

Meissner, Leonie P.

Working Paper

The More the Merrier? The Role of Green Research and Development Subsidies under Different Environmental Policies

CESifo Working Paper, No. 12002

Provided in Cooperation with:

Ifo Institute – Leibniz Institute for Economic Research at the University of Munich

Suggested Citation: Meissner, Leonie P. (2025) : The More the Merrier? The Role of Green Research and Development Subsidies under Different Environmental Policies, CESifo Working Paper, No. 12002, CESifo GmbH, Munich

This Version is available at:

<https://hdl.handle.net/10419/324993>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

Working Papers

The More the Merrier? The Role of Green Research and Development Subsidies under Different Environmental Policies

Leonie P. Meissner

Imprint:

CESifo Working Papers

ISSN 2364-1428 (digital)

Publisher and distributor: Munich Society for the Promotion
of Economic Research - CESifo GmbH

Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740

Email office@cesifo.de
<https://www.cesifo.org>

Editor: Clemens Fuest

An electronic version of the paper may be downloaded free of charge

- from the CESifo website: www.ifo.de/en/cesifo/publications/cesifo-working-papers
- from the SSRN website: www.ssrn.com/index.cfm/en/cesifo/
- from the RePEc website: <https://ideas.repec.org/s/ces/ceswps.html>

The More the Merrier? The Role of Green Research and Development Subsidies under Different Environmental Policies

Leonie P. Meissner^{1,*}

¹Kiel Institute for the World Economy (Kiel, Germany),

August 19, 2025

Abstract

This paper studies the role of green research and development (R&D) subsidies under different environmental policies. Using a stylized equilibrium model calibrated to the European electricity sector, I analyze the effects of R&D subsidies under (1) an emission tax, (2) an emission cap, and (3) no environmental policy, focusing on competitiveness, environmental outcomes, and welfare. I find that increasing R&D subsidies increases knowledge accumulation, reducing production costs and thus, increasing competitiveness of the clean sector. A production shift from dirty to clean output occurs but overall, output increases and lowers output prices. Environmental benefits from R&D subsidies occur only under an emission tax or in the absence of environmental policy. Under an emission cap, emissions remain constant and instead, the emission price falls due to an increase in the R&D subsidy, reducing compliance costs for the emitter. Our calibration further reveals that while patenting is unaffected by the environmental policy, there are interaction effects between the environmental policy stringency and the effectiveness of the R&D subsidy, emphasizing the importance of a policy mix for environmental innovations.

Keywords: climate policy; R&D support; innovation policy; renewable energy; environmental innovation;

JEL: D50; H23; O38; Q55; Q58

*E-mail: leonie.p.meissner@web.de

1 Introduction

To combat climate change, global anthropogenic emissions must be rapidly and permanently reduced. Therefore, it is essential that global economies are decarbonized. Nevertheless, achieving ambitious emission reductions are not feasible with current technologies alone but requires the development and deployment of novel environmental innovations (EI) (IEA, 2021). Notably, the global clean technology industry is projected to be worth USD 650 billion annually by 2030 (IEA, 2023). Consequently, investment in research and development (R&D) for EIs is crucial both for facilitating the green transition and securing long-term economic prosperity.

The economic literature has long established that (green) R&D is subject to multiple market failures, including knowledge spillovers (Grossman and Helpman, 1991), path dependencies (Aghion et al., 2016), and incomplete information (Jaffe et al., 2005). These market failures lead to the systematic underinvestment in private R&D, necessitating public intervention through instruments such as grants, subsidies, and tax credits. (Dechezleprêtre et al., 2022). Simultaneously, environmental market failures arise from the emission of pollutions. The combination of knowledge and environmental externalities creates a so-called double externality problem in the context of EIs (Jaffe et al., 2005), implying that an optimal policy mix should target both market failures through green R&D support and environmental regulation (Fischer and Newell, 2008). In practice, however, environmental policies often face significant political barriers, leading policymakers to rely disproportionately on green R&D support as a second-best solution, despite its inefficiency in addressing environmental targets (Requate and Unold, 2003).

In this context, the United States introduced the Inflation Reduction Act (IRA) as a flagship initiative to simultaneously reduce emissions and strengthen its national economy (The White House, 2023). The IRA encompasses a range of policy instruments, including subsidies, grants, and especially tax credits, aimed at fostering the development and diffusion of EIs.¹ Thereby, the IRA exemplifies a deliberate policy strategy that not only promotes green R&D but also seeks to bolster domestic economic competitiveness (Meissner, 2024). In response, the European Union announced the Green Deal Industrial Plan (European Commission, 2023), which similarly aims to advance decarbonization while safeguarding the EU’s economic interests through targeted investments and subsidies for green R&D.

Although both policy packages pursue the same goal, they are situated in vastly different policy

¹I am aware that with the new Trump administration, the IRA is slowly being disseminated. Nonetheless, the IRA was the instigator of the release of a suit of green industrial policy packages across the globe, which inspired this paper. In comparison to the IRA, other green industry policy packages are still in place and are situated in vastly different policy environments. Accordingly, I believe that there is still a great value in analyzing the effect of green industry policy packages.

regimes. In the US, the IRA functions as the primary environmental policy instrument. By contrast, the EU’s Green Deal Industrial Plan complements pre-existing measures – notably the EU Emissions Trading System (ETS) – which caps emissions across industry, energy, domestic aviation, and maritime sectors. This is supplemented by national carbon taxes in non-ETS sectors by several EU member states, like Sweden (Andersson, 2019), on sectors such as building, transport, and agriculture that are not yet covered by the ETS. Against this backdrop, the additional effects of green R&D subsidies across sectors regulated by different environmental policies in the EU are uncertain. This raises a critical question: What role can green R&D support play in advancing the green transition under varying environmental policy regimes?

Therefore, I study the role of green R&D subsidies under different environmental policy regimes in this paper. I deploy a stylized equilibrium model to analyze the role of R&D subsidies under 1) an emission tax, 2) an emission cap, and 3) no environmental policy. Since the goal of green R&D subsidies is diverse – aiming to increase competitiveness, the environment as well as acceptance among the general public, I study the effects of a R&D subsidy on output volume and price, emission volume and prices, as well as welfare. To quantify these effects, I calibrate the model to the EU electricity sector, assessing how changes in R&D subsidy levels influence these variables under different environmental policy regimes and degrees of policy stringency.

Our analytical results confirm that R&D subsidies are part of an optimal policy mix. In particular, the optimal R&D subsidy is proportional to the share of knowledge spillovers in total knowledge produced within the sector. Under the assumption of homogeneous firms, the optimal subsidy level rises with both the knowledge spillover rate and the number of firms in the sector.

An increase in the R&D subsidy increases the acquisition of knowledge, which reduces the production costs of the clean sector. This induces a shift in production from dirty to clean output. The expansion of clean output exceeds the reduction in dirty output, leading to a net increase in total output and a reduction in output prices. Accordingly, the domestic competitiveness of firms across all environmental policy settings is enhanced through higher R&D subsidies. In the absence of climate policy or under an emissions tax, this production shift is accompanied by a reduction in emissions, thereby improving welfare through lower environmental damages. However, under an emissions cap, the emission reduction through the production shift is fully rebounded implying higher emission intensity of dirty production. Furthermore, there is a reduction in the emission price, reducing the compliance costs for the dirty sector.

To study the size of the effects, I calibrate the baseline model to the EU electricity sector from 2008-2020, corresponding to Phase II and Phase III of the EU ETS. Creating a counterfactual tax scenario, I compare the effect of a 1% increase in the R&D subsidy across an emission cap and an emission tax at varying stringencies. Overall, the calibration results are consistent with the analytical findings

and provide additional insights. Specifically, I find that patenting responds solely to the R&D subsidy and is unaffected by environmental policy stringency: A 1% increase in the R&D subsidy increases patenting by 1.90% and 1.89% for an emission tax and cap, respectively. Therefore, the environmental policy also only plays a minor role for patenting. Nonetheless, the role of the environmental policy and its stringency is notable for all other variables. The effect of an increase in the R&D subsidy by 1% increases with the environmental policy stringency. Furthermore, there is a negative interaction effect between the R&D subsidy and the environmental policy stringency under both an emission cap and an emission tax. This results emphasizes the importance of a policy mix when dealing with environmental innovations because the environmental and innovation policies complement each other.

A comparison of effect sizes between an emission tax and an emission cap further shows that the impacts on renewable and non-renewable electricity output are larger under an emission tax, whereas the effects on total electricity output and the electricity price are larger under an emission cap. The largest difference is, however, found on the environmental effect. Since emissions are held fixed under an emission cap, any reduction in non-renewable electricity output and gains in efficiency are completely rebounded. In comparison, under an emission tax, there is also a notable environmental gain from increasing the R&D subsidy as the rebound effect only range between 8-10%. Accordingly, the choice of environmental policy instrument and its stringency are critical considerations when designing green R&D support as they shape the additional economic and environmental effects that can be achieved through such investments.

The role of green R&D has already been studied in multiple scenarios. Fischer and Newell (2008) analyze the respective roles of environmental and technology policies in climate change mitigation. They find that the optimal approach involves a policy mix combining both environmental regulation and innovation support. In the absence of such a mix, an emissions price is the most cost-effective instrument for achieving a given environmental target, whereas an R&D subsidy alone is the least cost-effective. Extending the previous model, Fischer et al. (2021) analyze the role of second-best policies in achieving welfare improvements. However, both models fix the emission level, hence, they do not study changes in emissions. Furthermore, they do not examine the interaction between carbon pricing and R&D subsidy as well as any deviations of these two from their optimum. Furthermore, Acemoglu et al. (2012) study the role of directed technological change in a growth model. They conclude that while an optimal policy mix includes both an environmental and innovation policy, a single environmental policy is sufficient to achieve sustainable growth if the output is sufficiently substitutable. Similarly, Acemoglu et al. (2016) show that a policy mix is indeed best, a R&D subsidy is more powerful in redirecting technological change to the clean sector than an environmental policy. Reichenbach and Requate (2012) also examine the role of knowledge spillovers in an environmental context. Their analysis, however, centers on spillovers arising from learning-by-doing (LBD) within the

energy sector in a setting involving multiple firms. Their findings indicate that, once again, a policy mix comprising an emissions tax and a subsidy is required to internalize the externalities associated with LBD-related knowledge spillovers.

In the empirical literature, the role of R&D subsidies in fostering innovation has been extensively examined and proven (e.g., Costantini et al., 2017; Johnstone et al., 2010; Plank and Doblinger, 2018). However, climate policies were often excluded from the regression (except for Hille et al., 2020) and thus, interactions between R&D and climate policies have not yet been examined (Meissner et al., 2024). Furthermore, few studies examined R&D in its ability to increase renewable energy capacity, i.e., increase clean production, to varying success (e.g., Polzin et al., 2015). Overall, R&D was often broadly defined as RD&D expenditures, including both private and public spending, and rarely focused on R&D subsidies (Meissner et al., 2024). Studies that have examined the nexus between R&D expenditures and emissions largely focus on the firm-level (e.g., Alam et al., 2019) and few on the country-level, where a small negative effect can be found (Alam et al., 2021; Paramati et al., 2021, though possibly u-shaped in the very long-run (Shahbaz et al., 2020). Consequently, the interaction between R&D subsidies and emissions warrants further analysis. It is this gap that this paper aims to fill.

Accordingly, this paper adds to the existing literature by expanding the theoretical literature by a stylized multi-firm climate-innovation model examining the interaction between climate and innovation policies. I explicitly model environmental damages from emissions, allowing me to study the differences across environmental policy regimes and its stringency. Additionally, by calibrating the model to the EU electricity sector, the relationship between R&D subsidies and different environmental policies can be quantified. By developing a counterfactual emission tax scenario, the calibration also allows me to compare different policy regimes that otherwise cannot be compared as they occur in vastly different settings.

The paper begins by introducing the baseline model to, firstly, find the optimal policy level required to capture the market failures (Section 2). Secondly, I analyze the role of an increase in R&D subsidy under 1) an emission tax – which also includes no environmental policy – (Section 4.1) and 2) under an emission cap (Section 4.2). To quantify the effect sizes of the stylized model, I calibrate the model to the EU electricity market (Section 5). The results of the calibration are again compared between an emission tax versus emission cap (Section 5.1), before being discussed in light of current climate-innovation policies (Section 6).

2 The Baseline Model

The model builds upon the seminal work by Fischer and Newell (2008) and Reichenbach and Requate (2012). I have a two-period, stylized, closed economy model with a clean and dirty sector, denoted by the superscript c and d , respectively.² They produce perfect substitutes, q_t^d and q_t^c where t are the two periods $= 1, 2$. The model includes a single environmental policy, which can either be an emission tax or an emission cap as well as a R&D subsidy. R&D is a dynamic process that occurs over time, and thus each period covers a time horizon of n_t time intervals (e.g. years or decades) and the future period is discounted by the discount factor δ .

Dirty Sector: There are m symmetric firms in the dirty sector and I assume no entry and exit. Each firm produces the identical output q_t^d , such that I do not have to differentiate output by manufacturer. Accordingly, total output of the sector is given by $Q_t^d = mq_t^d$. I assume that the production process is associated with the release of emissions e_t . Similarly, total emissions are $E_t = me_t$. Each firm faces production and abatement costs, $C(q_t^d, e_t)$, with $C_{q_t^d} > 0$ for all $t = 1, 2$, and $C_{q_t^d q_t^d} > 0$.³ In particular, I assume that the marginal abatement costs are a decreasing function of CO₂ emissions e and is convex: $-C_{e_t} > 0$ for $e_t < \hat{e}_t$ and $C_{e_t e_t} \geq 0$, where \hat{e}_t are the business-as-usual CO₂ emissions. I further assume that marginal abatement costs increase as firms produce more output, $-C_{q_t^d e_t} = -C_{e_t q_t^d} \geq 0$ or $C_{q_t^d e_t} = C_{e_t q_t^d} \leq 0$, and that the cost function is strictly convex, that is: $C_{q_t^d q_t^d} C_{e_t e_t} - (C_{q_t^d e_t})^2 > 0$. Due to the emissions it produces and the environmental damages thereby caused, the firm faces an emissions price $\tau \geq 0$. To analyze the absence of an environmental policy, I also allow the possibility of $\tau = 0$. Lastly, firms are price takers, facing a competitive price p_t per output and maximize profits according to:

$$\max_{q_1^d, e_1, q_2^d, e_2} \Pi^d = n_1[p_1 q_1^d - C(q_1^d, e_1) - \tau e_1] + \delta n_2[p_2 q_2^d - C(q_2^d, e_2) - \tau e_2] \quad (1)$$

The first-order conditions read:

$$C_{q_t^d} = p_t \quad \forall \quad t = 1, 2 \quad (2)$$

$$-C_{e_t} = \tau_t \quad \forall \quad t = 1, 2 \quad (3)$$

As usual, Equation (2) states that marginal costs must equal the output price and Equation (3) states that marginal abatement costs equal the emissions price in equilibrium.

Clean Sector: There are k symmetric producers in the clean sector with no entry or exit and firms act as price takers. The clean sector produces a perfect substitute to the product of the dirty sector.

²One can think about these sectors as, e.g., fossil versus renewable electricity or green versus dirty steel.

³Note that $C_{q_t^d} > 0$ is the first derivative of the cost function of the dirty firm with respect to the output q_t^d and $C_{q_t^d q_t^d} > 0$ the second derivative twice differentiated with respect to q_t^d .

Additionally, firms produce identical outputs, q_t^c , and total output of the clean sector is given by $Q_t^c = kq_t^c$. However, its production process is still in the early stages of development and thus, each firm benefits from investing in R&D. Following the notation of Fischer and Newell (2008), firms face R&D expenditures $R(h)$ which are increasing and convex in R&D knowledge h , $R_h > 0$ and $R_{hh} \geq 0$. Firms' R&D investments produce knowledge h_j , where j is the individual firm, but firms also gain knowledge from other firms R&D investments via knowledge spillovers, which occur at rate $\rho \in [0, 1]$. Following the notation by Reichenbach and Requate (2012), a firm's combined R&D knowledge is given by $H_j = n_1(h_j + \sum_{l \neq j}^J \rho h_l)$, i.e., the sum of private R&D knowledge and spilled over R&D knowledge. Since firms are symmetric, aggregate R&D knowledge is given by:

$$H = n_1(1 + \rho(k - 1))h \quad (4)$$

If $\rho = 0$, R&D expenditures are fully private and other firms do not derive knowledge from individual R&D expenditure and if $\rho = 1$, all knowledge is public. However, in line with Fischer and Newell (2008), I will assume that $0 < \rho < 1$, i.e., there are R&D spillovers in part such that other firms derive a benefit, proportional to ρ , from other firms' investments in R&D. Due to the presence of knowledge spillovers, firms receive a subsidy $\sigma \geq 0$ for R&D.

Each firm's costs in the first period depend solely on output, $K^1(q_1^c)$, with the usual assumptions, $K_{q_1^c}^1 > 0$, $K_{q_1^c q_1^c}^1 > 0$. Furthermore, R&D expenditures in the first period reap benefits in the second period by reducing costs, such that costs in the second period also depend on R&D knowledge: $K^2(q_2^c, H)$ with $K_H < 0$, $K_{HH}^2 > 0$ and $K_{q_2^c, H}^2 = K_{H, q_2^c}^2 < 0$, i.e., marginal production costs decrease with R&D expenditures. Each firm is a profit maximizer, facing the following maximization problem:

$$\max_{q_1^c, q_2^c, h} \Pi^c = n_1[p_1 q_1^c - K^1(q_1^c) - (1 - \sigma)R(h)] + \delta n_2[p_2 q_2^c - K^2(q_2^c, H)] \quad (5)$$

giving the following first-order conditions:

$$K_{q_t^c}^t = p_t \quad \forall \quad t = 1, 2 \quad (6)$$

$$(1 - \sigma)R_h = \delta n_2(-K_H^2). \quad (7)$$

Equation (6) states the usual result that marginal production costs equal output price in equilibrium and (7) states that a firm's marginal investment cost equals discounted gain from private R&D knowledge (since $-K_H^2 > 0$) in line with Fischer and Newell (2008).

Consumer: There is a consumer that is indifferent between the dirty good, q_t^d , and the clean good, q_t^c . The consumer derives utility from consumption, $u(Q_t)$ with $u_{Q_t} > 0$ and $u_{Q_t Q_t} < 0$, where Q_t is the aggregate output. The utility maximization problem of the consumer looks as follows:

$$\max_{Q_1, Q_2} U = n_1[u(Q_1) - p_1 Q_1] + \delta n_2[u(Q_2) - p_2 Q_2] \quad (8)$$

The first-order conditions of utility maximization read:

$$u_{Q_t} = p_t. \quad (9)$$

where (9) states that the marginal utility equals the price of the good in equilibrium.

Equilibrium: To close the model, I assume that demand equals to supply:

$$Q_t = Q_t^d + Q_t^c = m q_t^d + k q_t^c. \quad (10)$$

Environmental Damages: Emissions lead to environmental damages $D(E_t)$. Damages are represented by a weakly convex social damage function $D(E_t)$, i.e. $D_{E_t} > 0$ and $D_{E_t E_t} \geq 0$. As aforementioned, damages from emissions are priced at $\tau \geq 0$, which can either be an emission tax or cap.

Welfare: Lastly, I combine the aforementioned parts to define welfare. Note that the emissions price and the R&D subsidy are pure transfers and thus do not appear in the welfare function, which is defined as follows:

$$\begin{aligned} W = & n_1[u(Q_1) - mC(q_1^d, e_1) - kK^1(q_1^c) - kR(h) - D(E_1)] \\ & + \delta n_2[u(Q_2) - mC(q_2^d, e_2) - kK^2(q_2^c, H) - D(E_2)] \end{aligned} \quad (11)$$

where δ denotes the discount factor. The social planner maximizes welfare with respect to output q_t^i , emissions e_t , and knowledge h to obtain the respective first-order conditions:

$$U_{Q_t} = C_{q_t^d} \quad (12)$$

$$U_{Q_t} = K_{q_t^c} \quad (13)$$

$$-C_{e_t} = D_{E_t} \quad (14)$$

$$R_h = \delta n_2(-K_H^2)(1 + \rho(k - 1)). \quad (15)$$

Interpretation of the above conditions is straightforward: (12) and (13) state that in the optimum, the marginal utility must equal the marginal cost of production of the dirty and clean sector, respectively and (14) states that marginal abatement costs must equal marginal damages. Lastly, (15) states that marginal R&D investment costs must equal to the discounted gains from R&D in the optimum. Recall that $-K_H^2 > 0$ and hence the right-hand side is positive overall. In contrast to Fischer and Newell (2008), I consider multiple firms in each sector that create knowledge that spills over, hence (15) differs slightly.

3 Optimal Policy

In this section, the optimal policies under decentralized decision making are examined. To derive the optimal policies, I equate (14) and (3) as well as (15) and (7) to obtain the optimal emissions price and R&D subsidy, which are given by:

$$\tau^* = D_{e_i} \quad (16)$$

$$\sigma^* = \frac{\rho(k-1)}{1 + \rho(k-1)}. \quad (17)$$

As usual, the optimal emissions price equals to the marginal damages caused by an additional unit of emissions. To interpret (17), I expand the fraction by $n_1 h$, giving the following expression for the optimal R&D subsidy:

$$\sigma^* = \frac{n_1 \rho(k-1)h}{H}, \quad (18)$$

where the nominator is the total knowledge spillover and the denominator is total R&D knowledge of the clean sector. This leads to the first proposition:

Proposition 1. *The optimal R&D subsidy σ^* is the share of spilled over knowledge from total knowledge and increases in both the spillover rate ρ and the number of firms k in the clean sector.*

Proof. Differentiating (17) with respect to, firstly, ρ and, secondly, m , gives:

$$\frac{\delta \sigma^*}{\delta \rho} = \frac{k-1}{[1 + \rho(k-1)]^2} > 0 \quad (19)$$

$$\frac{\delta \sigma^*}{\delta k} = \frac{\rho}{[1 + \rho(k-1)]^2} > 0 \quad (20)$$

□

The intuition is that with an increasing number of homogeneous firms, total knowledge produced increases and with an increase in the spillover rate, more of the available knowledge will spill over. Accordingly, less knowledge is private for the individual firms, making investments in R&D less effective and hence, lower private investments in R&D must be corrected for by an increase in the R&D subsidy.

4 Policy Scenario Analysis

Having set up the model, I examine the effect of a change in the R&D subsidy under different environmental policies with regard to the output volume and price, emission volume and prices, as well as welfare. I differentiate between, firstly, an emission tax and, secondly, an emission cap.

4.1 Emission Tax

In this section, I assume that the environmental externality is regulated by a tax τ on emissions – with $\tau = 0$ as a special case. In the presence of an emission tax, the emissions price is fixed while emissions remain endogenous. I begin by conducting a comparative static analysis to examine the equilibrium effect of a small change in the R&D subsidy. Afterwards, I derive the second-best R&D subsidy in case of a suboptimal or nonexistent emission tax.

4.1.1 Comparative Statics

For the comparative static analysis, I totally differentiate all first-order conditions (Equations (2)-(3), (6)-(7), (9)-(10)) with respect to the R&D subsidy σ (See Appendix A.1).

Proposition 2. *In the presence of an emission tax, an increase in the R&D subsidy:*

- *has no impact on the emissions price:* $\frac{d\tau_1}{d\sigma} = \frac{d\tau_2}{d\sigma} = 0$
- *has no impact on the first-period:* $\frac{dq_1^c}{d\sigma} = \frac{dq_1^d}{d\sigma} = \frac{dQ_1}{d\sigma} = \frac{dp_1}{d\sigma} = \frac{de_1}{d\sigma} = 0$,
- *leads to an increase in knowledge, clean output, and overall output of the second period:* $\frac{dh}{d\sigma} > 0$, $\frac{dq_2^c}{d\sigma} > 0$, $\frac{dQ_2}{d\sigma} > 0$,
- *leads to a decrease in the output price, dirty output, and emissions of the second period:* $\frac{dp_2}{d\sigma} < 0$, $\frac{dq_2^d}{d\sigma} < 0$, $\frac{de_2}{d\sigma} < 0$.

Firstly, it must be noted that all effects are limited to the second period. This implies that there is no temporary rebound effect due to anticipatory behavior, such as reducing clean output of the first period due to expected cost reductions from R&D in the second period. Secondly, I find that an increase in an R&D subsidy leads to an increase in knowledge production, h , (direct effect) and an increase in clean output, q_2^c , due to $K_{q_2^c, H} < 0$ (indirect effect). Thus, the reduction in marginal production costs due to R&D increases the competitiveness of the clean sector. On the other hand, output of the dirty good, q_2^d , decreases as the dirty good becomes relatively more expensive. Due to $-C_{q_t^d, e_t} > 0$, emissions also decrease in the second period. Therefore, an increase in the R&D subsidy also leads to environmental gains in case of an emission tax. Overall, the increase in the clean good outweighs the decrease of the dirty good and, accordingly, output of the second period, q_2 , increases. This in turn leads to a decrease in the output price, p_2 , of the second period. While the price reduction is advantageous for the dirty sector which has lower production costs, it negatively impacts the competitiveness of the clean sector that must now compete at even lower prices. Accordingly, while the clean sector has a direct competitiveness gain by receiving higher subsidies, the dirty sector has indirect competitiveness gains from lower output prices. Furthermore, the reduction in output

	$D_{E_2} < \tau$	$D_{E_2} = \tau$	$D_{E_2} > \tau$
$\sigma < \sigma^*$	$\frac{dW}{d\sigma} > 0$	$\frac{dW}{d\sigma} > 0$	$\frac{dW}{d\sigma} = ?$
$\sigma > \sigma^*$	$\frac{dW}{d\sigma} = ?$	$\frac{dW}{d\sigma} < 0$	$\frac{dW}{d\sigma} < 0$

Table 1: Welfare effect of a change in σ in the presence of an emission tax

prices also benefits the consumer and in the light of cost pass-through of climate policies (Cludius et al., 2020, e.g.,), the reduction in output prices could increase the acceptance of the green transition.

To examine the overall welfare effect of an increase in the R&D subsidy, I totally differentiate (11) with respect to σ . Since an R&D subsidy has no effect on the first period (recall Proposition 2), these can be dropped and the expression can be simplified by inserting (17) (see Appendix A.2 for full calculation). Accordingly, the welfare effect is given by:

$$\frac{dW}{d\sigma} = \delta n_2 m [\tau - D_{E_2}] \frac{de_2}{d\sigma} + \delta n_2 n_1 k (-K_H^2) \left[\frac{(\sigma^* - \sigma)(1 + \rho(k - 1))}{1 - \sigma} \right] \frac{dh}{d\sigma}. \quad (21)$$

where $(\tau_2 - D_{E_t})$ gives the difference between the observed carbon price and the marginal damages caused. Recalling Proposition 2 and that $(-K_H^2) > 0$, the welfare effect can be summarized with the following proposition:

Proposition 3. *In the presence of an emission tax, τ , an increase in the R&D subsidy leads to a welfare gain (loss) if $\sigma < \sigma^*$ ($\sigma > \sigma^*$) and $\tau_2 \leq D_{E_t}$ ($\tau_2 \geq D_{E_t}$).*

Obviously, a welfare gain (loss) from increasing the R&D subsidy can be achieved if the R&D subsidy is lower (higher) than optimal and the observed carbon price is lower (higher) than the marginal damages caused. The effects are summarized in Table 1. The question arises what happens when either σ or τ is excessively high while the other policy is below optimal?

Lets define the elasticity of period 2 emissions and of knowledge with respect to a change in the R&D subsidy as $\varepsilon_\sigma^{e_2} = \frac{de_2}{e_2} \frac{\sigma}{d\sigma} < 0$ and $\varepsilon_\sigma^h = \frac{dh}{h} \frac{\sigma}{d\sigma} > 0$, respectively. (Note that the signs of the elasticities are given by Proposition 2.) Rearranging and inserting the elasticities into (21), the welfare effect can be simplified to:

$$\frac{dW}{d\sigma} = \delta n_2 E_2 [\tau - D_{E_2}] \varepsilon_\sigma^{e_2} + \delta n_2 n_1 (-K_H^2) k H \left[\frac{(\sigma^* - \sigma)}{1 - \sigma} \right] \varepsilon_\sigma^h \stackrel{\leq}{\geq} 0, \quad (22)$$

such that the sign of the welfare effect from a change in the R&D subsidy level is determined by the following condition:

$$E_2 [D_{E_2} - \tau] \varepsilon_\sigma^{e_2} \stackrel{\leq}{\geq} n_1 (-K_H^2) k H \left[\frac{(\sigma^* - \sigma)}{1 - \sigma} \right] \varepsilon_\sigma^h. \quad (23)$$

The left-hand side of (23) gives the welfare effect of a marginal change in the R&D subsidy on emissions, which is negative (positive) if $D_{E_2} > \tau$ ($D_{E_2} < \tau$), i.e, when the environmental damages

are not fully considered by the emission tax. The right-hand side gives the cost savings from the change in knowledge production due to a marginal subsidy change, which is positive (negative) if $\sigma^* > \sigma$ ($\sigma^* < \sigma$). In other words, the welfare effect from a marginal increase in the R&D subsidy depends on whether the change in the cost savings from increased knowledge production outweigh the change in the cost of additional emission reductions.

4.1.2 Second-Best Policy

To determine the second-best R&D policy level in case of a suboptimal or nonexistent environmental policy, I set equation (21) equal to zero, i.e., there should be no welfare loss under a second-best subsidy, insert the elasticities defined above, and solve for σ (see Appendix A.2.1). This gives the following second-best R&D subsidy level:

$$\sigma_{tax}^{**} = \frac{\rho(k-1)n_1kh(-K_H)\varepsilon_\sigma^h - E_2(D_{e_2} - \tau)\varepsilon_\sigma^{e_2}}{kH(-K_H)\varepsilon_\sigma^h - E_2(D_{e_2} - \tau)\varepsilon_\sigma^{e_2}} > 0 \quad \text{if and only if} \quad D_{E_2} > \tau. \quad (24)$$

The second-best subsidy can be summarized in the following proposition:

Proposition 4. *In case of a suboptimal or non-existent emission tax, $\tau < D_{E_2}$, there is a second-best R&D subsidy level greater than the first-best subsidy level, $\sigma_{tax}^{**} > \sigma^*$, which is the larger, the bigger the difference $|\tau - D_{E_2}|$ is, the higher the emission level, e_2 , and the lower the R&D knowledge level, h , is.*

Proof.

$$\frac{\partial \sigma_{tax}^{**}}{\partial \Delta^\tau} > 0, \quad \frac{\partial \sigma_{tax}^{**}}{\partial e_2} > 0, \quad \frac{\partial \sigma_{tax}^{**}}{\partial h} < 0. \quad (25)$$

where $\Delta^\tau := D_{E_2} - \tau$. (See Appendix A.2.1 for full calculation). \square

The second-best subsidy is larger than the first-best subsidy as it needs to counteract higher emissions and lower R&D output. The further the perceived emission tax is from the damages caused by emissions, i.e., the larger Δ^τ , the larger the second-best subsidy needs to be. Accordingly, the absence of a climate policy, $\tau = 0$, requires the largest R&D subsidy compared to a setting with an emission tax in place, $\tau > 0$.

4.2 Emission Cap and R&D Subsidy

Let me now assume that there is an individual emission cap for each period. In our model, this implies that the emission level is exogenous instead of the emissions price. All other variables are endogenous. The emission cap is given by \bar{E}_t . Since all m firms are symmetric, the emission cap boils down to the fact that each firm faces an identical emission cap at $\bar{e}_t = \bar{E}_t/m$. Again I totally differentiate the first-order conditions of the baseline model with respect to σ (see Appendix A.3).

Proposition 5. *In the presence of an emission cap, an increase in an R&D subsidy in the first period:*

- *has no effect on emissions: $\frac{de_t}{d\sigma} = 0 \quad \forall \quad t = 1, 2$,*
- *has no effect on the first period: $\frac{dq_1^c}{d\sigma} = \frac{dq_1^d}{d\sigma} = \frac{dQ_1}{d\sigma} = \frac{dp_1}{d\sigma} = \frac{d\tau_1}{d\sigma} = 0$,*
- *an increase in R&D knowledge, clean output, and overall output of the second period: $\frac{dh}{d\sigma} > 0$, $\frac{dq_2^c}{d\sigma} > 0$, $\frac{dq_2}{d\sigma} > 0$,*
- *and a decrease in the output, dirty output, and emissions price of the second period: $\frac{dp_2}{d\sigma} < 0$, $\frac{dq_2^d}{d\sigma} < 0$, $\frac{d\tau_2}{d\sigma} < 0$.*

Again, the effects are contained to the second period. Similar to the case under an emissions tax, an increase in the R&D subsidy under an emissions cap promotes greater knowledge accumulation, thereby reducing production costs and increasing clean output, q_2^c . As a result, the clean sector becomes more competitive. With clean output now relatively cheaper, production shifts away from the dirty sector, leading to a decline in dirty output, q_2^d . This reduction in dirty production lowers the demand for emission permits, causing the permit price, τ_2 , to fall and so too the compliance costs of the emitter. As environmental policies are often argued to reduce competitiveness of regulated firms, an increase in the clean R&D subsidy can partially offset the loss in competitiveness by lowering compliance costs. However, because total emissions are fixed under the cap but dirty output has decreased, the emission intensity of dirty production increases: Dirty production becomes dirtier. To avoid this rebound effect and ensure additional emission reductions when increasing green R&D subsidies, the emissions cap should be reduced alongside the increase in the R&D subsidy. Overall, the increase in clean output more than offsets the reduction in dirty output, resulting in a net rise in total production, q_2 , and a corresponding decrease in the output price, p_2 . Consequently, dirty firms benefit from enhanced competitiveness, while clean firms must now compete with an even lower price.

To find the effect on welfare, I again totally differentiate (11) with respect to the R&D subsidy σ . As emissions are exogenous in this scenario, the welfare effect of a change in R&D boils down to:

$$\frac{dW}{d\sigma} = \delta n_2 n_1 k (-K_H^2) \left[\frac{(\sigma^* - \sigma)(1 + \rho(k - 1))}{1 - \sigma} \right] \frac{dh}{d\sigma}. \quad (26)$$

That is, the welfare effect is solely driven by the effect of R&D on knowledge, $dh/d\sigma$. Recalling Proposition 2 and that K_H^2 is negative, the effect on welfare only depends on the sign of $(\sigma^* - \sigma)$, which can be summarized in the following proposition:

Proposition 6. *In the presence of an emission cap, an increase in the R&D subsidy leads to a welfare gain (loss) if $\sigma < \sigma^*$ ($\sigma > \sigma^*$)*

Under an emissions cap, emissions are fixed and can, hence, not cause any additional damages which could decrease welfare. Since any effect on output disappears as demand must equal supply,

Table 2: Summary of effects of an increase in the R&D subsidy for an emission tax versus cap (where $^+$ are results by assumption).

	$dp_2/d\sigma$	$dq_2/d\sigma$	$dq_2^d/d\sigma$	$de_2/d\sigma$	$d\tau_2/d\sigma$	$dq_2^c/d\sigma$	$dh_2/d\sigma$	$dW_2/d\sigma$
Tax	< 0	< 0	< 0	< 0	$= 0^+$	> 0	> 0	≤ 0
Cap	< 0	< 0	< 0	$= 0^+$	< 0	> 0	> 0	≤ 0

the welfare effect is solely driven by the effect of an increase in the R&D subsidy on knowledge. This means that there is a welfare gain from increasing the R&D subsidy level as long as the increase in the R&D subsidy is toward the optimal subsidy level. Obviously, any increase beyond the optimal R&D subsidy level leads to a welfare loss as the costs of subsidization outweighs the benefit from more knowledge.

Again, the second-best subsidy can be calculated by inserting the elasticity ε_σ^h , as defined previously, and setting (26) equal zero, which gives:

$$\frac{dW}{d\sigma} = \delta n_2 n_1 k (-K_H^2) \left[\frac{(1-\sigma)\rho(k-1)-\sigma}{1-\sigma} \right] \varepsilon_\sigma^h \frac{h}{\sigma} = 0 \quad (27)$$

and solving for σ gives:

$$\sigma_{cap}^{**} = \frac{\rho(k-1)}{1+\rho(k-1)} = \sigma^* \quad (28)$$

That is, the second-best subsidy is just the first-best subsidy. In other words:

Proposition 7. *In the presence of an emission cap, there is no second-best R&D subsidy.*

While this conclusion can already be drawn from equation (26), I calculated the second-best for clarification. Importantly, Proposition 7 implies that no additional welfare gains can be reaped from increasing the R&D subsidy beyond its first-best level, rather it will instigate a welfare loss. This result is independent of the size of the emission cap – whether optimal or suboptimal. Accordingly, any loss from an insufficient emission cap cannot be offset through higher R&D investments. This emphasizes the importance of setting an optimal emission cap.

4.3 Comparison

Table 2 summarizes the effects of an increase in the R&D subsidy for both an emission tax and cap. The comparison reveals that the effects of raising green R&D subsidies are largely consistent across both environmental policy regimes. In all cases, an increase in the R&D subsidy fosters additional knowledge, which reduces clean production costs and stimulates a shift in production from dirty to clean goods as clean output becomes relatively cheaper. Overall, the increase in clean output more than compensates for the reduction in dirty output, resulting in a net increase in total output volume and a corresponding decrease in output price.

In terms of the emission level and the emissions price, the difference is conditioned on the scenario assumptions: An increase in the R&D subsidy under an emission tax leads to a decrease in emissions but has no effect on the emissions price, whereas under an emission cap, it decreases the emissions price but has no effect on emissions. In other words, an increase in the R&D subsidy can only achieve additional emission reductions beyond what is achieved by the environmental policy under an emission tax. Moreover, the welfare effect depends on both the change in cost savings from R&D and the cost of mitigation resulting from an increase in the R&D subsidy. Since the former adds to welfare while the latter reduces welfare, there exists a second-best R&D subsidy that can offset an inefficient – or non-existent – emissions tax without causing a change in welfare. In comparison, under an emission cap, an increase in the R&D subsidy cannot achieve any additional emission reduction as emissions are fixed, but by decreasing the emission price, it reduces the compliance cost of the emitter. To achieve emission reductions in case of an emission cap, the environmental policy must be adjusted in line with the change in the R&D subsidy. Since the income from emission prices are pure transfers, they have no additional welfare benefit. Therefore, a welfare gain from an increase in a green R&D subsidy is only possible when the R&D subsidy itself has been suboptimal and moves towards its optimum. Thus, any increase beyond the optimal level solely produces additional policy costs that are not balanced by gains elsewhere. Nevertheless, the increase in the R&D subsidy reduces the price of emissions and thus, the compliance costs for the firms in the dirty sector. Therefore, there is an additional competitive gain to the dirty firms under an emission cap beyond the price reduction.

Overall, the effects from an increase in the R&D subsidy are very similar between an emission tax and an emission cap. However, while there is an additional environmental gain under an emission tax, there is an additional competitiveness gain for the emitter under an emission cap. This raises the question of whether the magnitudes of these effects differ across environmental policy instruments – a question addressed in the subsequent section.

5 Numerical Example

To evaluate the effect sizes of an increase in the clean R&D subsidy, I apply the baseline model developed in Section 2 to the European electricity sector. I focus on the electricity sector because dirty and clean electricity are perfect substitutes from the consumer’s perspective – electricity generated from fossil fuels and renewable sources is indistinguishable at the point of use. I focus on Europe for two primary reasons. First, the region has implemented the EU ETS for several decades, providing a stable and coherent environmental policy framework. Second, since the EU ETS spans across national boundaries and due to the high degree of interconnectedness within the European electricity market, I aggregate across countries rather than analyzing them individually. The analysis specifically targets

a group of twelve largely Western and Northern European countries with strong electricity trade linkages (see Figure 1). Due to data limitations, some countries – including Belgium and Poland – are excluded. Table 3 gives the special functional forms used and Table 4 lists the parameter values, which are explained in more detail below.

As aforementioned, I focus on the European electricity market from 2008 to 2020. The time horizon covers Phase II and Phase III of the EU ETS, according to which the two periods of the model are split into, with $t = 1$ corresponding to Phase II (2008-2012) and $t = 2$ to Phase III (2013-2020) of the EU ETS. Therefore, $n_1 = 5$ and $n_2 = 6.5$, which is the net present value of the second period of 8 years discounted at the discount factor $\delta = 0.78$. The discount factor corresponds to a discount rate of 5%.

While the electricity market is a clear example of perfect substitutability between clean and dirty goods from the consumer’s perspective, the production side is more complex: Most electricity is generated by firms that operate across both clean and dirty technologies. This raises a key challenge on how to categorize firms into clean

or dirty sectors when many are neither one nor the other exclusively. To this end, I examine the electricity capacity of the largest electricity firms in Europe, plus the largest electricity provider of each country if they are not among the largest electricity providers in Europe. This leads to a list of 18 firms, corresponding to approximately 70% of the installed electricity capacity in Europe in 2024. Using their annual reports, I derive information on the installed electricity capacity of RES to divide them into dirty and clean. Although nuclear energy is per se emissions free, I categorize it as dirty since it is non-renewable electricity source and it would overinflate investments into and production of clean electricity. Note that by including nuclear as dirty, it means that the emission intensity for the dirty sector is lower than when only focusing on fossil energy sources. Since the transition from fossil to renewable sources is a dynamic process, I use data from 2020 as our reference point to categorize firms. This allows me to identify firms that made substantial investments in clean R&D to successfully shifted their generation portfolio toward renewables. Based on this classification, I identify $k = 9$ clean and $m = 9$ dirty firms.



Figure 1: Countries included in Calibration

Table 3: Special functional forms.

Functional Form	Description
$C_t(q_t^d, e_t) = (c^d/4)(q_t^d)^2 + (c^d/4)(q_t^d - \alpha_t e_t)^2$	Cost function fossil energy producer
$K^1(q_1^c) = c_1^c q_1^c + (c_2^c/2)(q_1^c)^2$	Cost function renewable energy producer in $t = 1$
$K^2(q_2^c, H) = (c_1 - \xi H_i)q_1^c + (c_2^c/2)(q_2^c)^2$	Cost function renewable energy producer in $t = 2$
$R(h) = (\gamma/2)h_t^2$	R&D investment function
$H = h + \rho(k - 1)h$	R&D knowledge function
$D(E_t) = dme_t$	Environmental damage function
$U(Q) = a(mq_t^d + kq_t^c) - (b/2)(mq_t^d + kq_t^c)^2$	Utility function

The dirty sector is characterized by a quadratic cost function to ensure convexity. Data on electricity production by source is derived from EuroSTAT (2022a). Emissions are derived by using total electricity production weighted by the emission intensity of electricity (EEA, 2024), from which I then calculate the emission intensity of dirty production alone. Both data sets are annual and by country. Thus, I weigh the emission intensity by electricity production for each country to obtain an aggregate emission intensity for the selected list of countries.

The clean sector is characterized by a linear-quadratic cost function in both periods. Again, I obtain the country-level data on electricity production from RES from EuroSTAT (2022a). Additionally, the firm in the clean sector faces R&D investment costs. Data on public R&D expenditures is taken from the RD&D Data Explorer from the IEA 2025, which gives me annual data per country. Note that these investments are an upper bound as these are not only R&D investments but also include investments for demonstrations. Firms private investments in R&D are, however, hard to come by and range significantly across country (Gasser et al., 2022). Accordingly, I use information from the European Commission (2015) stating that in 2011, 55% of R&D funds for solar energy came from private R&D investments and estimate private investments thereby. In our sensitivity analysis (Section 5.2), I relax this constraint, looking at the effect of different R&D subsidies.

R&D affects the costs in the second period by reducing the linear term of the cost function, leading to a downward shift. Following the innovation literature, I use patent data to measure knowledge derived from R&D. Knowledge via patenting is derived by industry investments in R&D, which are characterized by a quadratic investment function. A quadratic function is more suitable for early stage R&D as it reflects network-effects of increased R&D investments – this idea of ”standing on the shoulder of giants”. Country-level patent data for RES is derived from IRENA (2025). Note that I cannot verify whether these patents are for electricity use or other non-electricity energy use like heating, thus the estimates for patent data will be upper-bound estimates.

While the length of the two periods is defined by the EU ETS, it also is in line with empirical estimates that there is at least a five year lag between investments and patent publication (Newell

Table 4: List of parameters and their values used in the baseline calibration.

Parameter	Base Value	Description
a	1.2006	Intercept demand function (electricity choke price) (\$/kWh)
b	4.4×10^{-13}	Slope of demand function (\$/kWh)
c^d	1.3131×10^{-12}	Scaling parameter of fossil fuels energy producers' cost function (\$/kWh ²)
c_1^c	0.0888	Intercept of renewable energy producers' cost function (\$/kWh)
c_2^c	4.8864×10^{-13}	Slope of renewable energy producers' cost function (\$/kWh ²)
d	42.35	Damage parameter (\$/tCO ₂)
k	9	Number of renewable energy producers
m	9	Number of fossil fuel energy producers
n_1	5	Length of period 1
n_2	6.5	Length of period 2
α_1	2693.60	Emissions scaling parameter period 1 (kWh/tCO ₂)
α_2	2911.89	Emissions scaling parameter period 2 (kWh/tCO ₂)
δ	0.78	Discount factor
ξ	1.3441×10^{-7}	Scaling Parameter Patents
γ	161.17	Effectiveness of R&D expenditures (\$/patent)
ρ	0.5	R&D knowledge spillover rate
σ	0.45	R&D subsidy level

et al., 1999) – though possibly longer (Wang and Hagedoorn, 2014) – hence matching our time horizon very well. From the patent data and data on R&D investments, I can calculate the effectiveness of R&D expenditures turning into patents in 5 years, γ . I set the knowledge spillover rate ρ to 50% to capture the social returns to knowledge (Jones and Williams, 1998). Note that I also examine different spillover rates in our sensitivity analysis (Section 5.2.1).

Demand side is represented by a linear-quadratic demand function, implying linear marginal demand. While I examine the entire electricity sector, I use data on household electricity prices from ESTAT (Eurostat, 2022b) as these prices reflect demand and supply shocks in comparison to industry prices, which are usually fixed years in advance. The data is biannual for each country. Accordingly, I use the mean for each country weighted with the country's gross electricity production to get an average electricity price.

Since I only examine one sector of the EU ETS, I cannot calibrate the model using the actual emission cap. Instead, I use data on the observed emissions prices to calculate a corresponding emission cap and use the emissions prices as a counterfactual "emission tax" scenario. The emissions prices used in the calibration are the average weekly future spot prices of the EU ETS obtained from Sandbag (Feb. 2025).

Lastly, I consider a linear damage function, which gives me constant marginal damages, as I only examine a very short time interval in terms of environmental effects. Since our damage function is

Table 5: The percentage change of a 1% increase in the R&D subsidy in the presence of an emission tax.

Tax	Patents ($k \times H$)	Renewable output (Q_2^c)	Non-renewable output (Q_2^d)	Emissions (E_2)	Electricity output (Q_2)	Electricity price (p_2)	Welfare (W)
<i>No</i>	1.8995%	0.0469%	−0.0167%	−0.0167%	0.0028%	−0.0167%	0.0008%
<i>Suboptimal</i>	1.8995%	0.0469%	−0.0187%	−0.0286%	0.0031%	−0.0176%	0.0008%
<i>Optimal</i>	1.8995%	0.0469%	−0.0208%	−0.0237%	0.0034%	−0.0185%	0.0008%
<i>Excessive</i>	1.8995%	0.0469%	−0.0230%	−0.0286%	0.0038%	−0.0193%	0.0009%

linear, the damage term d just equals to the social cost of carbon. I use an estimate of the weighted country social cost of carbon from Ricke et al., 2018, which gives me 42.35€/tCO₂ for the set of countries.⁴ Since the optimal emission price should equal to the marginal damages, d also corresponds to the optimal tax level. For comparability, the emission cap corresponds to the emission tax.

I use the calibration to examine the effect of an increase in R&D subsidies under 1) an emission tax and 2) an emission cap. Accordingly, I differentiate between a total of seven scenarios: "Optimal" policy, $\tau = \tau^*$ and $\bar{e}_t = e_t(\tau^*)$, a "Suboptimal" policy, $\tau = 0.5\tau^*$ and $\bar{e}_t = e_t(0.5\tau^*)$, and an "Excessive" policy, $\tau = 1.5\tau^*$ and $\bar{e}_t = e_t(1.5\tau^*)$ as well as "No" Policy, $\tau = 0$, under a tax to reflect the absence of an environmental policy. Recalling Propositions 2 and 5, the following analysis focuses on the changes in the second period.

5.1 Results

5.1.1 Emission Tax

Table 5 summarizes the results of a 1% increase in the R&D subsidy – from 0.45% to 0.46% – for the different tax levels. (The quantity effects are given in Appendix B.) Table 5 shows that the direction of effects are in line with Proposition 2 and the effect sizes are largest in the clean sector, where the subsidy is deployed: A 1% increase in the R&D subsidy leads to an increase in renewable energy by 0.05% and increases the patenting activity by 1.90%, due to an exponential R&D function. This result is in line with empirical work that shows increasing R&D subsidies are highly effective in inducing innovation through patenting (e.g., Hille et al., 2020) but not necessarily capacity expansion of RES (Carley et al., 2017). The large difference in the effect sizes between patenting and renewable energy output reveals that learning from searching is not directly translatable to cost reductions and output changes. Accordingly, the question arises to what extent patenting reflects effective innovations through actual changes in output (see e.g., Plank and Doblinger, 2018). Furthermore, the effect on patenting and renewable electricity output is the same across the scenarios, i.e., there is no interaction

⁴Although estimates for the social cost of carbon are considerably higher (see, e.g., EPA, 2023), I use a lower bound as it would otherwise diverge considerably from the actual EU ETS price.

between the R&D subsidy and the emission tax level and its stringency.

On the other hand, the other variables are affected by both the R&D subsidy and the environmental policy: The reduction in the electricity price, dirty output and emissions and the increase in total electricity grows with the stringency of the environmental policy. Lets begin by examining the "No" tax scenario, which gives the effect of increasing the R&D subsidy in the absence of an environmental policy and thus gives the undistorted, baseline effects of an increase in the R&D subsidy. I find that the baseline effect of a 1% in the R&D subsidy is a reduction of 0.0167% in non-renewable electricity, emissions, and notably also in the electricity price. That is, in the absence of an environmental policy, the effects from the output price to dirty output to emissions occur without distortion. Once the environmental policy is added to the mix, the effect sizes differ.

Looking at the dirty sector, I find that production of non-renewable electricity and thus emissions decrease across scenarios: A 1% increase in the R&D subsidy leads to a decrease in non-renewable electricity and emissions by 0.02% in the presence of an optimal emission tax. The effect size increases with policy stringency. In other words, the higher the tax level, the larger the reductions in non-renewable electricity and emissions. The decrease in non-renewable electricity is outweighed by the increase in renewable energy, such that overall, electricity production increases and output prices decrease. Again the effect sizes are the larger, the higher the emission tax. Overall, there is a small welfare gain from increasing the R&D subsidy because it moves closer towards the optimal subsidy level.

Moreover, since the difference in tax levels are linear, I can use the change in effect sizes from one policy scenario to the next as an indicator for interaction effect between the environmental policy stringency and the R&D subsidy. Since there is no difference between effects on patenting and renewable electricity output, there is also no interaction effect between the R&D subsidy and the environmental policy stringency. This result adds to the empirical literature on the effectiveness of R&D subsidies on patenting as empirical studies have yet to differentiate between climate policies and examine the interaction between the R&D subsidy and the environmental policy (see e.g., Ang et al., 2017; Hille et al., 2020). Only one report, a case study of the Sweden industry (Coria and Jaraite, 2024), corroborates our finding that there is no interaction effect between R&D subsidies and the environmental policy. On the other hand, for non-renewable output, electricity price, and emissions, there is a negative interaction effect – the higher the emission tax, the stronger the reduction in these variables – while there is a positive interaction effect between the total electricity output and welfare. Accordingly, an environmental tax complements the R&D subsidy to achieve even stronger effects. Therefore, an optimal policy mix is not only necessary to correct the double externality problem but also recommendable due to the interaction between R&D subsidies and the environmental policy.

Table 6: The effect of a 1% increase in the R&D subsidy in the presence of an emission cap.

Cap	Patents ($k \times H$)	Renewable output (Q_2^c)	Non-renewable output (Q_2^d)	Emissions price (τ_2)	Electricity output (Q_2)	Electricity price (p_2)	Welfare (W)
<i>Suboptimal</i>	1.9136%	0.0606%	-0.0116%	-0.1932%	0.0038%	-0.0218%	0.0007%
<i>Optimal</i>	1.9136%	0.0606%	-0.0129%	-0.1034%	0.0042%	-0.0229%	0.0008%
<i>Excessive</i>	1.9136%	0.0606%	-0.0143%	-0.0735%	0.0047%	-0.0239%	0.0010%

5.1.2 Emission Cap

From the tax levels used above, I calculate the corresponding emission caps to allow the comparison of effect sizes from an increase in the R&D subsidy by 1% – from 45% to 46%. Figure 6 summarizes the percentage changes from an increase in the R&D subsidy in the presence of an emission cap. Again, the signs of the effects are in line with Proposition 5. Specifically, I find that in the presence of an emission cap, an increase in the R&D subsidy by 1% leads to an increase in patenting and renewable electricity generation by 1.91% and 0.06%, respectively. As in the case of an emission tax, these effects are independent of the cap size, meaning that patenting and renewable electricity generation are unaffected by policy stringency.

In comparison, non-renewable electricity generation, the electricity price, and the emissions price decrease from an increase in the R&D subsidy and the effect size now depends on the stringency of the cap. For non-renewable electricity generation and the electricity price, the interaction effects are negative – the more stringent the cap, the larger the reductions – while it is positive for the emissions price – the more stringent the cap, the lower the reduction. Furthermore, the difference in effect sizes between the stringency levels highlights a weak negative effect for the electricity price but a strong positive interaction effect between the emissions price and the R&D subsidy. Accordingly, for some variables, the stringency of the emission cap matters more than for others. Although an increase in the R&D subsidy reduces both the emissions price and the electricity price to the benefit of the dirty producer, the interaction effects move in opposing direction and hence, the effects balance each other to a small extent. Lastly, overall electricity output and welfare increase slightly with the increase in the R&D subsidy and the effect sizes increase with policy stringency.

5.1.3 Comparison

Having examined the effect of an increase in the R&D subsidy under an emission tax and cap under different environmental policy stringency, I will now compare across the environmental policy types. Comparing the effect sizes, the effect of a 1% increase in the R&D subsidy level is generally larger for renewable and non-renewable electricity production and for total electricity output and electricity price under an emission tax than an emission cap. In terms of renewable electricity, the difference I

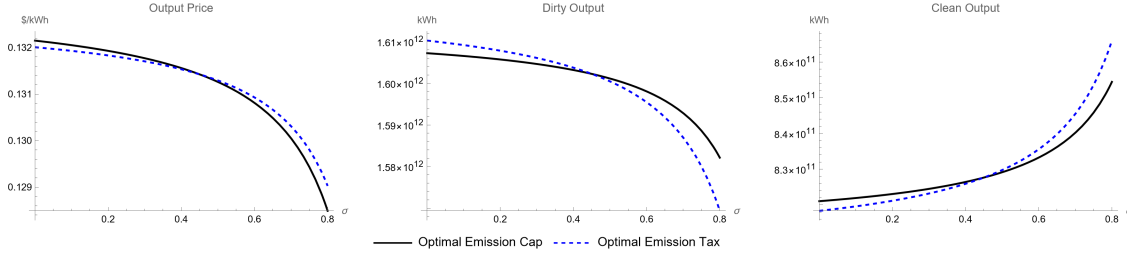


Figure 2: Emission taxes versus emission caps under suboptimal R&D policies

observe is in line with empirical studies, which have shown a higher effectiveness of an emission tax on renewable electricity capacity than an emission cap (Bento et al., 2020). However, Figure 2 reveals that this result is contingent on the size of the R&D subsidy level, σ . Under an optimal environmental policy, the output price, for example, is higher for a cap than a tax until $\sigma = 0.45$ – which is the R&D subsidy level assumed in the baseline calibration, after which the ordering changes. Furthermore, the difference in the magnitude of the effect on patenting is minimal between an emission cap and tax. While the difference may reflect rounding errors resulting from the conversion of emission prices into caps, there seems to be a slight tendency that a tax is minimally more effective than a cap when also taking the results of the sensitivity analyses into place (see Table 8 and 9).

The largest difference across the two environmental policies is, by definition, the effect on emissions and emissions prices. Under an emission cap, emissions are held fixed while emissions decrease with the R&D subsidy level and under an emission tax, emissions price is held fixed while the price decreases with the R&D subsidy level and under an emission cap. Figure 3 depicts this relationship and also reveals that in terms of quantities, the total emissions are higher under a tax than a cap until $\sigma = 0.45$ and afterwards, total emissions are lower for an emission tax. The opposite relationship is the case for the emissions price, where the cap is initially higher than the tax and at $\sigma = 0.45$ the relationship reverses. By increasing the baseline R&D subsidy rate, the switching point shifts accordingly.

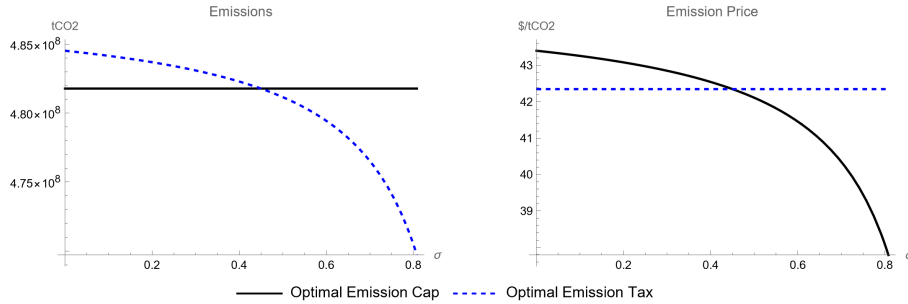


Figure 3: Relationship between emissions/emissions price and the R&D subsidy level under an optimal emission cap compared to the optimal emission tax

Table 7: Comparison of rebound effects from a 1% increase in the R&D subsidy rate under an emission tax and an emission cap.

Rebound Effect	Tax	Cap
<i>No</i>	10.4764%	-
<i>Suboptimal</i>	9.6157%	100%
<i>Optimal</i>	8.7336%	100%
<i>Excessive</i>	7.8293%	100%

Furthermore, the fact that emissions are held fixed under an emission cap implies that any reduction in the dirty output is linked to an increase in the emission intensity such that total emissions remain the same. In other words, the rebound effect is always 100% under an emission cap. For an emission tax, however, a reduction in dirty output can now also reduce emissions, which was shown in Table 5. While in the absence of a climate policies, the reduction in non-renewable electricity and emissions from an increase in the R&D subsidy by 1% occurred in a 1:1 relationship, the decrease in emissions exceed the reduction in non-renewable electricity in the presence of an environmental policy. To untangle the reduction in emissions from decreased output and reduced emission intensity, I calculate the rebound effect in case of an emission tax (see Table 7). I find that the rebound effects are higher in the absence of an environmental policy and decreases with the policy stringency. Overall, the rebound effects range from approximately 8-10%, and are, thus, relatively low. Therefore, an increase in the R&D subsidy can achieve notable emission reductions in the presence of an emission tax.

5.2 Sensitivity Analysis

For the baseline calibration I made assumptions on both the knowledge spillover rate and the R&D subsidy level. To check to what extent the results are contingent on these assumptions, I will relax them in this section. Since the knowledge spillover rate ρ determines the optimal R&D subsidy level and the assumed R&D subsidy level determines the distance from the optimum, both variables can affect the results.

5.2.1 Knowledge Spillover Rates

I have previously assumed a spillover rate of $\rho = 0.5$, reflecting the private returns of investments (Jones and Williams, 1998). However, more recent work shows spillover rates of 70% for renewable energies (Noailly and Shestalova, 2017). Accordingly, for the sensitivity analysis I use a spillover rate of $\rho = 0.7$, and for comparative purposes also $\rho = 0.3$. A higher spillover rate amplifies the effects resulting from a 1% increase in the R&D subsidy. This is because a higher spillover rate raises the first-best level of the subsidy. As I still consider an increase from $\sigma = 0.45$ to $\sigma = 0.46$, a 1% increase

Table 8: The percentage change of a 1% increase in the R&D subsidy in the presence of a first-best emission tax (top) and emission cap (bottom) with different spillover rates.

Tax	Patents ($k \times H$)	Renewable output (Q_2^c)	Non-renewable output (Q_2^d)	Emissions (E_2)	Electricity output (Q_2)	Electricity price (p_2)	Welfare (W)
$\rho = 0.3$	1.8850%	0.0325%	-0.0145%	-0.0165%	0.0024%	-0.0129%	0.0004%
$\rho = 0.5$	1.8995%	0.0469%	-0.0208%	-0.0237%	0.0034%	-0.0185%	0.0008%
$\rho = 0.7$	1.9136%	0.0606%	-0.0267%	-0.0305%	0.0044%	-0.0238%	0.0013%
Cap	Patents ($k \times H$)	Renewable output (Q_2^c)	Non-renewable output (Q_2^d)	Emissions price (τ_2)	Electricity output (Q_2)	Electricity price (p_2)	Welfare (W)
$\rho = 0.3$	1.8752%	0.0229%	-0.0089%	-0.0716%	0.0029%	-0.0159%	0.0004%
$\rho = 0.5$	1.8995%	0.0331%	-0.0129%	-0.1034%	0.0042%	-0.0229%	0.0008%
$\rho = 0.7$	1.8958%	0.0431%	-0.0167%	-0.1342%	0.0053%	-0.0230%	0.0013%

in the R&D subsidy is more effective when the spillover rate is higher, since it is further away from the optimum. Again, I compare the effects between an emission tax and cap but the focus will be placed on a first-best policy level. The results are found in Table 8.

In the presence of an emission tax, a change in the spillover rate only has a small effect on patenting despite the spillover rate determining the optimal R&D subsidy level: An increase in the green R&D subsidy by 1% leads to an increase in patenting between 1.89 – 1.91%. Although the effects of a 1% increase in the R&D subsidy on all other variables are generally small, the difference in effect sizes due to the change in the spillover rate is notable. The effect sizes for a spillover rate of $\rho = 0.7$ are approximately double than the effect for $\rho = 0.3$ and the effect on welfare more than triples. The difference in effects are also notable when comparing the quantity effects of Table 11 (see Appendix B). The effects of a change in the spillover rate in the presence of an emission cap are similar to that of a cap; While patenting only changes minimally, the effects are almost double for $\rho = 0.7$ compared to $\rho = 0.3$ and more than triple for the welfare effect. Furthermore, the effect sizes grow next to linearly for both an emission cap and a tax, which indicates that the interaction effects between the R&D subsidy and the environmental policy stringency are very small if present. Accordingly, the assumed spillover rate does matter in determining the size of the effects resulting from a 1% increase in the green R&D subsidy.

5.2.2 R&D Subsidy Levels

I assumed a subsidy level of 45% due to a statement by the European Commission on the role of private investments on solar PV advancements (European Commission, 2015). Since this statement was solely based on solar PV but was generalized for RES in general, the overall R&D subsidy level may differ. Accordingly, I run an additional sensitivity analysis assuming $\sigma = 0.25$, $\sigma = 0.65$ and

Table 9: The percentage change of a 1% increase in the R&D subsidy in the presence of a first-best environmental policy with different R&D subsidy levels.

Tax	Patents ($k \times H$)	Renewable output (Q_2^c)	Non-renewable output (Q_2^d)	Emissions (E_2)	Electricity output (Q_2)	Electricity price (p_2)	Welfare (W)
$\sigma = 0.25$	1.4291%	0.0767%	-0.0334%	-0.0381%	0.0054%	-0.0297%	0.0018%
$\sigma = 0.45$	1.8995%	0.0469%	-0.0208%	-0.0237%	0.0034%	-0.0185%	0.0008%
$\sigma = 0.65$	2.9762%	0.0340%	-0.0152%	-0.0174%	0.0025%	-0.0135%	0.0003%
$\sigma = 0.80$	5.2934%	0.0287%	-0.0129%	-0.0147%	0.0021%	-0.0114%	-0.0000%
Cap	Patents ($k \times H$)	Renewable output (Q_2^c)	Non-renewable output (Q_2^d)	Emissions price (τ_2)	Electricity output (Q_2)	Electricity price (p_2)	Welfare (W)
$\sigma = 0.25$	1.4078%	0.0557%	-0.0212%	-0.1716%	0.0069%	-0.0378%	0.0017%
$\sigma = 0.45$	1.8856%	0.0331%	-0.0129%	-0.1034%	0.0042%	-0.0229%	0.0008%
$\sigma = 0.65$	2.9657%	0.0238%	-0.0093%	-0.0747%	0.0031%	-0.0166%	0.0004%
$\sigma = 0.80$	5.2842%	0.0200%	-0.0079%	-0.0629%	0.0026%	-0.0137%	-0.0000%

$\sigma = 0.80$. Since I have data on public R&D spending but not private R&D spending, a change in the subsidy level affects overall R&D spending and thus, the spending per patent, γ . Since γ is used for the calibration, the parameters c_t^c and ξ are also subject to change from an increase in σ . The change in σ also implies that the 1% increase in the R&D subsidy occurs from the new level of σ . For example, for $\sigma = 0.25$, the 1% increase of the R&D subsidy is an increase from $\sigma = 0.25$ to $\sigma = 0.26$. The results of a 1% increase in the R&D subsidy are given in Table 9 for an optimal emission tax and cap, respectively.

Table 9 reveals that an increase of the R&D subsidy by 1% under different subsidy levels as a notable effect across variables and the environmental policy instrument. An increase in the R&D subsidy notably increases patenting activity because a quadratic function was assumed and hence, an increase in the R&D subsidy becomes increasingly effective. For all other variables, however, an increase in the R&D subsidy leads reduces the effect size for both an emission tax and cap as a higher R&D subsidy rate implies a lower level of overall R&D spending and thus reduces γ . For example, an increase in the R&D subsidy from 0.25 to 0.26 leads to an increase in renewable electricity by 0.08% while an increase from 0.80 to 0.81 reduces renewable electricity output by only 0.03% – about 2.5 times smaller. Therefore, the assumed R&D subsidy level can notably change the result of the calibration and the effectiveness of an increase in the R&D subsidy level.

The largest effect under different subsidy levels can be see for the welfare effect for both an emission tax and emission cap. The lower the initial R&D subsidy, the further away I am from the optimum and, hence, the more effective an increase in the R&D subsidy is. Since the optimal subsidy, $\sigma^* = 0.8$, an increase of 1% leads to an excessively high R&D subsidy, which in turn leads to a small welfare loss. Recalling Proposition 7, the negative effect holds for any emission cap – excessive, optimal,

or suboptimal – but from Proposition 4, it is known that the welfare effect depends on both the environmental policy stringency and the R&D subsidy level. Hence, the welfare effect is only negative for an excessive and optimal emission tax but in case of a suboptimal tax or in the absence of an environmental policy, a welfare gain can still be obtained by increasing the R&D subsidy to beyond its optimal amount. This comparison highlights the nuanced trade-offs between the environmental policy instruments, setting the stage for the broader discussion and conclusions subsequently.

6 Discussion and Conclusion

In this paper, I analyze the role of green research and development (R&D) subsidies under different environmental policy regimes – emission tax, emission cap, and no climate policy – using a stylized equilibrium model calibrated to the EU electricity sector. In line with the existing literature (Acemoglu et al., 2012; Fischer and Newell, 2008), our analytical and calibration results emphasize that green R&D subsidies form a key component of an optimal policy mix, with the optimal subsidy level increasing with knowledge spillovers and sector size.

Specifically, higher R&D subsidies promote knowledge accumulation, reduce clean production costs, and induce a production shift from dirty to clean output. This shift increases total output and lowers output prices. While this improves the competitiveness of the dirty firm, it comes at a cost to the clean firm. Under an emissions tax or no environmental policy, this also reduces emissions and improves welfare. Under an emissions cap, however, emission reductions from cleaner production are offset by higher emission intensity in the remaining dirty production, reducing permit prices and, thus, compliance costs. Accordingly, an increase in the R&D subsidy directly improves the competitiveness of the clean sector by lowering production costs, but also benefits the dirty sector by lower output prices and, in case of an environmental cap, also reduces compliance costs to the environmental policy. However, this comes at the cost of higher emission intensity as environmental gains can only be reaped under an emission tax. Therefore, a reduction in the emission cap alongside the increase in the R&D subsidy should be considered to also capture environmental gains.

The calibration supports the findings from our analytical analysis and provides additional insights by allowing me to determine the effect sizes. Specifically, I find that patenting responds solely to the R&D subsidy and is unaffected by environmental policy stringency: A 1% increase in the R&D subsidy increases patenting by 1.90% and 1.89% for an emission tax and cap, respectively. Therefore, the environmental policy also only plays a minor role for patenting. Nonetheless, the role of the environmental policy and its stringency is notable for all other variables. The effect of an increase in the R&D subsidy by 1% increases with the environmental policy stringency. Furthermore, there is a negative interaction effect between the R&D subsidy and the environmental policy stringency

under both an emission cap and an emission tax. This results emphasizes the importance of a policy mix when dealing with environmental innovations because the environmental and innovation policies complement each other.

A comparison of effect sizes between an emission tax and an emission cap further shows that the impacts on renewable and non-renewable electricity output are generally larger under an emission tax, whereas the effects on total electricity output and the electricity price tend to be larger under an emission cap. The largest difference is, however, found on the environmental effect. Since emissions are held fixed under an emission cap, any reduction in non-renewable electricity output and gains in efficiency are completely rebounded. In comparison, under an emission tax, there is also a notable environmental gain from increasing the R&D subsidy as the rebound effect only range between 8-10%.

Overall, my findings highlight the effectiveness of green R&D subsidies in supporting activities in the clean sector. On the economy as a whole, the effectiveness of green R&D subsidies hinges on the type of environmental policy and, importantly, the stringency of the environmental policies. Accordingly, the more is not always the merrier and hence, it is essential that policy makers consider the trade-off between environmental, innovation, and competitiveness gains when coordinating industrial policies with environmental policies.

While our paper contributes valuable insights on the interaction of innovation and environmental policies, it has several limitations that must be acknowledged. First, I only use a static, two period model but R&D investments and patenting are dynamic processes, which would be better represented by a discrete time model. Second, our general model does not include learning-by-doing, which is an important driver for technological change. To get a comprehensive understanding, learning-by-doing should ideally be included. Third, the model calibration is based on a selected subset of countries, which may limit the generalizability of our results to other regions with different economic structures or energy mixes. Fourth, the electricity sector – central to our analysis – is a unique sector, characterized by inelastic demand. This may limit the applicability of our findings to other sectors with different dynamics. Accordingly, future research should also examine other sectors. Fifth, the estimation of R&D subsidies presents inherent challenges, as these subsidies vary significantly across countries in both scale and structure. This variability introduces uncertainty into cross-country comparisons and the interpretation of policy effects. Furthermore, as I have shown in my sensitivity analysis, the results are conditional on both the assumed spillover rate and the actual R&D subsidy levels. Therefore, future research should investigate these parameters further to improve calibrations. Sixth, our emission tax scenario serves as a counterfactual to the emissions cap scenario, rather than as a reflection of an implemented or proposed policy. While this allows for comparison between environmental policy regimes, it does not capture reality. Despite these limitations, valuable insights can be drawn from this stylized settings on the interaction between innovation and environmental policies.

Data Availability

Data for the calibration can be received upon request from Leonie P. Meissner.

Acknowledgment I am deeply grateful to Sonja Peterson and Till Requate for their valuable comments and discussions that made the paper what it is today. I further thank participants at the FSR Climate Annual Conference 2024, AURö Workshop 2025, CESifo Doctoral workshop 2025, 31st Ulvön Conference on Environmental Economics and EAERE 2025 for their valuable feedback.

Funding I acknowledge financial support by the Federal Ministry of Education and Research under the grant number [01LA2101A].

A Appendix: Baseline Model

A.1 Comparative Statics Carbon Tax

For the comparative statics analysis, I totally differentiated equations (2)-(3), (6)-(7), (9), and (10) with respect to the R&D subsidy σ . Since I have an emission tax, I assume that $d\tau/d\sigma \stackrel{!}{=} 0$, giving the following equations, respectively:

$$\frac{dp_1}{d\sigma} = C_{q_1^d q_1^d}^1 \frac{dq_1^d}{d\sigma} + C_{q_1^d e_1}^1 \frac{de_1}{d\sigma} \quad (29)$$

$$\frac{dp_2}{d\sigma} = C_{q_2^d q_2^d}^2 \frac{dq_2^d}{d\sigma} + C_{q_2^d e_2}^2 \frac{de_2}{d\sigma} \quad (30)$$

$$0 = -C_{e_1 e_1}^1 \frac{de_1}{d\sigma} - C_{q_1^d e_1}^1 \frac{dq_1^d}{d\sigma} \quad (31)$$

$$0 = -C_{e_2 e_2}^2 \frac{de_2}{d\sigma} - C_{q_2^d e_2}^2 \frac{dq_2^d}{d\sigma} \quad (32)$$

$$\frac{dp_1}{d\sigma} = K_{q_1^c q_1^c}^1 \frac{dq_1^c}{d\sigma} \quad (33)$$

$$\frac{dp_2}{d\sigma} = K_{q_2^c q_2^c}^2 \frac{dq_2^c}{d\sigma} + K_{q_2^c H}^2 \frac{dH}{dh} \frac{dh}{d\sigma} \quad (34)$$

$$(1 - \sigma)R_{hh} \frac{dh}{d\sigma} - R_h = -\delta n_2 \left[K_{q_2^c H}^2 \frac{dq_2^c}{d\sigma} + K_{HH}^2 \frac{dH}{dh} \frac{dh}{d\sigma} \right] \quad (35)$$

$$\frac{dp_1}{d\sigma} = u_{Q_1 Q_1} \frac{dQ_1}{d\sigma} \quad (36)$$

$$\frac{dp_2}{d\sigma} = u_{Q_2 Q_2} \frac{dQ_2}{d\sigma} \quad (37)$$

$$\frac{dQ_1}{d\sigma} = m \frac{dq_1^d}{d\sigma} + k \frac{dq_1^c}{d\sigma} \quad (38)$$

$$\frac{dQ_2}{d\sigma} = m \frac{dq_2^d}{d\sigma} + k \frac{dq_2^c}{d\sigma} \quad (39)$$

where $dH/dh = 1$ from $H_i = n_1(h_i + \sum_{j=1}^K \rho h_j)$. Using Mathematica 14, I solve for the comparative statics effects. Due to the complexity of the equations, I separate the analysis of the nominator and the denominator. The denominator – which is the same for all comparative static effects – is given by:

$$\begin{aligned} det_{tax} = & \left(((C_{q_1^d e_1}^1)^2 - C_{e_1 e_1}^1 C_{q_1 q_1}) k U_{qq} - K_{q_1^c q_1^c}^1 ((C_{q_1^d e_1}^1)^2 - C_{e_1 e_1}^1 C_{q_1 q_1} + C_{e_1 e_1}^1 m U_{qq}) \right) \\ & \times [\delta n_2 (K_{q_2^c h}^2)^2 ((C_{q_2^d e_2}^2)^2 - C_{e_2 e_2}^2 C_{q_2 q_2} + C_{e_2 e_2}^2 m U_{qq}) \\ & - (k U_{qq} ((C_{q_2^d e_2}^2)^2 + C_{e_2 e_2}^2 C_{q_2 q_2}) + K_{q_2^c q_2^c}^2 ((C_{q_2^d e_2}^2)^2 - C_{e_2 e_2}^2 C_{q_2 q_2} + C_{e_2 e_2}^2 m U_{qq})) \\ & \times (\delta n_2 K_{hh} + n_1 (1 - \sigma) R_{hh})], \end{aligned} \quad (40)$$

and the nominators are:

$$\frac{dp_1}{d\sigma} = \frac{dq_1^d}{d\sigma} = \frac{dq_1^c}{d\sigma} = \frac{dq_1}{d\sigma} = \frac{de_1}{d\sigma} = 0 \quad (41)$$

$$\begin{aligned} \frac{dp_2}{d\sigma} &= kR_h U_{qq} K_{q_2^d h}^2 ((C_{q_2^d e_2})^2 - C_{e_2 e_2} C_{q_2^d q_2^d}) \\ &\quad \times \left(((C_{q_1^d e_1})^2 - C_{e_1 e_1} C_{q_1^d q_1^d}) kU_{qq} - K_{q_1 q_1} ((C_{q_1^d e_1})^2 - C_{e_1 e_1} C_{q_1^d q_1^d} + mU_{qq} C_{e_1 e_1}) \right) \end{aligned} \quad (42)$$

$$\frac{dq_2^d}{d\sigma} = kR_h U_{qq} K_{q_2^d h}^2 C_{e_2 e_2} \left((C_{e_1 e_1} C_{q_1^d q_1^d} - (C_{q_1^d e_1})^2) kU_{qq} + K_{q_1 q_1} ((C_{q_1^d e_1})^2 - C_{e_1 e_1} C_{q_1^d q_1^d} + mU_{qq} C_{e_1 e_1}) \right) \quad (43)$$

$$\frac{de_2}{d\sigma} = kR_h U_{qq} K_{q_2^d h}^2 C_{q_2^d e_2} \left(((C_{q_1^d e_1})^2 - C_{e_1 e_1} C_{q_1^d q_1^d}) kU_{qq} - K_{q_1 q_1} ((C_{q_1^d e_1})^2 - C_{e_1 e_1} C_{q_1^d q_1^d} + mU_{qq} C_{e_1 e_1}) \right) \quad (44)$$

$$\begin{aligned} \frac{dq_2^c}{d\sigma} &= -R_h K_{q_2^d h}^2 ((C_{q_2^d e_2})^2 - C_{e_2 e_2} C_{q_2^d q_2^d} - C_{e_2 e_2} mU_{qq}) \\ &\quad \times \left((C_{e_1 e_1} C_{q_1^d q_1^d} - (C_{q_1^d e_1})^2) kU_{qq} + K_{q_1 q_1} ((C_{q_1^d e_1})^2 - C_{e_1 e_1} C_{q_1^d q_1^d} + mU_{qq} C_{e_1 e_1}) \right) \end{aligned} \quad (45)$$

$$\begin{aligned} \frac{dq_2}{d\sigma} &= kR_h K_{q_2^d h}^2 ((C_{q_2^d e_2})^2 - C_{e_2 e_2} C_{q_2^d q_2^d}) \\ &\quad \times \left(((C_{q_1^d e_1})^2 - C_{e_1 e_1} C_{q_1^d q_1^d}) kU_{qq} - K_{q_1 q_1} ((C_{q_1^d e_1})^2 - C_{e_1 e_1} C_{q_1^d q_1^d} + mU_{qq} C_{e_1 e_1}) \right) \end{aligned} \quad (46)$$

$$\begin{aligned} \frac{\partial h}{\partial \sigma} &= R_h \left(-(C_{q_1^d e_1})^2 + C_{e_1 e_1} C_{q_1^d q_1^d} \right) kU_{qq} + K_{q_1^c q_1^c} (C_{q_1^d e_1})^2 - C_{e_1 e_1} C_{q_1^d q_1^d} + C_{e_1 e_1} mU_{qq} \\ &\quad \times \left(-(C_{q_2^d e_2})^2 + C_{e_2 e_2} C_{q_2^d q_2^d} \right) kU_{qq} + K_{q_2^c q_2^c} (C_{q_2^d e_2})^2 - C_{e_2 e_2} C_{q_2^d q_2^d} + C_{e_2 e_2} mU_{qq} \end{aligned} \quad (47)$$

A.2 Welfare Effect

To calculate the welfare effect of a change in the clean R&D subsidy, I begin by totally differentiating the welfare function (11) with respect to the R&D subsidy σ , which gives:

$$\begin{aligned} \frac{dW}{d\sigma} &= n_1 \left[u_{Q_1} \frac{dQ_1}{d\sigma} - mC_{q_1^d}^1 \frac{dq_1^d}{d\sigma} - mC_{e_1}^1 \frac{de_1}{d\sigma} - kK_{q_1^c}^1 \frac{dq_1^c}{d\sigma} - kR_h \frac{dh}{d\sigma} - mD_{E_1} \frac{de_1}{d\sigma} \right] \\ &\quad + \delta n_2 \left[u_{Q_2} \frac{dQ_2}{d\sigma} - mC_{q_2^d}^2 \frac{dq_2^d}{d\sigma} - mC_{e_2}^2 \frac{de_2}{d\sigma} - kK_{q_2^c}^2 \frac{dq_2^c}{d\sigma} - n_1 kK_H^2 (1 + \rho(k-1)) \frac{dh}{d\sigma} - mD_{E_2} \frac{de_2}{d\sigma} \right] \end{aligned} \quad (48)$$

From equation (10), I know that any change in demand must equal the change in supply, and the change in total emissions is the change of the sum of individual emissions. Furthermore, from Proposition 2 I know that a change in R&D has no effect on the first period. Accordingly, the equation can be simplified: to:

$$\frac{dW}{d\sigma} = -\delta n_2 m [C_{e_2}^2 + D_{E_2}] \frac{de_2}{d\sigma} - k [n_1 R_h + \delta n_2 n_1 K_H^2 (1 + \rho(k-1))] \frac{dh}{d\sigma} \quad (49)$$

Now, inserting (3), (7), and (14) I can further simplify this equation to:

$$\frac{dW}{d\sigma} = \delta n_2 m [\tau - D_{E_2}] \frac{de_2}{d\sigma} + \delta n_2 n_1 k (-K_H^2) \left[\frac{\rho(k-1) - \sigma(1 + \rho(k-1))}{1 - \sigma} \right] \frac{dh}{d\sigma} \quad (50)$$

Now, I multiply the second part of the right hand side by $\frac{1+\rho(k-1)}{1+\rho(k-1)}$ to get an equation in which the optimal subsidy value can be derived.

$$\begin{aligned}\frac{dW}{d\sigma} &= \delta n_2 m[\tau - D_{E_2}] \frac{de_2}{d\sigma} + \delta n_2 n_1 k(-K_H^2) \left[\frac{\rho(k-1)(1+\rho(k-1))}{(1-\sigma)(1+\rho(k-1))} - \frac{\sigma(1+\rho(k-1))^2}{(1-\sigma)(1+\rho(k-1))} \right] \frac{dh}{d\sigma} \\ &= \delta n_2 m[\tau - D_{E_2}] \frac{de_2}{d\sigma} + \delta n_2 n_1 k(-K_H^2) \left[\frac{(\sigma^* - \sigma)(1+\rho(k-1))}{1-\sigma} \right] \frac{dh}{d\sigma}\end{aligned}\quad (51)$$

A.2.1 Second-best subsidy:

To calculate the second-best subsidy, I insert the elasticities defined in Section 4.1 into equation (50) and set it equal to zero, which gives:

$$\frac{dW}{d\sigma} = \delta n_2 m[\tau - D_{E_2}] \varepsilon_{\sigma}^{e_2} \frac{e_2}{\sigma} + \delta n_2 n_1 k(-K_H^2) \left[\frac{\rho(k-1) - \sigma(1+\rho(k-1))}{1-\sigma} \right] \varepsilon_{\sigma}^h \frac{h}{\sigma} = 0. \quad (52)$$

This equation can than be solved for σ to obtain the second-best policy given in equation (24). To determine the size of the second-best subsidy, I calculate the difference to the first-best and second-best subsidy, (24)-(17):

$$\sigma_{tax}^{**} - \sigma^* = \frac{E_2(\tau - D_{E_2})\varepsilon^{e_2}}{E_2(\tau - D_{e_2})\varepsilon_{\sigma}^{e_2} + kH(-K_H)\varepsilon_{\sigma}^h} > 0 \quad \text{if and only iff} \quad \tau < D_{E_2}, \quad (53)$$

and differentiate equation (24) with respect to emissions e_2 , and R&D knowledge h :

$$\frac{\partial \sigma_{tax}^{**}}{\partial e_2} = \frac{n_1 k h(-K_H)\varepsilon_{\sigma}^{e_2} E_2 \varepsilon_{\sigma}^h (\tau - D_{E_2})}{[E_2(\tau - D_{e_2})\varepsilon_{\sigma}^{e_2} + (1+\rho(k-1))n_1 H(-K_H)\varepsilon_{\sigma}^h]^2} > 0 \quad (54)$$

$$\frac{\partial \sigma_{tax}^{**}}{\partial h} = \frac{-E_2(\tau - D_{E_2})\varepsilon_{\sigma}^{e_2} n_1 k h(-K_H)\varepsilon_{\sigma}^h}{[E_2(\tau - D_{e_2})\varepsilon_{\sigma}^{e_2} + kH(-K_H)\varepsilon_{\sigma}^h]^2} < 0 \quad (55)$$

if and only if $\tau < D_{E_2}$, which is the definition of a second-best tax. Furthermore, let's define $D_{E_2} - \tau := \Delta^{\tau} > 0$ and differentiate equation (24) with respect to Δ^{τ} :

$$\frac{\partial \sigma_{tax}^{**}}{\partial \Delta^{\tau}} = \frac{n_1 k h(-K_H)\varepsilon_{\sigma}^h (-E_2 \varepsilon_{\sigma}^{e_2})}{[kH(-K_H)\varepsilon_{\sigma}^h - (E_2 \Delta^{\tau} \varepsilon_{\sigma}^{e_2})]^2} > 0 \quad (56)$$

A.3 Comparative Statics Emission Cap

For the comparative statics analysis, I totally differentiated equations (2)-(3), (6)-(7), (9), and (10) with respect to the R&D subsidy σ . Since I now have an emission cap, I assume that $de_t/d\sigma \stackrel{!}{=} 0$. Since this is the only change compared to the comparative statics effects in the presence of an emission tax, only the equations of the dirty sector change and all else remains the same. Therefore, I only

give you below the new equations:

$$\frac{dp_1}{d\sigma} = C_{q_1^d q_1^d}^1 \frac{dq_1^d}{d\sigma} \quad (57)$$

$$\frac{dp_2}{d\sigma} = C_{q_2^d q_2^d}^2 \frac{dq_2^d}{d\sigma} \quad (58)$$

$$\frac{d\tau_1}{d\sigma} = -C_{q_1^d e_1}^1 \frac{dq_1^d}{d\sigma} \quad (59)$$

$$\frac{d\tau_2}{d\sigma} = -C_{q_2^d e_2}^2 \frac{dq_2^d}{d\sigma} \quad (60)$$

I solve the set of equations for the comparative static effects. Again I separate the analysis of the nominator and the denominator. The denominator is given by:

$$\begin{aligned} det_{cap} = & \left(K_{q_1^c q_1^c} C_{q_1^d q_1^d} - U_{qq} (k C_{q_1^d q_1^d} + m K_{q_1^c q_1^c}) \right) \left(\delta n_2 (K_{q_2^c h})^2 (m U_{qq} - C_{q_2^d q_2^d}) \right. \\ & \left. + (K_{q_2^c q_2^c} C_{q_2^d q_2^d} - (U_{qq} (k C_{q_2^d q_2^d} + m K_{q_2^c q_2^c})) (\delta n_2 K_{hh} + n_1 (1 - \sigma) R_{hh}) \right) \end{aligned} \quad (61)$$

and the nominators are:

$$\frac{dp_1}{d\sigma} = \frac{dq_1^d}{d\sigma} = \frac{dq_1^c}{d\sigma} = \frac{dq_1}{d\sigma} = \frac{d\tau_1}{d\sigma} = 0 \quad (62)$$

$$\frac{dp_2}{d\sigma} = K_{q_2 h} C_{q_2^d q_2^d} k R_h U_{qq} (-K_{q_1^c q_1^c} C_{q_1^d q_1^d} + C_{q_1^d q_1^d} k U_{qq} + K_{q_1^c q_1^c} m U_{qq}) \quad (63)$$

$$\frac{dq_2^d}{d\sigma} = K_{q_2 h} k R_h U_{qq} (-K_{q_1^c q_1^c} C_{q_1^d q_1^d} + C_{q_1^d q_1^d} k U_{qq} + K_{q_1^c q_1^c} m U_{qq}) \quad (64)$$

$$\frac{dq_2^c}{d\sigma} = K_{q_2 h} R_h (C_{q_2^d q_2^d} - m U_{qq}) (-K_{q_1^c q_1^c} C_{q_1^d q_1^d} + C_{q_1^d q_1^d} k U_{qq} + K_{q_1^c q_1^c} m U_{qq}) \quad (65)$$

$$\frac{dQ_2}{d\sigma} = K_{q_2 h} C_{q_2^d q_2^d} k R_h (-K_{q_1^c q_1^c} C_{q_1^d q_1^d} + C_{q_1^d q_1^d} k U_{qq} + K_{q_1^c q_1^c} m U_{qq}) \quad (66)$$

$$\frac{dh}{d\sigma} = -R_h (-K_{q_1^c q_1^c} C_{q_1^d q_1^d} + C_{q_1^d q_1^d} k U_{qq} + K_{q_1^c q_1^c} m U_{qq}) (K_{q_2^c q_2^c} C_{q_2^d q_2^d} - C_{q_2^d q_2^d} k U_{qq} - K_{q_2^c q_2^c} m U_{qq}) \quad (67)$$

$$\frac{d\tau_2}{d\sigma} = -K_{q_2 h} C_{q_2^d e_2} k R_h U_{qq} (-K_{q_1^c q_1^c} C_{q_1^d q_1^d} + C_{q_1^d q_1^d} k U_{qq} + K_{q_1^c q_1^c} m U_{qq}) \quad (68)$$

B Numerical

This section provides the quantity changes resulting from a 1% increase in the R&D subsidy for varying stringency of both an emission tax and emission cap for the baseline calibration (Table 10), for different spillover rates (Table 11) and assuming different baseline R&D subsidy rates (Table 12).

Table 10: The quantity effect of a 1% increase in the R&D subsidy across environmental policy scenarios.

Tax	Patents	Renewable output (kWh)	Non-renewable output (kWh)	Emissions (tCO ₂)	Electricity output (kWh)	Electricity price (€/kWh)	Welfare (€)
<i>No</i>	105.35	3.37×10^8	-2.89×10^8	-99141.80	4.79×10^7	-2.11×10^{-5}	1.12×10^8
<i>Suboptimal</i>	113.38	3.62×10^8	-3.11×10^8	-106696.00	5.15×10^7	-2.27×10^{-5}	1.17×10^8
<i>Optimal</i>	121.40	3.88×10^8	-3.33×10^8	-114250.00	5.52×10^7	-2.43×10^{-5}	1.21×10^8
<i>Excessive</i>	129.43	4.13×10^8	-3.55×10^8	-121804.00	5.88×10^7	-2.59×10^{-5}	1.24×10^8
Cap	Patents	Renewable output (kWh)	Non-renewable output (kWh)	Emissions price (€/tCO ₂)	Electricity output (kWh)	Electricity price (€/kWh)	Welfare (€)
<i>Suboptimal</i>	112.55	2.56×10^8	-1.93×10^8	-0.37	6.39×10^7	-2.89×10^{-5}	1.94×10^8
<i>Optimal</i>	120.51	2.75×10^8	-2.06×10^8	-0.39	6.84×10^7	-3.01×10^{-5}	1.94×10^8
<i>Excessive</i>	128.48	2.93×10^8	-2.20×10^8	-0.42	7.29×10^7	-3.21×10^{-5}	1.94×10^8

Table 11: The effect of a 1% increase in the R&D subsidy in the presence of a first-best environmental policy with different R&D subsidy levels.

Tax	Patents	Renewable output (kWh)	Non-renewable output (kWh)	Emissions (tCO ₂)	Electricity output (kWh)	Electricity price (€/kWh)	Welfare (€)
$\rho = 0.3$	120.81	2.70×10^8	-2.32×10^8	-79564.60	3.84×10^7	-1.69×10^{-5}	5.97×10^8
$\rho = 0.5$	121.40	3.88×10^8	-3.33×10^8	-114250.00	5.52×10^7	-2.43×10^{-5}	1.21×10^8
$\rho = 0.7$	121.97	5.00×10^8	-4.29×10^8	-147337.00	7.11×10^7	-3.13×10^{-5}	1.82×10^8
Cap	Patents	Renewable output (kWh)	Non-renewable output (kWh)	Emissions price (€/tCO ₂)	Electricity output (kWh)	Electricity price (€/kWh)	Welfare (€)
$\rho = 0.3$	120.18	1.90×10^8	-1.43×10^8	-0.27	4.73×10^7	-2.08×10^{-5}	5.93×10^7
$\rho = 0.5$	120.51	2.75×10^8	-2.06×10^8	-0.39	6.84×10^7	-3.01×10^{-5}	1.20×10^8
$\rho = 0.7$	120.83	3.56×10^8	-2.68×10^8	-0.51	8.87×10^7	-3.90×10^{-5}	1.81×10^8

Table 12: The effect of a 1% increase in the R&D subsidy in the presence of a first-best environmental policy with different R&D subsidy levels.

Tax	Patents	Renewable output (kWh)	Non-renewable output (kWh)	Emissions (tCO ₂)	Electricity output (kWh)	Electricity price (€/kWh)	Welfare (€)
$\sigma = 0.25$	90.28	6.27×10^8	-5.38×10^8	-184759.00	8.92×10^7	-3.92×10^{-5}	2.52×10^8
$\sigma = 0.45$	121.40	3.88×10^8	-3.33×10^8	-114250.00	5.52×10^7	-2.43×10^{-5}	1.21×10^8
$\sigma = 0.65$	191.17	2.83×10^8	-2.43×10^8	-83401.00	4.02×10^7	-1.77×10^{-5}	5.60×10^7
$\sigma = 0.80$	340.76	2.40×10^8	-2.06×10^8	-70593.00	3.41×10^7	-1.50×10^{-5}	-2.91×10^6
Cap	Patents	Renewable output (kWh)	Non-renewable output (kWh)	Emissions price (€/tCO ₂)	Electricity output (kWh)	Electricity price (€/kWh)	Welfare (€)
$\sigma = 0.25$	88.94	4.56×10^8	-3.42×10^8	-0.65	1.13×10^8	-4.99×10^{-5}	2.48×10^8
$\sigma = 0.45$	120.51	2.75×10^8	-2.06×10^8	-0.39	6.84×10^7	-3.01×10^{-5}	1.20×10^8
$\sigma = 0.65$	190.49	1.98×10^8	-1.49×10^8	-0.28	4.94×10^7	-2.17×10^{-5}	5.58×10^7
$\sigma = 0.65$	340.76	1.67×10^8	-1.25×10^8	-0.24	4.16×10^7	-1.83×10^{-5}	-2.90×10^6

References

- Acemoglu, D., Aghion, P., Bursztyn, L., & Hémous, D. (2012). The environment and directed technical change. *American Economic Review*, 102(1), 131–166. <https://doi.org/10.1257/aer.102.1.131>
- Acemoglu, D., Akcigit, U., Hanley, D., & Kerr, W. (2016). Transition to clean technology. *Journal of Political Economy*, 124(1), 52–104. <https://doi.org/10.1086/684511>
- Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., & van Reenen, J. (2016). Carbon taxes, path dependency, and directed technical change: Evidence from the auto industry. *Journal of Political Economy*, 124(1), 1–51. <https://www.jstor.org/stable/26549857>
- Alam, M. S., Apergis, N., Paramati, S. R., & Fang, J. (2021). The impacts of r&d investment and stock markets on clean-energy consumption and co 2 emissions in oecd economies. *International Journal of Finance & Economics*, 26(4), 4979–4992. <https://doi.org/10.1002/ijfe.2049>
- Alam, M. S., Atif, M., Chien-Chi, C., & Soytaş, U. (2019). Does corporate r&d investment affect firm environmental performance? evidence from g-6 countries. *Energy Economics*, 78, 401–411. <https://doi.org/10.1016/j.eneco.2018.11.031>
- Andersson, J. J. (2019). Carbon taxes and co2 emissions: Sweden as a case study. *American Economic Journal: Economic Policy*, 11(4), 1–30. <https://doi.org/10.1257/pol.20170144>
- Ang, G., Röttgers, D., & Burli, P. (2017). The empirics of enabling investment and innovation in renewable energy. *OECD Environment Working Papers*, (123). <https://doi.org/10.1787/67d221b8-en>
- Bento, N., Borello, M., & Gianfrate, G. (2020). Market-pull policies to promote renewable energy: A quantitative assessment of tendering implementation. *Journal of Cleaner Production*, 248, 119209. <https://doi.org/10.1016/j.jclepro.2019.119209>
- Carley, S., Baldwin, E., MacLean, L. M., & Brass, J. N. (2017). Global expansion of renewable energy generation: An analysis of policy instruments. *Environmental and Resource Economics*, 68(2), 397–440. <https://doi.org/10.1007/s10640-016-0025-3>
- Cludius, J., de Bruyn, S., Schumacher, K., & Vergeer, R. (2020). Ex-post investigation of cost pass-through in the eu ets - an analysis for six industry sectors. *Energy Economics*, 91, 104883. <https://doi.org/10.1016/j.eneco.2020.104883>
- Coria, J., & Jaraite, J. (2024). The role of environmental policy and public innovation subsidies in promoting green patenting in sweden (Swedish Agency for Growth Policy Analysis, Ed.; WP 2024:03).
- Costantini, V., Crespi, F., & Palma, A. (2017). Characterizing the policy mix and its impact on eco-innovation: A patent analysis of energy-efficient technologies. *Research Policy*, 46(4), 799–819. <https://doi.org/10.1016/j.respol.2017.02.004>

- Dechezleprêtre, A., Fabre, A., Kruse, T., Planterose, B., Sanchez Chico, A., & Stantcheva, S. (2022). Fighting climate change: International attitudes toward climate policies.
- EEA. (2024). Greenhouse gas emission intensity of electricity generation. <https://www.eea.europa.eu/en/analysis/maps-and-charts/co2-emission-intensity-15/@@download/file>
- EPA. (2023). Report on the social cost of greenhouse gases: Estimates incorporating recent scientific advances (U.S. Environmental Protection Agency, Ed.).
- European Commission. (2015). Capacity mapping: R&d investment in set-plan technologies.
- European Commission. (2023). Communication: A green deal industrial plan for the net-zero age (European Commission, Ed.).
- Eurostat. (2022a). Electricity prices for household consumers - bi-annual data (from 2007 onwards). <https://doi.org/10.2908/NRG{\textunderscore}PC{\textunderscore}204>
- Eurostat. (2022b). Gross and net production of electricity and derived heat by type of plant and operator. <https://doi.org/10.2908/NRG{\textunderscore}IND{\textunderscore}PEH>
- Fischer, C., Hübner, M., & Schenker, O. (2021). More birds than stones – a framework for second-best energy and climate policy adjustments. *Journal of Public Economics*, 203, 104515. <https://doi.org/10.1016/j.jpubeco.2021.104515>
- Fischer, C., & Newell, R. G. (2008). Environmental and technology policies for climate mitigation. *Journal of Environmental Economics and Management*, 55(2), 142–162. <https://doi.org/10.1016/j.jeem.2007.11.001>
- Gasser, M., Pezzutto, S., Sparber, W., & Wilczynski, E. (2022). Public research and development funding for renewable energy technologies in europe: A cross-country analysis. *Sustainability*, 14(9), 5557. <https://doi.org/10.3390/su14095557>
- Grossman, G. M., & Helpman, E. (1991). Trade, knowledge spillovers, and growth. *European Economic Review*, 35(2), 517–526. [https://doi.org/10.1016/0014-2921\(91\)90153-A](https://doi.org/10.1016/0014-2921(91)90153-A)
- Hille, E., Althammer, W., & Diederich, H. (2020). Environmental regulation and innovation in renewable energy technologies: Does the policy instrument matter? *Technological Forecasting and Social Change*, 153, 119921. <https://doi.org/10.1016/j.techfore.2020.119921>
- IEA. (2021). Net zero by 2050 - a roadmap for the global energy sector. <https://www.iea.org/reports/net-zero-by-2050>
- IEA. (2023). Energy technology perspectives 2023. <https://www.iea.org/reports/energy-technology-perspectives-2023>
- IEA. (2025). Energy technology rd&d budgets. <https://www.iea.org/data-and-statistics/data-product/energy-technology-rd-and-d-budget-database-2>
- IRENA. (2025). Inspire platform. www.irena.org/INSPIRE

- Jaffe, A. B., Newell, R. G., & Stavins, R. N. (2005). A tale of two market failures: Technology and environmental policy. *Ecological Economics*, 54(2), 164–174. <https://doi.org/10.1016/j.ecolecon.2004.12.027>
- Johnstone, N., Haščič, I., & Popp, D. (2010). Renewable energy policies and technological innovation: Evidence based on patent counts. *Environmental and Resource Economics*, 45(1), 133–155. <https://doi.org/10.1007/s10640-009-9309-1>
- Jones, C. I., & Williams, J. C. (1998). Measuring the social return to r&d. *The Quarterly Journal of Economics*, 113(4), 1119–1135. <https://doi.org/10.1162/0033553985555856>
- Meissner, L. P. (2024). A case for promoting negative emission technologies: Learning from renewable energy support. *Carbon Management*, 15(1). <https://doi.org/10.1080/17583004.2024.2319787>
- Meissner, L. P., Peterson, S., & Semrau, F. O. (2024). It’s not a sprint, it’s a marathon: Reviewing governmental r&d support for environmental innovation. *Journal of Environmental Planning and Management*, 1–27. <https://doi.org/10.1080/09640568.2024.2359442>
- Newell, R. G., Jaffe, A. B., & Stavins, R. N. (1999). The induced innovation hypothesis and energy-saving technological change. *The Quarterly Journal of Economics*, 114(3), 941–975. <https://doi.org/10.1162/003355399556188>
- Noailly, J., & Shestalova, V. (2017). Knowledge spillovers from renewable energy technologies: Lessons from patent citations. *Environmental Innovation and Societal Transitions*, 22, 1–14. <https://doi.org/10.1016/j.eist.2016.07.004>
- Paramati, S. R., Alam, M. S., Hammoudeh, S., & Hafeez, K. (2021). Long-run relationship between r&d investment and environmental sustainability: Evidence from the european union member countries. *International Journal of Finance & Economics*, 26(4), 5775–5792. <https://doi.org/10.1002/ijfe.2093>
- Plank, J., & Doblinger, C. (2018). The firm-level innovation impact of public r&d funding: Evidence from the german renewable energy sector. *Energy Policy*, 113, 430–438. <https://doi.org/10.1016/j.enpol.2017.11.031>
- Polzin, F., Migendt, M., Täube, F. A., & von Flotow, P. (2015). Public policy influence on renewable energy investments—a panel data study across oecd countries. *Energy Policy*, 80, 98–111. <https://doi.org/10.1016/j.enpol.2015.01.026>
- Reichenbach, J., & Requate, T. (2012). Subsidies for renewable energies in the presence of learning effects and market power. *Resource and Energy Economics*, 34(2), 236–254. <https://doi.org/10.1016/j.reseneeco.2011.11.001>
- Requate, T., & Unold, W. (2003). Environmental policy incentives to adopt advanced abatement technology: Will the true ranking please stand up? *European Economic Review*, 47(1), 125–146. [https://doi.org/10.1016/S0014-2921\(02\)00188-5](https://doi.org/10.1016/S0014-2921(02)00188-5)

- Ricke, K., Drouet, L., Caldeira, K., & Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, 8(10), 895–900. <https://doi.org/10.1038/s41558-018-0282-y>
- Sandbag. (Feb. 2025). Carbon price viewer. <https://sandbag.be/carbon-price-viewer/>
- Shahbaz, M., Nasir, M. A., Hille, E., & Mahalik, M. K. (2020). Uk’s net-zero carbon emissions target: Investigating the potential role of economic growth, financial development, and r&d expenditures based on historical data (1870–2017). *Technological Forecasting and Social Change*, 161, 120255. <https://doi.org/10.1016/j.techfore.2020.120255>
- The White House. (2023). Building a clean energy economy: A guidebook to the inflation reduction act’s investment in clean energy and climate action (The White House, Ed.).
- Wang, N., & Hagedoorn, J. (2014). The lag structure of the relationship between patenting and internal r&d revisited. *Research Policy*, 43(8), 1275–1285. <https://doi.org/10.1016/j.respol.2014.03.010>