\right)\right)$ and $\left(C''^{2}_{2_{2s,2d}} - C''_{2_{2d,2d}} C''_{2_{2s,2s}}\right)$ must both be negative for the necessary conditions for a local minimum to be satisfied. We see from (39) and (4) that $\frac{da_{1s}}{dP_2} = 0$, $\frac{da_{1d}}{dP_2} > 0$, $\frac{da_{2s}}{dP_1} = 0$, $\frac{da_{2d}}{dP_1} > 0$ for $C''_{t_{ts,td}}$ =0,

and $\frac{da_{1s}}{dP_2} > 0$, $\frac{da_{1d}}{dP_2} > 0$, $\frac{da_{2s}}{dP_1} > 0$, $\frac{da_{2d}}{dP_1} > 0$ for $C''_{t_{ts,td}}$ <0,

For $C''_{t_{ts,td}} > 0$;

$\frac{da_{1s}}{dP_2} < 0$ and $\frac{da_{1d}}{dP_2} > 0$ for $C''_{2_{2d,2d}} > C''_{2_{2d,2s}}$, $\frac{da_{1s}}{dP_2} > 0$ and $\frac{da_{1d}}{dP_2} < 0$ for $C''_{2_{2d,2d}} < C''_{2_{2d,2s}}$,

$\frac{da_{2s}}{dP_1} < 0$ and $\frac{da_{2d}}{dP_1} > 0$ for $C''_{1_{1d,1d}} > C''_{1_{1d,1s}}$, $\frac{da_{2s}}{dP_1} > 0$ and $\frac{da_{2d}}{dP_1} < 0$ for $C''_{1_{1d,1d}} < C''_{1_{1d,1s}}$.

For $C''_{t_{ts,td}}$ < 0, and given $C''_{t_{td,td}} > \left|C''_{t_{td,ts}}\right|$, we find:

$$0 < \frac{da_{1s}}{dP_2} < \frac{da_{1d}}{dP_2},\ 0 < \frac{da_{2s}}{dP_1} < \frac{da_{2d}}{dP_1}.$$

This proves Propositions 2 and 3.

Appendix B: Adjustment factor for investment costs

As explained in the main text, we need to account for the fact that the lifetime of the investments extends beyond the time horizon of our simulations (2050). To adjust for this, we have included a factor that scale down the investment costs based on the remaining lifetime of the investments after 2050. Here we explain how this factor is derived.

Assume that the annual value of an investment is the same before and after 2050 – when adjusting for depreciation and discounting. That is, the annual value after 2050 is equal to the average annual value until 2050 (again, adjusted for depreciation and discounting). This is a simplification, but it is not obvious in which direction (although the number of EVs increase, so does the number of stations). As explained in the main text, stations are assumed to have a lifetime of 40 years, with linear depreciation, i.e., 25% per decade (cf. the table in Appendix C).

Let V_{20}, V_{30} and V_{50} denote total values in respectively 2020-2030, 2030-2050 and beyond 2050, and r is the discount rate.

The total value of stations invested in 2030 is then (since the lifetime is 40 years, and the capital is depreciated by 50% after two decades):

$$V = V_{30} + \frac{0.5}{(1+r)^{20}} V_{50} = V_{30}\left(1 + \frac{0.5}{(1+r)^{20}}\right)$$

This gives the following relationship between the value in 2030-50 and total value:

$$\frac{V_{30}}{V} = \frac{1}{1 + \frac{0.5}{(1+r)^{20}}}$$

Thus, we adjust the investment costs in 2030 by this factor, i.e., multiply the investment cost function by the factor (which is less than one).

For investments in 2020 things are a bit more complicated as we model two periods. The total value is now (where we account for the fact that V_{30} covers two decades while V_{20} and V_{50} cover one decade each due to the 40 years lifetime):

$$V = V_{20} + 2\frac{0.75}{(1+r)^{10}} V_{30} + \frac{0.25}{(1+r)^{30}} V_{50}$$

La V_{2030} be the following weighted average of V_{20} and V_{30}:

$$V_{2030} = \frac{1}{1 + 2\frac{0.75}{(1+r)^{10}}}\left(V_{20} + 2\frac{0.75}{(1+r)^{10}}V_{30}\right)$$

We then assume that V_{50} is equal to V_{2030} (cf. initial assumption). We then have:

$$V = V_{20} + 2\frac{0.75}{(1+r)^{10}}V_{30} + \frac{0.25}{(1+r)^{30}}V_{50} = V_{20} + 2\frac{0.75}{(1+r)^{10}}V_{30} + \frac{0.25}{(1+r)^{30}}\frac{1}{1 + 2\frac{0.75}{(1+r)^{10}}}\left(V_{20} + 2\frac{0.75}{(1+r)^{10}}V_{30}\right)$$

$$= \left(V_{20} + 2\frac{0.75}{(1+r)^{10}}V_{30}\right)\left(1 + \frac{0.25}{(1+r)^{30}}\frac{1}{1 + 2\frac{0.75}{(1+r)^{10}}}\right)$$

This gives the following relationship between the value in 2020-2050 and total value:

$$\frac{\left(V_{20} + 2\frac{0.75}{(1+r)^{10}}V_{30}\right)}{V} = \frac{1}{\left(1 + \frac{0.25}{(1+r)^{30}}\frac{1}{1 + 2\frac{0.75}{(1+r)^{10}}}\right)}$$

The left hand side shows the value share in the two first periods of an investment in 2020 (the numerator corresponds to the two first terms in the expression of *V*). In the same way as explained above, we can then adjust the investment costs in 2020 by this factor, i.e., multiply the investment cost function by the factor (which is also less than one, but larger than the previous factor).

Appendix C: Parameter values

Parameter	Description	Value
$\bar{E}_1$	Number of cars in 2030	2,900,000
$\bar{E}_2$	Number of cars in 2050	2,900,000
G_0	Number of commercial fast chargers in 2020.	1,000
K_0	Number of fast chargers with governmental support in 2020	1,000
δ_1	Depreciation rate of infrastructure, 2020 to 2030	0.25
δ_2	Depreciation rate of infrastructure, 2030 to 2050	0.5
q_e	Annual user cost for an EV *before* subsidies	€ 10,300
q_f	Annual user cost for an ICEV *including* taxes	€ 10,900
s_0	Subsidies to EVs in 2020	€ 1.700
μ_0	Share of EVs in 2020	0.071
σ	Emissions coefficient; tons of CO_2 per year for an ICEV	2.2
ρ	Discount rate	0.04
$\theta_1 = \sum_{i=2020}^{2029} (1-\rho)^{-(i-2020)}$	Discount factor for period 1	8.44
$\theta_2 = (1-\rho)^{2030} \sum_{i=2030}^{2049} (1-\rho)^{-(i-2030)}$	Discount factor for period 2	9.18
B	Parameter representing indirect network effects	0.0051
η	Parameter in the investment cost function	24
α	Parameter in EV utility function	12,094

β	Parameter in EV utility function	0.00048
A_1	Parameter in urban charging anxiety function	4.35
A_2	Parameter in rural charging anxiety function	4.35
C	Parameter in range anxiety function	1,700,000
Π_f	Parameter in ICEV utility function	10,900

Table C1: Parameters in the numerical model