The Unintended Consequences of Carbon Markets

Lior Shabtai*

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Abstract

This paper shows that carbon markets create inefficiently weak incentives for green innovation in hard-to-abate industries by allowing firms to rely on purchasing emission allowances rather than independently decarbonizing. A triple-difference analysis of the heterogeneous effect of the EU Emissions Trading System (EU-ETS) on green innovation shows that the rise in green patenting is concentrated among easy-to-abate firms, which innovate at three times the rate of hard-to-abate firms. A directed technical change model of a carbon market with sectoral differences in abatement costs shows that carbon markets inefficiently direct most innovation efforts toward decarbonizing the easy-to-abate sector. Socially optimal sector-specific research subsidies redirect innovation toward a clean transition in the hard-to-abate sector and increase welfare by up to 5.8%. These subsidies need to be up to three times larger (in present value) than those provided to innovators in the easy-to-abate sector.

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Kellogg School of Management, Northwestern University. Email: lior.shabtai@kellogg.northwestern.edu

1 Introduction

Carbon pricing has been established as a key mechanism in the global decarbonization effort. To curb climate change, governments have implemented a variety of carbon pricing mechanisms, such as carbon taxes and carbon markets, with carbon markets emerging as the preferred approach, covering 18% of global emissions, which is 75% of emissions currently subject to pricing (World Bank 2024). Carbon markets operate by enforcing an emissions cap and allowing firms to trade emission allowances. Emissions trading relies on differences in abatement costs between firms and industries, integrating sectors with varying technological challenges. Firms in hard-to-abate industries (such as steel, cement, and chemicals) can purchase allowances from firms in easier-to-abate industries (such as power generation and light industry), creating gains from trade and concentrating emissions reduction where they are most cost-effective.

However, the very structure that facilitates cost-efficiency may also create a dynamic inefficiency: because participants can comply by purchasing emission allowances, hard-to-abate firms may meet regulatory obligations without adopting new production technologies, weakening their incentives to develop clean production methods. This distortion in innovation incentives could undermine the efficiency of the clean transition and may jeopardize timely progress toward climate neutrality. Despite the widespread adoption of carbon markets, this potential distortion remains unexplored.

This paper fills this gap by investigating, empirically and theoretically, the differential effect of carbon markets on green innovation and decarbonization across easy- and hard-to-abate industries. The empirical analysis focuses on the European Union Emissions Trading System (EU-ETS), which is the first and largest carbon market. I use a triple difference approach to analyze how carbon markets affect innovation in easy- versus hard-to-abate industries. Patenting activity serves as a measure of innovation, with 'green' patents identified using the Y02 category of the Cooperative Patent Classification (CPC) for "technologies or applications for mitigation or adaptation against climate change". I compare green innovation activity of firms regulated by the EU-ETS (EU-ETS firms) to those that are not (non EU-ETS firms) across easy- and hard-to-abate industries, in the pre- and post-policy periods. The findings show that the effect of the EU-ETS on innovation is centered in easy-to-abate firms, which increase green innovation at 3 times the rate compared to hard-to-abate firms. Using forward citations as a measure of innovation quality, I document a similar heterogeneous effect of the EU-ETS on the *quality* of green innovation. Finally, installations operated by easy-to-abate firms reduced emissions at an

annual rate almost twice as high as that of their hard-to-abate counterparts.

The reduced-form analysis alone cannot speak to the efficiency implications of the results. I therefore develop a directed technical change model to assess how the structure of carbon markets influences the efficiency of the global decarbonization effort in the presence of sectoral heterogeneity in abatement costs. The model builds on the canonical framework of directed technical change and the environment developed by Acemoglu et al. (2012). A representative household consumes a final good composed of two intermediary goods: an easy-to-abate and a hard-to-abate good, which are produced in separate sectors that differ in their cost of decarbonization. The heterogeneity in the cost of abatement stems from initial technological gaps. Each sector uses a mix of two substitutable inputs: a common 'dirty' input (fossil fuels) and a sector-specific 'clean' input (non-emitting production methods). The use of the dirty input generates carbon emissions, exacerbating global temperature increase and creating dis-utility to the household. Scientists, representing innovation efforts, consider expected profits and decide each period in which of the three input sectors to innovate (the dirty input, or one of the two sector-specific clean ones). Successful scientists improve the average technological level of the input sector of their choice and advance its innovation possibilities frontier. Climate policy operates through a declining emissions cap enforced by a carbon market. The rate at which the cap decreases reflects the rigidity of the policy and determines the pace of decarbonization. Each year, producers of intermediary goods are subject to an emissions cap and can trade emission allowances, generating a market price for carbon.

The model calibration compares the dynamics of the energy transition under (1) a carbon market whose rigidity matches climate neutrality by 2050 ambitions, with (2) the transition under the same conditions supplemented by optimally designed sector-specific research subsidies. Research subsidies increase expected returns for innovators in a given sector, redirecting innovation efforts to maximize welfare subject to the carbon market's rigidity. Calibration results of the first scenario provide theoretical support for the empirical findings: carbon markets disproportionately direct innovation toward the clean easy-to-abate sector, leaving clean hard-to-abate production technology underdeveloped. Furthermore, the model predicts a slower transition in the hard-to-abate sector. The addition of optimal sector-specific research subsidies shows that these dynamics are inefficient. In contrast with the empirical findings, the policymaker uses research subsidies to immediately draw innovation efforts to the clean hard-to-abate sector. These subsidies need to be up to 239% higher (depending on the specification) in present value than those

provided to scientists innovating in the clean easy-to-abate sector. This accelerates decarbonization and the transition to clean production in the hard-to-abate sector through advancement of clean technology and reduces the reliance on carbon trading. As a result, a prolonged stagnation in hard-to-abate intermediary good production - driven by rigid climate policy and a technological lag in clean technology - is mitigated, yielding welfare gains of up to 5.8% in consumption-equivalent terms.

These findings underscore the key role sectoral heterogeneity in abatement costs plays in our understanding of the economic effects of climate policy. Although carbon markets achieve cost-effective emissions reduction, they alone cannot ensure an efficient energy transition. Policymakers should prioritize support for clean innovation in hard-to-abate industries, where the incentives provided by carbon markets are inefficiently weak. However, suggestive evidence shows that climate finance flows are misaligned: as shown in Table 1, in recent years (2019-2022) easy-to-abate industries ("Energy Systems" in Table 1) benefited from substantially higher levels of public investment, with \$12.8 invested per ton of CO_2 emissions compared to just \$0.9 per ton for hard-to-abate industries ("Industry"). Correcting this disparity is critical to foster an efficient path to climate neutrality.

This paper builds on the theoretical literature on directed technical change and the environment. Acemoglu et al. (2012) and Acemoglu et al. (2016) find that a combination of short-lived subsidies and carbon taxes can trigger a transition to clean production, thereby preventing an environmental disaster. Aghion et al. (2024) study green technological transition along the supply chain, showing that even with Pigouvian taxes, targeted industrial policies are essential to avoiding inefficient steady states. Jo & Karydas (2022) shows that climate policy induces the exit of emission-intensive firms, increasing the average elasticity of substitution between clean and dirty inputs and lowering the carbon tax required for decarbonization.[1] This paper contributes to this literature by examining how carbon markets, the predominant carbon pricing mechanism, affect the direction of clean innovation. I develop a directed technical change model with a cap-and-trade system and show that emission allowance trading, combined with sectoral differences in abatement costs, inefficiently focus innovation resources in the easy-to-abate sector. The paper underscores the importance of efficiently setting research subsidies *at the sector level*, as targeted clean research subsidies to hard-to-abate industries can offset this distortion.

A large body of literature studies the impact of climate policy on directing innova-

[1]See also, for example, Acemoglu et al. (2014), Hémous (2016), Van den Bijgaart (2017), Shanker & Stern (2018), Fried (2018), Hassler et al. (2021) and Acemoglu et al. (2023). For reviews of the literature, see Hémous & Olsen (2021) and Dechezleprêtre & Hémous (2022).

tion toward clean production, and shows that climate policy can induce clean innovation (Popp (2002) and Aghion et al. (2016)). This paper is related mainly to studies of the effect of emissions trading schemes on green innovation. Calel & Dechezleprêtre (2016) and Calel (2020) provide causal evidence that the EU-ETS increased low-carbon innovation among regulated firms.[2] This paper extends this literature by showing that while the EU-ETS leads to an overall increase in green innovation, the effect is inefficiently weak in hard-to-abate industries.

This paper also contributes to the literature on the effectiveness of carbon markets. Bayer & Aklin (2020) show that the EU-ETS significantly reduced CO_2 emissions by acting as a credible institution capable of tightening over time, even with lower-than-expected carbon prices. Dechezleprêtre et al. (2023) and Colmer et al. (2024) find that the EU-ETS achieved sizable emissions reductions among regulated firms without harming economic performance. Akey et al. (2024) show that while EU-ETS firms with voluntary commitments reduce their own emissions, they subsequently sell surplus allowances, offsetting the reductions and undermining the net impact of private climate initiatives. I document that while total emissions fall among EU-ETS firms, reductions are concentrated in easy-to-abate industries, which decarbonize faster as a result of lower abatement costs.

The remainder of the paper is organized as follows. Section 2 provides institutional background on the EU-ETS and easy- and hard-to-abate industries. Section 3 outlines the data used in the empirical analysis, and Section 4 presents the empirical framework and results. Section 5 introduces the theoretical model, Section 6 presents calibration results, and Section 7 concludes.

2 Institutional Background

2.1 The EU Emissions Trading System

The EU Emissions Trading System (EU-ETS) is the first and largest carbon market currently operating. Following a pilot phase (2005-2007), the market began full operation in 2008 as the cornerstone of the EU's climate policy. It covers emissions from power plants, industrial facilities, aviation (since 2012), and maritime transport (since 2024), which together account for approximately 40% of total greenhouse gas emissions. Installations from all EU countries participate, as well as installations from the United Kingdom (until

[2]See also Lucena-Giraldo et al. (2022), Ren et al. (2022) and Rastegar et al. (2024) for a literature review.

2020), Iceland, Liechtenstein, and Norway. Under this cap-and-trade system, participants receive or purchase allowances to emit CO_2, and those that emit less than their allowances can sell the surplus to firms facing higher abatement costs, promoting a cost-effective allocation of emissions reductions. Firms exceeding their allowances must purchase additional ones or face penalties that have always been higher than the market price of emissions (See more details in European Commission (2024) Chapter 2).

The introduction of the EU Emissions Trading System (EU-ETS) marked a transformative shift in EU climate policy, replacing the fragmented and incomplete landscape of sector-specific and country-specific instruments with a unified mechanism. Before the EU-ETS, Denmark, Finland, the Netherlands, Norway, Poland, and Sweden implemented carbon taxes in the 1990s, targeting various industries (Martinsson et al. (2024)). In contrast, many member states, such as France, Spain and the UK, did not implement any carbon pricing mechanism prior to the establishment of the EU-ETS (see Online Appendix A of Metcalf & Stock (2023)). The European Commission's debates on the EU's Kyoto Protocol commitment to reduce GHG emissions by 8% by 2012 (compared to 1990 levels) highlight the limitations of disparate national policies. A harmonized, EU-wide emissions trading system was viewed as a superior approach to ensuring cost-effective and coordinated compliance.[3]

Inclusion in the EU-ETS is based on production capacity thresholds, capturing large emitters while balancing administrative efficiency. For example, power plants and industrial installations with a thermal input greater than 20 megawatts are included, along with iron and steel producers exceeding production capacity of 2.5 tons of pig iron or steel per hour.[4]

Initially, most allowances were freely allocated to ease the transition and mitigate carbon leakage - the risk of production moving to regions with weaker climate policies. Over time, the system shifted toward auction-based allocation. However, to maintain global competitiveness, participants in hard-to-abate industries continue to receive a diminishing share of free allowances, which remain substantial and counteract policy stringency.[5] This factor is a potential confounder in my analysis, which I address by controlling for emissions to free allowances ratio, as discussed in Section 4.

[3]See Document 52000DC0087 dated March 8, 2000, on EUR-Lex (Accessed on 01/20/2025).

[4]The complete list of inclusion criteria and activity-level thresholds (when applicable) can be found in Directive 2003/87/EC of the European Parliament and of the Council and its amendments (Accessed on 01/21/2025).

[5]See Commission Decision 2011/278/EU (Accessed on 01/20/2025) dated April 27, 2011 for further details).

Now in its fourth phase (2021-2030), the EU-ETS continues to evolve, with reforms aimed at reducing free allowances and aligning the system with the European Green Deal. The inclusion of additional sectors, such as maritime transport (starting in January 2024), reflects ongoing efforts to expand the scope of the EU-ETS and support the EU's goal of achieving climate neutrality by 2050.

The design of the EU-ETS guides the triple difference analysis in this paper. First, the structure of the inclusion criteria creates within-industry variation between regulated and unregulated firms, providing the basis for a difference in differences analysis (Calel & Dechezleprêtre (2016) and Dechezleprêtre et al. (2023)), comparing EU-ETS and non EU-ETS firms, before and after the introduction of the market. Together with the inclusion of a wide range of industries with differences in the cost of abatement, the EU-ETS is well-suited for a triple difference analysis that studies the heterogeneous effect of the EU-ETS on easy- versus hard-to-abate industries.

2.2 Easy and Hard to Abate Industries

Industries can be broadly categorized based on their abatement potential, reflecting the ease or difficulty of reducing greenhouse gas emissions in their operations. Hard-to-abate sectors, such as steel, cement, chemicals, oil and heavy transportation, account for roughly 40% of global emissions (World Economic Forum (2024)). Their reliance on energy-intensive processes and fossil fuels makes decarbonization particularly challenging. In contrast, easy-to-abate sectors, such as electricity generation and light industry, contribute a smaller share of total emissions per unit of output and face fewer barriers to implementing emission reduction given existing technologies.

The fundamental difference between easy- and hard-to-abate industries lies in the nature of their emissions and the feasibility of reducing them. Hard-to-abate producers, and particularly heavy manufacturers, often emit *process* emissions, which are byproducts of chemical reactions in production, such as the release of CO_2 from calcination in cement production or from iron ore reduction (into pig iron) in steelmaking. These emissions cannot simply be reduced by switching to renewable energy or improving efficiency, and require the development of breakthrough technologies such as non-lime based cement production methods or green hydrogen-based steelmaking. (Appendix A provides a detailed discussion of the technological landscape of the largest hard-to-abate industries). By contrast, easy-to-abate industries can reduce emissions by switching to renewables, which experienced rapid development in the previous decades. In this paper I show that

this distinction is critical for climate policy, as carbon markets tend to incentivize accelerated emissions reduction and increased green innovation in easy-to-abate sectors, leading to weaker incentives for decarbonization and innovation in hard-to-abate industries.

3 Data

This section details the data sources and the construction of the sample. The main sample used in the empirical section includes information on innovation activity of European firms in 2000-2020 in key industries that are regulated by the EU-ETS.

3.1 Data Sources

I construct the sample using two main data sources: (1) the EU Transaction Log (EUTL) provides information on participation in the EU-ETS and installation-level emissions; and (2) the World Patent Statistical Database (PATSTAT) provides patent information that are used to construct firm-level measures of green innovation activity.

EU Transaction Log (EUTL) The European Union Transaction Log (EUTL) tracks compliance behavior of installations that participate in the EU-ETS.[6] For each installation, the EUTL documents the yearly emissions and the amount of emission allowances that are freely allocated. In addition, the EUTL includes information on the accounts that manage the compliance of installations, allowing for a match with other data sources at the firm level. This provides a comprehensive list of all firms that operate EU-ETS installations, as well as information on annual emissions and free allocation at the installation level.

Patent Data I use patenting as a measure of innovation activity, with the European Patent Office (EPO)'s PATSTAT serving as the primary data source (European Patent Office (2025)). I extract all patents filed by firms registered in countries participating in the EU-ETS between 2000 and 2020. To identify "green" patents, I follow established literature (e.g., Calel & Dechezleprêtre (2016)) and use the Y02 category of the CPC classification, which covers "technologies or applications for mitigation or adaptation against climate change." (Cooperative Patent Classification (2025)). I focus on Y02 subcategories

[6] Data are accessed through euets.info. See Abrell (2021) and https://union-registry-data.ec.europa.eu/report/welcome for further details.

related to electricity generation, energy efficiency, production processes, and carbon capture, utilization, and storage (CCUS).[7]

3.2 Matching and Sample Construction

Matching To create a firm-level panel data, including patenting activity and classification of firms by exposure to climate policy through the EU-ETS, I match the patent data with the EUTL data. I first transform the patent data from patent level into firm-year level using the OECD Harmonized Applicant Name database (HAN database) that is constructed to standardize names of patentees for the purpose of matching PATSTAT to firm-level data (OECD (2020)). To avoid double counting of an invention that is filed multiple times (in different countries or due to slight variations of the technology), patent applications are grouped into patent families (Dugoua & Gerarden (2025)). The patent data are then matched to a list of Orbis Large or Very Large firms ((1) operational revenue $\geq$ €10 million; (2) total assets $\geq$ €20 million; or (3) number of employees $\geq$ 150), to avoid over-representation of small firms in the non EU-ETS firm sub-sample due to the inclusion criteria of EU-ETS discussed in Section 2.1 (Bureau van Dijk (2024)). The matching process involves pre-cleaning and standardization of firm names, followed by a stepwise matching procedure using exact and fuzzy matching techniques, employing LinkTransformer (Arora & Dell (2023)), a large language model (LLM) record linkage tool. Next, the firm-level panel is matched to the EUTL data, primarily relying on the crosswalk between EUTL and Orbis constructed by the Joint Research Centre (JRC) of the European Commission (Letout et al. (2021)). This is supplemented with the matching algorithm used to link PATSTAT and Orbis.

Sample Construction The main sample is constructed in the following steps. First, firms are considered to be in the treatment group if they operate at least one installation that participates in the EU-ETS. This definition follows the literature (e.g., Calel & Dechezleprêtre (2016)) and enables me to separate firms that are directly affected by the

[7] I classify patents as green if they fall under sub-categories Y02B (climate change mitigation technologies related to buildings), Y02C (capture, storage, sequestration, or disposal of greenhouse gases), Y02D (climate change mitigation technologies in information and communication technologies), Y02E (reduction of greenhouse gas emissions related to energy generation, transmission, or distribution), or Y02P (climate change mitigation technologies in the production or processing of goods). I do not consider patents with the classification code Y02T (climate change mitigation technologies related to transportation) as green, since patents related to sustainable transportation, such as electric vehicles, do not aim to reduce the direct emissions of the patenting firm.

introduction of the EU-ETS to those that are not.[8] To standardize firms across the treatment and control groups in terms of their patenting activity, I exclude firms that did not patent at least once in the pre- (2000-2007) and in the post- (2008-2020) periods. A robustness check relaxes this assumption and shows that the results hold (Section 4.1). Second, I exclude industries (at the 3-digit NACE code level) for which there are no firms in the control or treatment groups. Finally, following the discussion in Section 2.2, I consider power and light industry companies as Easy-to-Abate, and heavy industry and the oil industry as hard-to-abate.[9] The final sample includes 1,896 firms in 2000-2020, of which 478 firms are in the treatment group (EU-ETS firms). Tables 2 and 3 present the number of firms by country and industry, respectively. Notably, the tables indicate that despite including only large and very large firms (as explained above), most firms are non EU-ETS firms. In combination with the inclusion criteria discussed in 2.1, this motivates the exclusion of smaller firms.

4 Empirical Analysis

I start by documenting two stylized facts. First, easy-to-abate EU-ETS installations reduce emissions at twice the annual rate of their hard-to-abate counterparts. Second, the post-policy increase in green innovation is concentrated among easy-to-abate firms. These facts point to the two-sided effect of carbon markets. On the one hand, they promote cost-effective emissions reduction through carbon trading; On the other, they create weaker incentives for hard-to-abate firms to pursue the technological innovations necessary for clean production.

[8] When a parent firm has multiple subsidiaries, and at least one is treated, I classify the other subsidiaries that share the same 2-digit NACE code as treated. This approach aims to capture potential spillover effects within the parent firm. For instance, the Italian energy company ENEL has several subsidiaries, including ENEL Produzione, which operates at least one installation participating in the EU-ETS, and ENEL Green, which does not. Upon examining the data, it is evident that ENEL Green engages in green innovation activities, suggesting a spillover of the effect of the EU-ETS on green innovation through its relation to its sister company.

[9] Specifically, I consider NACE categories D35 (Electricity, gas, steam and air conditioning supply), C10 (Manufacture of food products), C11 (Manufacture of beverages), C12 (Manufacture of tobacco products), C29 (Manufacture of motor vehicles, trailers and semi-trailers) and C30 (Manufacture of other transport equipment) as Easy-to-Abate industries, and NACE categories B (Mining and quarrying), C17 (Manufacture of paper and paper products), C19 (Manufacture of coke and refined petroleum products), C20 (Manufacture of chemicals and chemical products), C23 (Manufacture of other non-metallic mineral products), C24 (Manufacture of basic metals) as hard-to-abate industries. Other industries are excluded from this study due to low participation in the EU-ETS (below 10% in the PATSTAT-EUTL matched dataset).

To analyze emissions reduction, I construct a panel dataset of all installations associated with the firms in the main sample constructed in Section 3.2 and estimate the following OLS regression:

$$\Delta log(emissions_{it}) = \alpha + \beta \cdot Hard_to_Abate_i + \gamma \cdot \Delta log(Free_Alloc_{it}) + \varepsilon_{it} \quad (1)$$

where $\Delta \log(emissions_{it})$ captures the annual percentage change in emissions of installation i, $Hard_to_Abate_i$ is a dummy variable set to 1 if the installation is operated by a hard-to-abate firm, and $\Delta \log(Free_Alloc_{it})$ is the annual percentage change in freely allocated emission allowances.

Table 4 presents the results of estimating Equation 1. Column (1), a univariate OLS regression excluding $\Delta \log(Free_Alloc_{it})$, shows that easy-to-abate installations reduce emissions at an average annual rate of 5.3%, whereas hard-to-abate installations reduce emissions at a significantly slower pace of 2.8% per year - roughly 50% slower. This finding remains of similar magnitude when controlling for $\Delta \log(Free_Alloc_{it})$ (Column (3)).

The second stylized fact regards green innovation. Figure 1 presents the trend in average *green* patenting per firm, comparing firms regulated by the EU-ETS to those that are not. The figure separates the sample into easy-to-abate industries (Panel A) and hard-to-abate industries (Panel B). Panel A shows a noticeable increase in green patenting activity among easy-to-abate firms covered by the EU-ETS following the system's full implementation in 2008. In contrast, hard-to-abate EU-ETS firms exhibit a much more modest increase. This pattern suggests that the EU-ETS may provide weaker incentives for clean innovation in hard-to-abate industries, motivating the empirical analysis presented below.

To identify the causal heterogeneous effect of the EU-ETS on green innovation, I employ a triple difference specification:

$$green_{it} = \alpha + \beta \cdot ETS_i \cdot Post_t \cdot Hard_i + \gamma \cdot ETS_i \cdot Post_t + \delta \cdot x_{it} + \phi_i + \theta_{ct} + \lambda_{jt} + \varepsilon_{it} \quad (2)$$

where $green_{it}$ is a measure of *green* innovation conducted by firm i in year t. The main outcome variable is a dummy variable equal to 1 if the firm files at least one green patent in a given year, capturing the extensive margin of green innovation (*engagement*). In Section 4.1, I show that the results are similar when the outcome captures the intensive margin of green innovation (*intensity*), measured as the number of green patents filed.

ETS_i is set to 1 for firms that are regulated by the EU-ETS (that is, operate at least one installation that participates in the EU-ETS), $Post_t$ is set to 1 for years after the full operation of the carbon market (2008),[10] and $Hard_i$ is set to 1 firms that operate in a hard-to-abate industry. The hypothesis is that the coefficient on the triple interaction term is negative $\beta < 0$, indicating that the post-policy difference in green innovation between treated and control firms is smaller within the hard-to-abate sector compared to within the easy-to-abate sector.

As discussed in Section 2.1, the European Commission has been using free allocation of emission allowances to reduce the abatement costs associated with the policy and alleviate the risk of carbon leakage, mainly for hard-to-abate industries. To account for this confounding factor, which in itself may disproportionately weaken green innovation incentives for hard-to-abate firms, I control (in x_{it}) for lagged emissions to free allocation ratio at the 2-digit (NACE) industry level.[11] To isolate the effect of the carbon market on innovation, I use a combination of high-dimensional fixed effects. Firm fixed effects (ϕ_i) are included to account for time-invariant firm characteristics that can influence clean innovation. Country-year fixed effects (θ_{ct}) capture time-varying country-specific determinants of firm green innovation, and specifically control for heterogeneity in energy input prices and supplementary carbon policies at the country-year level (such as the Swedish carbon tax system or other forms of country-level heterogeneity in carbon policy prior to the EU-ETS, as discussed in Section 2.1). Industry-year fixed effects (λ_{jt}) control for industry-specific characteristics or policies that vary over time and may influence green innovation such as the Trans-European Networks for Energy (TEN-E), which supports the integration of renewable energy in electricity production. The dimensionality of the data does not allow for controlling for country-industry-year fixed effects using the full sample. In Section 4.1 I present a robustness check with country-industry-year fixed effects restricting to the largest countries (Germany, France, Italy and the United Kingdom) and show that the findings are unchanged. Standard errors are clustered at the firm level.

Finally, the parallel trends identification assumption in this triple difference setting is that, in the absence of treatment, the difference in green innovation between treated and control firms would have evolved similarly across the easy- and hard-to-abate sec-

[10] The chemical industry was added in the third phase of the EU-ETS (2013-2020), and therefore this variable is set to 1 after 2013 for firms in the chemical industry (NACE code C20).

[11] For 2000-2007, I assign a value of 0 to this variable, which is conceptually equivalent to having an infinite amount of freely allocated emission allowances, capturing an economy in which carbon emissions are not regulated.

tors (Olden & Møen 2022). Figure 2 plots the triple interaction coefficients in a yearly event-study specification of Equation 2 (see the figure note for full details), and shows no evidence of pre-trends, supporting the validity of the parallel trends assumption.

Table 5 presents baseline estimation results of Equation 2. In Section 4.1, additional tests and robustness checks are presented. The estimate of the coefficient of interest, β, is negative in all specifications, and particularly when we control for firm, country-year, and industry-year fixed effects (column 4), indicating that the carbon market provides significantly weaker incentives to engage in *green* innovation for firms in hard- versus easy-to-abate industries. To illustrate the magnitude of this effect, Table 6 presents estimation results of a difference-in-differences regression splitting the sample by the "third" difference into firms in easy- and hard-to-abate industries. Columns 8 and 9, which control for firm, country-year and industry-year fixed effects, show that easy-to-abate regulated firms are 8.7 percentage points more likely to engage on the extensive margin in *green* innovation after 2008. The corresponding effect on firms in hard-to-abate industries is 2.9 percentage points. Scaling this result by the unconditional mean of the dependent variable, the effect for the easy-to-abate subsample is equivalent to a 134% increase in the likelihood of engaging in *green* innovation, compared to 41% increase for the hard-to-abate subsample. These results suggest that the EU-ETS has a threefold stronger impact on green innovation in easy-to-abate industries, underscoring that carbon markets may inadvertently concentrate innovation in that sector. Finally, column 7 of Table 6 shows that across both sectors, the EU-ETS led to an increase in green innovation, consistent with previous literature (e.g., Calel & Dechezleprêtre (2016)).

4.1 Additional Tests and Robustness Checks

Intensive Margin - The Effect on the Number of Green Patents The impact of carbon markets on the number of green patents filed by hard-to-abate firms is also notably smaller. Column 2 of Table 7 presents the results of estimating Equation 2 with the dependent variable set to $\log(1 + \#green_patents_{it})$, where $\#green_patents_{it}$ is the number of green patents filed by firm i in year t. Using the logarithm of green patents ensures that the measure captures proportional changes in innovation activity, accounting for the highly skewed (towards 0) distribution of patent filing across firms. The results show, that as a result of the policy, firms in hard-to-abate industries conduct significantly less green innovation on the intensive margin compared to easy-to-abate firms.

Quality Adjusted Patents To alleviate concerns that carbon markets led to a differential effect on green patent filing without affecting the quality of innovation, I adjust patents by their quality using forward citations in the four years following the patent application (see Hall et al. (2005), Calel & Dechezleprêtre (2016) and Acemoglu et al. (2023)). Column 3 of Table 7 presents estimation results of Equation 2 with the outcome variable set to 1 if the firm filed a green patent that has been cited within 4 years of application, and column 4 Table 7 revisits the analysis on the intensity of green innovation, counting only green patents that have been cited within 4 years of application. Both tests are in line with the main result and show that the EU-ETS also led to a differential increase in the quality of the green inventions of easy- compared to hard-to-abate firms.

Large Economies Sub-sample and Country-Industry-Year Fixed Effects While the main specification includes firm, country-year, and industry-year fixed effects, it does not account for yearly shocks to a specific industry in a given country.[12] Since including country-industry-year fixed effects in the full sample is infeasible, I restrict the sample to firms in Germany, France, Italy, and United Kingdom (the four largest economies) which together represent 73.5% of the main sample firms (see Table 2). Column 5 of Table 7 shows that the main result, with firm, country-year and industry-year fixed effects, is robust to this restriction. I then control for firm and country-industry-year fixed effects (Column 6 of Table 7) and the results remain consistent, confirming that the findings are not driven by unobserved country-industry trends.

Beginning of Pilot Phase (2005) as Treatment Year While the EU-ETS became fully operational in 2008 (Phase II), a three-year pilot phase began in 2005 (Phase I). It is possible that the carbon market's impact on green innovation activity started during this pilot period. I estimate Equation 2 using 2005 as the treatment year, setting $Post_t$ to 1 for years after 2005.[13] Column 7 of Table 7 shows that the results remain robust under this variation. While the significance and magnitude of the estimates weaken slightly, the core findings hold, suggesting that much of the differential response in innovation activity occurred after the market became fully operational. This pattern is consistent with a lagged reaction in patenting activity, as firms typically require several years to adjust their innovation strategies in response to new policies.

[12] E.g., the German 2006 Hydrogen R&D program; see https://www.now-gmbh.de/en/funding/funding-programmes/hydrogen-and-fuel-cell/ (accessed 01/24/2025).

[13] Treatment year of firms in the chemical industry remains 2013.

Relaxing Patenting Activity Restrictions In the baseline analysis, the sample is limited to firms that filed at least one patent pre- and post-policy. I relax this restriction by including all firms that patented at least once between 2000 and 2020 (regardless of the timing pre- or post-policy), addressing the concern that the original restriction may exclude firms that began or ceased innovating following the introduction of the carbon market, and thus overlook part of the policy's effect. Table 7 Column 8 estimates Equation 2 for the expanded sample, showing that while the magnitude of the coefficient of interest weakens, as expected when including firms less engaged in innovation, the qualitative findings remain unchanged.

Technology Level Analysis So far, the analysis focused on green patenting activity without distinguishing between different types of technologies. However, the first-order effect of the carbon market should be to induce innovation in clean production processes directly relevant to the firm's core economic activities. Therefore, I now refine the analysis by considering a patent filed by an easy-to-abate (hard-to-abate) firm as "green" only if it pertains to a technological solution relevant to an easy-to-abate (hard-to-abate) economic activity.

I begin by classifying CPC Y02 sub-categories into those that address easy- and hard-to-abate economic activities (Cooperative Patent Classification (2025)).[14] For example, technologies under "energy generation through renewable energy sources" (Y02E 10/00) are predominantly relevant to easy-to-abate activities because they help reduce direct emissions from electricity production. In contrast, patents classified under "technologies related to the processing of minerals" (Y02P 30/00) provide emissions-reducing solutions for cement, concrete, or glass manufacturing, which are hard-to-abate economic activities. Table A.1 presents the classification of Y02 CPC categories used to distinguish green patents in the baseline analysis according to whether the underlying technologies are predominantly applicable to easy-to-abate or hard-to-abate activities. In this approach, a patent filed by an easy-to-abate (hard-to-abate) firm is considered "green" only if it is exclusively classified as relevant to easy-to-abate (hard-to-abate) economic activities according to Table A.1. Column 9 of Table 7 presents the results of estimating Equation 2 using the technology-specific definition of green patenting, ensuring that the results hold

[14]Specifically, I input Y02B, Y02C, Y02D, Y02E, and Y02P CPC subcategories into OpenAI's ChatGPT and tasked it to classify each subcategory based on whether it covers technologies that are predominantly relevant to hard-to-abate economic activities (steel, cement, chemicals, additional heavy manufacturing and oil refining and extraction) or to easy-to-abate economic activities (light industry and electricity generation). The model was also allowed to assign "unclassified" to technologies relevant to both types of activities.

when accounting for the relevance of the patented technology to the firm's economic activity.

5 A Directed Technical Change Model of a Carbon Market

The empirical results show that (1) carbon markets provide weaker incentives for green innovation among hard-to-abate firms, and (2) hard-to-abate firms reduce emissions at a slower pace. However, the reduced-form analysis alone cannot speak to the implications of the findings on the efficiency of the transition to clean technology under a carbon market. Therefore, I develop a directed technical change model of an economy governed by a carbon market with heterogeneous abatement costs.

The model allows me to examine the interaction between carbon markets and sector-specific research subsidies, which are widely studied in the literature as a complementary tool to carbon pricing (e.g., Acemoglu et al. (2012), Acemoglu et al. (2016)) and Acemoglu et al. (2023). The model calibration compares two scenarios: (1) an economy governed by a carbon market whose stringency matches climate neutrality by 2050 ambitions, without research subsidies; and (2) an economy governed by the same carbon market with the addition of welfare-maximizing sector-specific research subsidies. Under the first scenario, clean innovation is centered in the easy-to-abate sector since hard-to-abate producers face weaker incentives for decarbonization, and rely on purchasing emission allowances from their easy-to-abate counterparts. This is in line with the empirical findings. However, optimal research subsidies realign innovation incentives and direct clean innovation towards the hard-to-abate sector, implying that the empirical findings point to an inefficiency of carbon markets.

5.1 Model Setup

The model operates in discrete time and infinite horizon, drawing on Acemoglu et al. (2012). Figure 3 provides a schematic representation.

Representative Household The economy consists of a representative household that derives utility from consuming a unique final good, C_t, and the quality of the environ-

ment, S_t, which reflects atmospheric CO_2 concentration:

$$\sum_{t=0}^{\infty} \frac{1}{(1+\rho)^t} u\left(C_t, S_t\right) \tag{3}$$

where $\rho > 0$ is the pure rate of time preference. I assume that $S_t \in [0, \bar{S}]$, where $\bar{S}$ represents the highest feasible quality of the environment in the absence of man-made pollution. The utility function $u(C_t, S_t)$ is increasing in both arguments and satisfies the following Inada-type conditions:

$$\lim_{C \downarrow 0} \frac{\partial u(C,S)}{\partial C} = \infty, \quad \lim_{S \downarrow 0} \frac{\partial u(C,S)}{\partial S} = \infty, \quad \text{and} \quad \lim_{S \downarrow 0} u(C,S) = -\infty \tag{4}$$

The last condition implies catastrophic welfare consequences when environmental quality reaches its lower bound. To ensure no benefit from improving environmental quality beyond $\bar{S}$, I impose:

$$\frac{\partial u(C,\bar{S})}{\partial S} = 0 \tag{5}$$

Final Good The unique final good, Y_t, is produced competitively using two intermediary goods: a hard-to-abate good, Y_t^H, representing industries such as steel, cement and chemicals, and an easy-to-abate good, Y_t^E, representing electricity generation and light industry. The final good is produced using the following CES production function:

$$Y_t = \left((Y_t^E)^{(\nu-1)/\nu} + (Y_t^H)^{(\nu-1)/\nu} \right)^{\nu/(\nu-1)}, \quad k \in \{E, H\} \tag{6}$$

where the intermediary goods are assumed to be complements, $\nu < 1$.

Intermediary Goods Each intermediary good, Y_t^k, $k \in \{E, H\}$, is produced competitively using a sector-specific clean input, Y_{ct}^k, and a common dirty input, Y_{dt}^k. The clean inputs represent renewable, non-emitting resources used to produce good k, while the dirty input represents GHG emitting production resources, such as fossil fuels. Sector-specificity of clean inputs accounts for differences in decarbonization pathways: electricity can be cleanly generated using solar or wind power, while green cement production may rely on innovations such as alternative low-carbon binders (See Section A for an

extensive discussion). The production function of each intermediary good is:

$$Y_t^k = \left((Y_{ct}^k)^{(\varepsilon-1)/\varepsilon} + (Y_{dt}^k)^{(\varepsilon-1)/\varepsilon} \right)^{\varepsilon/(\varepsilon-1)} \tag{7}$$

I follow widely used estimates of the elasticity of substitution between fossil fuels and renewables and assume that inputs are substitutes, $\varepsilon > 1$ (Papageorgiou et al. (2017).

Input Production The inputs are produced using labor and a continuum of sector-specific machines, according to:

$$Y_{ct}^k = (L_{ct}^k)^{1-\alpha} \int_0^1 (A_{cit}^k)^{1-\alpha} (x_{cit}^k)^{\alpha} di, \quad k \in \{E, H\} \tag{8}$$

$$Y_{dt} = (L_{dt})^{1-\alpha} \int_0^1 (A_{dit})^{1-\alpha} (x_{dit})^{\alpha} di \tag{9}$$

where $\alpha \in (0,1)$, A_{cit}^k (A_{dit}) represents the technological level of machine i in the clean input sector of intermediary good $k \in \{E, H\}$ (or the dirty input sector) at time t, and x_{cit}^k (x_{dit}) denotes the corresponding machine. The labor market clearing condition is (total labor is inelastically supplied and normalized to 1):

$$L_{ct}^E + L_{ct}^H + L_{dt} \leq 1, \tag{10}$$

Dirty input market clearing condition is (with demand not exceeding supply also in the two clean input sectors):

$$Y_{dt}^E + Y_{dt}^H \leq Y_{dt} \tag{11}$$

and final good market clearing condition is:

$$C_t = Y_t - \psi \left(\sum_{k \in \{E,H\}} \left(\int_0^1 x_{cit}^k di \right) + \int_0^1 x_{dit} di \right) \tag{12}$$

The last condition indicates that machines are supplied by monopolistically competitive firms, with each firm producing one machine at a constant exogenous cost $\psi > 0$.

Innovation Possibilities Frontier Innovation evolves as follows. In each period, scientists choose to innovate in either one of the clean input sectors or in the dirty input sector.

Assigned randomly to a machine in their chosen sector, scientists improve machine productivity by a factor of $(1+\gamma)$ with probabilities η_c^E, η_c^H, or $\eta_d \in (0,1)$. Clean technologies evolve as:

$$A_{cit}^k = \begin{cases} (1+\gamma)A_{cit-1}^k, & \text{w.p.} \quad \eta_c^k \\ A_{cit-1}^k, & \text{w.p.} \quad 1-\eta_c^k \end{cases}, \quad k \in \{E,H\} \tag{13}$$

and dirty technology evolves following:

$$A_{dit} = \begin{cases} (1+\gamma)A_{dit-1}, & \text{w.p.} \quad \eta_d \\ A_{dit-1}, & \text{w.p.} \quad 1-\eta_d \end{cases} \tag{14}$$

Successful scientists in the clean or dirty input sectors receive a payment that depends on the number of scientists innovating in that sector. Let π_{cit}^k denote the profit of the producer of machine x_{cit}^k at time t, (Payments from innovation in the dirty sector, π_{dit}, are defined analogously). If a scientist is assigned to this machine and successfully improves its technology, the scientist is paid $(1+\Gamma(s_{ct}^k))\pi_{cit}^k$, while the machine producer retains the remainder. $\Gamma(\cdot)$ is a decreasing function of s_{ct}^k, non-negative on $[0,1]$, and reflects that as more scientists work in a sector, the expected pay for each individual scientist decreases due to competition. Similar to labor, the total supply of scientists, s_t, is inelastic and normalized to 1. The market clearing condition for scientists is:

$$s_{ct}^E + s_{ct}^H + s_{dt} \leq 1 \tag{15}$$

The average sector-specific technology levels are defined as:

$$A_{ct}^k \equiv \int_0^1 A_{cit}^k di \quad k \in \{E,H\}, \qquad A_{dt} \equiv \int_0^1 A_{dit} di \tag{16}$$

which is useful for a discussion of the evolution of input technology over time. Based on the process described above, technology evolves following:

$$A_{ct}^k = \left(1+\gamma\eta_c^k s_{ct-1}^k\right) A_{ct-1}^k, \quad k \in \{E,H\} \tag{17}$$

$$A_{dt} = \left(1+\gamma\eta_d s_{dt-1}\right) A_{dt-1} \tag{18}$$

That is, technology has a *building on the shoulders of giants* structure, where advancements depend on past levels of technology.

Sector Heterogeneity in Abatement Cost To characterize that it is more challenging to transition from the dirty to the clean input in the hard-to-abate sector $k = H$, the initial level of the clean technology in the hard-to-abate sector $k = H$ is assumed to be less advanced than in the easy-to-abate sector $k = E$, relative to the clean technology:

$$\frac{A_{c0}^{E}}{A_{d0}} > \frac{A_{c0}^{H}}{A_{d0}} \iff A_{c0}^{E} > A_{c0}^{H}. \tag{19}$$

This reflects the initial underdevelopment of the clean hard-to-abate technology, while allowing it to catch up if innovation is directed towards this input sector.

The Carbon Cycle The carbon cycle (i.e., the change in the quality of the environment) is modeled as:

$$S_{t+1} = -\xi\left(Y_{dt}\right) + (1+\delta)S_t \tag{20}$$

The use of the dirty input, Y_{dt} (e.g., combustion of fossil fuels) generates environmental damage through the greenhouse effect at a rate $\xi > 0$, which represents the emissions rate. The environment regenerates at a rate $\delta > 0$, capturing natural absorption of GHGs and recovery processes.

Climate Policy The carbon market is modeled as a cap-and-trade system with two components: an economy-wide cap on emissions (corresponding to the dirty input) and trading of emission allowances.[15] Each intermediary good firm, $k \in \{E, H\}$, receives a quota of dirty input, $\bar{Y}_{dt}^{k}$, that it can use in each period. This quota corresponds to emission allowances. Firms that exceed this cap must purchase additional allowances from firms using less dirty input than their allocated quota, thereby creating a market for carbon. Consequently, in each intermediary goods sector, $k \in \{E, H\}$, firms are subject to the following emission constraint:

$$Y_{dt}^{k} \leq \bar{Y}_{dt}^{k} + Z_{t}^{k}, \quad k \in \{E, H\} \tag{21}$$

where Z_t^k represents the amount of emission allowances purchased by producers of intermediary good k from producers of intermediary good $-k$ at time t ($Z_t^k < 0$ indicates that this sector is a net seller of emission allowances). The carbon market clearing

[15] Equation 20 demonstrates that an emissions cap and a cap on the use of the "dirty" input are equivalent, since emissions are the use of the "dirty" input Y_{dt} scaled by the emissions rate ξ.

condition is:

$$Z_t^E + Z_t^H = 0 \tag{22}$$

which implies that the supply of allowances equals their demand.

Each period, intermediary good producers choose input quantities Y_{ct}^k and Y_{dt}^k, and demand for emission allowances Z_t^k to maximize profits, given input prices p_{ct}^k, p_{dt}, and carbon price p_{zt}:

$$\max_{Y_{ct}^k, Y_{dt}^k, Z_t^k} \left\{ p_t^k Y_t^k - p_{ct}^k Y_{ct}^k - p_{dt} Y_{dt}^k - p_{zt} Z_t^k \right\} \quad s.t. \quad Y_{dt}^k \leq \bar{Y}_{dt}^k + Z_t^k, \quad k \in \{E, H\} \tag{23}$$

Finally, reflecting the structure of carbon markets, the cap on emissions is designed to decrease over time:

$$\bar{Y}_{dt}^k = (1 - \theta)\bar{Y}_{dt-1}^k, \quad k \in \{E, H\} \tag{24}$$

where $\theta \in (0, 1)$ represents the rate of decrease in the emissions cap. This decreasing cap aligns with the structure of the EU-ETS, which progressively tightens emissions limits year by year.

5.2 Static Equilibrium

This subsection characterizes the static equilibrium, and Section 5.3 discusses the intertemporal dynamics of the model, which are generated by the equilibrium in the market for scientists.

Each period $t = 1, ..., \infty$, an equilibrium is a sequence of (for each $k \in \{E, H\}$): (i) wages (w_t), (ii) machine prices (p_{cit}^k, p_{dit}), (iii) input prices (p_{ct}^k, p_{dt}), (iv) intermediary good prices (p_t^k), (v) demands for machines (x_{cit}^k, x_{dit}), (vi) demands for inputs (Y_{jt}^k), (vii) demands for intermediary goods (Y_t^k), (viii) demands for labor (L_{ct}^k, L_{dt}), (ix) allocations of scientists (s_{ct}^k, s_{dt}), (x) carbon prices (p_{zt}), (xi) demands for carbon credits (Z_t^k), (xii) policy instruments ($\bar{Y}_{d0}^k$, θ^k) and (xiii) quality of the environment (S_t), such that:

- For each intermediary good sector $k \in \{E, H\}$:
  - (p_{cit}^k, x_{cit}^k) maximizes profits of the producer of clean machine i
  - (L_{ct}^k) maximizes the profits of clean input producers, given wages (w_t)
  - (Y_{ct}^k, Y_{dt}^k and Z_t^k) maximizes the profits of the intermediary good producers subject to policy constraints, given prices (p_{ct}^k, p_{dt}, p_{zt})

– (p_t^E, p_t^H) clears the intermediary goods markets

- (p_{dit}, x_{dit}) maximizes profits of the producer of clean machine i
- (L_{dt}) maximizes the profits of clean input producers, given wages (w_t)
- $(s_{ct}^E, s_{ct}^H, s_{dt})$ maximizes scientists' expected payoffs
- (Y_t^E, Y_t^H) maximizes final good producers' profits, given prices (p_t^E, p_t^H)
- Final good market clears:

$$C_t = Y_t - \psi \left(\sum_{k \in \{E,H\}} \left(\int_0^1 x_{cit}^k di \right) + \int_0^1 x_{dit} di \right) \tag{25}$$

- (w_t) clears the labor market: $L_{ct}^E + L_{ct}^H + L_{dt} \leq 1$
- The market for scientists clear: $s_{ct}^E + s_{ct}^H + s_{dt} \leq 1$
- The market for the clean input clears: $Y_{dt} = Y_{dt}^E + Y_{dt}^H$
- (p_{zt}) clears the carbon market: $Z_t^E + Z_t^H = 0$

Appendix B.1 shows that the only two feasible equilibrium cases are (1) no carbon trading in equilibrium (none of the sectors' emissions constraints (Equation 24) binds) and (2) carbon trading in equilibrium (both of the sectors' emissions constraints bind). Appendix B.2 outlines the equilibrium solution.

5.3 Inter-temporal Equilibrium Dynamics:

Finally, we turn to the decision of scientists, which determines the inter-temporal dynamics of input production technology. Given the structure of scientists' pay, the evolution of technology, equilibrium machine producer profits (Equation 43 in Appendix B.2), and the equilibrium supply of inputs (Equation 45 in Appendix B.2), the expected profits from innovating in each of the three sectors can be defined as:

$$\Pi_{ct}^k = \eta_c^k (1 + \Gamma(s_{ct}^k)) \alpha (1-\alpha) A_{ct}^k L_{ct}^k (p_{ct}^k)^{\frac{1}{1-\alpha}}, \quad k \in \{E, H\} \tag{26}$$

$$\Pi_{dt} = \eta_d (1 + \Gamma(s_{dt})) \alpha (1-\alpha) A_{dt} L_{dt} p_{dt}^{\frac{1}{1-\alpha}} \tag{27}$$

which simplify to:

$$\Pi_{ct}^k = \eta_c^k(1+\Gamma(s_{ct}^k))\alpha(1-\alpha)p_{ct}^k Y_{ct}^k, \quad k \in \{E,H\} \tag{28}$$

$$\Pi_{dt} = \eta_d(1+\Gamma(s_{dt}))\alpha(1-\alpha)p_{dt}Y_{dt} \tag{29}$$

Scientists' expected profit in each sector increase with the beginning-of-period average technological levels A_{ct}^k and A_{dt} (*building on the shoulders of giants effect*), the price of the input, p_{ct}^k or p_{dt} (*price effect*), and the demand for the input (*market-size effect*), Y_{ct}^k or Y_{dt}. These properties align with the standard features of directed technical change (as in Acemoglu et al. (2012)). At the same time, expected profits decrease with the number of scientists innovating in a sector, introducing a *competition effect*. To capture this, I assume $\Gamma(s) = \frac{\gamma}{s}$ for $s \in \{s_{ct}^E, s_{ct}^H, s_{dt}\}$. This formulation results in a unique interior equilibrium for the share of scientists in each sector, such that $s_{ct}^E, s_{ct}^H, s_{dt} \in (0,1)$ for each $t = 1, ..., \infty$, and allocations of scientists equalize expected pay across sectors:

$$\Pi_{ct}^E(s_{ct}^E) = \Pi_{ct}^H(s_{ct}^H) = \Pi_{dt}(s_{dt}) \tag{30}$$

Appendix B.3 provides a proof of this result.

5.4 Research Subsidies

The directed technical change literature has shown how carbon taxation and subsidies to clean research interact to lead to an efficient energy transition (Acemoglu et al. (2012), Acemoglu et al. (2016) and Acemoglu et al. (2023)). I therefore analyze the interaction between a carbon market and *sector-specific* subsidies to clean research. A subsidy of size $q_t^k > 0$ increases scientists' expected profits from innovation in clean input sector $k \in \{E,H\}$ at time t by a factor of $1+q_t^k$:

$$\Pi_{ct}^k = (1+q_t^k)\eta_c^k(1+\Gamma(s_{ct}^k))\alpha(1-\alpha)A_{ct}^k L_{ct}^k (p_{ct}^k)^{\frac{1}{1-\alpha}}, \quad k \in \{E,H\} \tag{31}$$

As discussed above regarding the equilibrium allocation of scientists, subsidies to clean research increase the equilibrium share of scientists innovating in the clean sector by providing a markup to their expected profits. These subsidies are financed by the household.

6 Model Calibration

This section presents the results from a calibration of the model. The purpose of the calibration is to provide theoretical foundations for the empirical findings on the differential effect of the EU-ETS on innovation activity and to shed light on their implications for the efficiency of the energy transition under a carbon market. After outlining the setup and specifying the parameter values, I present the calibration results, and finish by presenting several robustness checks demonstrating that the qualitative findings do hinge on specific parameter choices.

6.1 Setup

Optimal Policy Problem The optimal policy is defined as a sequence of subsidies $q_t \equiv \{q_t^E, q_t^H\}$ and an emissions cap decrease rate θ that maximize household utility, subject to the final good market clearing condition. Thus, the optimal policy can be characterized as the solution to the following planning problem:

$$\max_{\{q_t,\theta\}_{t=1}^{400}} \sum_{t=1}^{400} \frac{1}{(1+\rho)^t} u\left(C_t(q_t,\theta), S_t(q_t,\theta)\right) \tag{32}$$

s.t.

$$C_t(q_t,\theta) \leq \underbrace{Y_t(q_t,\theta)}_{\text{Final good}} - \underbrace{\psi\left(\sum_{k\in\{E,H\}}\left(\int_0^1 x_{cit}^k(q_t,\theta)di\right) + \int_0^1 x_{dit}(q_t,\theta)di\right)}_{\text{Cost of machines}} - \underbrace{Q_t(q_t,\theta)}_{\text{Subsidies cost}}$$

The results focus on the effect of subsidies on the transition to clean production. Therefore, the cap decrease rate θ is taken as given, so we can contrast the transition dynamics under (1) a no subsidies scenario ($q_t^H = q_t^E = 0, t = 1, 2, ..., \infty$) and (2) an optimal subsidies scenario ($\{q_t^H, q_t^E\}$ are the solution to the planning problem outlined above, given θ). $Q_t(\cdot)$ is the total amount paid in subsidies to scientists innovating in either clean input sectors, and is equal to:

$$Q_t(q_t,\theta) = \sum_{k\in\{E,H\}} q_t^k \eta_c^k (1+\Gamma(s_{ct}^k))\alpha(1-\alpha)A_{ct}^k L_{ct}^k (p_{ct}^k)^{\frac{1}{1-\alpha}} \tag{33}$$

As is common in the literature, the model is calibrated for an economy with 400 years time horizon, which provides a long horizon to allow (potential) climate damages to realize.[16]

Parameter Values Table 8 summarizes the parameter values used in the calibration. The share of machines is set to match the share of capital in the economy, $\alpha = 1/3$. The elasticity of substitution between inputs is set to $\varepsilon = 2.46$ following Papageorgiou et al. (2017), and the elasticity of substitution between intermediary goods is proxied using estimates of top-level elasticity in nested CES production functions (Van der Werf (2008)), and is set to $\nu = 0.36$.[17] Following Acemoglu et al. (2012) and Acemoglu et al. (2023), the utility function is assumed to take a CRRA form:

$$u\left(C_t, S_t\right) = \frac{\left(\phi\left(S_t\right) C_t\right)^{1-\sigma}}{1-\sigma} \tag{34}$$

The utility function is specified with a pure rate of time preference $\rho = 1\%$ and an elasticity of inter-temporal substitution $\sigma = 1.5$, following the 2023 version of the Dynamic Integrated Climate-Economy (DICE) model (Barrage & Nordhaus (2023)). $\phi\left(S_t\right)$ is a scaling function that maps the effect of temperature change on household utility to the interval $[0, 1]$ (a detailed discussion follows below).

The innovation incremental improvement is set to $\gamma = 1$ without loss of generality, and the probabilities of innovation success are set to $\eta_d = 0.02$, $\eta_c^E = 0.04$, and $\eta_c^H = 0.04$ to match a 2% growth rate in the balanced growth path (BGP).[18] The assumption of equal success probabilities of innovation in the two clean input sectors, $\eta_c^E = \eta_c^H = 0.04$, implies that although the clean hard-to-abate technology starts at a disadvantage, once the sector catches up and technological levels converge, the expected innovation step size will also equalize at $\eta_c^E\gamma = \eta_c^H\gamma$. Due to the convex nature of the innovation process (*standing on the shoulders of giants*), the clean hard-to-abate technology will initially advance with

[16] Acemoglu et al. (2012) and Acemoglu et al. (2023) consider 400 years as well and Cai & Lontzek (2019) use 600 years.

[17] For ε, I use the average CES-based estimate of the elasticity of substitution between clean and dirty inputs across electricity and non-energy sectors. For ν, I use the cross-country average of the estimated top-level elasticity of substitution between energy and production inputs. Section 6.3 confirms that the results are robust to variations in these parameters.

[18] In the decentralized equilibrium, without climate policy in place, all scientists innovate in the dirty sector, resulting in a BGP growth rate of $\eta_d\gamma$. In the equilibrium with a carbon market, the emission cap eventually becomes infinitely stringent, $\lim_{t\to\infty} \bar{Y}_{dt} = 0$, causing the number of scientists in each clean sector to converge to 0.5, $\lim_{t\to\infty} s_{ct}^k = 0.5, k \in \{E, H\}$. This implies a BGP growth rate of $0.5(0.5\eta_c^E\gamma + 0.5\eta_c^H\gamma)$.

smaller absolute gains.

I use the International Energy Agency's (IEA) World Energy Statistics and Balances to determine the initial usage of fossil fuels and renewable energy by each sector, Y^k_{d0} and Y^k_{c0} (International Energy Agency (2024)). These data provide detailed information on the use of over 60 energy sources (e.g., coal, crude oil, nuclear energy, and renewable energy) by nearly 100 intermediate- (e.g., electricity production) and end-users of energy (disaggregated industrial sectors, as well as residential, commercial, and transportation sectors), covering more than 150 countries since 1971. This information allows to determine the initial input values for each intermediary good sector and to derive initial technological levels based on equilibrium conditions.

In an effort to capture the global economy, the easy-to-abate sector includes light industry (transport equipment, machinery, food and tobacco, wood and wood products, textile and leather), rail transportation, and residential and commercial uses of energy. The hard-to-abate sector is defined to include mining and quarrying, construction, iron and steel, chemical and petrochemical, non-ferrous metals, non-metallic minerals, paper, pulp and printing, aviation, road transport, and maritime shipping (Industry titles as they appear in the data. See Sections 2.2 and Appendix A for further details).

Initial values of input use in each sector are set to the total amount of fossil fuels and renewable energy consumed by each sector,[19] including indirect energy use via electricity, during the period 2018-2021.[20]

The focus on end-users of energy rather than primary users ensures consistency with the interpretation of intermediary goods as consumption goods and avoids double counting of energy used for electricity. Including electricity as part of the easy-to-abate sector would double count its energy consumption - once for energy used in electricity generation and again for energy consumed by hard-to-abate industries. Additionally, this approach allows to include the residential and commercial sectors, which primarily derive their clean energy consumption indirectly through renewable electricity used for heating, cooling, and air conditioning. Thus, I adopt the end-user approach, including both direct and indirect energy use.

The initial values of dirty and clean inputs for the hard- and easy-to-abate sectors are

[19] Fossil fuels include Coal and Coal Products, Peat and Peat Products, Oil Shale and Oil Sands, Crude, NGL (Natural Gas Liquids) and Feedstocks, Oil Products, and Natural Gas. Renewable energy includes Nuclear, Hydro, Geothermal, Solar/Wind/Other, Biofuels, and Waste (names are as provided in the IEA data).

[20] A four-year period is used because the model is discretized into four-year intervals for computational reasons.

$Y_{c0}^E = 268,681,907$, $Y_{d0}^E = 550,475,222$, $Y_{c0}^H = 86,192,545$ and $Y_{d0}^H = 776,408,740$ Terajoules. These values indicate that fossil fuels account for 90% of energy consumption in the hard-to-abate sector and 67.2% in the easy-to-abate sector.

Initial input values subsequently determine the initial technology levels for the production of each input, based on equilibrium conditions. The implied technological gaps are:

$$\frac{A_{d0}}{A_{c0}^E} = 1.73, \quad \frac{A_{d0}}{A_{c0}^H} = 3.47 \tag{35}$$

These gaps imply that the easy-to-abate sector starts with a more advanced clean technology relative to the hard-to-abate sector, making it comparatively cheaper to produce using clean inputs in the easy-to-abate sector. Put simply, the initial clean easy-to-abate technology is twice as advanced as the initial clean hard-to-abate technology.

I rely on the initial values of input usage to define the environmental damage parameter, or emissions factor, ξ. The parameter ξ is set to half of the ratio of CO_2 emissions to fossil fuel consumption. This adjustment accounts for the fact that approximately half of CO_2 emissions are absorbed by the oceans or plants and do not reach the atmosphere, thereby not contributing to the greenhouse effect. The environmental regeneration parameter, δ, is calibrated to align with scientific estimates indicating that it would take several millennia for current atmospheric CO_2 concentrations to independently return to pre-industrial levels.[21]

Following Acemoglu et al. (2012), the quality of the environment, S, is directly linked to atmospheric CO_2 concentration (C_{CO_2}), which in turn determines temperature change since pre-industrial times (Δ). The relationship between temperature increases and atmospheric CO_2 concentration (in ppm) is given by:

$$\Delta = 3 \log_2 \left(C_{CO2} / 280 \right) \tag{36}$$

By this definition, a doubling of atmospheric carbon dioxide leads to a 3°C increase in current temperature, consistent with scientific forecasts.[22] Temperature increase of $\Delta_{disaster} =$

[21] See https://www.climate.gov/news-features/understanding-climate/climate-change-atmospheric-carbon-dioxide (Accessed on 01/17/2025) and https://royalsociety.org/topics-policy/projects/climate-change-evidence-causes/question-20/ (Accessed on 01/29/2025).

[22] Pre-industrial atmospheric carbon dioxide concentration was 280 ppm: https://www.climate.gov/news-features/understanding-climate/climate-change-atmospheric-carbon-dioxide (Accessed on 01/17/2025). Forecasts indicate that doubling atmospheric CO_2 will likely increase temperatures by 1.5-4.5 degrees Celsius:

6°C is widely considered disastrous (Stern (2007)), as it would likely trigger several tipping points, such as the melting of the Greenland Ice Sheet, which are widely expected to lead to catastrophic economic and social consequences. Equation 36 allows us to define the corresponding atmospheric CO_2 level, $C_{CO_2,\,\text{disaster}}$, which is used to define S:

$$S = C_{CO_2,\,\text{disaster}} - max\{C_{CO_2}, 280\} \tag{37}$$

The effect of environmental quality on utility is defined using the function $\phi(S)$, following Acemoglu et al. (2012):

$$\phi(S) = \varphi(\Delta(S)) \equiv \frac{(\Delta_{\text{disaster}} - \Delta(S))^{\lambda} - \lambda\Delta_{\text{disaster}}^{\lambda-1}(\Delta_{\text{disaster}} - \Delta(S))}{(1-\lambda)\Delta_{\text{disaster}}^{\lambda}} \tag{38}$$

where $\Delta(S)$ is the temperature change implied by S, and the parameter λ is set to $\lambda = 0.1443$. The initial environmental quality corresponds to contemporary atmospheric concentration of 417 ppm.[23] The emissions cap decrease rate is set to $\theta = 5.25\%$, which will allow achieving climate neutrality by 2050.[24] Robustness checks confirm that the results hold for less stringent climate policy (i.e., lower emissions cap decrease rate θ).

6.2 Calibration Results

This section presents calibration results and compares transition dynamics under (1) a carbon market consistent with climate neutrality by 2050 ambitions (the no-subsidies scenario) and (2) the same carbon market supplemented by optimal research subsidies (the optimal-subsidies scenario). In both cases, the stringency of climate policy is held constant via the same emissions cap decrease rate, θ. The comparison highlights the critical role of subsidies in facilitating a transition that achieves higher welfare by re-aligning incentives to increase clean innovation in the hard-to-abate sector.

Figure 4 presents the path of optimal subsidies to scientists innovating in the clean input of the easy- and hard-to-abate sectors, q^E and q^H. The social planner allocates

https://www.climate.gov/news-features/climate-qa/how-much-will-earth-warm-if-carbon-dioxide-doubles-pre-industrial-levels (Accessed on 01/17/2025).

[23] This matches 2021 levels: https://www.weforum.org/agenda/2021/03/met-office-atmospheric-co2-industrial-levels-environment-climate-change/ (Accessed on 01/29/2025).

[24] A decrease rate of $\theta = 5.25\%$ corresponds to the average yearly emissions decrease from 2021 global GHG emissions (36.3 Gigatons of GHG emissions, International Energy Agency (2022)) to the IEA's Net Zero by 2050 prediction for CO_2 capture levels in 2050 (7.6 Gigatons of GHG emissions will be captured and not abated, International Energy Agency (2021)).

much higher subsidies to scientists innovating in the hard-to-abate sector (170% higher in present value). As shown below, carbon trading prolongs the dependency of hard-to-abate producers on fossil fuels Y_{dt}^H, depressing the demand for the clean hard-to-abate input Y_{ct}^H, and reducing expected payoff from innovating in that sector Π_{ct}^H. Subsidies counteract this effect, and are used to draw scientists to the clean hard-to-abate input sector. Furthermore, as in Acemoglu et al. (2012), optimal subsidies are short-lived and phase out completely by 2050 and 2070 in the easy- and hard-to-abate sectors, respectively.

Figure 5 compares the allocation of scientists (s_{ct}^E, s_{ct}^H, s_{dt}) across the two scenarios. With optimal subsidies (Panel a), most scientists are immediately drawn to the hard-to-abate sector, increasing s_{ct}^H. Without subsidies (Panel b), scientists initially concentrate in the easy-to-abate sector, where carbon markets accelerate decarbonization, boosting demand for clean inputs Y_{ct}^E and raising expected payoffs Π_{ct}^E via market size and price effects.

Figure 6 compares the technological gap between the dirty and the clean input in each sector (A_{dt}/A_{ct}^k, $k \in \{E, H\}$). Without subsidies, the gap in the hard-to-abate sector widens at first (Panel a). In contrast, optimal subsidies immediately shrink the gap by increasing clean innovation in that sector. The role of subsidies in the easy-to-abate sector is marginal, and the dynamics of the technological gap under the two scenarios are very similar (Panel b).

Figure 7 presents the paths of emission allowances purchased by hard-to-abate firms, Z_t^H, under the no-subsidies and optimal-subsidies scenarios. The figure demonstrates the significant impact of subsidies on carbon trading. As subsidies align innovation incentives and accelerate advancements in clean hard-to-abate technology A_{ct}^H, total carbon trading volume shrinks by 75%, and the use of allowances Z_t^H is phased out decades earlier. This underscores the inefficiency of allowing hard-to-abate firms to rely heavily on emission allowances instead of undertaking direct emissions reduction. In the absence of targeted subsidies, carbon markets alone lead to excessive carbon trading, delaying technological progress and undermining the efficiency of the transition.

Figure 8 compares production in the easy- and hard-to-abate sectors, Y_t^E and Y_t^H, under both scenarios. Enforcing the emission reduction pace required to reach climate neutrality by 2050 through a carbon market causes an initial decline in intermediary good production and overall economic activity. Since clean technologies are initially underdeveloped, abatement combines technological transition, reduced production, and, solely in the hard-to-abate sector, purchase of emission allowances. Targeted research subsidies

soften this initial contraction in the hard-to-abate sector (Y_t^H) and accelerate its recovery (Panel a), while having a smaller long-run effect in the easy-to-abate sector, where the carbon market already delivers strong clean innovation incentives (Panel b).

Finally, the re-direction of innovation has a significant impact on household consumption C_t. Figure 9 shows that the initial decline in consumption under the no-subsidies scenario (due to the rigidity of the climate policy required to achieve net-zero emissions by 2050) is largely mitigated with optimally designed subsidies. In consumption equivalent terms, subsidies increase welfare by 3.8%, which is a result of avoiding the contraction in the production of the hard-to-abate intermediary good Y_t^H. Notably, conditional on the emission cap decrease rate θ, subsidies do not affect the economy-wide pace of decarbonization, which is equivalent to the emissions cap decrease rate θ. Thus, subsidies complement the cap-and-trade system by redirecting innovation to the hard-to-abate sector, allowing for a more efficient energy transition.

6.3 Robustness Checks

The robustness checks presented below explore variations in the main parameters. Table 9 summarizes these checks, demonstrating that the baseline calibration results do not qualitatively depend on the parameter values used in the main calibration of the model (Table 8). In each check, only the specified parameter is altered, and the others are specified in Table 8.

The pure rate of time preference in the robustness check, $\rho = 0.1\%$, is selected following Stern (2007). The discount rate is often particularly important for climate policy analyses and forecasts due to the long time horizons involved, where benefits from climate policy often materialize in the distant future. The Stern pure rate of time preference incorporates a moral concern for future generations, leading to a lower discount rate than the Barrage & Nordhaus (2023)'s market-based measures used in the main specification (Golosov et al. (2014)). Since these discount rates often lead to differing climate policy implications, it is reassuring to confirm that the results remain consistent under both assumptions.

Additionally, I vary the elasticity of substitution between intermediary goods, ν, ensuring that the results hold for varying levels of complementarity between the goods. For the elasticity of substitution between clean and clean inputs ε, I test higher and lower values within the estimation range provided by Papageorgiou et al. (2017). Finally, I assess the robustness of the results under a lower emissions cap decrease rate ($\theta = 2.2\%$), which

matches the 2021-2023 decrease rate of the EU-ETS. These checks confirm that carbon markets exhibit the side effect identified in this paper also under less stringent climate policy conditions.

7 Conclusions

This paper examines the unintended consequences of carbon markets and their implications for the efficiency of the transition to clean technology. The empirical analysis demonstrates that the EU-ETS spurred green patenting activity in easy-to-abate industries at rates three times higher than in hard-to-abate industries. Additionally, emissions reduction in hard-to-abate installations occurred at only half the annual pace of their easy-to-abate counterparts.

A directed technical change model of a carbon market and sectoral differences in abatement costs sheds light on the mechanisms behind these disparities and shows that the empirical findings point to an inefficiency of carbon markets. While carbon markets effectively accelerate decarbonization in the easy-to-abate sector, they inadvertently enable hard-to-abate producers to delay independent emissions reductions by relying on the purchase of emission allowances. These dynamics disincentivize clean innovation in the hard-to-abate sector. The model demonstrates that rebalancing innovation incentives through sector-specific research subsidies for clean innovation in the hard-to-abate sector can accelerate its transition, mitigate economic contraction, and generate welfare gains of up to 5.8%. However, suggestive evidence shows that current public funding is heavily skewed, with hard-to-abate industries receiving only 8% of the financial support per ton of emissions that easy-to-abate industries receive (Table 1).

As the climate neutrality by 2050 target approaches and adoption of carbon markets grows, it is crucial to recognize and address the trade-offs inherent in these systems. Rather than further strengthening incentives for the decarbonization pathways in easy-to-abate industries, policymakers should adopt complementary measures to ensure a more balanced transition. Specifically, subsidies and public financing should support innovation required for the transition in hard-to-abate industries, allowing for a more efficient energy transition.

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Tables

Table 1: Flows of Public Climate Finance

	Billions of $		$ Invested per tCO_2 Emitted	
	2019-2022	**2022**	**2019-2022**	**2022**
Energy Systems	728	292	12.8	19.9
Industry	30.8	14.4	0.9	1.6

Note: This table presents flows of climate finance from public institution towards the industrial sector and energy systems in billions of USD and as $1 invested per 1 ton of CO_2 emitted. Emissions data are from International Energy Agency (2023) and investment data are from the Global Landscape of Climate Finance (GLCF) 2023, collected by the Climate Policy Initiative. Public sources include development finance institutions (DFIs), governments and climate funds. Industry includes industrial, extraction and manufacturing processes, and industry intrastructure, and Energy Systems includes power and heat generation and transmission and fuel production. For more details, see GLCF 2023 methodology.

Table 2: Number of Firms by Country

Country	Non EU-ETS	EU-ETS	Total
Austria	39	18	57
Belgium	30	21	51
France	205	88	293
Germany	538	127	665
Italy	218	49	267
Netherlands	38	13	51
Other Countries	112	47	159
Spain	85	35	120
Sweden	38	25	63
United Kingdom	115	55	170

Note: This table presents the number of firms by country in the main sample constructed in Section 3.2 for the 9 largest countries that participate in the EU-ETS. The rest of the countries are aggregated under "Other Countries".

Table 3: Number of Firms by Industry

Industry	Non EU-ETS	EU-ETS	Total	Hard to Abate
Chemicals	384	136	520	Yes
Electricity & Power	33	30	63	No
Food, Beverages & Tobacco	147	47	194	No
Metals	140	57	197	Yes
Mining & Oil	20	22	42	Yes
Non-Metallic Minerals	164	77	241	Yes
Pulp, Paper & Cardboard	112	44	156	Yes
Trans. Manufacturing	418	65	483	No

Note: This table presents the number of firms by industry in the main sample constructed in Section 3.2. "Chemicals" is NACE code C20, "Electricity & Power" is D35, "Food Beverages & Tobacco" is C10, C11 and C12, "Metals" is C24, Mining & Oil is B and C19, "Non-Metallic Minerals" is C23, "Pulp, Paper & Cardboard" is C17 and "Trans. Manufacturing" is C29 and C30.

Table 4: Regression Results - Emissions Reduction Results

	(1)	(2)	(3)
	$\Delta log(Emissions)$	$\Delta log(Emissions)$	$\Delta log(Emissions)$
Hard to Abate	0.028***		0.023***
	(0.0084)		(0.0085)
$\Delta log(FreeAlloc.)$		0.11***	0.093**
		(0.038)	(0.038)
Constant	-0.053***	-0.028***	-0.044***
	(0.0078)	(0.0037)	(0.0084)
Observations	6,761	6,761	6,761
R-squared	0.0020	0.0024	0.0037

Note: This table presents regression results estimating Equation 1. The dependent variable is the one-year change in the natural log of yearly emissions. Hard to Abate is set to 1 for installations that are operated by firms in hard-to-abate industries, and $\Delta \log(FreeAlloc.)$ is the one-year change in the natural log of yearly freely allocated emission allowances. The sample includes all installations operated by main sample firms, as defined in Section 3.2, and that participate in the EU-ETS. Standard errors (in parentheses) are clustered at the installation-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: The Heterogeneous Effect of the EU-ETS on Green Innovation

	(1)	(2)	(3)	(4)
	All	All	All	All
Post	0.0055	0.014***	-	-
	(0.0051)	(0.0046)		
ETS	0.073***	-	-	-
	(0.021)			
Hard	0.0089	-	-	-
	(0.0070)			
Post × ETS	0.087***	0.087***	0.087***	0.090***
	(0.019)	(0.017)	(0.018)	(0.018)
Post × Hard	-0.012**	-0.018***	-0.016***	-
	(0.0062)	(0.0056)	(0.0059)	
ETS × Hard	0.028	-	-	-
	(0.026)			
Post × ETS × Hard	-0.074***	-0.053***	-0.056***	-0.060***
	(0.022)	(0.020)	(0.020)	(0.021)
Firm FE	N	Y	Y	Y
Country × Year FE	N	N	Y	Y
Industry × Year FE	N	N	N	Y
Observations	37,382	37,382	37,382	37,382
Adjusted R-squared	0.043	0.0060	0.0073	0.011

Note: This table presents triple difference regression results on engagement in green innovation. The dependent variable is a dummy variable set to 1 if the firm filed a green patent in that year. Post is set to 1 for observations in post EU-ETS years, ETS is set to 1 for firms that are regulated by the EU-ETS (that is, operate at least one installation that participates in the EU-ETS), and Hard is set to 1 for firms that operate in hard-to-abate industries. The sample is the main sample constructed as explained in Section 3.2. All columns control for lagged emissions to free allocation ratio, columns (2)-(4) control for firm fixed effects, columns (3) and (4) control for country-year fixed effects, and column (4) controls for industry-year fixed effects. Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: The Heterogeneous Effect of the EU-ETS on Green Innovation - Split Difference in Differences

	(1) All	(2) Easy	(3) Hard	(4) All	(5) Easy	(6) Hard	(7) All	(8) Easy	(9) Hard
Post	0.0016	0.013***	0.011*	-0.022***	0.090	-0.013	-0.051**	0.30	-0.012
	(0.0032)	(0.0046)	(0.0063)	(0.0072)	(0.061)	(0.011)	(0.020)	(0.26)	(0.13)
Post × ETS	0.047***	0.086***	0.033***	0.046***	0.085***	0.030***	0.049***	0.087***	0.029***
	(0.0090)	(0.017)	(0.010)	(0.0089)	(0.018)	(0.010)	(0.0092)	(0.019)	(0.010)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	N	N	N	Y	Y	Y	Y	Y	Y
Industry × Year FE	N	N	N	N	N	N	Y	Y	Y
Unconditional Mean	0.068	0.065	0.070	0.068	0.065	0.070	0.068	0.065	0.070
Observations	37,382	14,537	22,845	37,382	14,537	22,845	37,382	14,537	22,845
Adjusted R-squared	0.0038	0.013	0.0021	0.0053	0.012	0.0051	0.010	0.018	0.0063

Note: This table presents difference-in-differences regression results on engagement in green innovation for all firms (columns (1), (4) and (7)), firms in easy-to-abate industries (columns (2), (5) and (8)) and firms in hard-to-abate industries (columns (3), (6) and (9)). The dependent variable is a dummy variable set to 1 if the firm filed a green patent in that year. Post is set to 1 for observations in post EU-ETS years, ETS is set to 1 for firms that are regulated by the EU-ETS (that is, operate at least one installation that participates in the EU-ETS), and Hard is set to 1 for firms that operate in hard-to-abate industries. The sample is the main sample constructed as explained in Section 3.2. "Unconditional Mean" is the unconditional mean of the dependent variable. All columns control for lagged emissions to free allocation ratio and include firm fixed effects, columns (4)-(9) include country-year fixed effects, and columns (7)-(9) include industry-year fixed effects. Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: The Heterogeneous Effect of the EU-ETS on Green Innovation - Additional Tests and Robustness Checks

	(1) Baseline	(2) Intensive Margin	(3) Quality Adj. Ext. Margin	(4) Quality Adj. Int. Margin	(5) Large Economies	(6) Large Economies	(7) Treat. Year = 2005	(8) All Firms	(9) Tech. Level Analysis
Post × ETS	0.090***	0.13***	0.076***	0.24***	0.095***	0.092***	0.072***	0.034***	0.077***
	(0.018)	(0.029)	(0.016)	(0.052)	(0.023)	(0.023)	(0.018)	(0.0077)	(0.017)
Post × ETS × Hard	-0.060***	-0.078**	-0.054***	-0.15**	-0.072***	-0.068***	-0.036*	-0.019**	-0.064***
	(0.021)	(0.032)	(0.018)	(0.060)	(0.026)	(0.026)	(0.021)	(0.0087)	(0.019)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	N	Y	Y	Y
Industry × Year FE	Y	Y	Y	Y	Y	N	Y	Y	Y
Country × Industry × Year FE	N	N	N	N	N	Y	N	N	N
Observations	37,382	37,382	37,382	37,382	27,377	27,377	37,382	135,332	37,382
Adjusted R-squared	0.011	0.019	0.011	0.017	0.014	0.022	0.0096	0.0033	0.011

Note: This table presents regression results of the tests discussed in Section 4.1. The dependent variable in column (2) is the natural logarithm of 1 plus the number of green patents filed by the firm in that year, in column (3) a dummy set to 1 if the firm filed a green patent that was cited within 4 years of application, in column (4) the natural logarithm of 1 plus the number of green patents filed by the firm in that year that were cited within 4 years of application, in columns (5)-(8) a dummy set to 1 if the firm filed a green patent in that year, and in column (9) a dummy set to 1 if the firm filed a green patent that matches its easy- or hard-to-abate category (see Table A.1) in that year. Post is set to 1 for observations in post EU-ETS years, ETS is set to 1 for firms that are regulated by the EU-ETS (that is, operate at least one installation that participates in the EU-ETS), and Hard is set to 1 for firms that operate in hard-to-abate industries. The sample in columns (1)-(4) and (9) is the main sample constructed as explained in Section 3.2, in column (5) and (6) the sample is limited to firms in France, Germany, Italy and the United Kingdom, and in column (8), the restriction on patenting activity is relaxed, including all firms that patented at least once during 2000-2020. All columns control for lagged emissions to free allocation ratio and firm fixed effects, Columns (1)-(5) and (7)-(9) control for country-year and industry-year fixed effects and column 6 controls for country-industry-year fixed effects. Standard errors (in parentheses) are clustered at the firm-level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Calibration Setup - Parameter Values

Parameter	Definition	Value	Source
α	machine share	1/3	Capital share
ε	subs. of inputs	2.46	Papageorgiou et al. (2017)
ν	subs. of interm. goods	0.36	Van der Werf (2008)
σ	intertemp. subs.	1.5	Barrage & Nordhaus (2023)
ρ	pure rate of time pref.	1%	Barrage & Nordhaus (2023)
γ	innovation step size	1	Match 2% BGP growth rate
$\eta_d, \eta_c^H, \eta_c^E$	innov. success prob.	0.02, 0.04, 0.04	Match 2% BGP growth rate
ξ	emission rate	$0.5 \cdot \text{emissions}_0 / Y_{d0}$	Climate forecasts
δ	regeneration rate	$1 - (280/416)^{1/2000}$	Climate forecasts
θ	Cap decrease rate	5.25%	Climate neutrality by 2050 targets
$\frac{A_{d0}}{A_{c0}^E}, \frac{A_{d0}}{A_{c0}^H}$	Initial tech. gaps	1.73, 3.47	Equilibrium conditions and IEA World Energy Balances data

Note: This table presents the values of the parameters used in the baseline calibration analysis.

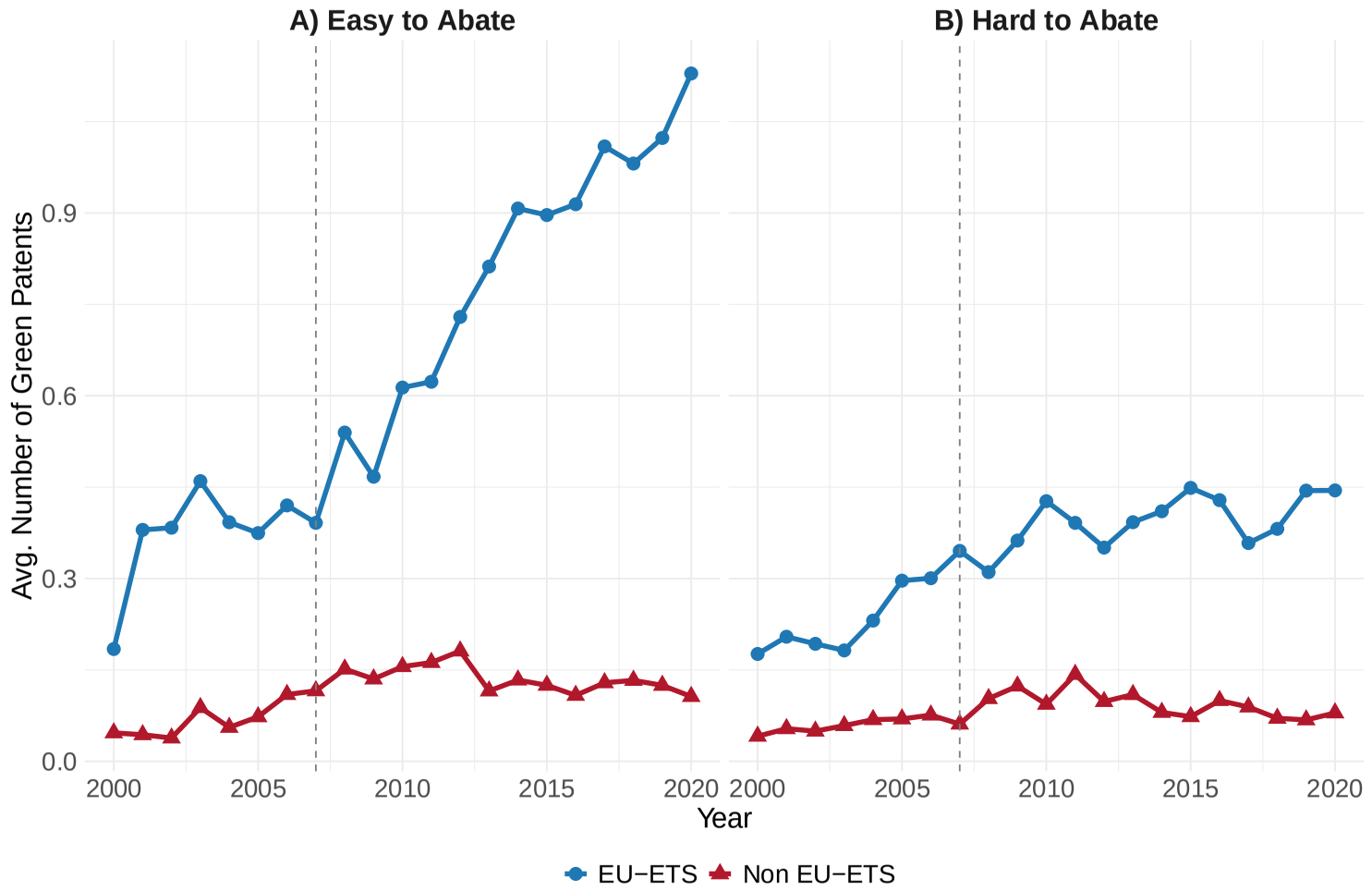
Table 9: Robustness Checks - Summary

Specification	Param. Value	Ratio of PV(Subs.)	Welfare Effect of Subs.	Results
Main	-	170%	3.8%	Fig. 4-9
Pure rate of time pref. $\downarrow$	$\rho = 0.1\%$	122%	5.8%	Fig. A.1
Subs. of interm. goods $\uparrow$	$\nu = 0.75$	37%	3.4%	Fig. A.2
Subs. of interm. goods $\downarrow$	$\nu = 0.2$	211%	3.9%	Fig. A.3
Subs. of inputs $\uparrow$	$\varepsilon = 2.87$	128%	3.8%	Fig. A.4
Subs. of inputs $\downarrow$	$\varepsilon = 2.05$	239%	3.7%	Fig. A.5
Cap decrease rate $\downarrow$	$\theta = 2.2\%$	63%	5%	Fig. A.6

Note: This table presents results from robustness checks, varying different parameters. In each check, only the parameter referred to changes in value, and the rest of the parameters are set as in Table 8. "Ratio of PV(Subs.)" is the ratio of the present value of subsidies paid to scientists innovating in the hard-to-abate sector over the present value of subsidies paid to scientists innovating in the easy-to-abate sector minus 1. "Welfare Effect of Subs." is the percent increase in equivalent consumption terms comparing the optimal subsidies to the no subsidies case.

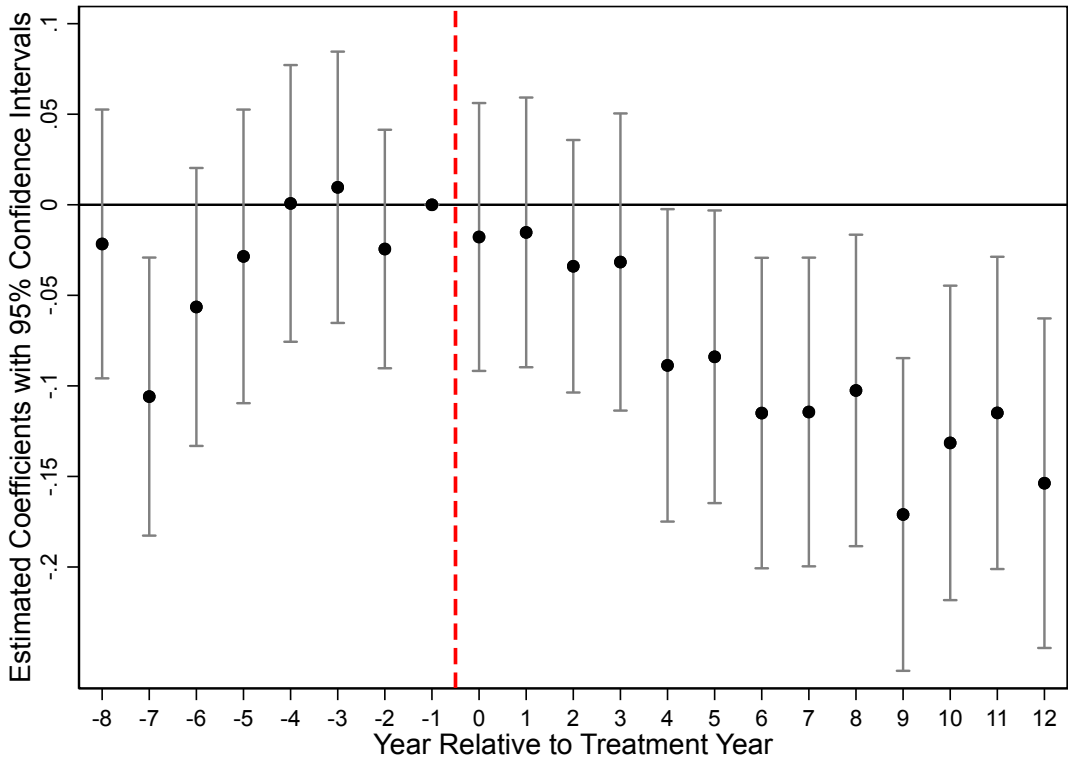
Figures

Figure 1: The EU-ETS and the Trend in Green Patenting of Easy- and Hard-to-abate Firms



Note: This figure presents the per firm average number of green patents filed by EU-ETS (blue, dots) and non EU-ETS (red, triangles) firms in 2000-2020. Panel A includes firms in easy-to-abate industries and Panel B includes firms in hard-to-abate industries. The dashed vertical line indicates 2007, one year prior to the full operation of the EU-ETS.

Figure 2: Dynamic Effect of EU-ETS on Green Patenting in Hard-to-Abate Industries

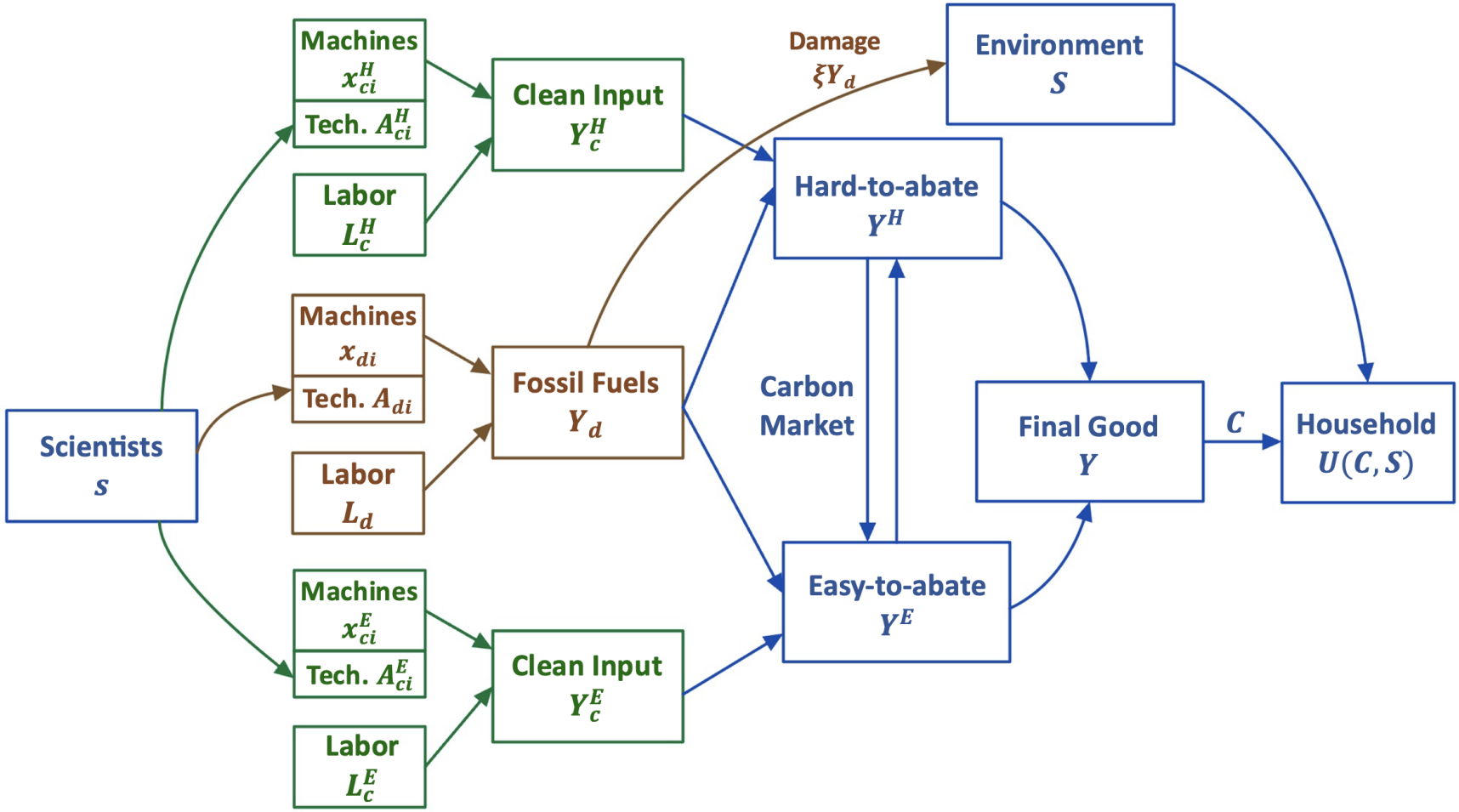


Note: This figure plots the estimated β_k coefficients from the following event study specification:

$$green_{it} = \sum_{k=-8}^{12} \beta_k \cdot I\{t = k\} \cdot ETS_i \cdot Hard_i + \sum_{k=-8}^{12} \gamma_k \cdot I\{t = k\} \cdot ETS_i + \delta \cdot x_{it} + \phi_i + \theta_{ct} + \lambda_{jt} + \varepsilon_{it}$$

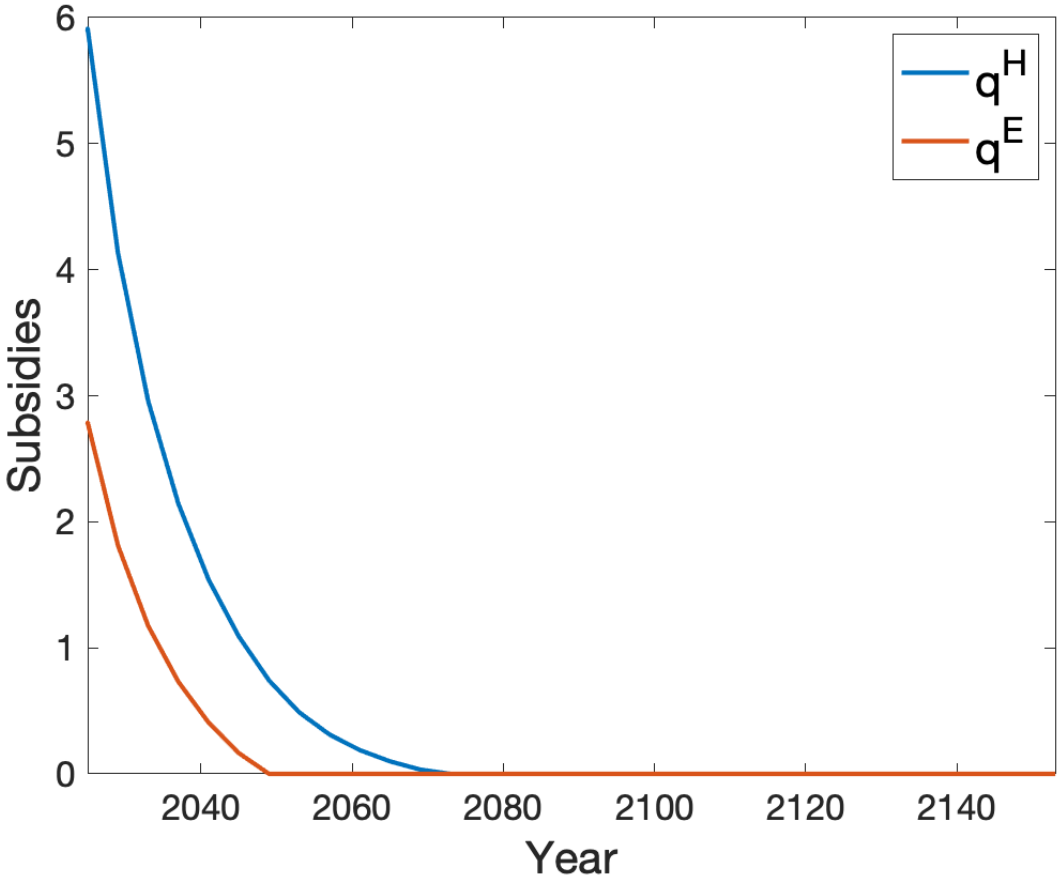
The outcome variable $green_{it}$ is a dummy equal to 1 if firm i files at least one green patent in year t. ETS_i is set to 1 for firms that are regulated by the EU-ETS (that is, operate at least one installation that participates in the EU-ETS), and $Hard_i$ is set to 1 if the firm operates in a hard-to-abate industry. $I\{t = k\} \cdot ETS_i \cdot Hard_i$ are year-relative-to-treatment dummy variables interacted with $ETS_i \cdot Hard_i$, and $I\{t = k\} \cdot ETS_i$ are year-relative-to-treatment dummy variables interacted with ETS_i. The omitted year is $k = -1$. The regression includes firm fixed effects (ϕ_i), country-year fixed effects (θ_{ct}), and industry-year fixed effects (λ_{jt}), and controls for the lagged free allocation ratio (x_{it}). Standard errors are clustered at the firm level. The treatment year ($k = 0$) is 2008 for all industries apart from chemicals, which joined the EU-ETS in 2013 (and $k = 0$ in year 2013).

Figure 3: Model Scheme



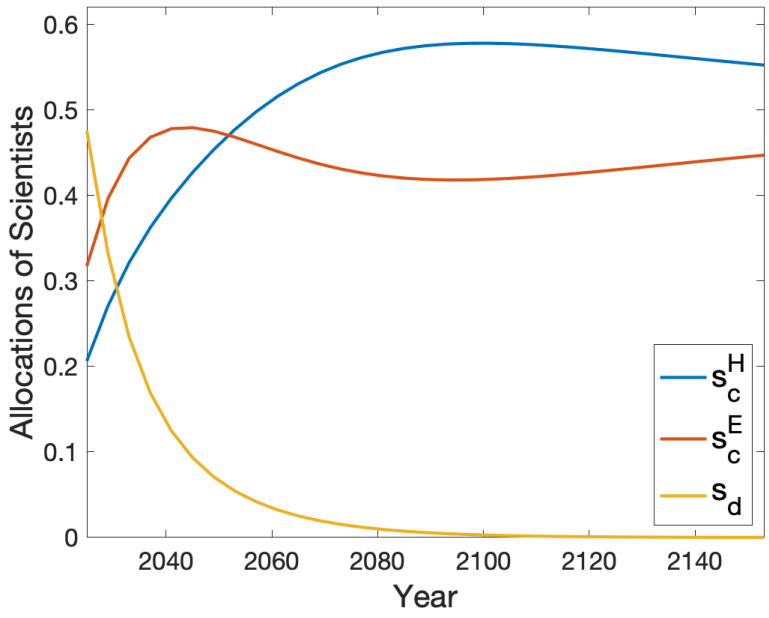
Note: This figure presents a scheme of the model. Complete details are in Section 5.

Figure 4: Optimal Subsidies

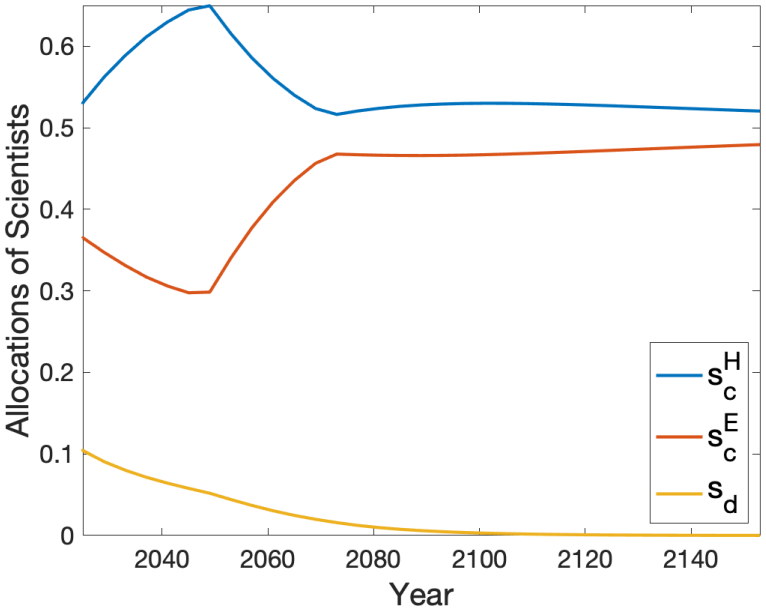


Note: This figure presents the path of optimal subsidies to scientists innovating in the clean hard-to-abate input sector (q^H) and the clean easy-to-abate input sector (q^E). The parameter values used are in Table 8.

Figure 5: Transition Dynamics - Scientists



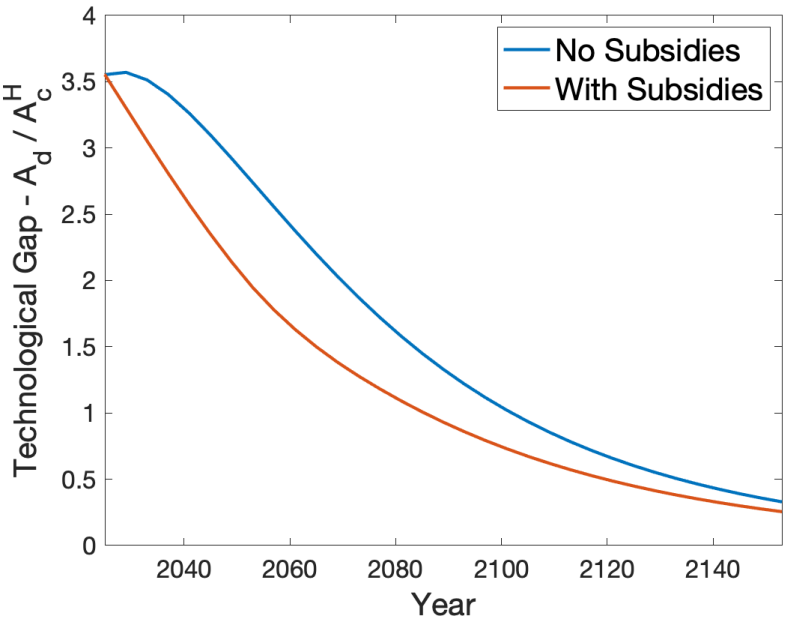
(a) No Subsidies



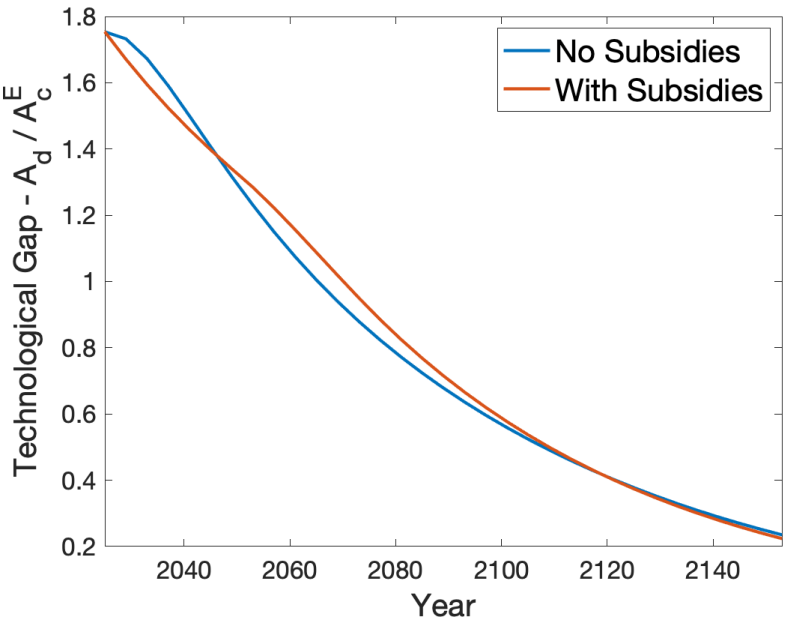
(b) Optimal Subsidies

Note: This figure presents the paths of the allocations of scientists innovating in the clean hard-to-abate input sector (s_c^H), the clean easy-to-abate input sector (s_c^E) and the dirty input sector (s_d). Panel A and Panel B present the paths under the no subsidies and optimal subsidies scenarios, respectively. The parameter values used are in Table 8.

Figure 6: Transition Dynamics - Technological Gaps



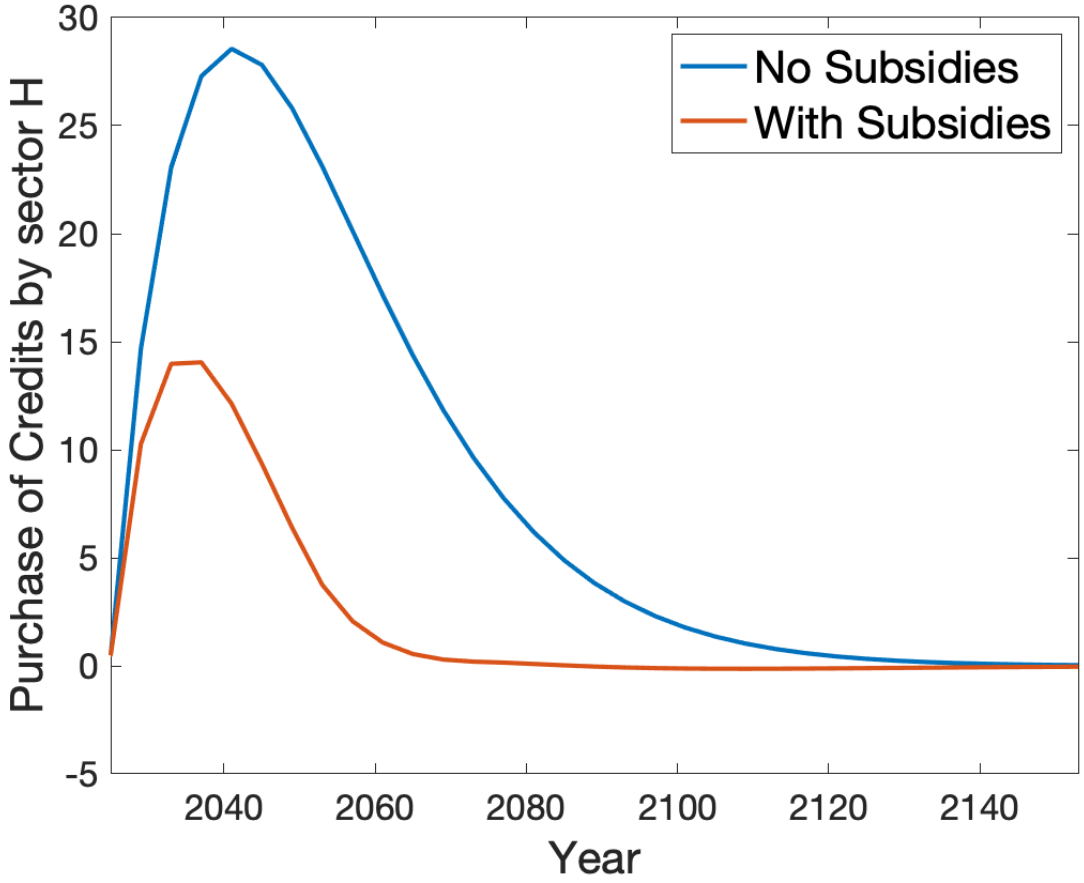
(a) No Subsidies



(b) Optimal Subsidies

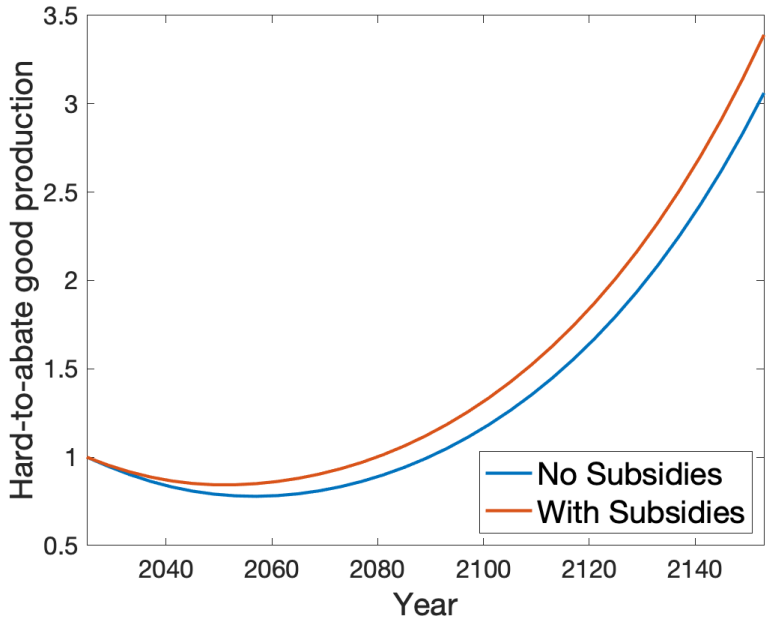
Note: This figure presents dynamics of the technological gaps between the dirty and sector specific clean technology. Panel A (Panel B) presents the dynamics of the gap between the dirty and the clean hard-to-abate (easy-to-abate) inputs under the no-subsidies and optimal subsidies cases. The parameter values used are in Table 8.

Figure 7: Emissions Trading

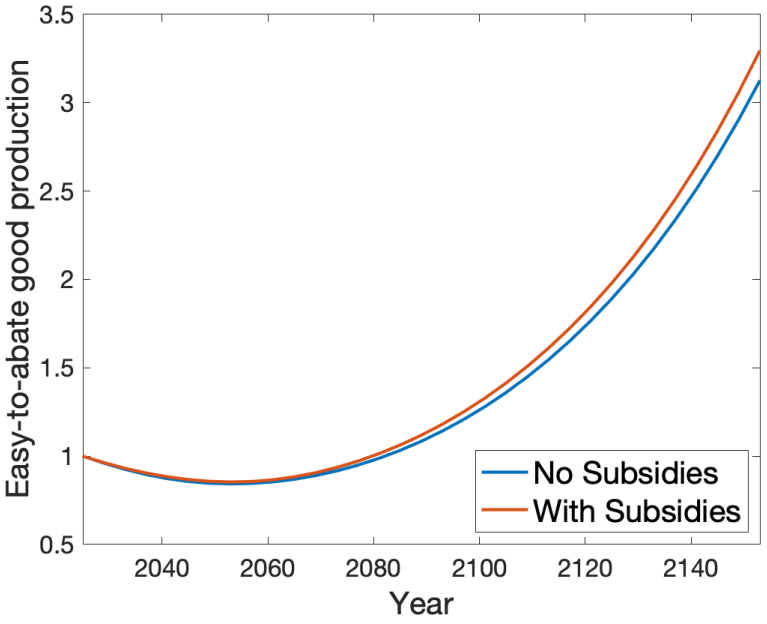


Note: This figure presents the path of emissions purchased by hard-to-abate firms under the no-subsidies and optimal-subsidies scenarios, given the parameter values in Table 8.

Figure 8: Production of Intermediary Goods



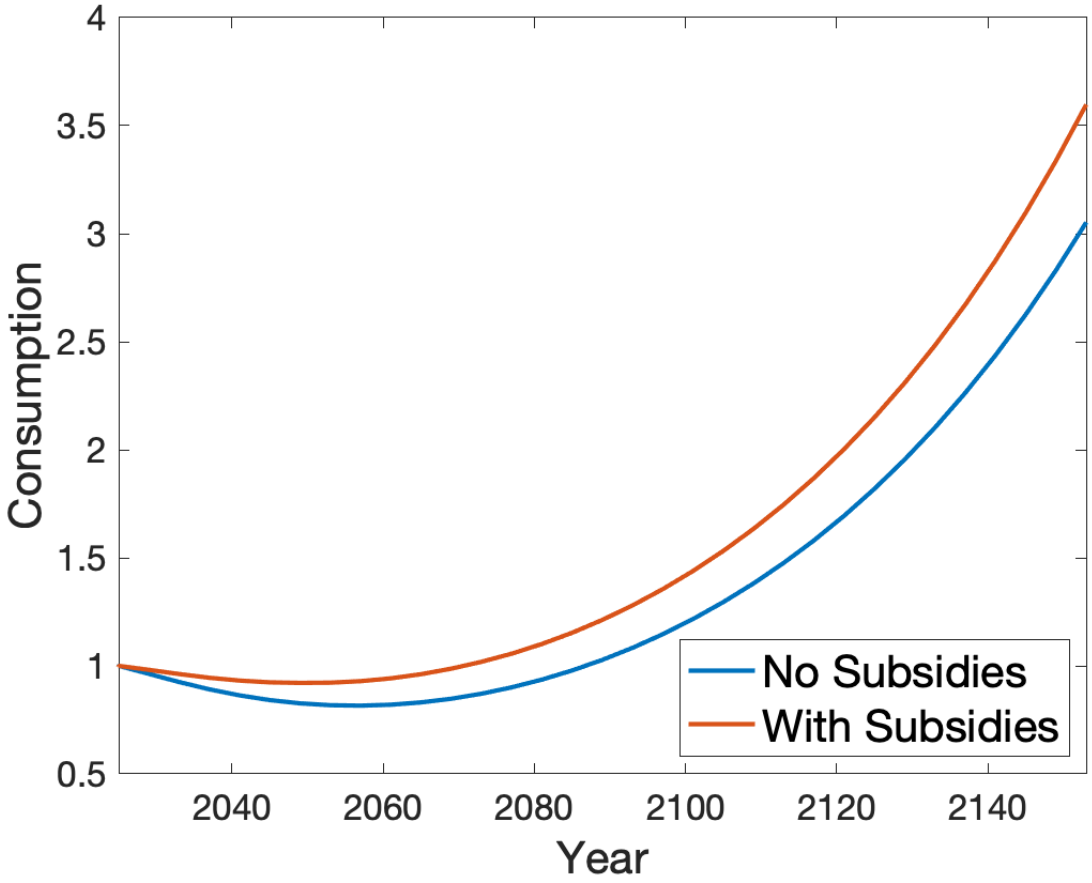
(a) Hard-to-abate (Y^H) Good Production



(b) Easy-to-Abate (Y^E) Good Production

Note: This figure presents the paths of the production of the hard-to-abate intermediary good Y^H (Panel A) and the easy-to-abate intermediary good Y^E (Panel B), normalized by the respective 2021 levels, comparing the no subsidies and optimal subsidies scenarios. The parameter values used are in Table 8.

Figure 9: Effect of Subsidies on Household Consumption



This figure presents the dynamics of household consumption C, normalized by the 2021 level of consumption, comparing the no subsidies and optimal subsidies scenarios. The parameter values used are in Table 8.

A Extended Technological Background

While policy reports indicate that the prices of renewable energy keep falling (International Renewable Energy Agency (2022)), hard-to-abate industries face stubborn emissions reduction challenges. For example, a recent report by the US Department of Energy (Brooks (2022)) shows that the US has a renewable energy technical potential to produce more than 100 times its electricity with renewable resources, and that "every region of the country has access to multiple renewable energy resources".[25] On the other hand, reducing emissions in the hard-to-abate industries requires substantial technological advancements, and 35% of emissions reductions in the IEA's Net Zero Emissions by 2050 Scenario come from technologies that are not yet developed (International Energy Agency (2021)). It is common to distinguish GHG emissions into two types: *heat emissions*, which are generated from the combustion of fossil fuels, and *process emissions*, in which GHGs are emitted due to chemical processes as part of production. Hard-to-abate industries face decarbonization challenges in both types. In the following section I discuss the core challenges the three largest hard-to-abate industries face.

A.1 Steel Industry

Steel production, which accounts for 7-9% of global CO_2 emissions (World Steel Association (2021)), involves two main steps. First, iron ore (Fe_2O_3) is smelted in a blast furnace at temperatures of around 900°C with a carbon rich substance, mainly coke (C), in order to separate iron (Fe) from oxygen (O):

$$Fe_2O_3 + 3\,C \longrightarrow 2\,Fe + 3\,CO_2$$

Emissions are generated because oxygen binds with carbon to form CO_2, which is released as a by-product, and because this process requires extremely high temperatures, achieved by combustion of fossil fuels.[26] The product, pig iron, is then processed and alloyed with other elements to produce steel with the desired properties. Thus, decarbonizing the industry requires technological alternatives to pig iron smelting.[27] Two such

[25] Renewable energy technical potential "[...] represents the achievable energy capacity and generation of a particular technology given the resource potential, system performance, topographic limitations, environmental constraints, and land use constraints." (Cox et al. (2018))

[26] https://www.energy.gov/eere/iedo/iron-and-steel-manufacturing (Accessed on 01/29/2025).

[27] https://www.iea.org/energy-system/industry/steel (Accessed on 01/29/2025).

prominent early stage methods are Low Temperature Electrolysis and Molten Oxygen Electrolysis. Additionally, smelting pig iron using hydrogen (H_2) produced using renewable energy as a reducing agent, often referred to as "green steel", relies on smelting iron ore with hydrogen to reduce it to pig iron, with water (H_2O) as the sole by-product. These low-emission technologies still need to be perfected and scaled up in order for the steel industry to decarbonize.[28] As the World Steel Association states in a policy report: "...to achieve the drastic [emissions] reductions needed, an entirely new, transformative approach to ironmaking is required and there are several promising initiatives under development." (World Steel Association (2021)).

A.2 Cement Industry

The cement industry accounts for roughly 8% of global CO_2 emissions (Ellis et al. (2020)). More than half of these are *process* emissions generated when limestone ($CaCO_3$) is decomposed in a kiln at around 1,450°C to produce calcium oxide (CaO), emitting CO_2:

$$CaCO_3 \longrightarrow CaO + CO_2$$

The rest of the emissions are *heat* emissions, resulting from combustion of fossil fuels to achieve such high temperatures.[29] The US Department of Energy notes that "to help tackle the challenge of decarbonizing the cement industry, research and development (R&D) is needed across the following areas: (1) Next-generation cement/concrete formulations and production routes; (2) Low-carbon fuels and (3) Carbon-capture technologies" (An example for (1) is production of cement from calcium silicate, which will eliminate *process* emissions[30]).[31]

A.3 The Chemical Industry

The chemical industry accounts for about 5% of global CO_2 emissions (Gabrielli et al. (2023)). The main challenge in decarbonizing production of chemicals is that over half of the energy input is used as a feedstock, with fossil fuels supplying carbon and hydrogen as raw materials. Therefore, it requires inventing low-emitting substitutes for

[28] https://www.iea.org/energy-system/industry/steel (Accessed on 01/29/2025)
[29] https://www.energy.gov/eere/iedo/cement-and-concrete-manufacturing (Accessed on 01/29/2025).
[30] https://www.iea.org/energy-system/industry/cement (Accessed on 01/29/2025)
[31] https://www.energy.gov/eere/iedo/cement-and-concrete-manufacturing (Accessed on 01/29/2025).

the emissions-intensive inputs. Therefore, key milestones in the energy transition of the chemicals industry include using biofuels and waste gases as inputs and increasing the recyclability of chemical products.[32]

B Model Appendix

B.1 Are Carbon Markets Active in Equilibrium?

Whether intermediary good producers trade emission allowances in equilibrium depends on the stringency of the emissions caps $\bar{Y}_{dt}^k$. I analyze the three potential equilibrium cases, of which only two are feasible:

1. **None of the constraints bind - No trade:** For all $k \in \{E, H\}$, $Y_{dt}^k < \bar{Y}_{dt}^k + Z_t^k$.
   In this case, the first-order conditions (FOCs) of Equation 23 imply that $p_{zt} = 0$, resulting in no trade of emission allowances. Thus, $Z_t^H = Z_t^E = 0$.

2. **Both constraints bind - Active trade:** For all $k \in \{E, H\}$, $Y_{dt}^k = \bar{Y}_{dt}^k + Z_t^k$.
   Here, intermediary good producers actively trade emission allowances. By the FOCs of Equation 23, $p_{zt} > 0$, and the carbon market clearing condition $Z_t^H + Z_t^E = 0$ determines the price. One sector (as shown later, the hard-to-abate) is a net seller of allowances, while the other is a net buyer (the easy-to-abate).

3. **The constraint binds only for one sector (not feasible):** $Y_{dt}^k = \bar{Y}_{dt}^k + Z_t^k$ for some $k \in \{E, H\}$ while $Y_{dt}^{-k} < \bar{Y}_{dt}^{-k} + Z_t^{-k}$.
   This scenario cannot constitute an equilibrium. Suppose it can. Then, the FOCs of Equation 23 for sector $-k$ imply that $p_{zt} = 0$ since the constraint does not bind. However, with $p_{zt} = 0$ (the shadow price of the emissions constraint for sector k), the constraint of sector k also cannot bind, leading to a contradiction.

[32] https://www.energy.gov/eere/iedo/chemical-and-petrochemical-manufacturing (Accessed on 01/29/2025).

B.2 Equilibrium Solution

We start with the input producers. In each sector $k \in \{E, H\}$, clean input producers choose the number of machines x^k_{cit} and labor L^k_{ct} to maximize profits:

$$\max_{x^k_{cit}, L^k_{ct}} \left\{ p^k_{ct} (L^k_{ct})^{1-\alpha} \int_0^1 (A^k_{cit})^{1-\alpha} (x^k_{cit})^{\alpha} di - w_t L^k_{ct} - \int_0^1 p^k_{cit} x^k_{cit} di \right\} \tag{39}$$

which yields the following demand function: $x^k_{cit} = \left(\frac{\alpha p^k_{ct}}{p^k_{cit}} \right)^{\frac{1}{1-\alpha}} A^k_{cit} L^k_{ct}$.
Analogously, dirty input producers choose the number of machines x_{dit} and labor L_{dt} to maximize profits:

$$\max_{x_{dit}, L_{dt}} \left\{ p_{dt} (L_{dt})^{1-\alpha} \int_0^1 (A_{dit})^{1-\alpha} (x_{dit})^{\alpha} di - w_t L_{dt} - \int_0^1 p_{dit} x_{dit} di \right\} \tag{40}$$

which yields the following demand function: $x_{dit} = \left(\frac{\alpha p_{dt}}{p_{dit}} \right)^{\frac{1}{1-\alpha}} A_{dit} L_{dt}$.

The first order conditions with respect to labor of each of the three problems yield the following relations between relative levels of technology and relative prices:

$$\frac{p^k_{ct}}{p_{dt}} = \left(\frac{A^k_{ct}}{A_{dt}} \right)^{-(1-\alpha)}, \quad \text{for each } k \in \{E, H\} \tag{41}$$

The monopolistic producer of clean machine i in intermediary good sector $k \in \{E, H\}$ chooses p^k_{cit} and x^k_{cit} to maximize profits subject to the demand function above:

$$\max_{x^k_{cit}, p^k_{cit}} \pi^k_{cit} = \left(p^k_{cit} - \psi \right) x^k_{cit} \quad s.t. \quad x^k_{cit} = \left(\frac{\alpha p^k_{ct}}{p^k_{cit}} \right)^{\frac{1}{1-\alpha}} A^k_{cit} L^k_{ct} \tag{42}$$

Using the assumption that $\psi = \alpha^2$, we derive that $p^k_{cit} = \alpha$. Thus, equilibrium profits are

$$\pi^k_{cit} = (1-\alpha) \alpha A^k_{cit} L^k_{ct} (p^k_{ct})^{\frac{1}{1-\alpha}} \tag{43}$$

and the demand for machines can be written as:

$$x^k_{cit} = A^k_{cit} L^k_{ct} (p^k_{ct})^{\frac{1}{1-\alpha}} \tag{44}$$

Combining 8, 16 and 44, we obtain the equilibrium supply of clean input c in intermediary good sector k:

$$Y_{ct}^k = A_{ct}^k L_{ct}^k \left(p_{ct}^k\right)^{\frac{\alpha}{1-\alpha}} \tag{45}$$

Analogously, we obtain that dirty input supply is:

$$Y_{dt} = A_{dt} L_{dt} p_{dt}^{\frac{\alpha}{1-\alpha}} \tag{46}$$

As to the demand side, intermediary good producers in each sector $k \in \{E, H\}$ choose input quantities, Y_{ct}^k and Y_{dt}^k, and amount of emission allowances purchased, Z_t^k, to maximize profits subject to the policy constraint:

$$\max_{Y_{ct}^k, Y_{dt}^k, Z_t^k} \left\{ p_t^k Y_t^k - p_{ct}^k Y_{ct}^k - p_{dt} Y_{dt}^k - p_{zt} Z_t^k \right\} \quad s.t. \quad Y_{dt}^k \leq \bar{Y}_{dt}^k + Z_t^k \tag{47}$$

This problem yields the following ratio between input demands and input and carbon prices, implying that relative demand of the cheaper input is higher:

$$\frac{Y_{ct}^k}{Y_{dt}^k} = \left(\frac{p_{ct}^k}{\tilde{p}_{dt}}\right)^{-\varepsilon} \tag{48}$$

where $\tilde{p}_{dt}$ is the *effective* price of the clean input and is defined as $\tilde{p}_{dt} \equiv p_{dt} + p_{zt}$. Importantly, as the carbon price p_{zt} increases, relative demand of the dirty input decreases. We also obtain the following relation between *effective* input prices and the price of intermediary good k:

$$\left((\tilde{p}_d^k)^{1-\varepsilon} + (p_c^k)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} = p^k \tag{49}$$

and that $Y_{dt} \leq \bar{Y}_{dt} + Z_t^k$. I discuss below the two equilibrium cases: (1) no-trade and (2) active trade cases.

Final good producers choose intermediary good quantities, Y_t^H and Y_t^E, to maximize profits:

$$\max_{Y_t^E, Y_t^H} \left\{ Y_t - p_t^E Y_t^E - p_t^H Y_t^H \right\} \tag{50}$$

which yields the following relation between intermediary goods demands and prices ratios:

$$\frac{Y_t^E}{Y_t^H} = \left(\frac{p_t^E}{p_t^H}\right)^{-\nu} \tag{51}$$

and the following intermediary good price relation:

$$(p^H)^{1-\nu} + (p^E)^{1-\nu} = 1 \tag{52}$$

Note that we normalize the price of the final good is normalized to 1.

B.3 Scientists' Equilibrium Decision

This section proves that in the unique equilibrium, the allocation of scientists $s^* \equiv (s_{dt}^*, s_{ct}^{H*}, s_{ct}^{E*})$ is such that scientists innovate in all sectors $s^* \in (0,1)^3$ and expected profits are equal across sectors. I start by showing that there exists a unique allocation $s^* \in (0,1)^3$, with $s_{ct}^{H*} + s_{ct}^{E*} + s_{dt}^* = 1$ for all $t = 1, .., \infty$ such that Equation 30 holds. I then show that this is an equilibrium. The proof is concluded by showing that this equilibrium is unique.

Existence of $s^* \in (0,1)^3$, with $s_{ct}^{H*} + s_{ct}^{E*} + s_{dt}^* = 1$ for all $t = 1, .., \infty$:

Define $X_{ct}^k \equiv \eta_c \alpha(1-\alpha) p_{ct}^k Y_{ct}^k, k = H, E$ and $X_{dt} \equiv \eta_d \alpha(1-\alpha) p_{dt} Y_{dt}$. By Equation 30, define x such that:

$$x \equiv (1 + \frac{\gamma}{s_{ct}^H}) X_{ct}^H = (1 + \frac{\gamma}{s_{ct}^E}) X_{ct}^E = (1 + \frac{\gamma}{s_{dt}}) X_{dt} \tag{53}$$

Combining this with scientists' market clearing condition, we obtain the following equation with one unknown, x:

$$\frac{\gamma X_{ct}^H}{x - X_{ct}^H} + \frac{\gamma X_{ct}^E}{x - X_{ct}^E} + \frac{\gamma X_{dt}}{x - X_{dt}} = 1 \tag{54}$$

Define $f(x)$ to be:

$$f(x) = \frac{\gamma X_{ct}^H}{x - X_{ct}^H} + \frac{\gamma X_{ct}^E}{x - X_{ct}^E} + \frac{\gamma X_{dt}}{x - X_{dt}} - 1 \tag{55}$$

By $s^* \in [0,1]^3$ (which holds from (1) the share of scientists in each sector is non-negative; and (2) market clearing), we have

$$x \in X_{ct}^H \cdot (1+\gamma, \infty) \cap X_{ct}^E \cdot (1+\gamma, \infty) \cap X_{dt} \cdot (1+\gamma, \infty) \tag{56}$$

implying that $x \geq max\{X_{ct}^H(1+\gamma), X_{ct}^E(1+\gamma), X_{dt}(1+\gamma)\} \equiv \underline{x}$.
Showing that there exists $x^* \in (\underline{x}, \infty)$ such that $f(x^*) = 0$ will conclude this part of the proof, because the definition of x above implies a unique allocation of scientists:

$$s_{ct}^E = \frac{\gamma X_{ct}^E}{x - X_{ct}^E}, \quad s_{ct}^H = \frac{\gamma X_{ct}^H}{x - X_{ct}^H}, \quad s_{dt} = \frac{\gamma X_{dt}}{x - X_{dt}} \tag{57}$$

.

To that end, I show that (1) $f(x)$ is continuous and strictly decreasing for $x \in (\underline{x}, \infty)$, (2) $f(\underline{x}) > 0$, and (3) $\lim_{x\to\infty} f(x) < 0$, and use the Intermediate Value Theorem to conclude that there exists $x^* \in (\underline{x}, \infty)$ such that $f(x^*) = 0$.

1. It is clear to see that $f(x)$ is continuous for $x \in (\underline{x}, \infty)$. It is also strictly decreasing:

$$f'(x) = -\frac{\gamma X_{ct}^H}{(x - X_{ct}^H)^2} - \frac{\gamma X_{ct}^E}{(x - X_{ct}^E)^2} - \frac{\gamma X_{dt}}{(x - X_{dt})^2} < 0 \tag{58}$$

2. Suppose without loss of generality that $\underline{x} = X_{dt}(1+\gamma)$. Thus:

$$f(\underline{x}) = \frac{\gamma X_{ct}^H}{X_{dt}(1+\gamma) - X_{ct}^H} + \frac{\gamma X_{ct}^E}{X_{dt}(1+\gamma) - X_{ct}^E} + \frac{\gamma X_{dt}}{X_{dt}(1+\gamma) - X_{dt}} - 1 = \tag{59}$$

$$= \frac{\gamma X_{ct}^H}{X_{dt}(1+\gamma) - X_{ct}^H} + \frac{\gamma X_{ct}^E}{X_{dt}(1+\gamma) - X_{ct}^E} + 1 - 1 > 0 \tag{60}$$

since $X_{dt} > X_{ct}^H$ and $X_{dt} > X_{ct}^E$.

3. When $x \to \infty$:

$$lim_{x\to\infty} f(x) = lim_{x\to\infty} \left(\frac{\gamma X_{ct}^H}{x - X_{ct}^H} + \frac{\gamma X_{ct}^E}{x - X_{ct}^E} + \frac{\gamma X_{dt}}{x - X_{dt}} \right) - 1 = -1 \tag{61}$$

By the Intermediate Value Theorem, there exists a unique $x^* \in (\underline{x}, \infty)$ such that $f(x^*) = 0$. Therefore, there exists $s^* \in (0,1)^3$ such that $s_{ct}^{H*} + s_{ct}^{E*} + s_{dt}^* = 1$ for all $t = 1, .., \infty$ and Equation 30 holds.

Why s^* is an equilibrium?

The scientist allocations that satisfy Equation 30 equalize expected pay in all sectors. Given that s^* satisfies Equation 30, no scientist has an incentive to deviate and innovate in another sector since it would yield a lower expected pay, because $\Gamma(\cdot)$ is a decreasing

function and $s_{ct}^{H*} + s_{ct}^{E*} + s_{dt}^{*} = 1$. Therefore, these allocations constitute an equilibrium.

Why the equilibrium is unique?

Suppose there is another allocation of scientists $s' \equiv (s_{ct}^{H'}, s_{ct}^{E'}, s_{dt}') \in (0,1)^3$, with $s_{ct}^{H'} + s_{ct}^{E'} + s_{dt}' = 1$ that is an equilibrium. By uniqueness of s^* that satisfy Equation 30, it must be that expected pay in at least one of the sectors is higher. However, this cannot be an equilibrium since scientists in the sector(s) with lower expected pay will switch to the sector(s) with higher. Finally, we need to show that there is no equilibrium for which $s = 0$ for at least some $s \in \{s_{ct}^{H}, s_{ct}^{E}, s_{dt}\}$ (which also implies that there is no $s = 1$ for one $s \in \{s_{ct}^{H}, s_{ct}^{E}, s_{dt}\}$), which will allow us to conclude that the unique equilibrium is the one we found above. There is no such $s = 0$ for some $s \in \{s_{ct}^{H}, s_{ct}^{E}, s_{dt}\}$ because expected pay in the corresponding sector will be ∞ (since $\lim_{s \to 0+} \Gamma(s) = \infty$), and scientists innovating in other sectors will receive higher expected pay from switching to this sector.

Appendix Tables

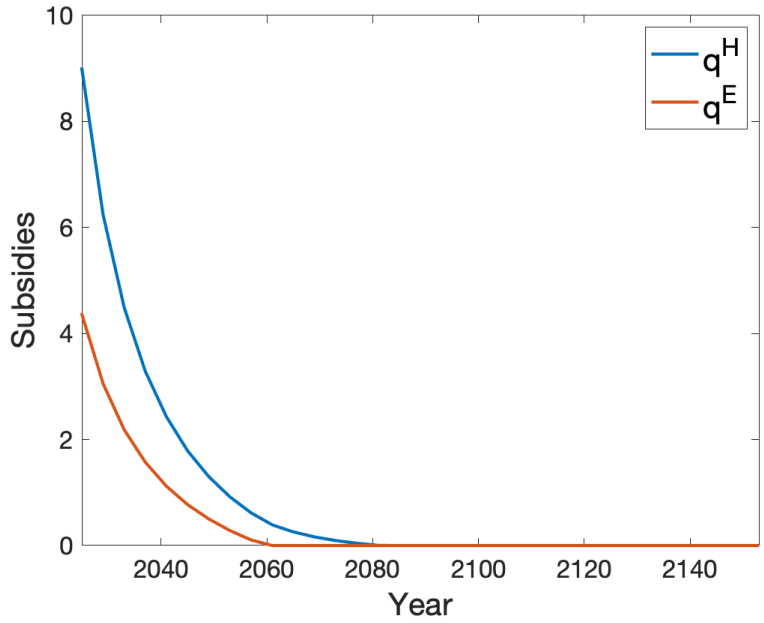
Table A.1: CPC Y02 Technology Classification

CPC Code	Technology Description	Category
Y02B	**Climate change mitigation tech. related to buildings**	
Y02B 10/00	Integration of renewable energy sources in buildings	Easy
Y02B 20/00	Energy efficient lighting tech.	Easy
Y02B 30/00	Energy efficient heating, ventilation or air conditioning [HVAC]	Easy
Y02B 90/00	Enabling tech. or tech. with a potential or indirect contribution to GHG emissions mitigation	Easy
Y02C	**Capture, storage, sequestration or disposal of GHG**	Hard
Y02D	**Climate change mitigation tech. in information and communication tech. [ICT]**	Easy
Y02E	**Reduction of GHG emissions, related to energy generation, transmission or distribution**	
Y02E 10/00	Energy generation through renewable energy sources	Easy
Y02E 20/00	Combustion tech. with mitigation potential	Easy
Y02E 30/00	Energy generation of nuclear origin	Easy
Y02E 40/00	Tech. for an efficient electrical power generation, transmission or distribution	Easy
Y02E 50/00	Tech. for the production of fuel of non-fossil origin	Hard
Y02E 60/00	Enabling tech.; Tech. with a potential or indirect contribution to GHG emissions mitigation	
Y02E 60/10	Energy storage using batteries	Easy
Y02E 60/13	Energy storage using capacitors	Easy
Y02E 60/14	Thermal energy storage	Easy
Y02E 60/16	Mechanical energy storage, e.g. flywheels or pressurised fluids	Easy
Y02E 60/60	Arrangements for transfer of electric power between AC networks or generators via a high voltage DC link [HVDC]	Easy
Y02E 70/00	Other energy conversion or management systems reducing GHG emissions	Easy
Y02P	**Climate change mitigation tech. in the production or processing of goods**	
Y02P 10/00	Tech. related to metal processing	Hard
Y02P 20/00	Tech. relating to chemical industry	Hard
Y02P 30/00	Tech. relating to oil refining and petrochemical industry	Hard
Y02P 40/00	Tech. relating to the processing of minerals	Hard
Y02P 60/00	Tech. relating to agriculture, livestock or agroalimentary industries	
Y02P 60/80	Food processing, e.g. use of renewable energies or variable speed drives in handling, conveying or stacking	Easy
Y02P 90/40	Fuel cell tech. in production processes	Hard
Y02P 90/45	Hydrogen tech. in production processes	Hard
Y02P 90/60	Electric or hybrid propulsion means for production processes	Easy
Y02P 90/70	Combining sequestration of CO2 and exploitation of hydrocarbons by injecting CO2 or carbonated water in oil wells	Hard

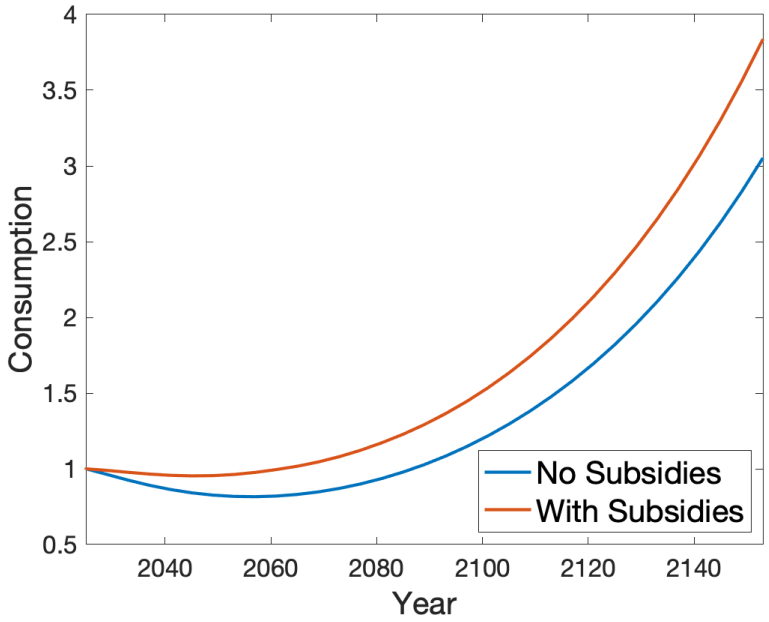
Note: This table presents a classification of CPC Y02 patent categories into technologies that are predominantly related to easy-to-abate or hard-to-abate economic activities

B.4 Appendix Figures

Figure A.1: Robustness Check - Low Pure Rate of Time Preference $\rho = 0.1\%$



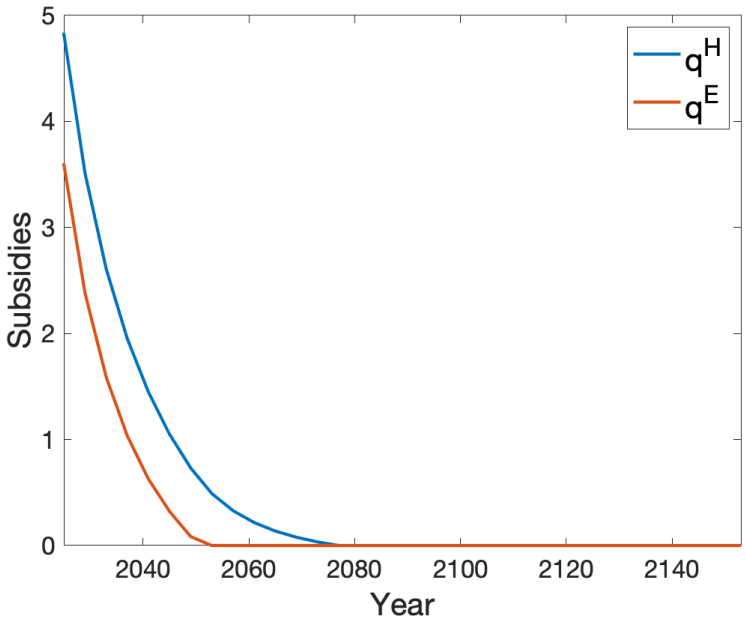
(a) Optimal Subsidies



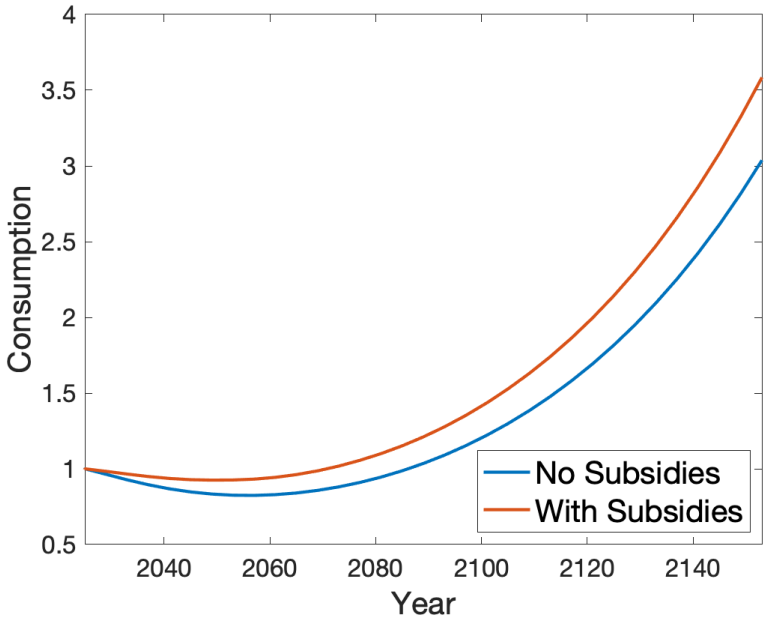
(b) Effect of Subsidies on Household Consumption

Note: This figure presents the main results of the calibration, conducting a robustness check to a lower value of the pure rate of time preference $\rho = 0.1\%$. The rest of the parameter values are in 8. Panel A presents the optimal path of subsidies to scientists innovating in the clean hard-to-abate (easy-to-abate) sector q^H (q^E), and Panel B presents the effect of subsidies on household consumption.

Figure A.2: Robustness Check - High Intermediary Goods Substitution $\nu = 0.75$



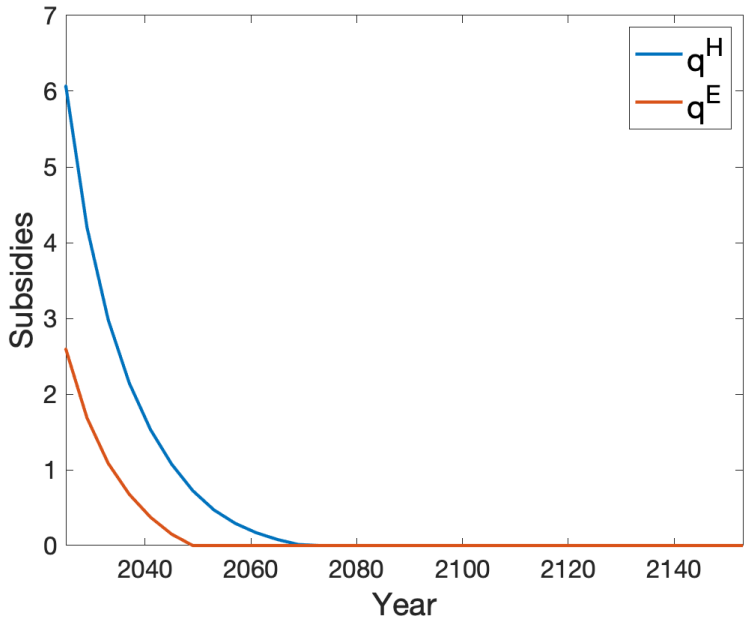
(a) Optimal Subsidies



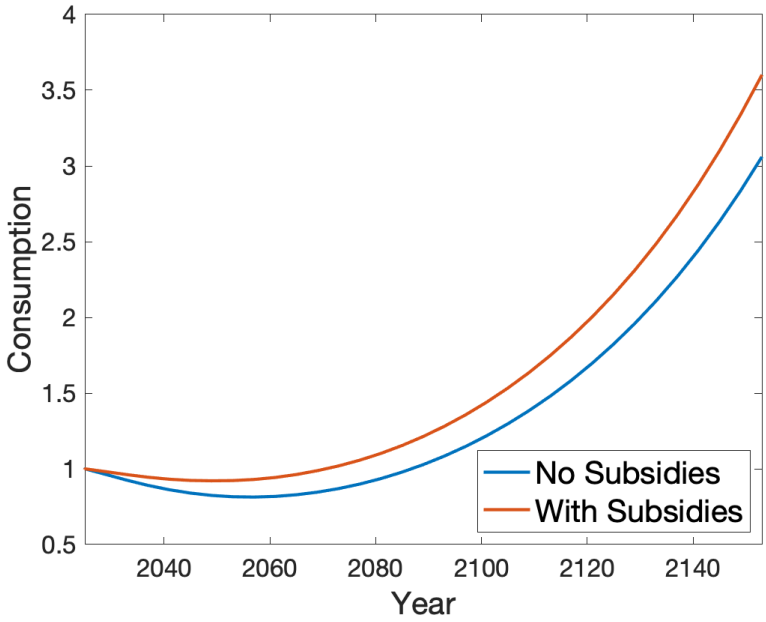
(b) Effect of Subsidies on Household Consumption

Note: This figure presents the main results of the calibration, conducting a robustness check to a higher value of the elasticity of substitution of intermediary goods $\nu = 0.75$. The rest of the parameter values are in 8. Panel A presents the optimal path of subsidies to scientists innovating in the clean hard-to-abate (easy-to-abate) sector q^H (q^E), and Panel B presents the effect of subsidies on household consumption.

Figure A.3: Robustness Check - Low Intermediary Goods Substitution $\nu = 0.2$



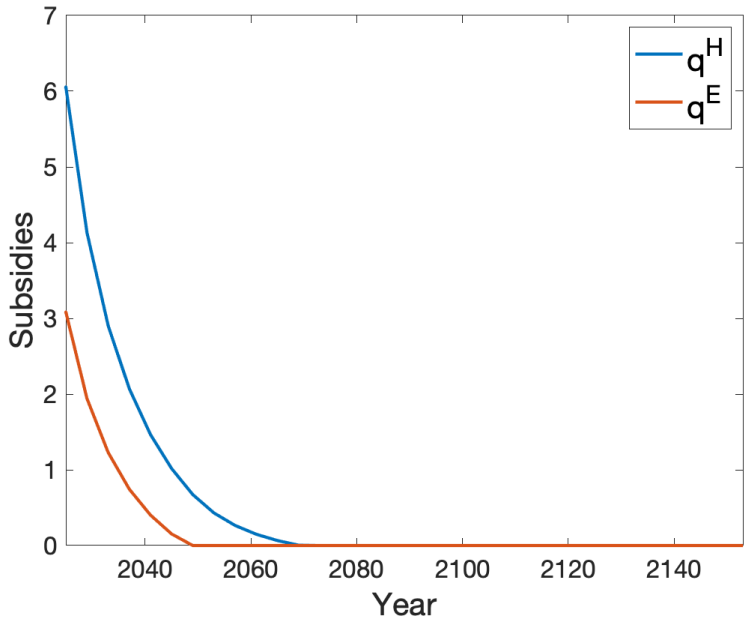
(a) Optimal Subsidies



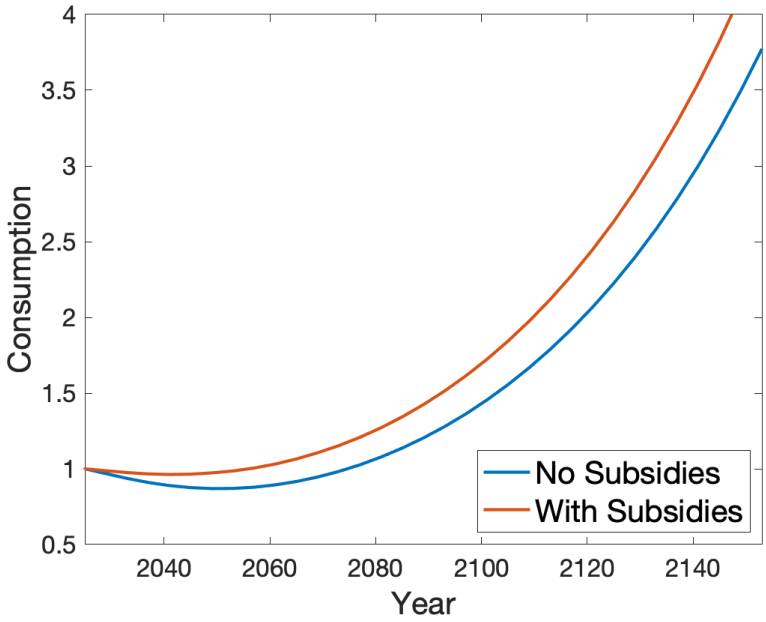
(b) Effect of Subsidies on Household Consumption

Note: This figure presents the main results of the calibration, conducting a robustness check to a lower value of the elasticity of substitution of intermediary goods $\nu = 0.2$. The rest of the parameter values are in 8. Panel A presents the optimal path of subsidies to scientists innovating in the clean hard-to-abate (easy-to-abate) sector q^H (q^E), and Panel B presents the effect of subsidies on household consumption.

Figure A.4: Robustness Check - high Input Elasticity of Substitution $\varepsilon = 2.87$



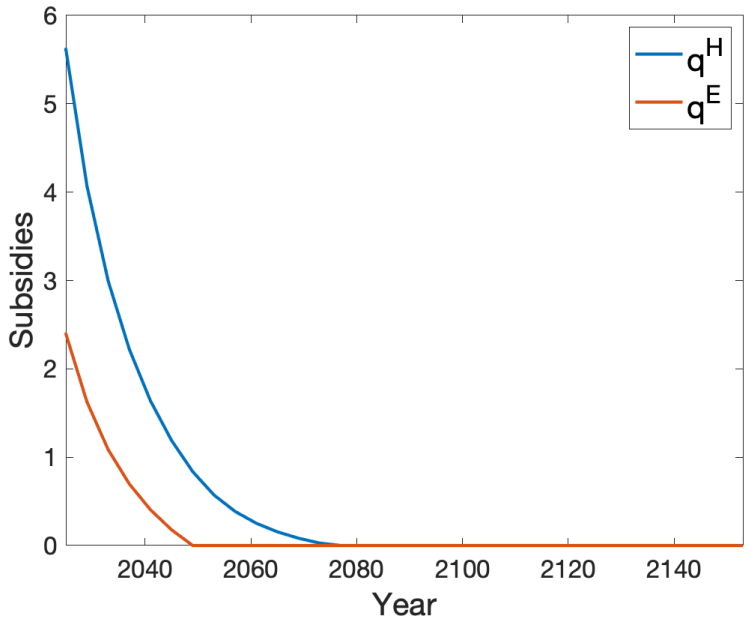
(a) Optimal Subsidies



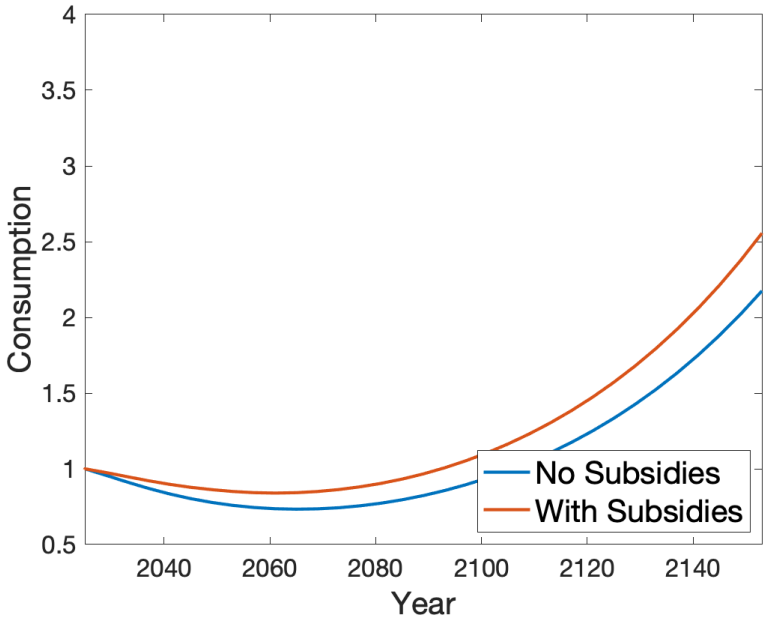
(b) Effect of Subsidies on Household Consumption

Note: This figure presents the main results of the calibration, conducting a robustness check to a higher value of the elasticity of substitution between the inputs $\varepsilon = 2.87$. The rest of the parameter values are in 8. Panel A presents the optimal path of subsidies to scientists innovating in the clean hard-to-abate (easy-to-abate) sector q^H (q^E), and Panel B presents the effect of subsidies on household consumption.

Figure A.5: Robustness Check - Low Input Elasticity of Substitution $\varepsilon = 2.05$



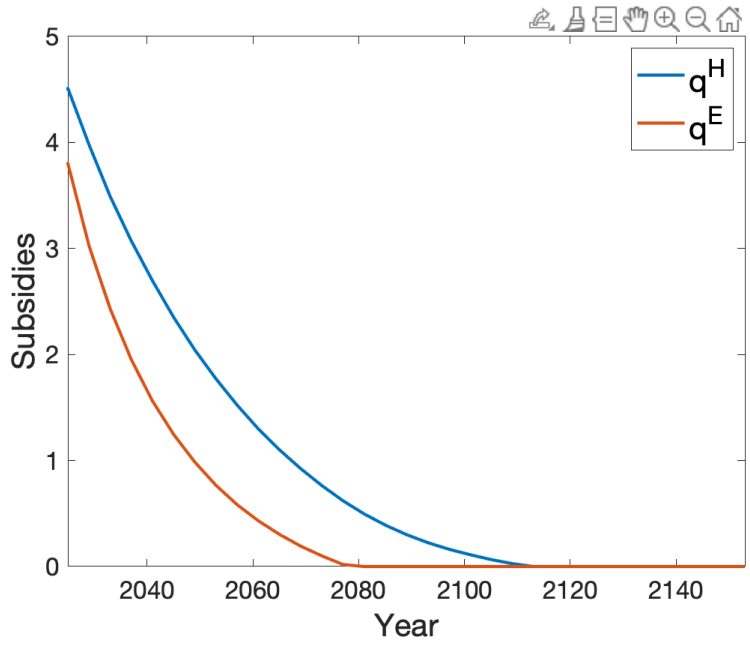
(a) Optimal Subsidies



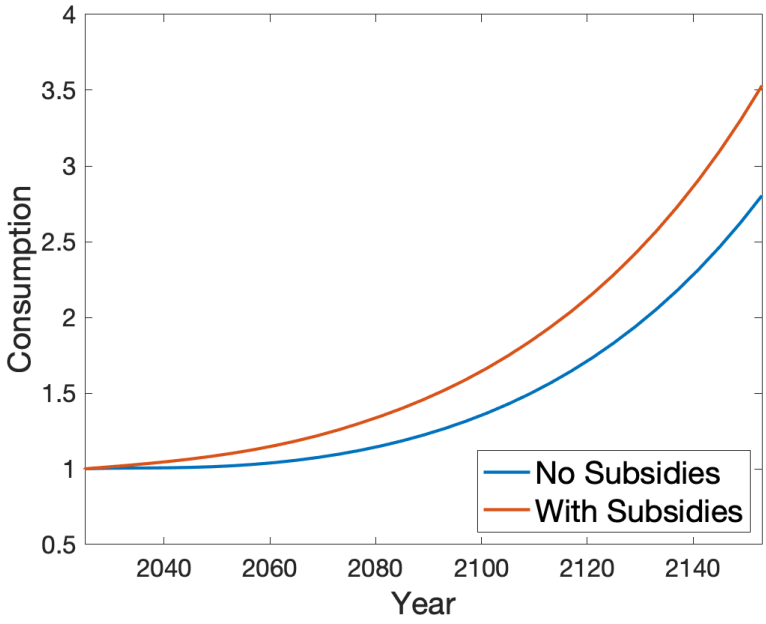
(b) Effect of Subsidies on Household Consumption

Note: This figure presents the main results of the calibration, conducting a robustness check to a higher value of the elasticity of substitution between the inputs $\varepsilon = 2.05$. The rest of the parameter values are in 8. Panel A presents the optimal path of subsidies to scientists innovating in the clean hard-to-abate (easy-to-abate) sector q^H (q^E), and Panel B presents the effect of subsidies on household consumption.

Figure A.6: Robustness Check - Low Emissions Cap Decrease Rate $\theta = 2.2\%$



(a) Optimal Subsidies



(b) Effect of Subsidies on Household Consumption

Note: This figure presents the main results of the calibration, conducting a robustness check to a lower value of the emissions decrease rate $\theta = 2.2\%$. The rest of the parameter values are in 8. Panel A presents the optimal path of subsidies to scientists innovating in the clean hard-to-abate (easy-to-abate) sector q^H (q^E), and Panel B presents the effect of subsidies on household consumption.