# Charging the Transition: Energy Storage Innovation and Climate Policy

**[Draft]**

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**Abstract**

This paper examines the critical role of energy storage innovation in achieving environmental targets. Traditional macroeconomic models have often overlooked the importance of enabling technologies to overcome the intermittency of clean energy. We incorporate storage technology into an endogenous growth model. Due to the complementarity between renewables and storage technology, the productivity of storage technology becomes a key determinant of the private incentives to innovate in clean energy relative to fossil fuels. We calibrate it to the U.S. economy and find four main results: First, models that neglect the role of energy storage overestimate the effectiveness of climate policy. Second, clean and dirty energy are currently complementary inputs due to the low productivity of storage technologies. Third, the low productivity of storage technologies may have reduced clean innovation with a magnitude similar to the shale gas boom. Fourth, current policy such as the Inflation Reduction Act is not

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sufficient to decarbonize U.S. energy supply. To reach decarbonization targets, we need additional policy effort to close the productivity gap between renewables and storage technology.

**Keywords**: Economic growth, endogenous technical change, storage, sub-optimal climate policy

**JEL classification**: O33, O44, Q43, Q48

# 1 Introduction

To meet the ambitious targets set by the Paris Agreement, the efficient use of renewable energy is essential. A critical element in the successful integration of renewables into the energy system is storage, as these technologies allow excess energy to be stored during periods of high production and released when demand is high, thus ensuring a stable and reliable clean energy supply.[1] Although innovation in renewable technologies has been a central theme in climate policy discussions, the dependence of renewables on effective storage solutions has often been underemphasized.[2] Moreover, the climate-economy macro literature has mostly overlooked the complementary role of energy storage. Consequently, the need for innovation and deployment of storage technologies—alongside its importance for achieving environmental goals—remains largely unexplored.

This paper analyses the role of storage technology innovation and deployment in achieving environmental targets and advancing toward a carbon-neutral economy. Traditional endogenous growth macroeconomic models (e.g., Acemoglu, 2002) have shown that as long as competing technologies are substitutes, policies that improve the productivity of one of the sectors can shift innovation to this sector. In the context of the energy transition, this

[1] We use the term "storage" in a broad sense, encompassing all enabling technologies, including batteries, hydrogen fuel cells, and similar systems.

[2] The share of renewable energy R&D has been approximately 4 times higher than that of storage R&D since the mid-2000's in the International Energy Agency members (see Figure A1).

implies that temporary carbon taxes and research subsidies are sufficient to ensure the clean energy transition (Acemoglu et al., 2012) (henceforth AABH). However, these frameworks often overlook the intermittency challenge posed by renewables—and the essential role of storage in mitigating this issue, thus limiting their ability to assess the transition accurately. This raises several pressing questions: Can limited storage technology and capacity hinder the energy transition even in the presence of stringent climate policies? How does dependency on storage affect the efficiency of these policies? How does storage alter the substitutability between renewables and fossil fuels? Are current and prospective climate policies sufficient to meet environmental goals?

To answer these questions, we develop a climate-economy model with clean and dirty energy inputs, along with directed technological development a la AABH. Unlike traditional models, our framework requires both renewable energy and storage capacity to produce the clean input.[3] As renewables and storage are complements, their relative profitability of innovation is subject to a negative path dependency, which incentivizes innovation in the less advanced sector. Furthermore, we show that private innovation incentives between dirty and renewable energy inputs are shaped by two forces: (i) the direct path dependency effect, which promotes innovation in the more advanced sector; and (ii) the indirect path dependency effect, which reduces the profitability of innovation in renewables relative to dirty when the productivity gap between renewables and storage widens. The second force implies that, unlike in the traditional paradigm, advances in renewable technology do not necessarily increase incentives to further improve the productivity of renewable energy. Instead, the progress of storage technology becomes a pivotal factor in driving the shift away from dirty innovation and production. Thus, the energy transition is made substantially more difficult given the currently low productivity of storage technologies.

Our model further rationalizes the recent trends in patenting activity across different

[3]This is in line with Andrés-Cerezo and Fabra (2023), which finds empirical complementarity between renewables and storage as long as the share of renewables in the grid is above a critical threshold.

energy technologies. Innovation in renewable energy—measured by the number of patent applications—saw a marked decline around 2010. This downturn has been attributed to several factors, including the technological maturation of renewable energy solutions, the advent of the shale gas boom (Acemoglu et al., 2023), and broader economic constraints following the Great Recession (Popp et al., 2022). Innovation in energy storage, on the other hand, followed a distinctly different path, which has not been previously documented in the literature. In contrast to renewables, patent applications in storage technologies not only avoided a decline but actually increased during the same period. Figure 1 presents these trends for the United States Patent and Trademark Office (USPTO).[4] Our model provides an additional explanation for these patterns through the productivity gap between renewables and storage: When the gap is large, incentives to innovate in renewables are low, while incentives for storage innovation are high.[5]

To assess the effectiveness of climate policies, we calibrate our model to match the U.S. economy in 2006-2010. First, we show that climate policy is substantially less effective in a framework that accounts for storage compared to the traditional AABH model. Second, we examine the U.S. Inflation Reduction Act (IRA) on economic and climate outcomes. Before the IRA, the U.S. paradigm was characterized by a public support for R&D that was strongly biased towards renewables. However, the IRA introduces significant funding for clean energy production. Despite some improvements, our findings suggest that the U.S. energy mix will remain largely dominated by fossil fuels over the next decades. As a result, the COP28 Agreement, which aims to triple the global share of renewable energy capacity by 2030, will not be achieved in the U.S. context. To meet this target, we find that the IRA would need to increase its efforts by 2.3 times. Interestingly, had the technological gap between renewables and storage been 50% smaller, the necessary efforts to achieve the international

[4]Figure A2 reproduces Figure 1 as a share of total patent applications. Notably, these trends are not exclusive to the USPTO; Figures A3 and A4 in the appendix show similar patterns across other patent offices, including the U.S., Japan and France.

[5]Unlike our framework, the AABH model is not able to explain the post-2010 decline in renewables and Acemoglu et al. (2023) overlooks the evolution of storage innovation.

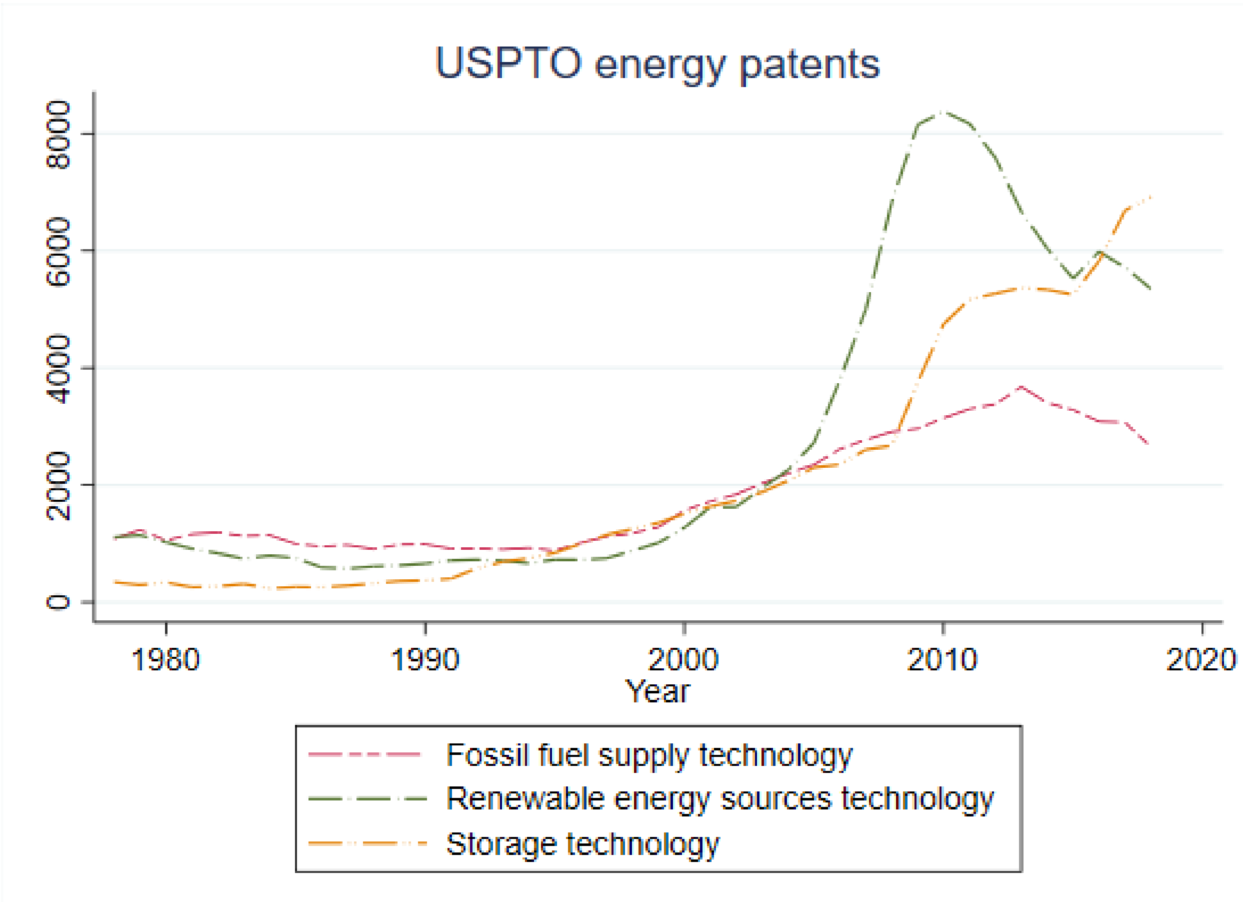



Figure 1: Patent applications filed at the USPTO, 1978-2018, in energy technologies. To be classified as a renewable patent, the application must have a CPC (cooperative patent classification) code included in the "Low-carbon energy supply" category from the IEA (2021). Storage patents are those classified as batteries and hydrogen storage. Source: Patstat.

goal would be only 1.7 times higher than current levels. Third, we find that both pre- and post-IRA policy can reduce consumer welfare in a scenario in which the rest of the world will limit its emissions to the 2ºC target, especially if the international goal were to be achieved through increased IRA-style provisions. This is because, in the suboptimal setting we study, the avoided climate damages of emission reductions in the U.S. do not compensate for the innovation and production distortions that these types of policies create.

In addition, our model reinforces the notion that the substitutability between clean and dirty energy is not constant over time. Although our model assumes a constant elasticity of substitution between clean and dirty energy, the substitutability between renewables and fossil fuels is nonetheless a function of energy storage due to its complementarity with renewables. After analytically deriving its expression, we compute the substitutability between renewables and fossil fuels for different levels of storage capacity, finding that renewables and fossil fuels are, in fact, complements due to the current low levels of storage capacity. However, increasing the storage capacity increases the substitutability between renewables and fossil fuels, which become substitutes when storage capacity equals that of renewables. This complements the findings from earlier studies showing that the elasticity of substitution between fossil fuels and clean energy depends on the clean energy share (Jo and Miftakhova, 2024)[6], the development of storage technology (Gentile, 2024),[7] or the investments in the substitutability itself (Stöckl, 2020, Stöckl and Zerrahn, 2023)[8].

[6]Using French manufacturing data, Jo and Miftakhova (2024) find that clean and dirty energy have become more substitutable over time. By employing a "variable elasticity of substitution" (VES) production function within a directed technical change model, they show that a VES accelerates the clean energy transition, reducing reliance on policy intervention.

[7]Gentile (2024) incorporates directed innovation into a microfounded model of energy production with intermittency to study optimal climate policy. She finds that the elasticity of substitution between clean and dirty energy sources depends on the degree of intermittency and the technological level in the energy sectors.

[8]Stöckl (2020) build a growth model with endogenous investment in substitutability between clean and dirty energy. Due to decreasing marginal returns, it becomes eventually profitable to invest in increased substitutability. Thus, in a growing economy, fossil fuels are gradually replaced by renewable energy, even in the absence of a carbon tax. Stöckl and Zerrahn (2023) develop a bottom-up optimization model of the electricity market with clean and dirty energy inputs, which they use to derive production isoquants from German market data. They find that the elasticity of substitution is above unity as long as some energy storage is available. However, they also find that the elasticity may decrease at very high shares of renewables

**Related literature.** The evaluation of climate policies using macroeconomic growth models has a long tradition in economics, with numerous studies highlighting the effectiveness of carbon taxes on emissions reductions (e.g. Nordhaus, 1993, Golosov et al., 2014, Hassler, Krusell, and Olovsson, 2021, Barrage and Nordhaus, 2024). A significant advancement in this field emerged with the recognition of innovation in renewable energy technologies as a crucial factor in addressing climate issues. This insight led researchers to adapt the literature on endogenous technical change (notably through the work of Romer, 1990, Acemoglu, 2002), culminating in seminal studies such as Goulder and Mathai (2000), Popp (2004) and AABH. Their findings underscored the importance of coupling carbon taxes with additional policies—specifically, research subsidies aimed at fostering renewables innovation—to effectively drive the transition to a carbon-free economy.[9] However, this literature still falls short in accurately representing the energy transition, as it often overlooks a critical limitation of renewable energy: its inability to fully substitute fossil fuels without the simultaneous development of effective energy storage solutions. Our main contribution to this strand of literature is to show—both analytically and quantitatively—that this omission leads to a substantial overestimation of the efficiency of policies target at renewables.

Our findings align with those of Arkolakis and Walsh (2023) and Gentile (2024), as they also highlight that storage requirements can significantly slow the energy transition and the IRA policy can increase the clean energy share. However, our methodological approaches differ. Arkolakis and Walsh (2023) develop a spatial dynamic model with different energy sectors, learning-by-doing, and different exogenous scenarios for storage capacities and costs. On the other hand, Gentile (2024) constructs a micro-founded energy model that integrates intermittency and innovation, coupling it with a macroeconomic framework. Our approach

in electricity generation that are currently not observed, which could be due to low availability of energy storage.

[9] Other papers in this literature have analyzed optimal policy when the degree of substitutability grows over time. E.g., Mattauch, Creutzig, and Edenhofer (2015) find that the carbon tax must be permanent when there is an exogenous growth in the elasticity of substitution in a model with learning-by-doing spillovers, while Growiec and Schumacher (2008) find that exogenous growth in the substitutability of energy inputs is sufficient to overcome resource constraints in a Ramsey growth model.

adopts a purely macroeconomic perspective through a macro-climate model that incorporates three energy sectors: dirty energy, renewables, and storage. In this framework, intermittency is represented by the complementarity between renewables and storage. This enables us to explicitly explore how this complementarity reshapes existing theoretical insights about path dependency in clean innovation. We further demonstrate that a nested CES structure addresses a common critique of non-nested CES approaches: their inability to model variables with non-constant elasticities of substitution. Specifically, we show that the implicit substitution elasticity between renewables and dirty energy depends on storage capacity. Additionally, our model provides a new explanation for the observed collapse in renewable energy innovation and the simultaneous rise in storage innovation. Finally, we contribute to this recent literature by examining the achievement of key environmental targets and estimating the additional policy stringency required when these targets are not met.

This paper further contributes to the literature that studies the intermittency issue from a static—and partial equilibrium—perspective (e.g., Ambec and Crampes, 2019, Helm and Mier, 2019). These studies focus on the design of an efficient electric mix but they use a static framework, thus ignoring the energy transition. As a result, they tend to find a less vital role of storage technology due to its current low productivity. Pommeret and Schubert (2022) study the optimal transition to renewables, explicitly distinguishing between intermittency and variability,[10] in a dynamic general equilibrium framework, but do not account for endogenous innovation. They show that when the intermittency is severe, it is optimal to build storage capacity early.

In addition, the literature on industrial organizations has extensively analyzed the role of storage in wholesale electricity markets (e.g. Butters, Dorsey, and Gowrisankaran, 2024, Andrés-Cerezo and Fabra, 2023, Karaduman, 2023, Lamp and Samano, 2022). These studies commonly focus on investigating the value of storage in electricity markets, its impact on

[10] They define variability as "being predictable: it follows a natural pattern such as the alternation of day and night, or of seasons." On the other hand, they define intermittency as "being stochastic, due to unpredictable weather events like cloud formation"

electricity prices, and on the congestion of the electricity grid. We contribute to these studies by analyzing the role of storage in the energy transition from a macroeconomic perspective and, importantly, taking into account innovation incentives and climate policies.

Finally, our paper helps shed light on the impacts of the Inflation Reduction Act on the energy transition, climate outcomes, and welfare. A growing body of literature is engaging in this endeavor, recognizing the Inflation Reduction Act as a landmark policy with significant implications for the U.S. economy and climate goals. For instance, Bistline, Mehrotra, and Wolfram (2023a) evaluate the macroeconomic effects of the policy, while Bistline et al. (2023) study the emissions reductions induced by the policy using a number of existing models. Our model provides new insights into the medium- and long-term effects of this policy, from an endogenous growth perspective and exploring its effects on innovation in storage.

The remainder of the paper is organized as follows. In Section 2 we present our theoretical model. Section 3 details the model calibration, illustrates numerically the main analytic results, evaluates the effectiveness of climate policies in the context of storage, and analyses the elasticity of substitution between fossil fuels and renewables. Section 4 presents the main quantitative results, Section 5 explores the renewables collapse and Section 6 assesses the evolution of carbon emissions and consumers' welfare. Finally, section 7 concludes.

# 2 Theoretical model

The following describes the theoretical framework and derives the main analytical results.

## 2.1 The economy: model set-up

### Consumption

A representative household has well-behaved preferences over consumption $C_t$ and environmental quality $S_t$. Their lifetime utility is given by

$$U_0 = \sum_{t=0}^{\infty} \beta^t u(C_t, S_t)$$

where $u$ is the instantaneous utility of consumption and $\beta$ is the utility discount factor. The standard properties of $u$ apply: it is increasing in $C_t$ ($u'(C_t) > 0$), twice differentiable and concave ($u''(C_t < 0$), and satisfies $\lim_{C_t \to 0} u'((C_t) = \infty$.

**Production**

The final good, $Y_t$, is produced by perfectly competitive firms that combine a dirty energy ($Y_{dt}$) input with a clean energy input ($Y_{ct}$) according to a CES production function,

$$Y_t = \left( Y_{dt}^{\frac{\epsilon-1}{\epsilon}} + Y_{ct}^{\frac{\epsilon-1}{\epsilon}} \right)^{\frac{\epsilon}{\epsilon-1}}, \tag{1}$$

where $\epsilon$ is the elasticity of substitution between the dirty and clean input.

The use of one unit of the dirty input releases $\xi$ units of CO2 emissions

$$E_t = \xi_t Y_{dt}.$$

The clean input is produced by firms that combine renewable energy ($Y_{rt}$) with storage production ($Y_{st}$) under perfect competition and according to a CES production function,

$$Y_{ct} = \left( \delta Y_{rt}^{\frac{\rho-1}{\rho}} + (1-\delta) Y_{st}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \tag{2}$$

where $\rho$ is the elasticity of substitution between renewables and storage and $\delta$ is the input share of renewables in clean production.

In what follows, we make the following assumption.

**Assumption 1.** *$\epsilon > 1$ and $\rho \in (0, 1)$.*

Assumption 1 states that dirty and clean sources of energy are substitutes. This is based on existing empirical evidence on the substitutability between dirty and clean sources of energy (Papageorgiou, Saam, and Schulte, 2017, Jo, 2024, Stöckl and Zerrahn, 2023). However, renewables and energy storage are complements in the production of clean energy.[11]

The intermediate input in sector $j$, where $j \in \{d, r, s\}$, is produced by perfectly competitive firms that combine labor with a unit continuum of machines according to a Cobb-Douglas production function,

$$Y_{jt} = L_{jt}^{1-\alpha} \int_0^1 A_{ijt}^{1-\alpha} x_{ijt}^{\alpha} di. \tag{3}$$

A machine $i$ in sector $j$ is used only in that sector. There is a fixed supply of workers normalized to unity, and market clearing implies that $L_{dt}+L_{rt}+Lst \leq 1$. Profit-maximization by producers of intermediate input $j$ results in the following demand for machines

$$x_{ijt} = \left( \frac{\alpha p_{jt}}{p_{ijt}} \right)^{\frac{1}{1-\alpha}} A_{ijt} L_{jt}, \tag{4}$$

and in the following wage rate

$$w_{jt} = (1-\alpha) p_{jt} \frac{Y_{jt}}{L_{jt}}. \tag{5}$$

Machines are produced by using $\psi$ units of the final good. In each machine $i$ there is a single monopolist that maximizes profits,

$$\max_{\{p_{ijt},\ x_{ijt}\}} (p_{ijt} - \psi) x_{ijt}. \tag{6}$$

This results in the standard monopoly price,

$$p_{ijt}^{x} = \frac{\psi}{\alpha}, \tag{7}$$

[11]This is consistent with the notion that the intermittency of renewable energy sources can be mitigated through energy storage solutions. The assumption is empirically supported by both Andrés-Cerezo and Fabra (2023), when renewables capacity is sufficiently high, and our own analysis (see section A.3.1 for more details). Pommeret and Schubert (2022)'s quantitative results further support it.

which is a constant mark-up above marginal costs.[12] Combining Eqs. (7) and (4), the optimal demand for machines becomes

$$x_{ijt} = \left(\frac{\alpha^2 p_{jt}}{\psi}\right)^{\frac{1}{1-\alpha}} A_{ijt} L_{jt}. \tag{8}$$

Finally, using the price of machines from Eq. (7) and the demand for machines from Eq. (8), the per-period profit of a producer of a machine $i$ used in sector $j$ is

$$\pi_{ijt} = (1-\alpha)\left(\frac{\alpha}{\psi}\right)^{\frac{\alpha}{1-\alpha}} (\alpha p_{jt})^{\frac{1}{1-\alpha}} A_{ijt} L_{jt}. \tag{9}$$

**Innovation**

In each period, there is a fixed mass of scientists that is normalized to unity. Scientists are free to choose the sector to focus their innovation efforts, and they can choose between dirty, renewable, or storage technology. Successful innovation leads to an increase in technology productivity by a factor $(1+\gamma)$. If successful, the new productivity of machine $i$ is

$$A_{ijt+1} = (1+\gamma)A_{ijt}.$$

The aggregate (and average) machine quality in sector $A_{jt}$ is denoted by

$$A_{jt} = \int_0^1 A_{ijt} di.$$

This assumes that there are no innovation spillovers across sectors. Such an assumption grants us some non-negligable degree of analytical tractability and allows us to provide analytical insights on storage technology and the clean transition. However, it is at odds with the empirical evidence on knowledge spillovers (e.g. Dechezleprêtre, Martin, and Mohnen,

[12] Note that this distortion could be eliminated by providing a subsidy to equate the price of machines with the marginal cost, $p^x_{ijt} = \psi$. However, we choose to keep the monopoly distortion in the model.

2017). For that reason, in the quantitative exercise, we incorporate knowledge spillovers into the model as detailed in section 2.3.

Each scientist has a probability of $\eta_j$ of making a successful innovation in sector $j$. However, due to duplication of ideas, there are decreasing returns to the number of scientists in a sector given by $s_{jt}^{\omega}$, where $\omega \in (0,1)$. Hence, the average technology level in sector $j$ evolves according to

$$A_{jt} = (1 + \gamma \eta_j s_{jt}^{\omega}) A_{jt-1}. \tag{10}$$

Taking into account the probability of success and the evolution of productivity, the expected profits of a scientist in sector $j$ are given by

$$\Pi_{jt} = \eta_j s_{jt}^{\omega-1} (1+\gamma)(1-\alpha) \left(\frac{\alpha}{\psi}\right)^{\frac{\alpha}{1-\alpha}} (\alpha p_{jt})^{\frac{1}{1-\alpha}} L_{jt} A_{jt-1}. \tag{11}$$

The expected profit of research in sector $j$ relative to sector $k$ is given as

$$\frac{\Pi_{jt}}{\Pi_{kt}} = \frac{1+q_{jt}}{1+q_{kt}} \times \frac{\eta_j}{\eta_k} \left(\frac{s_{jt}}{s_{kt}}\right)^{\omega-1} \left(\frac{p_{jt}}{p_{kt}}\right)^{\frac{1}{1-\alpha}} \times \frac{L_{jt}}{L_{kt}} \times \frac{A_{jt-1}}{A_{kt-1}}, \tag{12}$$

where $j$ and $k \in \{c, s, d\}$, and $q_{jt}$ and $q_{kt}$ are potential subsidies given to research in sector $j$ and $k$. As in AABH, the last three terms in (12) capture the price effect, the market size effect and the direct productivity effect, respectively.[13] In the following section, we detail the qualitative changes that these effects experience.

Market clearing requires $s_{dt} + s_{rt} + s_{st} \leq 1$, and in equilibrium, scientists must be indifferent between the different sectors, which implies that $\Pi_{dt} = \Pi_{rt} = \Pi_{st}$.

[13]The first one pushes innovation towards the sector with higher prices; the second one, towards the sector with larger employmet; and the thrid one towards the sector with a higher technological level (building on the shoulder of giants-effect).

## 2.2 Characterization of the decentralized equilibrium

A detailed derivation of the decentralized equilibrium is provided in the Appendix. Section A.2 details each agent's maximization problem, as well as the equilibrium level of prices, labor shares, and output. In what follows, we characterize the equilibrium allocation of scientists.

**Definition 1.** *The equilibrium consists of a sequence of wages ($w_t$), input prices ($p_{jt}$), machine prices ($p_{jit}$), labor demands ($L_{jt}$), input demands ($Y_{jt}$), machine demands ($x_{jit}$), scientists allocations ($s_{jt}$) and exogenously given policies ($z_{jt}$, $q_{jt}$) for each sector $j \in (d, r, s)$, such that, in each period $t$, (i) ($p_{jit}$, $x_{jit}$) maximizes machine $i$ producer's profits; (ii) $L_{jt}$ maximizes input producers' profits; (iii) $Y_{jt}$ maximizes final good producer's profits; (iv) ($s_{jt}$) maximizes the expected profits of researchers at time $t$; (v) the labor market clears; and (vi) the inputs market clears.*

### Allocation of scientists

The allocation of scientists is implicitly given by Eq. (12). Using the relative price in Eq. (A8) and labor shares from Eqs. (A16), the profitability of research in renewables relative to storage can be expressed as

$$\frac{\Pi_{rt}}{\Pi_{st}} = \frac{1+q_{rt}}{1+q_{st}}\frac{\eta_r}{\eta_s}\left(\frac{s_{rt}}{s_{st}}\right)^{\omega-1}\left(\frac{\delta}{1-\delta}\right)^{\rho}\left(\frac{A_{rt}}{A_{st}}\right)^{-(1+\sigma)}\frac{A_{rt-1}}{A_{st-1}}. \tag{13}$$

Inserting for the evolution of technology in Eq. (19), the relative profitability can be written as a function of past productivity levels, current environmental policy, and the allocation of scientists,

$$\frac{\Pi_{rt}}{\Pi_{st}} = \frac{1+q_{rt}}{1+q_{st}}\frac{\eta_r}{\eta_s}\left(\frac{s_{rt}}{s_{st}}\right)^{\omega-1}\left(\frac{\delta}{1-\delta}\right)^{\rho}\left(\frac{1+\gamma\eta_r s_{rt}^{\omega}}{1+\gamma\eta_s s_{st}^{\omega}}\right)^{-(1+\sigma)}\left(\frac{A_{rt-1}}{A_{st-1}}\right)^{-\sigma}. \tag{14}$$

Note that this expression is equal to the relative profitability of clean innovation in AABH. Given Assumption 1 we can easily prove the following lemma:

**Lemma 1.** *Assume that Assumption 1 holds. Then, the evolutions of renewable and energy storage technologies experience a negative path dependence. That is, the expected profitability of innovation in renewables relative to energy storage is decreasing in the productivity of renewables and increasing in the productivity of energy storage.*

*Proof.* Under Assumption 1, $\sigma > 0$, from which it follows that $\frac{\partial \frac{\Pi_{rt}}{\Pi_{st}}}{\partial A_{rt-1}} < 0$ and $\frac{\partial \frac{\Pi_{rt}}{\Pi_{st}}}{\partial A_{st-1}} > 0$. $\square$

Since the two inputs are complements, the price effect introduced in (12) and detailed in (A8) dominates. Note also that an increase in the number of scientists in renewables makes innovation in renewables less profitable relative to storage.

In addition to Eq. (23), the profitability of innovation in renewables can also be expressed relative to fossil fuels, using the relative price in Eq. (A8) and the relative labor given by Eqs. (A17 and A21) as:

$$\frac{\Pi_{rt}}{\Pi_{dt}} = \frac{1+q_{rt}}{1+q_{dt}}\frac{\eta_r}{\eta_d}\left(\frac{s_{rt}}{s_{dt}}\right)^{\omega-1}\left(\frac{1-z_d}{1-z_c}\right)^{\epsilon}\left(\frac{A_{rt}}{A_{dt}}\right)^{-1-\phi}\frac{A_{rt-1}}{A_{dt-1}}\delta^{\rho}\left[\delta^{\rho}+(1-\delta)^{\rho}\left(\frac{A_{rt}}{A_{st}}\right)^{\sigma}\right]^{\frac{\rho-\epsilon}{1-\rho}}, \tag{15}$$

where $\phi \equiv (1-\alpha)(1-\epsilon)$. Inserting for the evolution of technology in Eq. (19), the relative profitability can again be written as a function of past productivity levels, current environmental policy, and the allocation of scientists,

$$\frac{\Pi_{rt}}{\Pi_{dt}} = \frac{1+q_{rt}}{1+q_{dt}}\frac{\eta_r}{\eta_d}\left(\frac{s_{rt}}{s_{dt}}\right)^{\omega-1}\left(\frac{1-z_d}{1-z_c}\right)^{\epsilon}\underbrace{\left(\frac{1+\gamma\eta_r s_{rt}^{\omega}}{1+\gamma\eta_d s_{dt}^{\omega}}\right)^{-1-\phi}\left(\frac{A_{rt-1}}{A_{dt-1}}\right)^{-\phi}}_{\text{Direct path dependency effect}}$$
$$\times\underbrace{\delta^{\rho}\left[\delta^{\rho}+(1-\delta)^{\rho}\left(\frac{1+\gamma\eta_r s_{rt}^{\omega}}{1+\gamma\eta_s s_{st}^{\omega}}\right)^{\sigma}\left(\frac{A_{rt-1}}{A_{st-1}}\right)^{\sigma}\right]^{\frac{\rho-\epsilon}{1-\rho}}}_{\text{Indirect path dependency effect}}. \tag{16}$$

When clean and fossil fuel energy are substitutes ($\epsilon > 1$), an increase in the productivity of renewables relative to fossil fuels increases the relative profitability of research in renewables (Direct path dependency effect). As in AABH, the effect of an increase in the share of scientists in renewables on the relative profitability of research depends on whether clean energy and fossil fuels are weak or strong substitutes ($\epsilon > (2-\alpha)(1-\alpha)$).

However, compared to AABH, the profitability of renewable research relative to dirty research is expanded by an additional term that takes into account the productivity of renewable relative to storage technology. This leads to the following lemma:

**Lemma 2.** *Under Assumption 1 and holding all else equal, it is ambiguous whether an increase in $A_r$ pushes scientists to innovate in the renewable or in the dirty sector. Specifically, higher levels of $A_r$ affect the relative profitability of renewables over fossil fuels through two opposing forces: firstly, positively via the direct path dependence effect, and secondly, negatively via the indirect path dependence effect.*

*Proof.* Under Assumption 1, $\phi < 0$ and $\rho - \epsilon < 0$. Thus, an increase in $A_{rt-1}$ increases $\frac{\Pi_{rt}}{\Pi_{dt}}$ via the direct path dependency effect and decreases it via the indirect path dependency effect. □

Lemma 2 highlights a relevant feature of our framework that departs from the existing literature. It summarizes the fact that an increase in the productivity of renewables does not necessarily induce innovation towards better renewable technologies. In particular, an increase in $A_r$ has two counteracting effects on the profitability of research in renewables relative to fossil fuels. On the one hand, since clean and dirty inputs are substitutes, then $\phi < 0$, which leads to a positive path dependence (captured by the *direct path dependence effect*). On the other hand, since $\epsilon > \rho$ and $\rho < 1$, the *indirect path dependence effect* pushes innovation away from renewables and towards the dirty sector.

Although the full path dependency effect is ambiguous, we can still explore the relative strength of the indirect path dependency effect.

**Proposition 1.** *All else equal and under Assumption 1, an increase in the technology ratio between renewables and energy storage $\frac{A_{rt-1}}{A_{st-1}}$ or a decrease in the input share of renewables, $\delta$, increases the strength of the indirect path dependency effect.*

*Proof.* Under Assumption 1, $\frac{\partial(\text{Indirect path dependency effect})}{\partial \frac{A_{rt-1}}{A_{st-1}}} < 0$. Furthermore, with lower values of $\delta$, the negative component of $\frac{\partial(\text{Indirect path dependency effect})}{\partial \delta}$ is larger, which makes it more plausible to satisfy that $\frac{\partial(\text{Indirect path dependency effect})}{\partial \delta} < 0$. □

That is, when the gap between renewables and storage productivity widens, research in renewables becomes less profitable, inducing less innovation in renewables compared to fossil fuels (see section A.4 in the Appendix for a graphical illustration of the proposition). This reflects the need to balance the technological development of the two complement inputs in order to avoid an environmental disaster. Furthermore, the negative indirect effect is more pronounced if the input share of renewables is lower.

Finally, we can show the following.

**Proposition 2.** *Assume that Assumption 1 holds. Then, all else equal, higher levels of historical storage technology increase the profitability of renewables relative to dirty research.*

*Proof.* Under Assumption 1, $\sigma$ is positive and $\epsilon > \rho$, from which follows that $\frac{\partial \frac{\Pi_{rt}}{\Pi_{dt}}}{\partial A_{st-1}} > 0$. □

Proposition 2 results from the complementarity between renewables and storage, ($\rho < 1$). Even though the *direct path dependence effect* in (16) is unaffected by an increase in $A_{st}$, the complementarity between storage and renewables activates the new *indirect path dependency effect*. Compared to a framework with only clean and dirty inputs, the introduction of storage makes research in renewables less profitable, all else equal. That is, with storage, the two technologies have to increase simultaneously, making it more difficult to increase renewables. Looking closer at the *indirect path dependency effect*, one can also see that higher historical levels of storage technology push innovation towards renewables to ensure that the technologies of the renewable good is not left behind.

## 2.3 Incorporating technology spillovers across different sectors

In what follows, we extend the previous model to incorporate technology spillovers across sectors. The intuition for the cross-sector spillovers is that whenever a sector is less advanced relative to other sectors, it benefits from ideas that other sectors have already developed. To incorporate this into our model, we assume that the probability of making a successful innovation in a machine from sector $j$, $Prob_{jt}$, now depends not only on the number of scientists in the sector but also on the technological level, following

$$Prob_{jt} = \eta_j s_{jt}^{\omega} \left( \frac{A_{t-1}}{A_{jt-1}} \right)^{\nu}, \tag{17}$$

where $A_{t-1}$ is the average technological level across sectors,

$$A_t = \frac{A_{dt} + A_{rt} + A_{st}}{3}. \tag{18}$$

As in Fried (2018), the term $\left( \frac{A_{t-1}}{A_{jt-1}} \right)^{\nu}$ accounts for the technological spillovers across sectors by increasing the productivity of research in a relatively backward sector. The parameter $\nu \in (0, 1)$ reflects the strength of the cross-sector spillovers.

Hence, the average technology level in sector $j$ evolves according to

$$A_{jt} = A_{jt-1} \left[ 1 + \gamma \eta_j s_{jt}^{\omega} \left( \frac{A_{t-1}}{A_{jt-1}} \right)^{\nu} \right], \tag{19}$$

Taking into account the probability of success and the evolution of productivity, the expected profits of a scientist in sector $j$, given by (11) without spillovers, become

$$\Pi_{jt} = \eta_j s_{jt}^{\omega-1} (1+\gamma)(1-\alpha) \left( \frac{\alpha}{\psi} \right)^{\frac{\alpha}{1-\alpha}} (\alpha p_{jt})^{\frac{1}{1-\alpha}} L_{jt} A_{jt-1}^{1-\nu} A_{t-1}^{\nu}. \tag{20}$$

With spillovers, the expected profit of research in sector $j$ relative to sector $k$ in (12) is given by

$$\frac{\Pi_{jt}}{\Pi_{kt}} = \frac{1+q_{jt}}{1+q_{kt}} \times \frac{\eta_j}{\eta_k} \left(\frac{s_{jt}}{s_{kt}}\right)^{\omega-1} \left(\frac{p_{jt}}{p_{kt}}\right)^{\frac{1}{1-\alpha}} \times \frac{L_{jt}}{L_{kt}} \times \left(\frac{A_{jt-1}}{A_{kt-1}}\right)^{1-\nu}. \tag{21}$$

Specifically, the expected profitability of innovation in renewables relative to energy storage is given by

$$\frac{\Pi_{rt}}{\Pi_{st}} = \frac{1+q_{rt}}{1+q_{st}} \frac{\eta_r}{\eta_s} \left(\frac{s_{rt}}{s_{st}}\right)^{\omega-1} \left(\frac{\delta}{1-\delta}\right)^{\rho} \left(\frac{A_{rt}}{A_{st}}\right)^{-(1+\sigma)} \left(\frac{A_{rt-1}}{A_{st-1}}\right)^{1-\nu}. \tag{22}$$

As before, it can be written as a function of past productivity levels,

$$\frac{\Pi_{rt}}{\Pi_{st}} = \frac{1+q_{rt}}{1+q_{st}} \frac{\eta_r}{\eta_s} \left(\frac{s_{rt}}{s_{st}}\right)^{\omega-1} \left(\frac{\delta}{1-\delta}\right)^{\rho} \underbrace{\left(\frac{1+\gamma\eta_r s_{rt}^{\omega} A_{rt-1}^{-\nu}}{1+\gamma\eta_s s_{st}^{\omega} A_{st-1}^{-\nu}}\right)^{-(1+\sigma)} \left(\frac{A_{rt-1}}{A_{st-1}}\right)^{-\sigma-\nu}}_{\text{Direct path dependency effect}}. \tag{23}$$

And, similarly for renewables over dirty,

$$\frac{\Pi_{rt}}{\Pi_{dt}} = \frac{1+q_{rt}}{1+q_{dt}} \frac{\eta_r}{\eta_d} \left(\frac{s_{rt}}{s_{dt}}\right)^{\omega-1} \left(\frac{1-z_d}{1-z_c}\right)^{\epsilon} \left(\frac{A_{rt}}{A_{dt}}\right)^{-1-\phi} \left(\frac{A_{rt-1}}{A_{dt-1}}\right)^{1-\nu} \delta^{\rho} \left[\delta^{\rho} + (1-\delta)^{\rho} \left(\frac{A_{rt}}{A_{st}}\right)^{\sigma}\right]^{\frac{\rho-\epsilon}{1-\rho}}. \tag{24}$$

which, as a function of past productivity levels, becomes

$$\frac{\Pi_{rt}}{\Pi_{dt}} = \frac{1+q_{rt}}{1+q_{dt}} \frac{\eta_r}{\eta_d} \left(\frac{s_{rt}}{s_{dt}}\right)^{\omega-1} \left(\frac{1-z_d}{1-z_c}\right)^{\epsilon} \underbrace{\left(\frac{1+\gamma\eta_r s_{rt}^{\omega} A_{t-1}^{\nu} A_{rt-1}^{-\nu}}{1+\gamma\eta_d s_{dt}^{\omega} A_{t-1}^{\nu} A_{dt-1}^{-\nu}}\right)^{-1-\phi} \left(\frac{A_{rt-1}}{A_{dt-1}}\right)^{-\phi-\nu}}_{\text{Direct path dependency effect}}$$

$$\times \underbrace{\delta^{\rho} \left[\delta^{\rho} + (1-\delta)^{\rho} \left(\frac{1+\gamma\eta_r s_{rt}^{\omega} A_{t-1}^{\nu} A_{rt-1}^{-\nu}}{1+\gamma\eta_d s_{dt}^{\omega} A_{t-1}^{\nu} A_{dt-1}^{-\nu}}\right)^{\sigma} \left(\frac{A_{rt-1}}{A_{st-1}}\right)^{\sigma}\right]^{\frac{\rho-\epsilon}{1-\rho}}}_{\text{Indirect path dependency effect}}. \tag{25}$$

Although cross-sector technology spillovers increase the realism of the model, they come at the expense of analytical tractability. That is, we can no longer analytically show the effect of changes in initial productivity levels on the relative profitability of innovation in the different energy sectors. Therefore, we evaluate the nature of the path dependency effects in the quantitative analysis.

# 3 Quantification

The following section serves four key purposes. First, it presents the calibration of the model parameters. Second, it provides a numerical illustration of Propositions 1 and 2, offering concrete examples that support the theoretical insights. Third, it compares the predictions of our model to those of existing models, focusing on the effectiveness of climate policy. Finally, the section estimates the degree of substitutability between renewable energy sources and fossil fuels, shedding light on the dependence of this elasticity of substitution on storage capacity.

## 3.1 Calibration

In the model runs, we begin the simulations in 2011 and simulate the model for 16 periods, with each period equal to five years. Table 1 shows the parameter values used in the simulations. In our theoretical model in Section 2, we assumed that clean energy and fossil fuels were substitutes in the production of final energy, which is in line with the findings of the empirical literature.[14] The elasticity chosen in previous papers has ranged from 0.7 in Karydas and Zhang (2019) to 10 in Acemoglu et al. (2012). We use an elasticity of substitution of 1.8561, which is an average of the elasticity estimated by Papageorgiou, Saam, and Schulte (2017) in the electricity sector. Due to the lack of empirical estimates of the substitution elasticity between renewables and energy storage, we use an estimate of 0.5, which ensures

[14] Papageorgiou, Saam, and Schulte (2017) use sector-level data in a panel of countries and find evidence that the elasticity of substitution exceeds unity in most sectors. However, there is generally a sizeable heterogeneity between sectors. In a panel of French manufacturing firms, Jo (2024) finds estimates of the elasticity ranging between 2 and 5 in different sectors.

that the two inputs are strong complements in producing clean energy.[15] However, to balance this strong complementarity, we assume a distribution parameter of renewables of 0.85 in the production function of clean energy.

Following convention, we set the share of machines to 1/3 in the production of the inputs. Without loss of generality, we normalize the cost of machines to $\alpha$. To begin simulations, we must assign initial productivity levels to fossil fuels, renewables and energy storage. We calibrate productivity levels using the average power generation capacity in the United States from 2006 to 2010. According to the US Energy Information Administration, the average net summer power generation capacity in this period was 769.95 million kilowatts for fossil fuels, 117.20 million kilowatts for renewables, and 21.94 million kilowatts for energy storage.[16] This leads to an initial productivity of fossil fuels that is 1.2 times greater than renewables (1503.0/1257.7), and an initial productivity of renewables 11.3 times larger than energy storage (1257.7/111.3).

In the research sector, we normalize the quality step of a successful innovation to unity and follow Acemoglu et al. (2012) by assuming that each scientist has a 2% probability of making a successful innovation each year. This ensures that the long-run annual growth rate is equal to 2% in the simulations and that the allocation of scientists between sectors is not driven by differences in research productivity. The level of decreasing returns to innovation is given by $\omega$, which we set equal to 0.5 following Acemoglu et al. (2016). For the cross-sector spillover parameter, we choose a conservative estimate of 0.3.

[15] This is in line with Andrés-Cerezo and Fabra (2023)'s empirical estimate. Furthermore, in section A.3.1 in the Appendix, we clarify our empirically informed choice of the elasticity of substitution between renewables and energy storage.

[16] The data is found in table 7.7a in the Monthly Energy Review published by the EIA: `https://www.eia.gov/totalenergy/data/monthly/`

Table 1: Parameter values used in model simulations

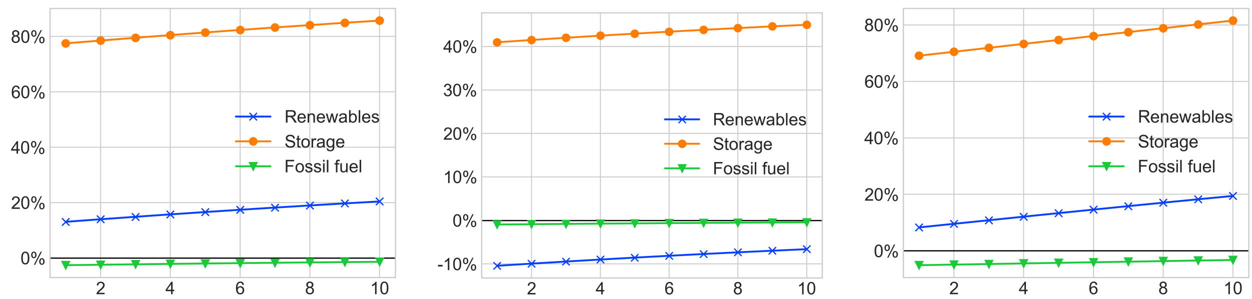
| Parameter | Model value | Source |
|---|---|---|
| *Final good production* | | |
| Electricity elasticity of substitution, $\epsilon$ | 1.8561 | Papageorgiou et al. (2017) |
| Clean energy elasticity of substitution, $\rho$ | 0.5 | See section A.3.1 |
| Distribution parameter in clean energy, $\delta$ | 0.85 | - |
| *Intermediate production* | | |
| Share of machines in production, $\alpha$ | 1/3 | - |
| Cost of machines, $\psi$ | $\alpha$ | Normalization |
| Initial productivity of renewables, $A_{r0}$ | 1257.7 | Calibration |
| Initial productivity of energy storage, $A_{s0}$ | 111.3 | Calibration |
| Initial productivity of fossil fuels, $A_{d0}$ | 1503.0 | Calibration |
| *Research sector* | | |
| Size of innovations, $\gamma$ | 1 | Normalization |
| Probability of innovation in renewables, $\eta_r$ | 0.2 | Acemoglu et al. (2012) |
| Probability of innovation in energy storage, $\eta_s$ | 0.2 | Acemoglu et al. (2012) |
| Probability of innovation in fossil fuels, $\eta_d$ | 0.2 | Acemoglu et al. (2012) |
| Decreasing returns to scientists, $\omega$ | 0.5 | Acemoglu et al. (2016) |
| Spillover parameter, $\nu$ | 0.3 | - |

### 3.2 Illustration of Propositions 1 and 2

According to Propositions 1 and 2, an increase in the productivity of renewables is no longer guaranteed to increase the relative profitability of innovation in renewables. In fact, the increase in the productivity of renewables may instead *decrease* innovation efforts in renewables due to the widening of the productivity gap between renewables and storage technology. In general, this indirect path dependency effect depends on the initial productivity gap between renewables and storage and the input share of renewables in the production of clean energy.

To illustrate the propositions, we simulate the model following a +100% increase in the initial productivity of renewables ($A_{r0}$) in three different scenarios. In the first scenario, the simulations are based on the parameters in Table 1. In the second scenario, we instead assume a lower input share of renewables in the production of clean energy ($\delta = 0.5$), that is, storage technology becomes more important in overcoming the intermittency of renewables. In the third scenario, we again assume a lower input share of renewables ($\delta = 0.5$), but in addition, we close the productivity gap between renewables and storage by setting the initial productivity of storage equal to that of renewables ($A_{s0} = A_{r0}$). All other parameters are equal to their values in Table 1, except for the spillover effect ($\nu$), which we set to zero to align the simulations with the propositions. For each scenario, we simulate the model for 10 periods and compare the change in the allocation of scientists to a baseline scenario without the productivity shock in renewables.

Figure 2 illustrates the percentage change in the allocation of scientists in renewables, storage, and fossil fuels caused by the +100% increase in $A_{r0}$ in the three scenarios. For reference, Figure A6 in the Appendix provides the detailed allocation of scientists both before and after the change in $A_{r0}$. In all scenarios, the figure shows a reduction of scientists in fossil fuels and an increase of scientists in storage caused by the productivity shock. However, the effect of the shock on innovation efforts in renewables depends on the initial productivity gap between renewables and storage technology and the input share of renewables in clean production. When these are equal to our baseline parameters, the shock induces more sci-




(a) Baseline parameters (b) $\delta = 0.5$ (c) $\delta = 0.5$ and $A_{s0} = A_{r0}$

Figure 2: Illustration of Propositions 1 and 2. The graphs show the percentage change in the allocation of scientists following a +100% increase in $A_{r0}$ in three different scenarios: (a) baseline parameters, (b) a lower input share of renewables in clean production, and (c) a lower input share of renewables in clean production when storage is initially as productive as renewables. Note that there are no spillovers in innovation in the scenarios ($\nu = 0$).

entists to renewables (panel a). However, if the input share of renewables is lower, then the productivity shock in renewables is instead reducing the number of scientists in renewables (panel b). In that case, the widening of the productivity gap between renewables and storage technology is causing the indirect path dependency effect to dominate the direct path dependency effect in the profitability of innovation in renewables relative to fossil fuels. Finally, if we also close the productivity gap between renewables and storage, then the productivity shock in renewables is again inducing more scientists to renewables despite the lower input share of renewables (panel C).

This exercise illustrates the ambiguity of increasing the productivity of renewables on future innovation in the technology when renewables also depend on storage technology. Figure A7 uses a heat map to illustrate the range of values of the indirect path dependency effect in Eq. 16 under varying levels of $A_{s0}$ and $\delta$.

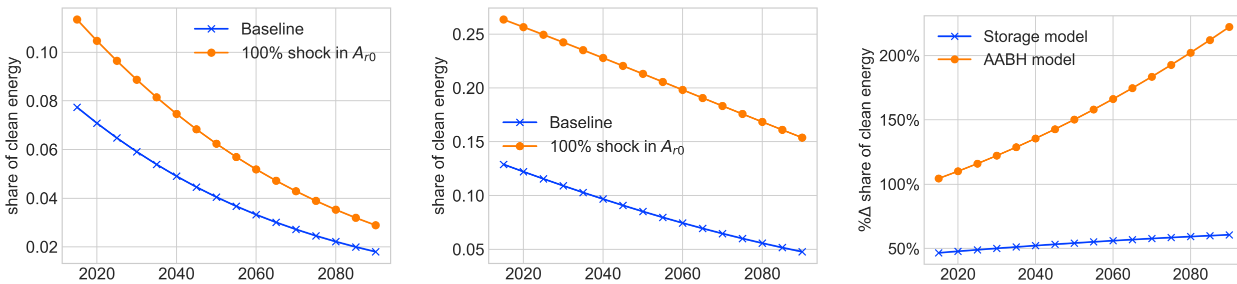
## 3.3 Effectiveness of climate policy with storage

Standard environment and endogenous growth models do not incorporate the intermittency issue of renewables. In what follows, we show that this omission causes standard models to overestimate the effectiveness of climate policies in inducing the use of clean energy. In general, the requirement of energy storage in the production of clean energy makes it more difficult to induce the transition to clean energy because policymakers must now push two technologies (renewables and storage) simultaneously to phase out fossil fuels. To illustrate this, we compare the efficiency of climate policy in our model with and without storage technology. Note that the storage sector in our model can be turned off by assuming that $\delta = 1$, in which case clean production simplifies to the production of renewables ($Y_{ct} \equiv Y_{rt}$). In the absence of a storage sector, the model is reduced to the familiar setup in AABH, in which energy is produced solely by combining fossil fuels with renewables, and we therefore refer to the model without storage as the "AABH model".

In this exercise, we assume a scenario in which climate policy in the past had ambitious targets to increase the use of renewables, and as a result, renewables have become substantially more productive compared to their current level. The purpose of this exercise is to compare the increase in clean energy caused by a policy-induced improvement in the productivity of renewables when clean energy also requires energy storage. Specifically, we simulate both models to the end of the century with and without a +100% increase in the initial productivity of renewables ($A_{r0}$) and compare the effect of the productivity shock on the share of clean energy. All other parameters are equal to their values in Table 1, except for the spillover effect ($\nu$), which we assume for simplicity to be zero (note that in this case, the allocation of scientists in the storage model is as in the previous exercise).

Panels a and b in Figure 3 show the share of clean energy with and without the productivity shock in renewables in the storage model and the AABH model, respectively. Panel c shows the percentage change in the share of clean energy caused by the shock relative to the baseline level in both models.[17] In the AABH model, the share of clean energy doubles instantly following a policy-driven improvement in renewable productivity (panel c). In con-

[17] Note that the positive slope in panel c is due to the decrease of the absolute values of panels a and b over time.




(a) Storage model (b) AABH model (c) Comparison

Figure 3: Comparison of storage model and AABH model. The graphs show the share of clean energy with and without a +100% increase in the initial productivity of renewables ($A_{r0}$) in the model with storage technology (panel b) and in the AABH model without energy storage (panel b). Panel c shows the percentage change in the share of clean energy caused by the productivity shock relative to the baseline in both models. Note that there are no spillovers in innovation in the scenarios ($\nu = 0$) and no climate policy in place.

trast, our storage model predicts only a 50 percent increase. This is because, in our model, higher renewable productivity must be accompanied by advances in storage technologies to fully realize its impact on clean energy use, making the transition more challenging. Note that the share of clean energy decreases over time due to the lack of climate policy in the simulations.

## 3.4 Variable elasticity of substitution between renewables and fossil fuels

The standard environment and endogenous growth literature further assumes a constant elasticity of substitution between fossil fuels and renewable energy sources. However, this assumption conflicts with recent empirical findings that indicate that this elasticity changes over time. For example, Jo and Miftakhova (2024) examine the elasticity of substitution in the French manufacturing sector and find that it increases as the share of clean energy grows. Our framework reconciles this by employing a nested CES structure that integrates renewables and storage to produce clean energy. We demonstrate that this approach enables a variable elasticity of substitution between renewables and fossil fuels, which can range significantly—from complementary to substitutable—depending on the level of storage capacity.

In our model, the elasticity of substitution of clean and dirty energy is denoted by $\epsilon$. Clean energy is modeled as a composite of renewables and energy storage. To determine the elasticity of substitution between renewables and dirty energy, we adapt the standard definition of elasticity of substitution to our model

$$el_{r,d} \equiv \frac{\Delta \ln\left(\frac{Y_{dt}}{Y_{rt}}\right)}{\Delta \ln(MRTS_{r,d})}, \tag{26}$$

where

$$MRTS_{r,d} = \frac{\frac{\partial Y_t}{\partial Y_{rt}}}{\frac{\partial Y_t}{\partial Y_{dt}}} = Y_{dt}^{\frac{1}{\epsilon}} \delta Y_{rt}^{-\frac{1}{\rho}} \left(\delta Y_{rt}^{\frac{\rho-1}{\rho}} + (1-\delta) Y_{st}^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho+\epsilon}{\epsilon(\rho-1)}}.$$

Eq. 26 shows that the elasticity of substitution between renewables, $el_{r,d}$, is a function of the capacity to store energy $Y_{st}$. Specifically, the elasticity increases in the level of energy storage because of the complementarity between energy storage and renewables.

In Figure 4, we use our definition in (26) to estimate the elasticity of substitution between renewables and fossil fuels for a percentage change in $Y_r$ between +1 to +100%. In the calculations, we use the initial capacity of renewables and fossil fuels, $Y_{d0}$ and $Y_{r0}$, observed at the beginning of our simulation period, as well as the parameter values in Table 1 for $\epsilon$, $\rho$ and $\delta$. In the baseline exercise (blue line), we calculate the elasticity of substitution given the initial capacity level of energy storage, $Y_{s0}$. At this low level of energy storage, the elasticity between renewables and fossil fuels is always below unity, and the two inputs are complements. Increasing the storage capacity increases the substitutability, but the elasticity is still below unity even for doubling of the storage capacity (orange line). If we instead assume that we have the same amount of capacity in storage as we do in renewables (green line), the two goods become weak substitutes.

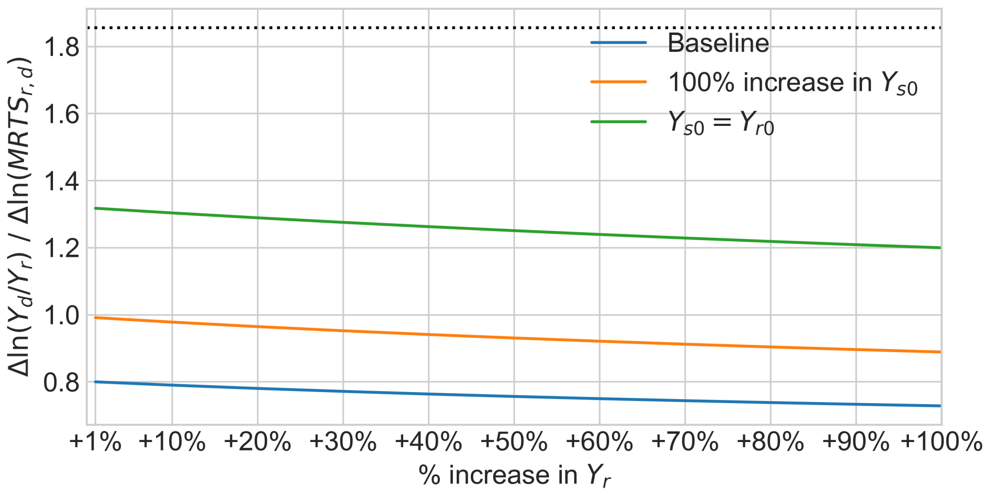



Figure 4: Elasticity of substitution between renewables and fossil fuels given the initial capacities of the technologies ($Y_{r0}$ and $Y_{d0}$) for different levels of storage capacity ($Y_{s0}$). The dotted black line indicates the estimate for the elasticity of substitution between clean and fossil fuel energy ($\epsilon$).

# 4 Policy analysis

In this section, we use the calibrated model to evaluate the capacity of current U.S. energy policy to achieve the energy transition and meet international environmental goals. Specifically, we simulate the calibrated model for different assumptions regarding the production and R&D subsidies to clean and dirty production.

## 4.1 Current U.S. energy policy

We first evaluate the outcome of both current and planned U.S. energy policy. Table 2 gives an overview of the policy rates in the different scenarios. As a baseline, we define a **No policy** scenario, in which we assume that there is no energy policy in place, that is, both production and R&D subsidies are set to zero. In the **Current policy** scenario, production and R&D subsidies are set at the observed rates in the energy sector during 2011–2015 and remain constant at these levels throughout the simulation period.

From 2010 to 2016, the US government gave on average 11756.33 and 1204.5 million US dollars (in 2016 dollars) each year to clean and dirty energy production, respectively.[18] To convert these subsidies to shares of the private value of clean and dirty energy production, we proceed in two steps. First, we estimate the private value of clean and dirty energy generation. From 2010 to 2016, the US generated an annual average of 2,761,098 GWh and 521,375 GWh of electricity from fossil fuels and renewables, respectively.[19] Based on estimates of the levelized cost of energy (LCOE) from 2010 to 2016 from Lazard (2024), we calculate an average LCOE of 148.5 and 90.4 dollars per MWh for clean and dirty energy production, respectively.[20] Second, we take the ratio of the public energy subsidies and the private value of energy production to find an estimate of the subsidy rate. This gives us an estimated subsidy rate of 15.2% for clean energy $(11,756,000,000/((521,375 \times 1000) \times 148.5))$ and 0.5% for dirty energy $(1,204,000,000/((2,761,098 \times 1000) \times 90.4))$.

To estimate the public R&D subsidies, we use the data on public R&D expenditures from the IEA (2023). In the period 2011 to 2015, 13.5% and 2.4% of total U.S. public energy R&D expenditures were allocated to renewables and fossil fuels, respectively. In the same period, R&D in battery technology was subsidized with 1.9% of total public R&D expenditures.[21] Hence, renewables receive a subsidy that is 7.1 times higher than storage (13.5/1.9) and 5.6 times higher than fossil fuels (13.5/2.4).

Finally, we consider a scenario based on the plans of the U.S. Inflation Reduction Act (IRA) of 2022. This federal law, introduced by the Biden administration, aims to accelerate

[18] The data is found in table 3 in the report "Direct Federal Financial Interventions and Subsidies in Energy in Fiscal Year 2016" published by the EIA: `https://www.eia.gov/analysis/requests/subsidy/archive/2016/pdf/subsidy.pdf`. Note that the subsidies contain both direct expenditures and tax expenditures.

[19] The data is found in table 7.2a in the Monthly Energy Review published by the EIA: `https://www.eia.gov/totalenergy/data/monthly/`

[20] Note that the LCOE for clean is an average of LCOE estimates for solar and wind energy, taking into account recent estimates that add storage, whereas the LCOE for dirty energy is an average of the estimates for coal and natural gas.

[21] Note that R&D subsidies for battery technologies include expenditures on battery technology in electric vehicles. For transparency, section A.5 provides results excluding this assumption. This assumption reflects the plausible impact of innovation subsidies for electric vehicle batteries on advancements in energy storage technologies in general.

Table 2: Overview of policy rates in policy scenarios

| | Production | | Innovation | |
|---|---|---|---|---|
| | $z_d$ | $z_c$ | $(1+q_r)/(1+q_d)$ | $(1+q_r)/(1+q_s)$ |
| **No policy** | 0 | 0 | 1 | 1 |
| **Current policy** | 0.005 | 0.152 | 5.6 | 7.1 |
| **+ IRA subsidy** | 0.005 | 0.2 | 5.6 | 7.1 |

the transition to a clean energy economy. Its proponents have described it as "the most significant action Congress has taken on clean energy and climate change in the nation's history" (The White House, 2023). The IRA allocates substantial energy- and climate-related public expenditures for renewable electricity and energy storage, primarily through tax credits and direct support for production and investments. These provisions account for nearly half of the IRA's estimated costs (see Table 1 in Bistline, Mehrotra, and Wolfram (2023b)). Recent estimates suggest these measures are equivalent to a 20% production subsidy for electricity generated from clean energy sources (Bistline, Mehrotra, and Wolfram (2023b), Figure 7).[22] Therefore, in the **+ IRA subsidy** scenario, we increase the clean production subsidy to 20%.

Figure 5 compares the allocation of scientists and the share of clean energy under each policy scenario in Table 2. In the absence of production and R&D subsidies (blue line), the high productivity of fossil fuels drives most scientists to the dirty sector, causing the share of clean energy to fall from 8% to below 4% at the end of the simulation period. Introducing the current energy policy (orange line) causes a large shift in scientists from fossil fuels to renewables. The increase in innovation in renewables causes a substantial increase in the clean energy share, which is persistent and slightly increasing over time. However, since fossil fuels are still subsidized more than energy storage, a substantial share of scientists remain in the

[22] Other studies have used the same estimate to summarize the IRA provisions on clean energy production, e.g. Casey and Gao (2024).

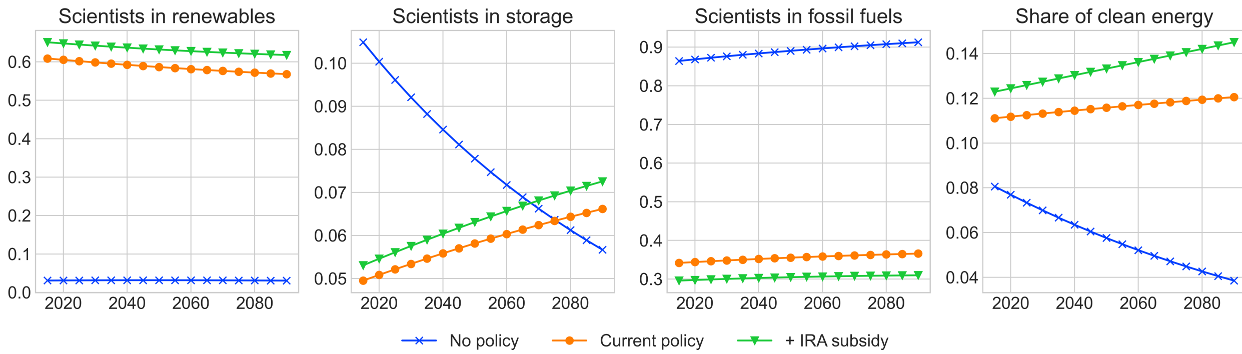



Figure 5: Allocation of scientists and share of clean energy from 2015 to 2090 from simulations in absence of policy and with current policy (with and without the IRA clean production subsidy).

fossil fuels sector, and there is only a small increase in the share of clean energy at the end of the simulation period.[23] The share of scientists in energy storage continues to increase throughout the simulations, which is due to the large productivity gap between renewables and energy storage, which pushes scientists into the storage sector in the short term.

In the **+ IRA subsidy** scenario with a 20% clean production subsidy (green line), the higher clean production subsidy causes an increase in the share of clean energy. However, despite the large increase in the production subsidy, the increase is relatively small. According to our simulations, the IRA will cause only an increase in the initial share of clean energy of one percentage point. Due to the high share of scientists in fossil fuels, there is only a modest increase in the share of clean energy during the simulation period.

In conclusion, our policy analysis reveals a decline in innovation efforts for renewables under the current climate policies. In contrast, innovation in storage technology is increasing, despite limited support for storage innovation. This trend is driven by the significant productivity gap between renewables and storage, which shifts innovation efforts toward energy storage. Both trends are consistent with the observed innovation patterns of renewables and energy storage patents displayed in Figure 1. We believe this represents a key contribution

[23]Specifically, the subsidy to fossil fuels is 1.3 times larger than the subsidy to energy storage (7.1/5.6).

of our framework: By incorporating storage into a model of technological change, we can explain the observed rise in patenting activity in energy storage technologies and the collapse in renewables.[24]

## 4.2 Decarbonization targets and sufficient subsidy rates

A primary motivation for countries to implement climate policies is to contribute to international climate goals. Here, we evaluate the effectiveness of current and planned energy policies in meeting decarbonization targets. Specifically, we focus on the COP28 Agreement, which aims to triple the global share of renewable energy capacity by 2030, and adapt this goal to the U.S. context. If the targets are projected to fall short, we calculate the clean production subsidy required to meet them. Table 3 summarizes the results. In all scenarios, R&D subsidies and the dirty production subsidy are kept constant at their current levels, whereas the clean production subsidy is adjusted across scenarios. Figure 6 illustrates the evolution of scientists and the share of clean energy. For comparison, the **IRA subsidy** scenario (green line) reproduces the results from Figure 5.

Our first finding is that the current IRA clean production subsidy is insufficient to meet the COP28 target by 2030. Column 3 in Table 3 shows that it achieves only a 78% increase in renewable capacity. Given this disparity, we calculate the clean production subsidy that would be necessary to achieve the goal within the IRA-framework, that is, holding R&D subsidies and the dirty production subsidy constant at their current levels. We find that tripling the initial renewable energy capacity by 2030 requires increasing the clean production subsidy to 46% (column 3 in the second row). As Figure 6 shows (red line), this adjustment significantly boosts the share of scientists working in the renewable and storage sectors compared to the IRA scenario, while the share of scientists in the dirty sector decreases sharply, as expected.

Finally, we examine how the initial productivity of storage technology affects the subsidy

[24] See section 5 for a deeper investigation of the collapse in renewables.

Table 3: Decarbonization targets by 2030.

| | Parameters | | Outcomes | | | | |
|---|---|---|---|---|---|---|---|
| | $A_{s0}$ (1) | $z_c$ (2) | $\%\Delta Y_{r30}$ (3) | $s_{r30}$ (4) | $s_{s30}$ (5) | $s_{d30}$ (6) | COP28 (7) |
| **IRA subsidy** | 111.3 | 0.2 | 78 | 0.64 | 0.06 | 0.30 | No |
| **Sufficient subsidy** | 111.3 | 0.46 | 200 | 0.83 | 0.08 | 0.09 | Yes |
| **Sufficient subsidy w/ higher** $A_{s0}$ | 222.6 | 0.345 | 200 | 0.85 | 0.04 | 0.11 | Yes |

required to achieve the COP28 target. Specifically, we calculate the clean production subsidy needed to triple the renewable energy capacity by 2030 in a scenario in which the initial level of storage productivity, $A_{s0}$, is 100% higher. This represents a 50% reduction in the technological gap between renewables and storage. With this improved productivity, the required subsidy decreases to 34.5%. As Figure 6 shows (purple line), the initial share of clean energy is still very similar to the **Sufficient subsidy** scenario, despite the lower subsidy for clean energy. This highlights the critical role of closing the technology gap between renewables and storage to facilitate the energy transition. Note also that the higher technological level of storage, combined with the cross-sector spillovers, causes a reallocation of scientists from energy storage to renewables and fossil fuels.

In the **Sufficient Subsidy** scenario, clean energy capacity reaches 351 GW by 2030, compared to just 208 GW in the IRA subsidy scenario. This is driven by the significantly higher clean production subsidy, which raises the initial share of clean energy to nearly 25% and directs almost all innovation efforts toward clean energy sectors. However, because of the substantial productivity gap between renewables and storage, the share of scientists in renewables decreases over time, whereas the share in storage technology steadily increases.

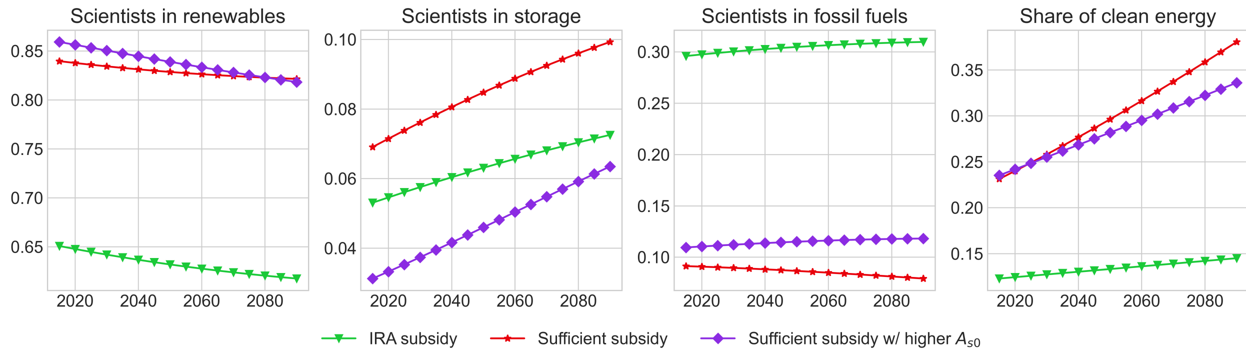



Figure 6: Allocation of scientists and share of clean energy from 2015 to 2090 from simulations with the IRA clean production subsidy and with the required clean production subsidy to achieve the COP28 decarbonization target (with and without a +100% increase in $A_{s0}$).

# 5 Collapse in renewable innovation

We now turn to investigating the role that a lagged storage technological level plays in determining the well-documented collapse in patents in renewable technology after 2010 (see Figure 1). The literature has attributed this collapse to the maturity of the technology, the tightening of capital after the financial crisis (Popp et al., 2022), as well as the technological developments in hydraulic fracturing, also known as the shale gas boom (Acemoglu et al., 2023). Our model offers a new and complementary explanation for the collapse, namely the large technological gap between energy storage and renewables, which reduces the relative profitability of innovation in renewables. In the following analysis, we explore the magnitude of this new mechanism by comparing the effect of a reduction in the productivity gap to that of the shale gas boom on the allocation of scientists and the share of clean energy in the economy.

To do so, we simulate the economy to the end of the century in different scenarios. First, we simulate the economy assuming that a shale gas boom occurred prior to the simulation period. Following Acemoglu et al. (2023) we define the shale gas boom as a +100% increase in the initial productivity of fossil fuels. Second, we simulate the economy with a smaller initial technological gap between renewables and energy storage. For comparison, we assume that the initial productivity of energy storage is +100% higher than its observed value. We remain agnostic about the cause of this improvement, which could stem, for example, from greater historical public support for storage R&D. While the first shock captures the effect of the shale gas boom on the economy, the second shock represents a counterfactual scenario in which past policy has partially closed the productivity gap between renewables and storage.

Figure 7 shows the output of these different scenarios. For comparison, we define a baseline scenario (orange line) as the scenario without shocks and the current energy policy from the previous policy exercises. The figure shows that the fracking boom resulted in a reallocation of innovation from renewables and storage to fossil fuels (brown line), in line with Acemoglu et al. (2023). As a result, the share of clean energy is significantly lower. However, if instead of the fracking boom, we had a +100% increase in the initial productivity of energy storage (pink line), this would have substantially increased innovation efforts in renewables due to the lower productivity gap between renewables and energy storage.

Consequently, the lack of more productive storage technology leads to a reduction in the share of clean energy with a magnitude similar to that of the shale gas boom. Specifically, if we had more productive storage technology, the initial share of clean energy would increase from 11.1% to 15.7%, whereas the shale gas boom decreases the initial share of clean energy from 11.1% to 5%. This exercise illustrates how the large technological gap between renewables and storage can reduce the level of innovation in renewables by a magnitude similar to that of the shale gas boom.

# 6 Welfare and emissions

In this section, we first describe the carbon cycle and the climate damage function, and then estimate the impact of climate policy on carbon dioxide emissions (CO2) and consumer welfare.

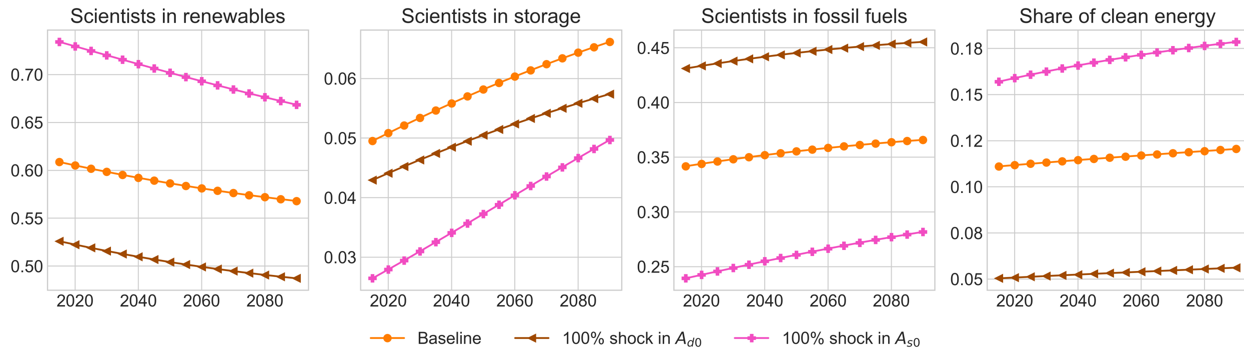



Figure 7: Allocation of scientists and share of clean energy from 2015 to 2090 from simulations with +100% increase in $A_{d0}$ (shale gas boom) or a +100% increase in $A_{s0}$ (more efficient storage technology). Baseline is the scenario with current energy policy (without the IRA clean production subsidy) in absence of the shocks.

### Carbon cycle and damage function

We assume that global warming causes damages that reduce consumption, denoted as $C_t$. US consumers derive utility from their national consumption after accounting for these damages. In addition, they care about the ROW after-damages consumption. To capture these preferences, we parameterize the per-period utility function as

$$u(C_t, S_t) = \frac{(\Omega(S_t)C_t)^{1-\upsilon}}{1-\upsilon} = \frac{\left(\Omega(S_t)\left(C_t^{US} + \iota C_t^{ROW}\right)\right)^{1-\upsilon}}{1-\upsilon}$$

where $S_t$ represents the quality of the environment, measured by the increase in atmospheric concentrations above pre-industrial times. $\Omega \in [0,1]$ is the fraction of consumption preserved after climate damages. When accumulated emissions are low, that is, when $S_t$ is low, climate damages to consumption are minimal, and $\Omega_t \to 1$. $C_t^{US}$ and $C_t^{ROW}$ represent consumption before accounting for climate damages in the US and in the ROW, respectively. The parameter $\iota \in [0,1]$ captures altruism, reflecting the extent to which US citizens care about ROW consumption. Finally, we follow AABH by setting $\upsilon = 2$ to match Nordhaus's intertemporal substitution elasticity.

The atmospheric concentration of CO2 emissions above pre-industrial levels at time $t$ is given by

$$S_t = S_t^{US} + S_t^{ROW}$$

where $S_t^{US}$ and $S_t^{ROW}$ are the accumulated CO2 emissions in the U.S. and the rest of the world, respectively. By assumption, $S_t$ can take values only in the interval $[0, \bar{S}]$. The upper bound on accumulated emissions, $\bar{S}$, captures the concern that there exists some tipping point that once reached, there is a climate catastrophe, in which case $\Omega_t = 0 \ \forall \ t$. Emissions in the U.S. accumulates according to a the following difference equation

$$S_{t+1}^{US} = \xi Y_{dt} + S_t^{US}$$

where emissions from one additional unit of $Y_d$ cause an increase in CO2 concentrations by $\xi$ units. We assume that accumulated CO2 emissions from the rest of the world grows at a constant rate

$$S_t^{ROW} = (1+g)^t S_0^{ROW}$$

where $g$ is the growth rate and $S_0^{ROW}$ is the initial level of CO2 emissions from the rest of the world prior to the simulations.

Total CO2 emissions from energy and industrial processes from 2006 to 2010 were 29.76 GtCO2 in the U.S. and 140.42 GtCO2 in the rest of the world.[25] In the same period, the average capacity of fossil fuel power generation in the U.S. was 769.95 million kilowatts in the US.[26] Therefore, we set $S_0^{ROW} = 140.42$ and $\xi = 29.76/769.95 \approx 0.039$. To calibrate the growth rate of emissions in the rest of the world, we assume that the world is on a path to reach the $2°C$ target, independent of the US. Therefore, we choose a per-period growth rate

[25]From BP. Emissions include carbon dioxide emissions from energy, carbon dioxide emissions from flaring, methane emissions in carbon dioxide equivalent and carbon dioxide emissions from industrial processes. Note that these numbers do not include emissions from residential, agriculture and transportation.

[26]From the Monthly Energy Review by the EIA. See Table 7.7a: https://www.eia.gov/totalenergy/data/monthly/

of 15%, which corresponds to approximately $2°C$ of warming by the end of the simulation period in the **No policy** scenario.[27]

An increase in accumulated emissions, $S_t$, causes an increase in the global mean temperature, resulting in damages. The relationship between CO2 emissions and global warming can be approximated by a linear function in accumulated emissions (Dietz and Venmans, 2019, Dietz et al., 2021). We therefore map emissions to temperature change by using the following linear function

$$\Delta(T_t) = \Delta(T_0) + TCRE \times S_t$$

where $\Delta(T_t)$ is the increase in the global mean temperature at time $t$ and $\Delta(T_0)$ is the increase in temperatures that we have already experienced at the beginning of our simulations. $TCRE$ is the transient response of the climate to cumulative carbon emissions, which measures the temperature change of an additional unit of accumulated CO2 emissions. Dietz et al. (2021) suggests a $TCRE$ of $1.7°C$ per trillion tons of cumulative carbon emissions (TtC). We increase the estimate by 10% to take into account the warming from non-CO2 greenhouse gases (Allen, 2016). This results in a $TCRE$ of $1.87°C$/TtC, which corresponds to $0.00051°C$/GtCO2.[28] As our simulations start after 2010, we assume global warming of $1°C$ at the start of our simulation period.[29]

We follow AABH and relate global warming to economic damages by using the following function

$$\Omega(\Delta(T)) = \frac{(\Delta_{disaster} - \Delta(T))^{\lambda} - \lambda \Delta_{disaster}^{\lambda-1}(\Delta_{disaster} - \Delta(T))}{(1-\lambda)\Delta_{disaster}^{\lambda}},$$

where $\Delta(T)$ is the increase in the global mean temperature above its pre-industrial level given accumulated emissions at time $t$. We set the disaster temperature, $\Delta_{disaster}$, equal

[27]As each period in the simulations is 5 years, the per-period growth rate corresponds to an approximate annual growth rate of 3%.

[28]Note that the conversion factor from TtC to TtCO2 is 12/44.

[29]The temperature anomaly in 2010 was approximately $0.7°C$ for the ocean average temperature and $1.5°C$ for the land average temperature in 2010: https://berkeleyearth.org/global-temperature-report-for-2023/

to $6°C$, which corresponds to a maximum carbon budget, $\bar{S}$, of 9,804 GtCO2.[30] When the carbon budget is used up, climate damages are a 100% of consumption. In a scenario of $3°C$ temperature increase by 2100, van der Wijst et al. (2023) found global damages to be in the range of 10-12% of GDP. Therefore, we match our damage function to correspond to a 10% reduction in consumption at $3°C$ warming, which leads to a value of $\lambda = 0.5958$.

### Welfare analysis

We explore the welfare implications of the policy analysis in Section 4. Specifically, we use the carbon cycle and damage function explained above to calculate and compare the welfare for each of the different policy scenarios. In each policy scenario, the discounted sum of utility is calculated as

$$\sum_{t=1}^{T} \beta^t \frac{\left(\Omega(S_t)\left(C_t^{US} + \iota C_t^{ROW}\right)\right)^{1-\upsilon}}{1-\upsilon}$$

where $\beta$ is the per-period discount factor. We use Nordhaus' preferred choice of 1.5% per annum discounting and set $\beta = 0.985^5$ since one period corresponds to 5 years. As there are no efficiency losses in the model, per-period consumption is simply total energy capacity minus the input used to produce the machines. That is, the economy budget restriction is

$$C_t^{US} = Y_t - \varphi\left(\int_0^1 x_{idt} di + \int_0^1 x_{irt} di + \int_0^1 x_{ist} di\right) \tag{27}$$

In our model of the US economy, $C_t^{ROW}$ is exogenous, meaning that the US can only influence ROW consumption after climate damages, through its pollution activity. $C_t^{ROW}$ is represented by global electricity capacity, excluding US capacity.[31] We assume $C_t^{ROW}$ grows exogenously at a 2% annual rate.

[30] $\bar{S} = (\Delta_{disaster} - \Delta(T_0))/TCRE = (6-1)/0.00051 \approx 9,804$

[31] According to the EIA, the average global electricity capacity for fossil fuels, renewables and hydroelectric pumped storage between 2006 and 2010 was 4330 million kilowatts: https://www.eia.gov/international/data/world/electricity/electricity-capacity. After subtracting total US capacity (909.09 million kW), the resulting a ROW capacity is 3420.91 kW.

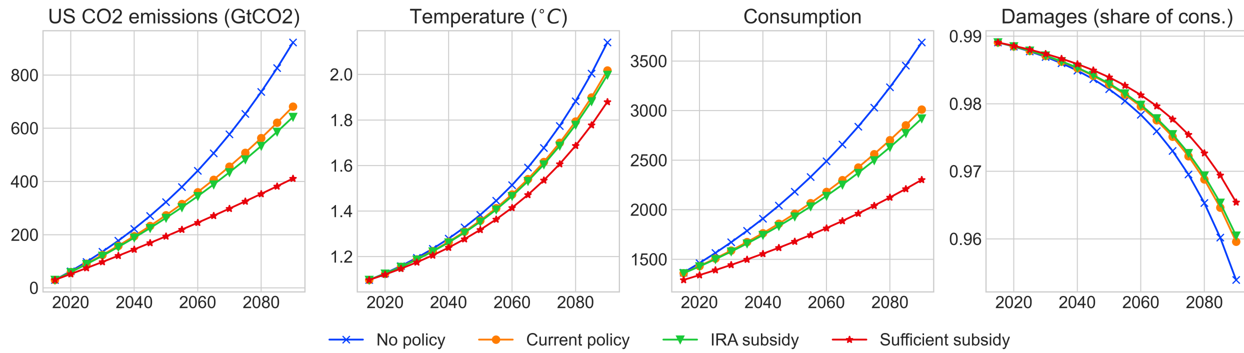



Figure 8: Output from the carbon cycle and damage function in the policy scenarios. Note that CO2 emissions is the accumulated sum of emissions only in the US, whereas the temperature change is the global warming caused by CO2 emissions in the rest of the world as well.

Figure 8 shows the output of the carbon cycle and the damage function for each of the four policy scenarios explored in Section 4. As expected, emissions and temperature change are highest in the **No policy** scenario, and lowest in the **Sufficient subsidy** scenario. Furthermore, both consumption and damage from climate change are highest in the **No policy** scenario, and lowest in the **Sufficient subsidy** scenario. Although shifting production to clean energy has a positive impact on utility through reduced climate damage, there is also a large reduction in consumption due to the fact that clean energy is substantially less productive than fossil fuel energy. However, note that the difference in temperature by the end of the simulation period between the **No policy** and **Sufficient subsidy** scenarios is relatively modest ($< 0.3°C$), which is due to our assumption of emissions from the rest of the world being unaffected by U.S. climate policy.

Table 4 shows the welfare analysis of the different policy scenarios and for different values of the altruism parameter $\iota$. For $iota = 0$, column 1 shows the percentage loss in consumption-equivalent welfare relative to the **No policy** scenario, and shows a reduction in welfare in all policy scenarios relative to the **No policy** scenario. For example, current policy implies a loss of 7.66% compared to the scenario without any climate policy. This indicates that the gain from a reduction in economic damages is less than the cost of reduced consumption caused by switching to a less productive energy source (i.e., clean energy). Furthermore, the welfare loss increases in the stringency of climate policy. Column 2 shows the percentage change in consumption-equivalent welfare compared to the **Current policy** scenario. The column shows that implementing the IRA clean production subsidy results in a welfare reduction that is 15.24% higher compared to the current policy, while implementing the sufficient subsidy to reach the COP28 results in a welfare reduction that is 187.53% higher.

Table 4: Welfare analysis of policy scenarios.

| | iota = 0 | | iota = 0.5 | | iota = 1 | |
|---|---|---|---|---|---|---|
| | %loss (1) | %gain (2) | %loss (3) | %gain (4) | %loss (5) | %gain (6) |
| No policy | N/A | N/A | N/A | N/A | N/A | N/A |
| Current policy | 7.66 | N/A | 2.4380 | N/A | 1.4349 | N/A |
| IRA subsidy | 8.82 | -15.24 | 2.7745 | -13.80 | 1.63 | -13.49 |
| Sufficient subsidy | 22.02 | -187.53 | 6.52 | -167.45 | 3.8060 | -165.26 |
| Carbon tax | 102.94 | -1244.43 | 23.33 | -856.88 | 13.17 | -818.05 |

In other words, in all of our policy scenarios, we find that climate policy is causing a reduction in welfare relative to a scenario without climate policy due to the inefficiency of clean energy. However, there are several important caveats to the simple welfare analysis presented here. First, we have assumed that the rest of the world is already on the $2°C$ path, and therefore damages from climate change will be low in the U.S. regardless of national policy. Second, the policy rates in the different scenarios are based on either observed or hypothetical values, and they could potentially be far from the optimal policy rates. For example, current climate policy severely distorts the decision to innovate in storage due to the large innovation subsidy given to renewables, and as a consequence, storage innovation is actually higher in the absence of climate policy.

Unsurprisingly, increasing the level of altruism reduces the losses associated with policy stringency because the benefits of US emissions reductions in ROW are part of US utility.

Finally, we examine a hypothetical scenario in which a carbon tax is in place, alongside research subsidies but without production subsidies. We implement a 0.5 tax on the use of dirty inputs. The welfare results under this carbon tax are shown in the last row of Table 4. As expected, the tax leads to significantly larger welfare losses. This outcome is not surprising for several reasons. The first is methodological: although we apply a close approximation of a globally optimal carbon tax, our model follows the directed technical change framework, where the optimal policy involves a combination of a carbon tax and research subsidies. The latter, however, is likely far from optimal in this case. Second, a carbon tax places a significant short-term burden on the dirty sector, which is relatively more advanced. This explains why the short-term welfare losses are so substantial.

# 7 Conclusions

Both the endogenous growth literature and policymakers have largely overlooked the importance of storage technologies in the energy transition. While endogenous growth models often narrow the problem down to a trade-off between fossil fuels and renewables, public support has disproportionally focused on renewable innovation, sidelining storage technologies. This project seeks to bridge the gap between the endogenous growth literature and studies addressing the intermittency challenges of renewable energy, which are typically confined to short-term analysis. The ultimate goal is to provide a better, yet simplified, framework that allows us to shed light on the role of storage to meet the ambitious environmental goals ahead and ensure the energy transition.

Unlike previous studies, we develop a framework that has the ability to explain the innovation patterns observed over recent decades. Our framework demonstrates that the gap between renewables and storage technologies plays a critical role in the transition away from fossil fuel illovation. It also conveys a variable elasticity of substitution between renewables and dirty sources of energy. In our quantitative analysis, we find that current policies in the U.S. are insufficient to meet the ambitious environmental goals over the next decades.

Substantially greater efforts are needed if the current policy framework—based on subsidies to clean energy production—is to be maintained, which is not only ineffective but also incurs a non-negligible welfare cost for consumers.

# References


Acemoglu, Daron. 2002. "Directed technical change." *Review of Economic Studies* 69 (4):781–809.

Acemoglu, Daron, Philippe Aghion, Lint Barrage, and David Hemous. 2023. "Climate Change, Directed Innovation, and Energy Transition: The Long-run Consequences of the Shale Gas Revolution." *NBER Working Paper No. 31657* .

Acemoglu, Daron, Philippe Aghion, Leonardo Bursztyn, and David Hemous. 2012. "The Environment and Directed Technical Change." *American Economic Review* 102 (1):131–166.

Acemoglu, Daron, Ufuk Akcigit, Douglas Hanley, and William Kerr. 2016. "Transition to clean technology." *Journal of Political Economy* 124 (1):52–104.

Aghahosseini, Arman, A. A. Solomon, Christian Breyer, Thomas Pregger, Sonja Simon, Peter Strachan, and Arnulf Jäger-Waldau. 2023. "Energy system transition pathways to meet the global electricity demand for ambitious climate targets and cost competitiveness." *Applied Energy* 331 (September 2022).

Ambec, Stefan and Claude Crampes. 2019. "Decarbonizing electricity generation with intermittent sources of energy." *Journal of the Association of Environmental and Resource Economists* 6 (6):1105–1134.

Andrés-Cerezo, David and Natalia Fabra. 2023. "Storage and Renewable Energies: Friends or Foes?" *CEPR Discussion Paper 19294* .

Arkolakis, Costas and Conor Walsh. 2023. "Clean Growth." *NBER Working Paper No. 31615* URL http://www.nber.org/papers/w31615.

Barrage, Lint and William Nordhaus. 2024. "Policies, projections, and the social cost of carbon: Results from the DICE-2023 model." *Proceedings of the National Academy of Sciences* 121 (13).

Bistline, John, Geoffrey Blanford, Maxwell Brown, Dallas Burtraw, Maya Domeshek, Jamil Farbes, Allen Fawcett, Anne Hamilton, Jesse Jenkins, Ryan Jones, Ben King, Hannah Kolus, John Larsen, Amanda Levin, Megan Mahajan, Cara Marcy, Erin Mayfield, James McFarland, Haewon McJeon, Robbie Orvis, Neha Patankar, Kevin Rennert, Christopher Roney, Nicholas Roy, Greg Schivley, Daniel Steinberg, Nadejda Victor, Shelley Wenzel, John Weyant, Ryan Wiser, Mei Yuan, and Alicia Zhao. 2023. "Emissions and energy impacts of the Inflation Reduction Act." *Science* 380 (6652):1324–1327.

Bistline, John, Neil Mehrotra, and Catherine Wolfram. 2023a. "Economic Implications of the Climate Provisions of the Inflation Reduction Act." *Brookings Paper on Economic Activity* 1:77–182.

Bistline, John E.T., Neil R. Mehrotra, and Catherine Wolfram. 2023b. "Economic Implications of the Climate Provisions of the Inflation Reduction Act." *Brookings Papers on Economic Activity* 2023:77–182.

Butters, R. Andrew, Jackson Dorsey, and Gautam Gowrisankaran. 2024. "Soaking Up the Sun: Battery Investment, Renewable Energy, and market Equilibirum." *NBER Working Paper No. 2913* .

Casey, Gregory and Yang Gao. 2024. "Energy Efficiency Dynamics and Climate Policy." *CESifo Working Paper No. 11303* (August). URL https://www.cesifo.org/en/publications/2024/working-paper/energy-efficiency-dynamics-and-climate-policy.

Dechezleprêtre, Antoine, Ralf Martin, and Myra Mohnen. 2017. "Knowledge spillovers from clean and dirty technologies." *Grantham Research Insitute on Climate Change and the Environemnt Working Paper* 135.

Fried, Stephie. 2018. "Climate Policy and Innovation: A Quantitative Macroeconomic Analysis." *American Economic Journal: Macroeconomics* 10 (1):90–118.

Gentile, Claudia. 2024. "Relying on Intermittency : Clean Energy , Storage , and Innovation in a Macro Climate Model." *Working paper* :1–62.

Golosov, Mikhail, John Hassler, Per Krusell, and Aleh Tsyvinski. 2014. "Optimal Taxes on Fossil Fuel in General Equilibrium." *Econometrica* 82 (1):41–88.

Goulder, Lawrence H. and Koshy Mathai. 2000. "Optimal CO2 abatement in the presence of induced technological change." *Journal of Environmental Economics and Management* 39 (1):1–38.

Growiec, Jakub and Ingmar Schumacher. 2008. "On technical change in the elasticities of resource inputs." *Resources Policy* 33 (4):210–221.

Hassler, John, Per Krusell, and Conny Olovsson. 2021. "Suboptimal Climate Policy." *Journal of the European Economic Association* 19 (6):2895–2928. URL https://doi.org/10.1093/jeea/jvab048.

Helm, Carsten and Mathias Mier. 2019. "On the efficient market diffusion of intermittent renewable energies." *Energy Economics* 80 (2019):812–830. URL https://doi.org/10.1016/j.eneco.2019.01.017.

IEA. 2021. "Patents and the Energy Transition." Tech. rep., IEA, Paris. URL https://www.iea.org/reports/patents-and-the-energy-transition.

———. 2023. "Energy Technology RD&D Budgets Data Explorer." URL https://www.iea.org/data-and-statistics/data-tools/energy-technology-rdd-budgets-data-explorer.

Jo, Ara. 2024. "Substitution Between Clean and Dirty Energy With Biased Technical Change." *International Economic Review* 0 (0).

Jo, Ara and Alena Miftakhova. 2024. "How constant is constant elasticity of substitution? Endogenous substitution between clean and dirty energy." *Journal of Environmental Economics and Management* 125 (August 2022):102982. URL https://doi.org/10.1016/j.jeem.2024.102982.

Karaduman, Ömer. 2023. "The Economics of Grid-Scale Energy Storage in Wholesale Electricity Markets." *Working Paper* .

Karydas, Christos and Lin Zhang. 2019. "Green tax reform, endogenous innovation and the growth dividend." *Journal of Environmental Economics and Management* 97:158–181.

Lamp, Stefan and Mario Samano. 2022. "Large-scale battery storage, short-term market outcomes, and arbitrage." *Energy Economics* 107 (May 2021):105786. URL https://doi.org/10.1016/j.eneco.2021.105786.

Lazard. 2024. "Levelized Cost of Energy+." Tech. Rep. 2. URL https://www.lazard.com/media/%0Axemfey0k/lazards-lcoeplus-june-2024-_vf.pdf.

Mattauch, Linus, Felix Creutzig, and Ottmar Edenhofer. 2015. "Avoiding carbon lock-in: Policy options for advancing structural change." *Economic Modelling* 50:49–63.

Nordhaus, William D. 1993. "Optimal Greenhouse-Gas Reductions and Tax Policy in the DICE model." *The American Economic Review* 83 (2):313–317.

Papageorgiou, Chris, Marianne Saam, and Patrick Schulte. 2017. "Substitution between clean and dirty energy inputs: A macroeconomic perspective." *Review of Economics and Statistics* 99 (2):281–290.

Pommeret, Aude and Katheline Schubert. 2022. "Optimal energy transition with variable and intermittent renewable electricity generation." *Journal of Economic Dynamics and Control* 134:104273. URL https://doi.org/10.1016/j.jedc.2021.104273.

Popp, David. 2004. "ENTICE: endogenous technological change in the DICE model of global warming." *Journal of Environmental Economics and Management* 48 (1):742–768.

Popp, David C., Jacquelyn Pless, Ivan Haščič, and Nicholas Johnstone. 2022. "Innovation and Entrepreneurship in the Energy Sector." In *The Role of Innovation and Entrepreneurship in Economic Growth*, edited by Michael J Andrews, Aaron Chatterji, Josh Lerner, and Scott Stern. Chicago: University of Chicago Press, 175–248. URL https://doi.org/10.7208/chicago/9780226810645-006.

Romer, Paul M. 1990. "Endogenous technological change." *Journal of Political Economy* 98 (5):S71–S102.

Stöckl, Fabian. 2020. "Is Substitutability the New Efficiency? Endogenous Investment in the Elasticity of Substitution between Clean and Dirty Energy." *DIW Berlin Discussion Paper* 1886.

Stöckl, Fabian and Alexander Zerrahn. 2023. "Substituting Clean for Dirty Energy: A Bottom-Up Analysis." *Journal of the Association of Environmental and Resource Economists* 10 (3):819–863.

The White House. 2023. "Building a clean energy economy: a guidebook to the inflation reduction act's investments in clean energy and climate action." (January):1–183. URL https://www.whitehouse.gov/wp-content/uploads/2022/12/Inflation-Reduction-Act-Guidebook.pdf.

van der Wijst, Kaj Ivar, Francesco Bosello, Shouro Dasgupta, Laurent Drouet, Johannes Emmerling, Andries Hof, Marian Leimbach, Ramiro Parrado, Franziska Piontek, Gabriele

Standardi, and Detlef van Vuuren. 2023. "New damage curves and multimodel analysis suggest lower optimal temperature." *Nature Climate Change* 13 (5):434–441.

# A Appendix

## A.1 Stylized facts

### Public support of clean innovation has been directed towards renewables

The patterns in public R&D spending of the recent decades reveal intriguing aspects of public support for renewable and storage energy technologies. First, there has been a persistent bias for renewables over storage in public funding for clean research, especially since 2005. Second, the fossil fuel R&D public spending over total energy spending has been mostly stable, especially since 2000. These patterns are summarized in Figure A1, which showcases the public budgets allocated to different types of energy technology R&D for all IEA members.

## Evolution of patent applications

Figure A2 presents the data from Figure 1 expressed as a proportion of total patents. Figures A3 and A4 illustrate that the evolution of renewables and storage patent applications is similar across patent offices.

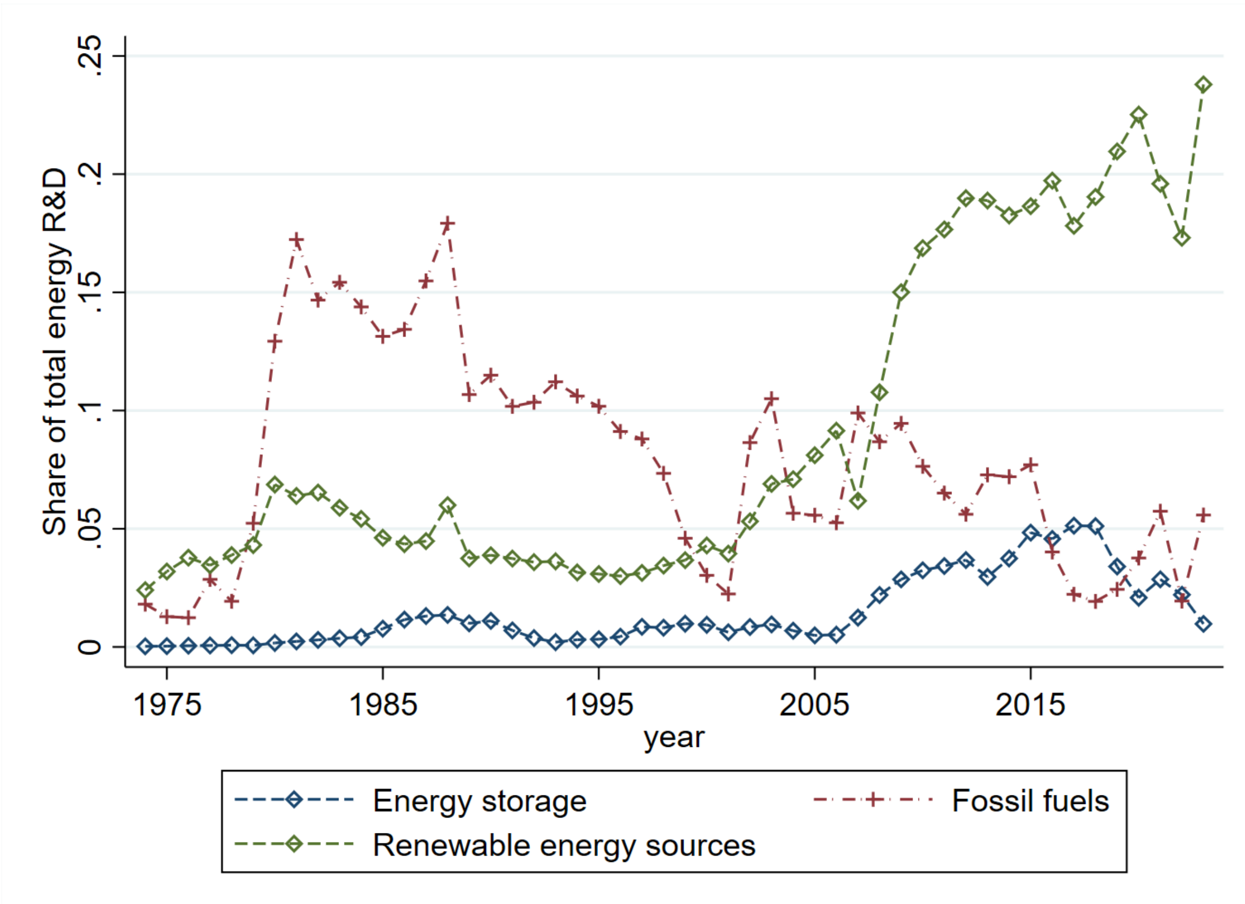



Figure A1: Public R&D spending on energy research. All IEA members Source: IEA (2023)

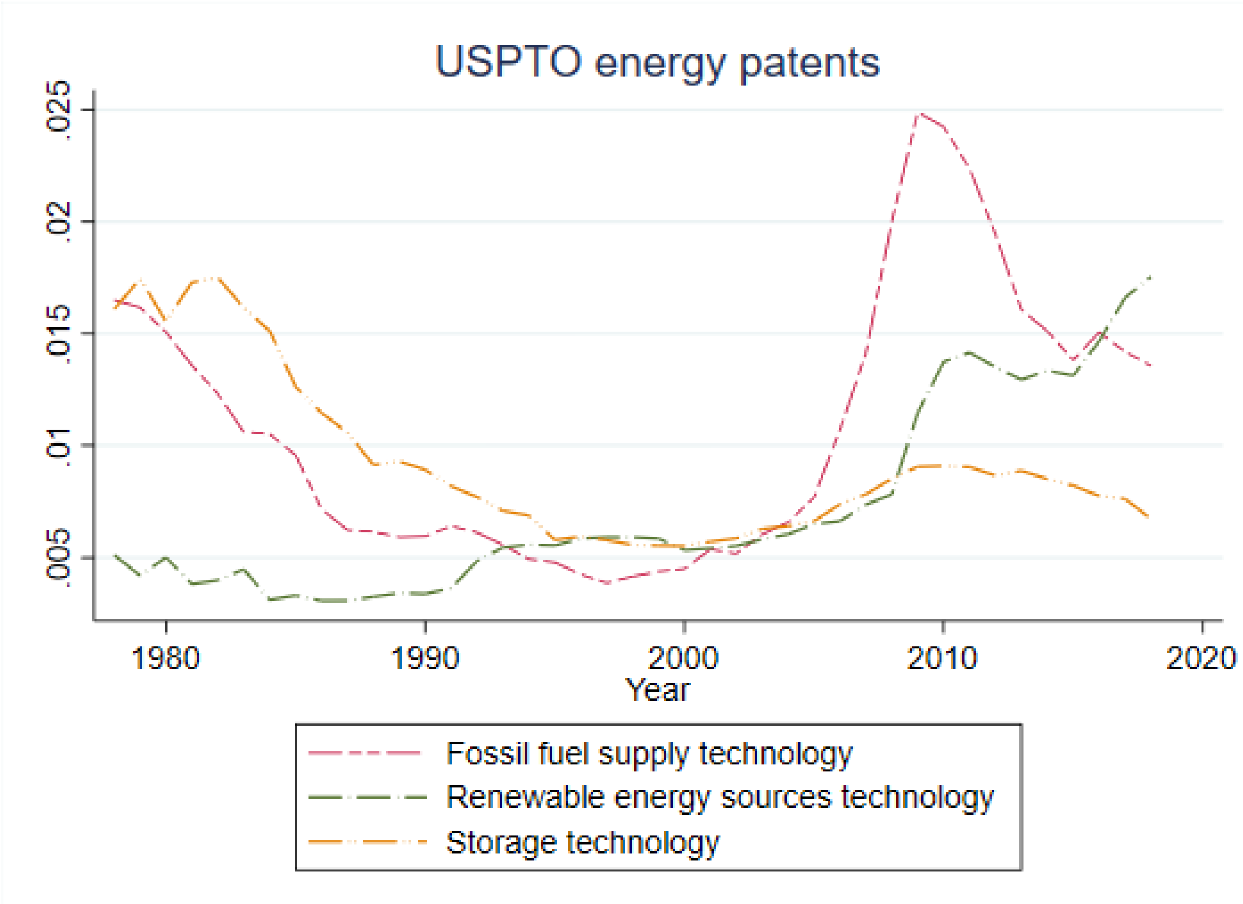



Figure A2: Patent applications over total patents filed at the USPTO, 1978-2018, in energy technologies. To be classified as a renewable patent, the application must have a CPC (cooperative patent classification) code included in the "Low-carbon energy supply" category from the IEA (2021). Storage patents are those classified as batteries, hydrogen storage and fuel cells. Source: Patstat

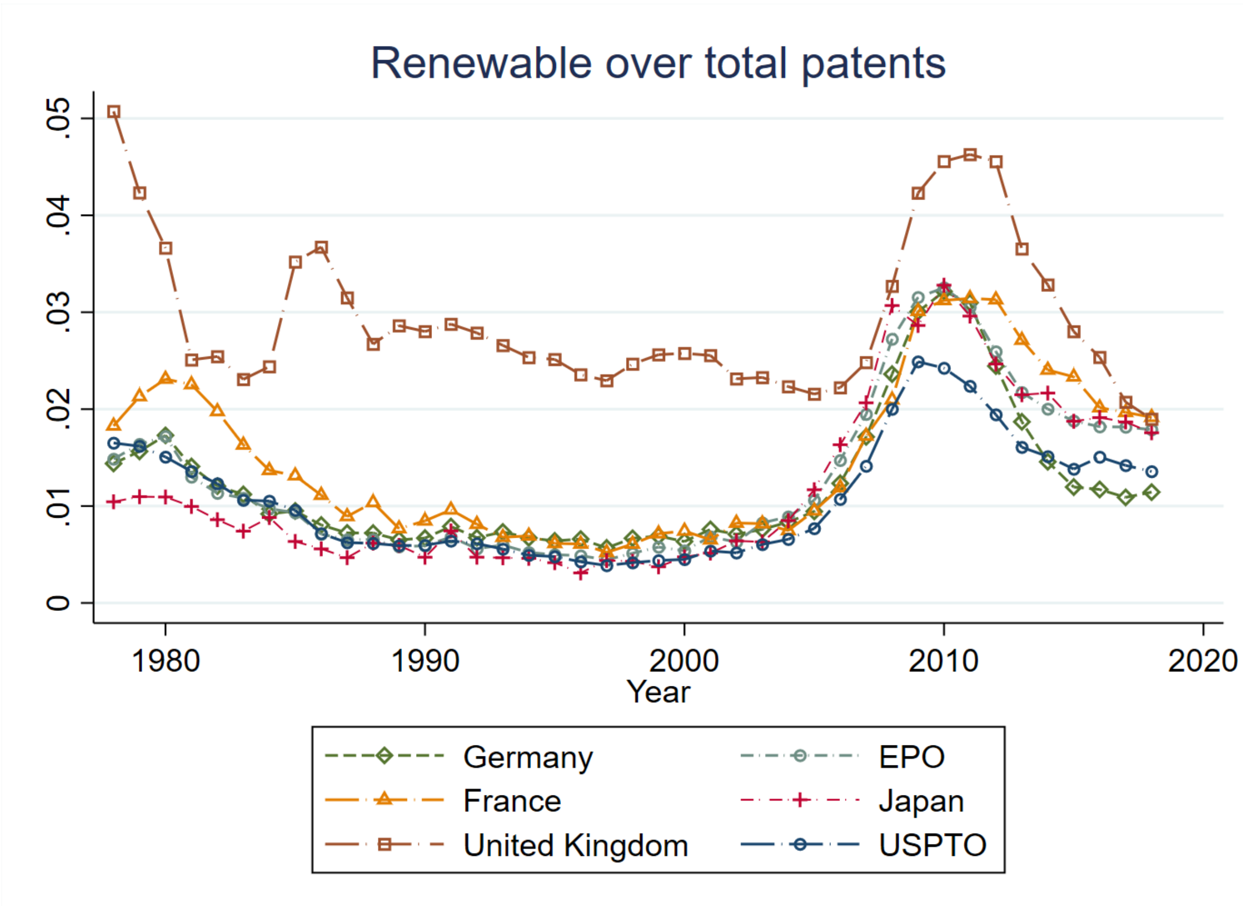



Figure A3: Number of renewable technology patents over total applications filled at selected patent offices, 1978-2018. To be classified as a renewable patent, the application must have a CPC (cooperative patent classification) code included in the "Low-carbon energy supply" category from the IEA (2021).

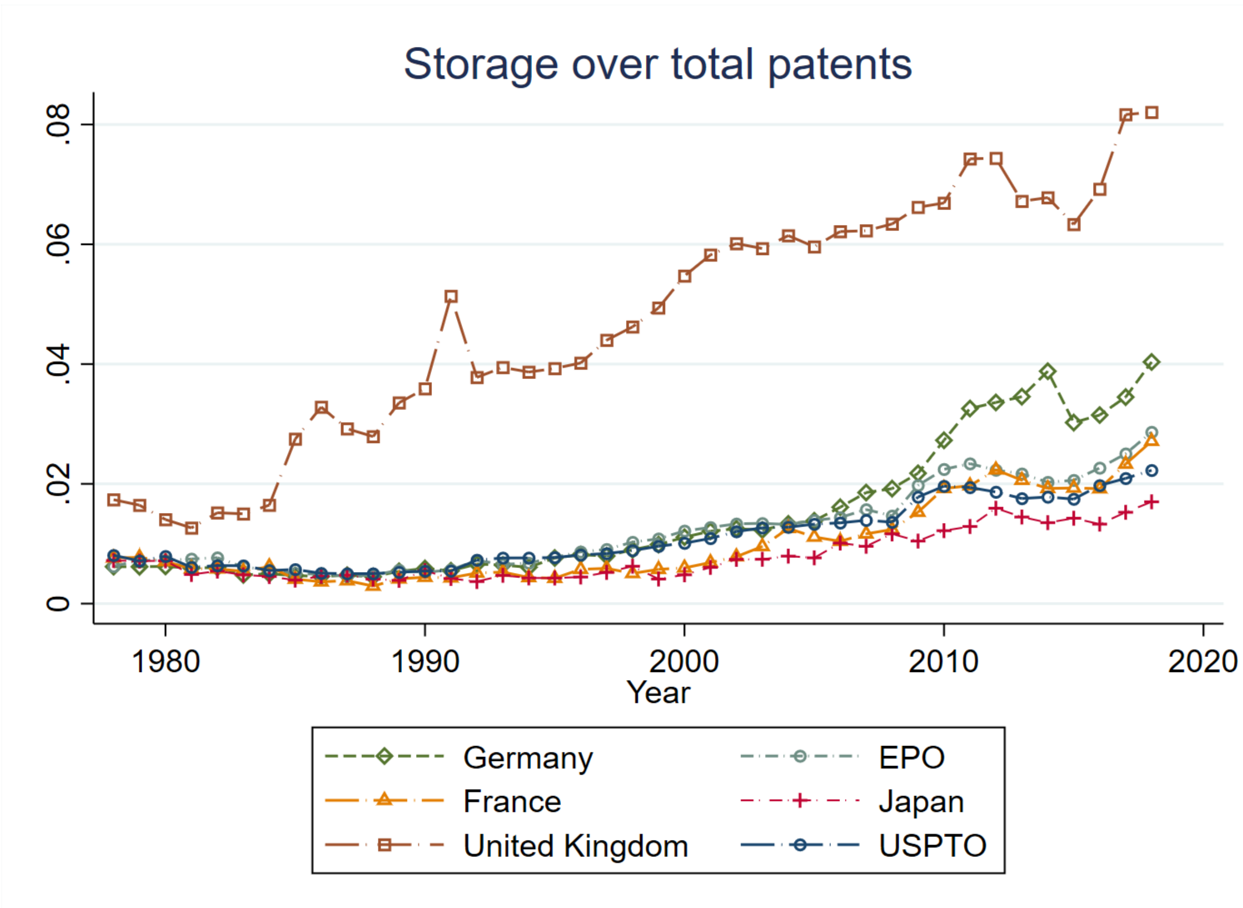



Figure A4: Number of storage technology patents over total applications filled at selected patent offices, 1978-2018. Storage patents are those classified as batteries and hydrogen storage. Source: Patstat

## A.2 Characterization of the decentralized equilibrium

Producers of the final consumption good, $Y_t$, maximize their profits while taking into account the taxes and subsidies of using each input, $z_{jt}$

$$\max_{\{Y_{dt},Y_{ct}\}} P_t Y_t - p_{dt}(1 - z_{dt})Y_{dt} - p_{ct}(1 - z_{ct})Y_{ct}. \tag{A1}$$

The subsidies can either be positive (effective subsidy) or negative (effective tax). A negative subsidy for the dirty input corresponds to a carbon tax. From the FOC's we find the following price of the effective clean input relative to the dirty input,

$$\frac{p_{ct}(1-z_{ct})}{p_{dt}(1-z_{dt})} = \left(\frac{Y_{ct}}{Y_{dt}}\right)^{-\frac{1}{\epsilon}}. \tag{A2}$$

Perfect competition implies the following price index of the final consumption good,

$$(p_{ct}(1-z_{ct}))^{1-\epsilon} + (p_{dt}(1-z_{dt}))^{1-\epsilon} = P_t^{1-\epsilon} \equiv 1, \tag{A3}$$

where the price of final energy is used as the numeraire.

Producers of the effective clean input maximize their profits,

$$\max_{\{Y_{rt},Y_{st}\}} p_{ct}Y_{ct} - p_{rt}Y_{rt} - p_{st}Y_{st}, \tag{A4}$$

and from the FOC's we find the following price of renewables relative to storage,

$$\frac{p_{rt}}{p_{st}} = \frac{\delta}{1-\delta}\left(\frac{Y_{rt}}{Y_{st}}\right)^{-\frac{1}{\rho}}. \tag{A5}$$

From equations (A2) and (A5) follows that

**Remark 1.** Under Assumption 1, the clean price relative to the dirty price and the renewable price relative to the storage price are both decreasing in clean and renewable supply, respectively. However, this relationship is more pronounced between renewable and storage.

Perfect competition implies the following price index of the effective clean good

$$\delta^\rho p_{rt}^{1-\rho} + (1-\delta)^\rho p_{st}^{1-\rho} = p_{ct}^{1-\rho}. \tag{A6}$$

Inserting for optimal demand of machines from Eq. (8) into the input production function in Eq. (3), intermediate production in sector $j$ can be written as,

$$Y_{jt} = \left(\frac{\alpha^2}{\psi}\right)^{\frac{\alpha}{1-\alpha}} p_{jt}^{\frac{\alpha}{1-\alpha}} L_{jt} A_{jt}, \tag{A7}$$

where $A_{jt} \equiv \int_0^1 A_{ijt} di$.

### Prices

Combining the expressions of intermediate production in Eq. (A7) and the wage rate in Eq. (5) with the fact that the wage rates must be equal in all three sectors, we find the following relative prices of the inputs,

$$\frac{p_{rt}}{p_{dt}} = \left(\frac{A_{rt}}{A_{dt}}\right)^{-(1-\alpha)}, \quad \frac{p_{rt}}{p_{st}} = \left(\frac{A_{rt}}{A_{st}}\right)^{-(1-\alpha)} \quad \text{and} \quad \frac{p_{st}}{p_{dt}} = \left(\frac{A_{st}}{A_{dt}}\right)^{-(1-\alpha)}. \tag{A8}$$

Hence, the input with a higher technological level is cheaper. As in AABH, Eq. (A8) illustrates that the price effect, defined in Eq. (12), favors innovation towards the least advanced sector. Combining the relative price of renewables in Eq. (A8) with the price index of clean energy in Eq. (A6), we find the following expressions for renewables and storage input prices

$$p_{st}^{1-\rho}\left(\frac{(1-\delta)^\rho A_{rt}^\sigma + \delta^\rho A_{st}^\sigma}{A_{rt}^\sigma}\right) = p_{ct}^{1-\rho} \quad \text{and} \quad p_{rt}^{1-\rho}\left(\frac{(1-\delta)^\rho A_{rt}^\sigma + \delta^\rho A_{st}^\sigma}{A_{st}^\sigma}\right) = p_{ct}^{1-\rho} \tag{A9}$$

where $\sigma \equiv (1-\alpha)(1-\rho)$. Inserting the price of renewables relative to dirty energy in Eq. (A8) into Eq. (A9), we find the following relationship between the prices of clean and dirty energy,

$$p_{ct} = p_{dt}\left(\frac{A_{dt}}{A_{rt}A_{st}}\right)^{1-\alpha} \left((1-\delta)^\rho A_{rt}^\sigma + \delta^\rho A_{st}^\sigma\right)^{\frac{1}{1-\rho}}. \tag{A10}$$

Insert the expression for the price of $p_{ct}$ above into the price index of the final consumption good in Eq. (A3), we find the following price of the dirty input,

$$p_{dt} = \frac{(A_{rt}A_{st})^{1-\alpha}}{\left[(A_{rt}A_{st})^{\phi}(1-z_{dt})^{1-\epsilon} + A_{dt}^{\phi}\left((1-\delta)^{\rho}A_{rt}^{\sigma} + \delta^{\rho}A_{st}^{\sigma}\right)^{\frac{1-\epsilon}{1-\rho}}(1-z_{ct})^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}} \tag{A11}$$

where $\phi \equiv (1-\alpha)(1-\epsilon)$. By inserting for the price of the dirty input into Eq. (A10), we find the following price of clean energy,

$$p_{ct} = \frac{A_{dt}^{1-\alpha}\left((1-\delta)^{\rho}A_{rt}^{\sigma} + \delta^{\rho}A_{st}^{\sigma}\right)^{\frac{1}{1-\rho}}}{\left[(A_{rt}A_{st})^{\phi}(1-z_{dt})^{1-\epsilon} + A_{dt}^{\phi}\left((1-\delta)^{\rho}A_{rt}^{\sigma} + \delta^{\rho}A_{st}^{\sigma}\right)^{\frac{1-\epsilon}{1-\rho}}(1-z_{ct})^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}}. \tag{A12}$$

Lastly, insert the price of the clean good into the expressions in Eq. (A9), the prices of renewables and storage inputs can be expressed as

$$p_{st} = \frac{(A_{rt}A_{dt})^{1-\alpha}}{\left[(A_{rt}A_{st})^{\phi}(1-z_{dt})^{1-\epsilon} + A_{dt}^{\phi}\left((1-\delta)^{\rho}A_{rt}^{\sigma} + \delta^{\rho}A_{st}^{\sigma}\right)^{\frac{1-\epsilon}{1-\rho}}(1-z_{ct})^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}}, \tag{A13}$$

and

$$p_{rt} = \frac{(A_{st}A_{dt})^{1-\alpha}}{\left[(A_{rt}A_{st})^{\phi}(1-z_{dt})^{1-\epsilon} + A_{dt}^{\phi}\left((1-\delta)^{\rho}A_{rt}^{\sigma} + \delta^{\rho}A_{st}^{\sigma}\right)^{\frac{1-\epsilon}{1-\rho}}(1-z_{ct})^{1-\epsilon}\right]^{\frac{1}{1-\epsilon}}}. \tag{A14}$$

All prices are now expressed as functions of the average productivity levels of the three input sectors—dirty, renewable, and storage technology.

### Labor shares

Combining the expressions for the relative price of renewables in Eqs. (A5) and (A8) with the production for renewables and storage in Eq. (A7), the relative labor share used to produce renewables can be expressed as

$$\frac{L_{rt}}{L_{st}} = \left(\frac{\delta}{1-\delta}\right)^{\rho} \left(\frac{p_{rt}}{p_{st}}\right)^{-\rho} \left(\frac{A_{rt}}{A_{st}}\right)^{-(1-\alpha)}. \tag{A15}$$

Inserting for the prices of these inputs from Eqs. (A13) and (A14), the relative labor share can be expressed as,

$$\frac{L_{rt}}{L_{st}} = \left(\frac{\delta}{1-\delta}\right)^{\rho} \left(\frac{A_{rt}}{A_{st}}\right)^{-\sigma}. \tag{A16}$$

Since $L_{rt} + L_{st} = L_{ct}$, where $L_{ct}$ is total labor used in the production of clean energy, the shares of labor used to produce renewables and storage can be expressed as functions of the technology levels and the total labor used to produce clean energy,

$$L_{rt} = \frac{\delta^{\rho} A_{st}^{\sigma}}{(1-\delta)^{\rho} A_{rt}^{\sigma} + \delta^{\rho} A_{st}^{\sigma}} \times L_{ct} \quad \text{and} \quad L_{st} = \frac{(1-\delta)^{\rho} A_{rt}^{\sigma}}{(1-\delta)^{\rho} A_{rt}^{\sigma} + \delta^{\rho} A_{st}^{\sigma}} \times L_{ct}. \tag{A17}$$

To find the relative labor share of clean energy, we use the expression of the relative price of clean energy in Eq. (A2), and insert for production of the inputs. Notice that production of the dirty good is given directly by Eq. (A7), while the production of the clean good is found by first inserting for intermediate production of renewables and storage from Eq. (A7) into the production function of the clean good in Eq. (2). This gives us the following expression.

$$\left(\left(\frac{p_{ct}(1-z_{ct})}{p_{dt}(1-z_{dt})}\right)^{-\epsilon}\right)^{\frac{\rho-1}{\rho}} = \delta \left(\left(\frac{p_{rt}}{p_{dt}}\right)^{\frac{\alpha}{1-\alpha}} \frac{L_{rt}}{L_{dt}} \frac{A_{rt}}{A_{dt}}\right)^{\frac{\rho-1}{\rho}} + (1-\delta) \left(\left(\frac{p_{st}}{p_{dt}}\right)^{\frac{\alpha}{1-\alpha}} \frac{L_{st}}{L_{dt}} \frac{A_{st}}{A_{dt}}\right)^{\frac{\rho-1}{\rho}} \tag{A18}$$

Inserting for relative prices from Eq. (A8), then for the renewable and storage labor in terms of clean labor in Eq. (A17), the relative labor share of the clean good can be expressed as

$$\frac{L_{ct}}{L_{dt}} = \left(\frac{p_{ct}(1-z_{ct})}{p_{dt}(1-z_{dt})}\right)^{-\epsilon} \left(\frac{A_{dt}}{A_{rt}A_{st}}\right)^{1-\alpha} \left((1-\delta)^{\rho} A_{rt}^{\sigma} + \delta^{\rho} A_{st}^{\sigma}\right)^{\frac{1}{1-\rho}}. \tag{A19}$$

We then insert for the prices of inputs from Eqs. (A11) and (A12), which results in the following expression for the relative labor share used to produce clean energy,

$$\frac{L_{ct}}{L_{dt}} = \left(\frac{A_{dt}}{A_{rt}A_{st}}\right)^{\phi} ((1-\delta)^{\rho} A_{rt}^{\sigma} + \delta^{\rho} A_{st}^{\sigma})^{\frac{1-\epsilon}{1-\rho}} \left(\frac{1-z_{ct}}{1-z_{dt}}\right)^{-\epsilon}. \tag{A20}$$

**Remark 2.** From expression (A16) and (A20) follows that the more advanced sector hires more labor if the two goods are substitutes and hires less labor if the two goods are complements.

*Proof.* The remark follows from the fact that in (A16), the $\frac{\partial(\frac{L_r}{L_s})}{\partial(\frac{A_r}{A_s})} < 0$ and in (A20), the $\frac{\partial(\frac{L_c}{L_d})}{\partial(\frac{A_d}{A_r A_s})} < 0$. □

Remark 2 summarizes the following. Both Eqs. (A15) and (A19) show that the allocation of labor into each sector depends on the relative technologies and the relative prices. Relative prices depend, ultimately, on relative technologies (see Eqs. (A8) and (A10), respectively). The two channels work in opposite directions. That is, a relative increase in $A_{rt}$ ($A_{dt}$) reduces relative $L_{rt}$ ($L_{dt}$) via the direct technology force (see eqs. (A15) and (A19)), and increases relative $L_{rt}$ ($L_{dt}$) via the price effect (see Eqs. (A8) and (A10 combined with A15) and (A19). However, under Assumption 1, the net effect of these two opposing forces, captured by expressions (A16) and (A20), differs between relative renewable and relative clean. While the technology force dominates the price force in the relative labor of the two complement inputs (renewable-storage), the price force dominates when inputs are substitutes (clean-dirty). Hence, an increase in relative $A_{rt}$ ($A_{dt}$) leads to a net reduction (increase) in relative $L_{rt}$ ($L_{dt}$).

**Remark 3.** From Remark 2 follows that the market size effect in eq. (12) pushes innovation towards the more advanced sector for the two substitute inputs but towards the least advanced sector for the two complement inputs.

Lastly, using the market clearing condition, $L_{ct} + L_{dt} = 1$, we can express the shares of labor used to produce the clean and dirty inputs as functions of the technology levels and the carbon tax,

$$L_{dt} = \frac{\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_c\right)^{\epsilon}}{\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_c\right)^{\epsilon} + A_{dt}^{\phi}\left((1-\delta)^{\rho}A_{rt}^{\sigma} + \delta^{\rho}A_{st}^{\sigma}\right)^{\frac{1-\epsilon}{1-\rho}}\left(1-z_d\right)^{\epsilon}} \quad \text{and}$$

$$L_{ct} = \frac{A_{dt}^{\phi}\left((1-\delta)^{\rho}A_{rt}^{\sigma} + \delta^{\rho}A_{st}^{\sigma}\right)^{\frac{1-\epsilon}{1-\rho}}\left(1-z_d\right)^{\epsilon}}{\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_c\right)^{\epsilon} + A_{dt}^{\phi}\left((1-\delta)^{\rho}A_{rt}^{\sigma} + \delta^{\rho}A_{st}^{\sigma}\right)^{\frac{1-\epsilon}{1-\rho}}\left(1-z_d\right)^{\epsilon}}. \quad \text{(A21)}$$

**Output**

Inserting for the prices and labor shares found above into the production function of intermediate inputs in Eq. (A7), we find the following expressions for the production of the renewable input,

$$Y_{rt} = \left(\frac{\alpha^2}{\psi}\right)^{\frac{\alpha}{1-\alpha}} \frac{\delta^{\rho}A_{rt}A_{st}^{\alpha+\sigma}A_{dt}^{\alpha+\phi}\left(1-z_d\right)^{\epsilon}K^{\frac{\rho-\epsilon}{1-\rho}}}{\left[\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_d\right)^{1-\epsilon} + A_{dt}^{\phi}K^{\frac{1-\epsilon}{1-\rho}}\left(1-z_c\right)^{1-\epsilon}\right]^{\frac{\alpha}{\phi}}\left[\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_c\right)^{\epsilon} + A_{dt}^{\phi}\left(1-z_d\right)^{\epsilon}K^{\frac{1-\epsilon}{1-\rho}}\right]} \quad \text{(A22)}$$

the storage input,

$$Y_{st} = \left(\frac{\alpha^2}{\psi}\right)^{\frac{\alpha}{1-\alpha}} \frac{(1-\delta)^{\rho}A_{st}A_{rt}^{\alpha+\sigma}A_{dt}^{\alpha+\phi}\left(1-z_d\right)^{\epsilon}K^{\frac{\rho-\epsilon}{1-\rho}}}{\left[\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_d\right)^{1-\epsilon} + A_{dt}^{\phi}K^{\frac{1-\epsilon}{1-\rho}}\left(1-z_c\right)^{1-\epsilon}\right]^{\frac{\alpha}{\phi}}\left[\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_c\right)^{\epsilon} + A_{dt}^{\phi}\left(1-z_d\right)^{\epsilon}K^{\frac{1-\epsilon}{1-\rho}}\right]} \quad \text{(A23)}$$

and the dirty input,

$$Y_{dt} = \left(\frac{\alpha^2}{\psi}\right)^{\frac{\alpha}{1-\alpha}} \frac{A_{dt}\left(A_{rt}A_{st}\right)^{\alpha+\phi}\left(1-z_c\right)^{\epsilon}}{\left[\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_d\right)^{1-\epsilon} + A_{dt}^{\phi}K^{\frac{1-\epsilon}{1-\rho}}\left(1-z_c\right)^{1-\epsilon}\right]^{\frac{\alpha}{\phi}}\left[\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_c\right)^{\epsilon} + A_{dt}^{\phi}\left(1-z_d\right)^{\epsilon}K^{\frac{1-\epsilon}{1-\rho}}\right]} \quad \text{(A24)}$$

where,

$$K \equiv (1-\delta)^{\rho}A_{rt}^{\sigma} + \delta^{\rho}A_{st}^{\sigma}.$$

To find an expression for the production of the clean input, we insert the production of renewables and storage inputs into the production function of the clean good in Eq. (2),

$$Y_{ct}=\left(\frac{\alpha^2}{\psi}\right)^{\frac{\alpha}{1-\alpha}}\frac{A_{rt}A_{st}A_{dt}^{\alpha+\phi}\left(1-z_d\right)^{\epsilon}K^{\frac{\epsilon}{\rho-1}}}{\left[\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_d\right)^{1-\epsilon}+A_{dt}^{\phi}K^{\frac{1-\epsilon}{1-\rho}}\left(1-z_c\right)^{1-\epsilon}\right]^{\frac{\alpha}{\phi}}\left[\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_c\right)^{\epsilon}+A_{dt}^{\phi}\left(1-z_d\right)^{\epsilon}K^{\frac{1-\epsilon}{1-\rho}}\right]}. \tag{A25}$$

Lastly, insert the production of the clean input and the dirty input into the production function of the final good in Eq. (1), we find the following expression for the production of the final consumption good,

$$Y_t=\frac{\left(\frac{\alpha^2}{\psi}\right)^{\frac{\alpha}{1-\alpha}}A_{rt}A_{st}A_{dt}\left(1-z_d\right)^{\epsilon}}{\left[\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_d\right)^{1-\epsilon}+A_{dt}^{\phi}K^{\frac{1-\epsilon}{1-\rho}}\left(1-z_c\right)^{1-\epsilon}\right]^{\frac{\alpha+\epsilon(1-\alpha)}{\phi}}\left[\left(A_{rt}A_{st}\right)^{\phi}\left(1-z_c\right)^{\epsilon}+A_{dt}^{\phi}\left(1-z_d\right)^{\epsilon}K^{\frac{1-\epsilon}{1-\rho}}\right]}. \tag{A26}$$

## A.3 Data sources and calibration

### A.3.1 Alternative estimations of $\rho$

Given the lack of empirical estimates of the substitution elasticity between renewables and energy storage, we collect various datasets on renewable and storage electricity generation and capacity to determine which elasticity values best fit our data within a CES function. First, we use bid information from the US solar-plus-storage and wind-plus-storage markets. This data reveals how electricity companies plan to integrate renewable and storage technologies to fulfill specific demand requirements. Second, we use Aghahosseini et al. (2023)'s forecasts on 2050 electricity generation by source, including storage, under an IEA scenario that reaches net-zero generation by mid-century. With these datasets we are able to calculate the elasticities that best fit the data to a CES renewable electricity generation data. We obtain values that range from 0.33 to 0.75. In our calibration, we use an estimate of 0.5, which lies within the estimated range and ensures that the two inputs are strong complements in producing clean energy.

### A.3.2 Heat maps

The heat map in Figure A5 shows the relative price and labor ratios in the period prior to our simulations (2006-2010) for different combinations of $\rho$ and $\delta$. $\rho$ varies between 0.1 and 0.9, while delta varies from 0.05 to 0.95. All other parameters are as in the table in the main text.

Our estimates from the data are:

- LCOE for renewables (wind and PV) and energy storage (battery) in 2013: $87/272.5 \approx 0.32$

- Average LCOE for renewables (wind and PV) and fossil fuels (coal, natural gas and natural gas peaker) from 2009-2013: $140.2/146.5 \approx 0.96$

- Average LCOE for renewables (wind and PV) and fossil fuels (coal and natural gas): $93.7/146.5 \approx 0.64$

- Average number of employees (in thousands) in clean and fossil fuel electric power production from 2006 to 2010 (from Current Employment Statistics): $(66.3 \times 0.49)/101 \approx 0.32$

  - Note that we adjust the number of employees in clean to account for the share of workers in nuclear. From 2006 to 2010, the ratio between renewable and nuclear power generation was 0.49.

Panel a shows the price of renewables relative to storage, and cells are annotated with the calculated price ratio if the ratio is greater than or equal to 0.1. Panel b shows the price of fossil fuels relative to renewables, and cells are annotated with the calculated price ratio if it is less than or equal to 1.5. Panel c shows the share of labor in clean technology relative to fossil fuels, and cells are annotated if the labor ratio is greater than or equal to 0.25.

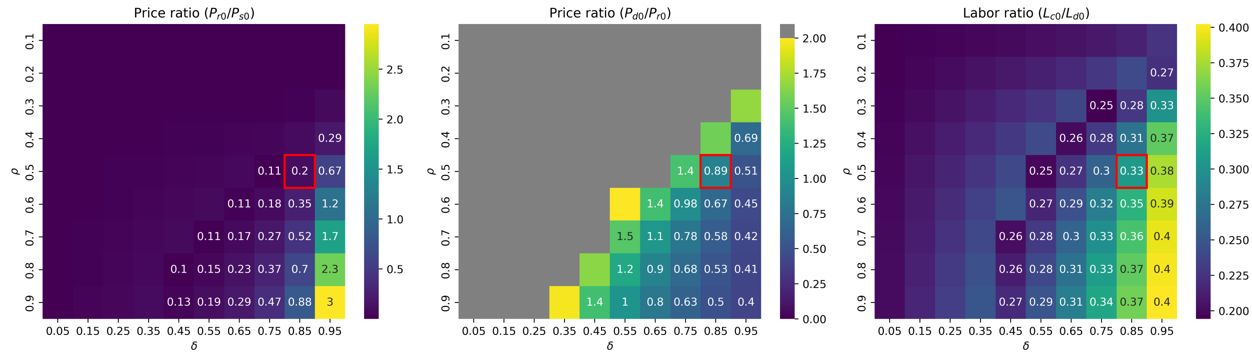



Figure A5: Caption

As seen in the figure, our chosen combination of rho and delta delivers ratios close to the empirical estimates. For the labor ratio of clean to fossil fuels, our model estimate is almost identical to the empirical estimate (0.33 vs 0.32). However, for both the price ratio of renewables to energy storage and fossil fuels to renewables, our model estimates are below the empirical estimates (0.32 vs 0.2 and 0.89 vs 0.96). In order to bring the model estimate closer to the empirical estimate for the price ratio of renewables to storage, we could for example increase rho from 0.5 to 0.6. However, this would increase the gap between the model estimate and empirical estimate for the price ratio of fossil fuels to renewables. Hence, the figure illustrates that our chosen combination of rho and delta results in reasonable values of the price and labor ratios.

## A.4 Numerical illustrations

Figure A6 zooms in Figure 2, illustrating the actual allocation of scientists following a +100% increase in $A_{r0}$ under each scenario.

Figure A7 illustrates the indirect path dependency effect from Eq. (16) using a heat map. It shows how the effect varies under different values of $A_{s0}$ (initial storage technological level) and $\delta$ (share of renewables in clean production). The value of the effect is always below one, but gets closer to zero (one) as $A_{s0}$ and $\delta$ decrease (increase). That is, when the productivity gap between renewables and storage incresases (because $A_{s0}$ decreases), or when storage is more relevant in clean production (because $\delta$ is lower), the indirect path dependency effect has more impact in reducing the profitability of innovation in renewables relative to fossil fuels. On the contrary, when the productivity gap between renewables and storage is reduced (because $A_{s0}$ increases), or when renewables are more important in clean production (because $\delta$ is higher), the indirect path dependency effect has a lower impact on this relative profitability.

## A.5 Additional results

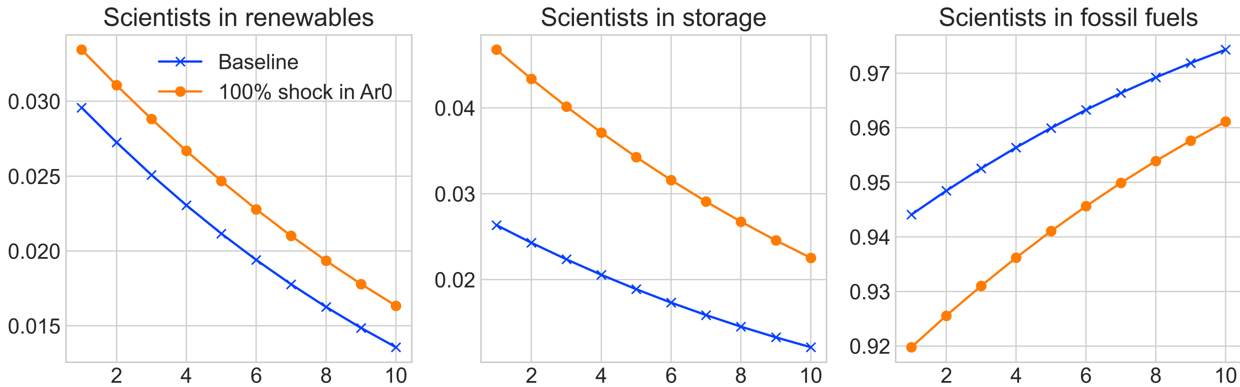
### Policy scenarios with and without electric vehicle batteries R&D subsidies

The baseline results in section 4 include electric vehicle batteries' R&D subsidies as part of the **Current policy** scenario because we believe this is the most reasonable approach to storage innovation. For transparency, we now show the results when these subsidies are excluded. More specifically, batteries received only 0.4% of total energy R&D expenditures, while in the same period, R&D in battery technology in electrical vehicles was subsidized with 1.5% of total public R&D expenditures. Hence, with electric vehicle batteries, renewables receive a subsidy that is 7.1 times higher than storage (13.5/1.9), while without batteries for electric vehicles, renewables receive a subsidy that is 33.8 times higher than storage (13.5/0.4). In order to ease comparison, we reproduce some of the baseline settings. The four policy scenarios are summarized in Table A1. The **Energy policy** scenario assumes that production and R&D subsidies are equal to the observed rates in the energy sector in 2011 to 2015 and remain constant at these rates throughout the simulation period. However, unlike the previous **Current policy** scenario, the **Energy policy** scenario excludes R&D subsidies for electric vehicle batteries. As a result, the relative renewable subsidy is nearly five times higher than before (column 4). In contrast, the **+ EV R&D Subsidy** scenario includes these subsidies and is equivalent to the original **Current Policy** scenario.

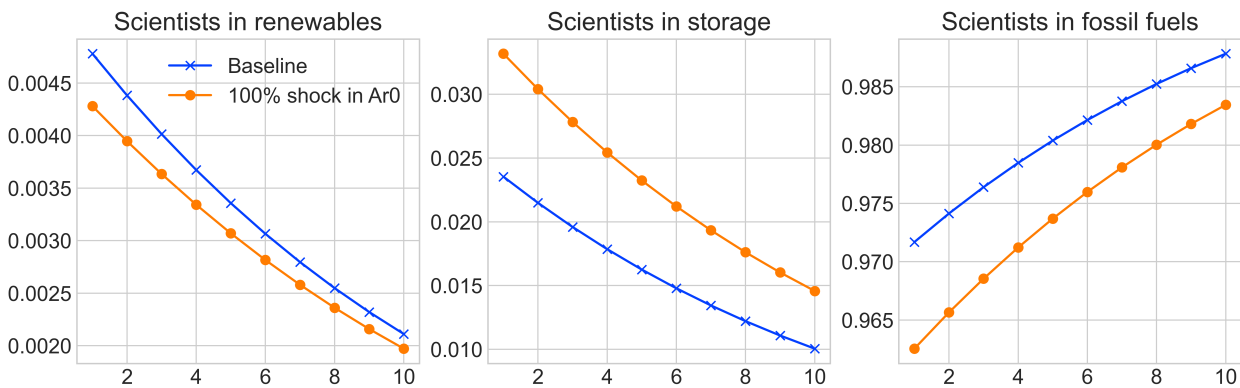
Table A1: Overview of policy rates in alternative policy scenarios

| | $z_d$ | $z_c$ | $(1+q_r)/(1+q_d)$ | $(1+q_r)/(1+q_s)$ |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **No policy** | 0 | 0 | 1 | 1 |
| **Energy policy** | 0.005 | 0.152 | 5.6 | 33.8 |
| **+ EV R&D subsidy** | 0.005 | 0.152 | 5.6 | 7.1 |
| **+ IRA subsidy** | 0.005 | 0.2 | 5.6 | 7.1 |

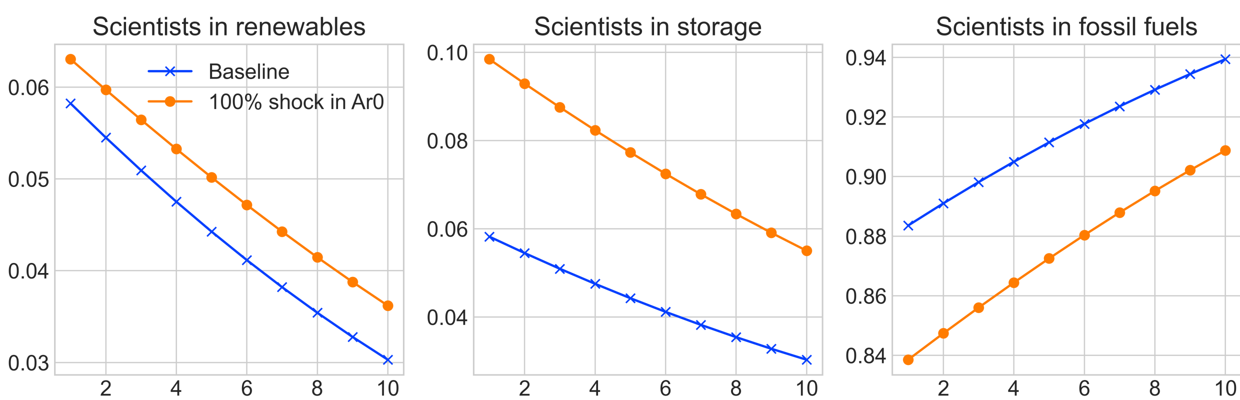
Figure A8 summarizes the results for the first three scenarios. As before, in the absence of production and R&D subsidies, the high productivity of fossil fuels drives most scientists to the dirty sector, causing the share of clean energy to fall from 8% to below 4% at the end of the simulation period. Introducing energy policy causes a large shift in scientists from fossil fuels to renewables, but due to the low R&D subsidy in energy storage relative to renewables, the number of scientists in storage is reduced from an initial share of 10% to almost zero. Despite the increase in innovation in renewables, the lack of innovation in energy storage causes a reduction in the share of clean energy at the end of the simulation period. If innovators in energy storage also benefit from the subsidy to battery technology in electric vehicles, then the R&D subsidy to energy storage increases, which induces scientists to the storage sector, benefiting the share of clean energy.




(a) Baseline parameters (Table 1)




(b) $\delta = 0.5$




(c) $\delta = 0.5$ and $A_{s0} = A_{r0}$

Figure A6: Numerical example of Propositions 1 and 2. Panels (a) to (c) show the effect of a 100% increase in the initial productivity of renewables on the allocation of scientists for different parameter values.

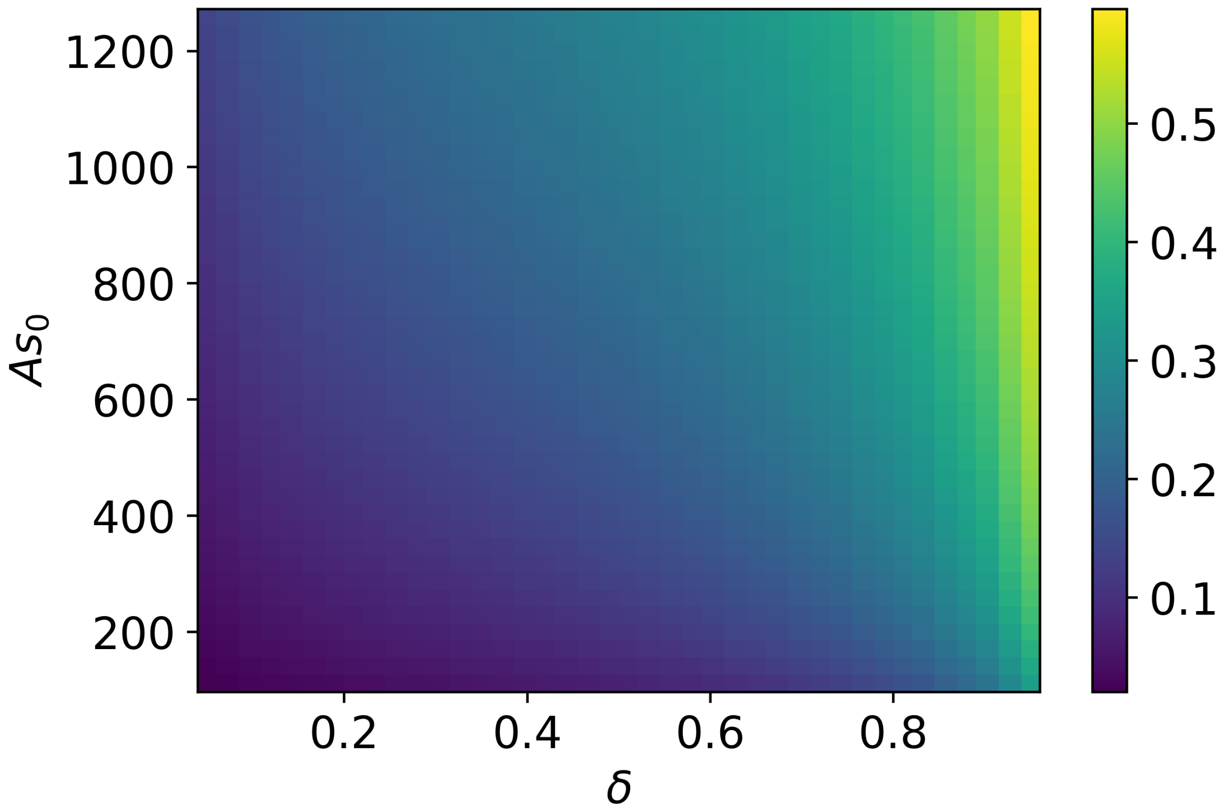



Figure A7: Heat map visualizing the indirect path dependency effect in Eq. (16), under different values of $A_{st}$ (storage technological level) and $\delta$ (share of renewables in clean production). The values in the heatmap are derived by simulating the model with parametres detailed in Table 1. The allocation of scientists is assumed to be equally distributed among the three sectors, meaning one-third of scientists work in each sector. The x-axes represents the range of $\delta$, varying from 0.05 and 0.95. The y-axes represents $A_{st}$, ranging from the initial value of storage technology to that of renewables technology, i.e., from $A_{s0}$ to $A_{rt}$.

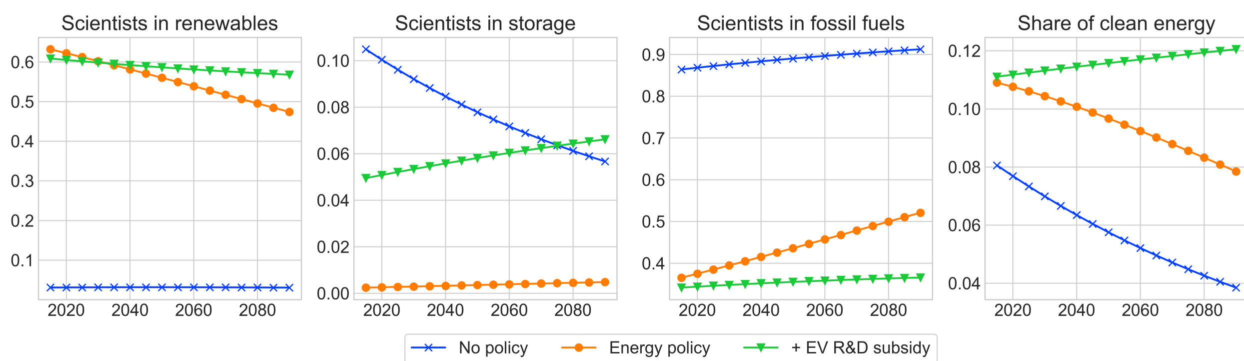



Figure A8: Simulated allocation of scientists and share of clean energy from 2015 to 2090 for no policy and current policy (with and without R&D subsidy to EV battery technology).