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Meeting Climate Targets: The Role of Fossil Research Subsidies

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Abstract

What is the optimal mix of carbon taxes and research subsidies to meet emission targets? I study a model of directed technical change in which an emission limit renders the use of fossil energy socially costly. Novel to the literature, the existence of a third non-energy research sector makes fossil research taxes or subsidies form part of efficient emission mitigation. In a calibration to the US, I find that the optimal policy mix subsidizes research on fossil-based technologies to engineer a smooth transition to greener research. Key to this result are cross-sectoral knowledge spillovers through which fossil-based knowledge facilitates green innovation tomorrow. In the presence of such spillovers, maintaining some fossil research allows to (i) lower the risk of duplicating ideas and (ii) to profit from the stock of fossil-related knowledge on which scientists in the fossil sector can build. Importantly, subsidizing fossil R&D is optimal only in conjunction with carbon taxes.

JEL classification: H21, H23, O3, Q54, Q55

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1 Introduction

We need to transition to net-zero economies meaning a massive shift in how we produce, and fostering green technology growth is a key aspect to lower the costs of a green transition. The economics literature has established that carbon taxes and green research subsidies jointly implement the efficient allocation in the two-sector models studied thus far.¹ However, the grant majority of scientists works in sectors unrelated with energy or emission mitigation.² I argue that accounting for the existence of a third, non-energy research sector renders additional policy instruments relevant to efficiently lower emissions: fossil research taxes.

Whether research on fossil-related technologies, however, should be taxed or subsidized is a quantitative question. On the one hand, high carbon taxes and green research subsidies may cause an undesirable reduction in non-energy research. Taxing research on fossil energy instead of green research subsidies prevents such repercussion. On the other hand, a fossil research subsidy can smooth the transition of research activity towards green sector thereby lowering transition costs through stranded assets and decreasing returns to research.

In my three sector, directed-technical-change set-up calibrated to the US, I find that the optimal policy mix features fossil research subsidies in combination with high carbon taxes and green research taxes to meet emission targets. The rationale is that the generation of knowledge is non-linear: first, research in established sectors is relatively productive as it can build on past technology advances.³ Second, the risk of duplicating ideas makes a rapid shift to green research inefficient.⁴ But, advances in fossil-related knowledge would be useless when only green technologies are used in the future. Only if knowledge fertilizes new ideas

¹See, for instance, [Acemoglu et al. \(2012\)](#), [Golosov et al. \(2014\)](#), or [Acemoglu et al. \(2016\)](#).

²In the US, the share of non-energy R&D over the 1975-2005 period amounts to 98% (calculations based on data from the National Center for Science and Engineering Statistics (NCSES)).

³A substantial stock of fossil-related knowledge has been accumulated in past decades (see [Figure 1](#)), and evidence points to a strong positive relation between past innovation and new ideas within a sector (generally referred to as *building-on-the-shoulder-of-giants*); for an empirical investigation see [Aghion et al. \(2016\)](#). Theoretical considerations of knowledge spillovers are provided by, e.g., [Jones and Williams \(1998\)](#) or [Aghion and Jaravel \(2015\)](#).

⁴This so-called *stepping-on-toes* effect is a well-known aspect in the endogenous growth literature; for instance, see [Jones and Williams \(1998\)](#), [Hart \(2019\)](#), or [Hémous and Olsen \(2021\)](#).

across sectors, fossil research today remains valuable.⁵

In more detail, the modeling follows [Fried \(2018\)](#). A final consumption good is produced from energy and non-energy goods. The energy good, in turn, is composed of green and fossil energy. The fossil sector exerts emissions. Imperfectly monopolistic producers of machinery invest in research to increase the productivity of their machines in the intermediate sectors: non-energy, fossil, and green energy. The model features a rich description of technological growth: innovation builds on already existing knowledge, first, within a sector (*within-sector knowledge spillovers*) and, second, across sectors (*cross-sectoral knowledge spillovers*). Third, returns to research decrease with the number of scientists employed within a sector (*stepping-on-toes effect*).

Special care is given to calibrate the research process. Initial knowledge stocks are key to determine the technology advantage in the fossil sector. Therefore, I extend the model by differentiating knowledge from productivity. This allows me to estimate initial knowledge stocks from patent data which is not subject to market distortions as would be the case when productivity is calibrated residually from output data. One challenge in this approach is to classify patents into green, fossil, and non-energy sectors. To this end, I revert to classifications provided by a joint effort of the International Energy Agency and the European Patent Office. Based on their classification, I collect a novel dataset of innovation activity in energy and non-energy sectors. I find that the knowledge stock in fossil energy supply was 30% higher than in the green sector over the 2010-2014 period. Other key drivers of the optimal policy, knowledge spillovers and the returns to research, follow from fitting the model to time-series data on R&D investment and knowledge stocks.

In this framework, a benevolent government chooses the dynamic path of carbon taxes, green, and fossil research subsidies (or taxes) to maximize welfare. In so doing, it anticipates that net emissions are limited in the short run and have to be zero at some point in the future.

⁵Empirical evidence for cross-sectoral knowledge spillovers is, for instance, provided by [Aghion et al. \(2016\)](#). [Barbieri et al. \(2023\)](#) provide evidence for the positive relatedness of green to non-green innovation. An example are rotors in steam turbines. They are used for the generation of electricity from fossil sources and applicable in energy generation from wind.

As exogenous emission limit, I use estimates on global emissions compatible with a 1.5°C temperature target from the latest IPCC assessment report (IPCC, 2022). I derive a national emission target for the US using an *equal-per-capita* allocation of admissible emissions.

I find that the optimal policy to implement this emission target is a combination of carbon taxes, fossil research subsidies, and green research taxes. The fossil research subsidy amounts to slightly below 60% in 2020 and steadily rises to around 90%.⁶ The high level of the fossil research subsidy has to be understood in combination with the tax on carbon. The carbon tax rises from 50\$ in 2020 to slightly below 350\$ in 2070. The two instruments jointly implement both (i) a small and diminishing share of fossil energy in production and (ii) a constant share of research on fossil-related knowledge. Surprisingly, green research is taxed as part of efficient emission mitigation. The reduction reflects the idea that carbon taxes—necessary to reduce emissions to their target level already today—direct research to the green sector in a more than sufficient way. A smoother allocation of researchers would allow to diminish the risk of duplicating ideas and to profit from the knowledge stock on fossil technologies.

To set my findings into context, it is important to stress that it is only in combination with massive carbon prices that fossil research subsidies are optimal. Only then the government achieves a low share of fossil energy in production and sustained fossil research activity. Essentially, it is fossil-related research and not production which should be promoted.

In a counterfactual calibration with less rapidly decreasing returns to research, my findings demonstrate that fossil research taxes are optimal. In this scenario, maintaining fossil research is not beneficial as the green sector can absorb more scientists without lowering researchers' productivity too much. I show that in this case, rising fossil research taxes are preferred above rising carbon taxes under the net-zero emission target. The intuition is that halting fossil technology advances, thereby boosting green technology, allows to rely on markets to sufficiently direct energy production to green sources.⁷

⁶These numbers are relative to an undistorted allocation without emission target.

⁷This result is in spirit of the argument made by Acemoglu et al. (2016). However, my findings reveal

Literature I want to highlight the main contribution of the paper which is to the literature on optimal environmental policies in endogenous growth models. Thus far, these papers focus on carbon taxation and green research subsidies (Fischer and Newell, 2008; Acemoglu et al., 2012, 2016; Hart, 2019). Adding a third, non-energy research sector to the model motivates a second research tax instrument to implement the first-best allocation. To the best of my knowledge, the present paper is the first to discuss the role of fossil research subsidies.

In more detail, Acemoglu et al. (2012) highlight the efficiency of green research subsidies in conjunction with carbon taxes. Acemoglu et al. (2016) quantify the optimal climate policy to consist of a small carbon tax combined with massive green research subsidies in the short run. The reason is that boosting green growth allows to rely on market forces to direct production to the green sector which is less costly than distorting the mixture of production inputs. This is in stark contrast to my findings. The reason are cross-sectoral knowledge spillovers which spill asymmetrically across sectors in my model. The more backward a sector, the more researchers can learn from other sectors. In Acemoglu et al. (2016), in contrast, cross-sectoral knowledge spillovers are symmetric.⁸ As a consequence of asymmetric knowledge spillovers, a green research subsidy also spurs profitability of research on fossil-based technologies. Absent a carbon tax, demand for fossil goods surges, and the economy transgresses emission targets. Hence, carbon taxes early on in the transition are indispensable.

Hart (2019) also discusses *fossil* research subsidies in his paper; however, the term refers to subsidies on fossil-augmenting technologies which is emissions saving. Conversely, I focus on research that facilitates the extraction and generation of fossil fuels. This sort of technology improvements per se leads to an increase of emissions as market mechanisms result in an increase of the share of fossil energy.

Fischer and Newell (2008) find that combining corrective taxes with research subsidies

that fossil taxes are preferred above green research subsidies as they induce a transition away from fossil and not a pulling of non-energy scientists caused by a green subsidy.

⁸Acemoglu et al. (2016) model cross-sectoral knowledge spillovers in the form of quantum leaps of breakthrough innovations across sectors. As a result, the laissez-faire allocation features only one type of research. Historic data, however, displays parallel movements in fossil and green R&D investment.

for the green sector is preferable above a carbon tax only as the research subsidy spurs green R&D investment today thereby allowing for a smaller carbon tax. This different outcome results from the lack of cross-sectoral knowledge spillovers in [Fischer and Newell \(2008\)](#) who only model research on green energy.

Outline The remainder of the paper is structured as follows. Section 2 presents the model which I calibrate in Section 3. Results are discussed in Section 4. Section 5 concludes.

2 Model

This section presents a quantitative framework building on [Fried \(2018\)](#). I extend her model by differentiating between technological advances, also referred to as *knowledge*, and productivity, which is important to get a reasonable calibration of initial knowledge stocks. Furthermore, I study optimal policies under a dynamic emission target which attaches social costs to the use of fossil energy. The exogenous limit prohibits any shifting of emissions over time beyond the target.

Households A representative household describes the household side. The household chooses consumption, C_t , taking prices as given. The household works a constant amount of hours, H , each period. The household owns machine producing firms from which it receives profits, Π_t ⁹. It also supplies scientific work in a fixed amount: S .¹⁰ The household behaves according to solving the below problem each period:

$$\max_{C_t} \log(C_t)$$

⁹Where $\Pi_t = \sum_J \left(\int_0^1 \pi_{xJit} di \right)$.

¹⁰These modeling choices simplify the households budget constraint as profits from firms and scientists' income, and subsidies to machine producers cancel. It is common to fix the supply of scientists in the literature on directed technical change in order to simplify the analysis ([Acemoglu et al., 2012](#); [Fried, 2018](#)). The assumption mutes the importance of the level of research and helps focus the discussion on the allocation of research which is the purpose of this paper.

$$s.t. \quad p_t C_t \leq w_t H + w_{st} S + T_t + \Pi_t.$$

The variables w_t and p_t indicate prices for labor and the final consumption good. Lump-sum transfers from the carbon tax and subsidies for machine producers and research are denoted by T_t .

Production Production separates into final good production, energy production, intermediate good production, and the production of machines. The final sector is perfectly competitive combining non-energy and energy goods according to:

$$Y_t = \left[\delta_y^{\frac{1}{\varepsilon_y}} E_t^{\frac{\varepsilon_y - 1}{\varepsilon_y}} + (1 - \delta_y)^{\frac{1}{\varepsilon_y}} N_t^{\frac{\varepsilon_y - 1}{\varepsilon_y}} \right]^{\frac{\varepsilon_y}{\varepsilon_y - 1}}.$$

I take the final good as the numeraire and define its price as $p_t = \left[\delta_y p_{Et}^{1 - \varepsilon_y} + (1 - \delta_y) p_{Nt}^{1 - \varepsilon_y} \right]^{\frac{1}{1 - \varepsilon_y}}$. Energy producers perfectly competitively combine fossil and green energy to a composite energy good:

$$E_t = \left[F_t^{\frac{\varepsilon_e - 1}{\varepsilon_e}} + G_t^{\frac{\varepsilon_e - 1}{\varepsilon_e}} \right]^{\frac{\varepsilon_e}{\varepsilon_e - 1}}.$$

The price of energy is determined as $p_{Et} = \left[(p_{Ft} + \tau_{Ft})^{1 - \varepsilon_e} + p_{Gt}^{1 - \varepsilon_e} \right]^{\frac{1}{1 - \varepsilon_e}}$. The government levies a sales tax per unit of fossil energy bought by energy producers, τ_{Ft} . This tax is henceforth referred to as carbon tax.

Intermediate goods, fossil, F_t , green, G_t , and non-energy, N_t , are again produced in competitive sectors using a sector-specific labor input good and machines. The production function in sector $J \in \{F, G, N\}$ reads

$$J_t = L_{Jt}^{1 - \alpha_J} \int_0^1 A_{Jit}^{1 - \alpha_J} x_{Jit}^{\alpha_J} di.$$

The variable A_{Jit} indicates the productivity of machine i in sector J at time t : x_{Jit} . Capital

shares, α_J , are sector specific. Intermediate good producers maximize profits:

$$\pi_{Jt} = p_{Jt}J_t - w_{lJt}L_{Jt} - \int_0^1 p_{xJit}x_{Jit}di,$$

where w_{lJt} is the price of sector J 's labor input good, L_{Jt} , and p_{xJit} denotes the price of machines from producer i in sector J .

Machine producers are imperfect monopolists searching to maximize profits. They choose the price at which to sell their machines to intermediate good producers and decide on the amount of scientists to employ. Demand for machines increases with their productivity which again is a function of technological progress. This provides the incentive to invest in research. Irrespective of the sector, the costs of producing one machine is set to one unit of the final output good similar to [Fried \(2018\)](#) and [Acemoglu et al. \(2012\)](#). Following the same literature, machine producers only receive returns to innovation for one period. Afterwards, patents expire. Machine producer i 's profits in sector J are given by

$$\pi_{xJit} = p_{xJit}(1 + \zeta_{Jt})x_{Jit} - x_{Jit} - w_{st}(1 - \tau_{sJt})s_{Jit}.$$

The government subsidizes machine production by ζ_{Jt} financed by lump-sum taxes on the household to correct for the monopolistic structure.¹¹ More importantly, the government can subsidize or tax sector-specific research via τ_{sJt} which are financed through lump-sum taxes. I normalize subsidies in the non-energy sector to zero. Equipped with these instruments, the Ramsey planner can correct for the externalities of knowledge spillovers and implement an efficient allocation.

Research and knowledge I differentiate between knowledge, K_{Jt} , and productivity, A_{Jt} . In [Fried \(2018\)](#)'s model, technology, A_J , has two functions: first, it makes labor more productive in working with machines, and, second, it facilitates the generation of new ideas

¹¹I introduce this policy to abstract from market imperfections as a driver of the results.

in the sense of knowledge. Calibrating *knowledge* as a residual from output data would allow market distortions such as monopolistic competition or subsidies which are not modeled to shape sector-specific knowledge stocks.¹² A more reasonable level of initial knowledge stocks is measured from patent data.¹³

Innovation is driven by research and spillovers. The law of motion of the knowledge stock from firm i in sector J is modeled as

$$K_{Jit} = K_{Jt-1} (1 - \delta_K) + \gamma \left(\frac{s_{Jit}}{\rho_J} \right)^\eta K_{-Jt-1}^\phi K_{Jt-1}^{1-\phi}.$$

The parameter γ governs the productivity of researchers, δ_K the depreciation of knowledge adding the notion of creative destruction in my model or that knowledge becomes obsolete for production (Li and Hall, 2020), and η determines returns to scale of research (a “stepping-on-toes” effect arising from the duplication of ideas or a notion of creative destruction in that not all new ideas are used but only the best ideas.). Aggregate technology levels are defined as

$$K_{Jt} = \int_0^1 K_{Jit} di,$$

$$K_{-J,t} = \frac{\sum_{j \in \{-J\}} \rho_j K_{jt}}{\sum_{j \in \{-J\}} \rho_j},$$

where the set $\{-J\}$ refers to all sectors except for sector J . The parameters ρ_J capture the number of research processes by sector. This ensures that returns to scale refer to the ratio of scientists to research processes (Fried, 2018). Private benefits of research diverge from social ones for two reasons. First, the rate of innovation depends on the knowledge that has been generated in past periods introduced through the term K_{Jt-1} , that is, knowledge spills within sectors over time. From a theoretical point of view the effect of past knowledge on the generation of new knowledge could also be negative, $\phi > 1$. Intuitively, this can be the case

¹²Compare, for example, the discussion in Kogan et al. (2017).

¹³A vast literature has used information on patents as a proxy for “knowledge” or innovative activity: Acemoglu et al. (2016); Kogan et al. (2017); Noailly and Smeets (2015).

because the innovations with the highest quality are made first, while later innovation is only incremental, a *fishing-out* effect (Jones and Williams, 1998). Most empirical results looking at the importance of past firm or sector specific innovation for new innovation find a positive relation (compare Aghion et al., 2016; Hart, 2019; Hémous and Olsen, 2021): a *building-on-the-shoulder-of-giants* effect dominates. However, producers do not internalize the effect of today’s research on tomorrow’s research productivity under one-period patents. Second, they neither consider knowledge spillovers to other sectors captured by the term K_{-Jt-1}^ϕ . The parameter ϕ captures the relative importance of cross-sectoral and within-sector knowledge spillovers. There are no cross-sectoral knowledge spillovers when $\phi = 0$.

The marginal (private) product of research determines the amount of researchers employed within a sector. It equals the competitive wage for scientists given by

$$w_{st} = \frac{\eta\gamma K_{-Jt-1}^\phi K_{Jt-1}^{1-\phi} s_{Jt}^{\eta-1} (1 - \alpha_J)}{\rho_J^\eta (1 - \tau_{sJt})} \frac{(\alpha_J p_{Jt})^{\frac{1}{1-\alpha_J}} L_{Jt} \frac{\iota_K \kappa_J}{K_{Jt}^{1-\iota_K}}}{\alpha_J}$$

Today’s knowledge stock, K_{Jt} , shows up in the second fraction because the higher the knowledge stock, the smaller the marginal effect of new knowledge on productivity due to decreasing returns to knowledge as discussed next.

Productivity and knowledge To link productivity and knowledge, I assume the following relationship:

$$A_{Jt}^{1-\alpha_J} = \kappa_J K_{Jt}^{\iota_K}.$$

The parameter κ_J can be perceived as measuring for example the experience of workers to handle new machines in the sens of learning, while ι_K captures the elasticity of productivity to innovation.¹⁴

¹⁴See Fischer and Newell (2008) for a discussion of how R&D affects productivity.

Markets In equilibrium, markets clear. I explicitly model markets for workers, scientists, and the final consumption good:

$$\begin{aligned}
H &= L_{Ft} + L_{Gt} + L_{Nt}, \\
S &= s_{Ft} + s_{Gt} + s_{Nt}, \\
C_t &= Y_t - \int_0^1 (x_{Fit} + x_{Git} + x_{Nit}) di.
\end{aligned}$$

Following [Fried \(2018\)](#) I assume free movement of scientists across sectors, which is justified by the 5-year duration of one period and certain research skills being applicable across sectors.

Government The government seeks to maximize lifetime utility of the representative household. Each period, the government is constrained by an emission limit, Ω_t , in line with the Paris Agreement. It is characterized as a Ramsey planner taking the behavior of firms and households as given and discounting period utility with the household's time discount factor, β . The planner chooses time paths for carbon taxes and research subsidies to solve:

$$\begin{aligned}
&\max_{\{\tau_{Ft}\}_{t=0}^{\infty}, \{\tau_{sFt}\}_{t=0}^{\infty}, \{\tau_{sGt}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \log(C_t) \\
&\quad s.t. \quad \omega F_t - \delta \leq \Omega_t,
\end{aligned} \tag{1}$$

$$\tau_{Ft} F_t + T_{\pi t} = T_t, \tag{2}$$

subject to the behavior of firms and households, and feasibility.¹⁵ Constraint (1) is the emission limit. The parameter δ captures the capacity of the environment to reduce emitted CO₂ through natural sinks, such as forests and moors, and carbon capture technologies. The parameter ω determines CO₂ emissions per unit of fossil energy produced. Revenues from the carbon tax are rebated lump sum, eq. (2), as are taxes and subsidies from research and

¹⁵Feasibility means that the government is constrained by initial technology levels, time endowments of workers and scientists, and production processes prescribed by the model.

machines, $T_{\pi t}$.¹⁶

3 Calibration

This section describes the calibration of the model. I calibrate the model to the US in the baseline period from 2015 to 2019.¹⁷ Special emphasis is given to the measurement of initial knowledge stocks and calibration of the research sector (subsection 3.1). Values of all other parameters are discussed in subsection 3.2. Calibration of the emission target follows in subsection 3.3. The section closes with discussing the laissez-faire behavior of the model (subsection 3.4).

3.1 Knowledge and research

Initial knowledge stocks The distribution of initial knowledge stocks is a crucial driver of the optimal environmental policy, as it determines the relative productivity of researchers across sectors through within sectoral knowledge spillovers. To measure sectoral knowledge stocks, I use the universe of patents granted by the United States Patent and Trademark Office (USPTO) and filed by US applicants¹⁸ from the European Patent Office (EPO)'s database PATSTAT. I consider patents filed between 1950 to 2017.¹⁹ To classify patents into the three distinct sectors of the model, I rely on the classification provided by a joint work of the International Energy Agency (IEA) and the EPO.²⁰ Fossil energy patents relate to the

¹⁶Equipped with these instruments, the government implements the first-best or social planner allocation; defined in Appendix A.

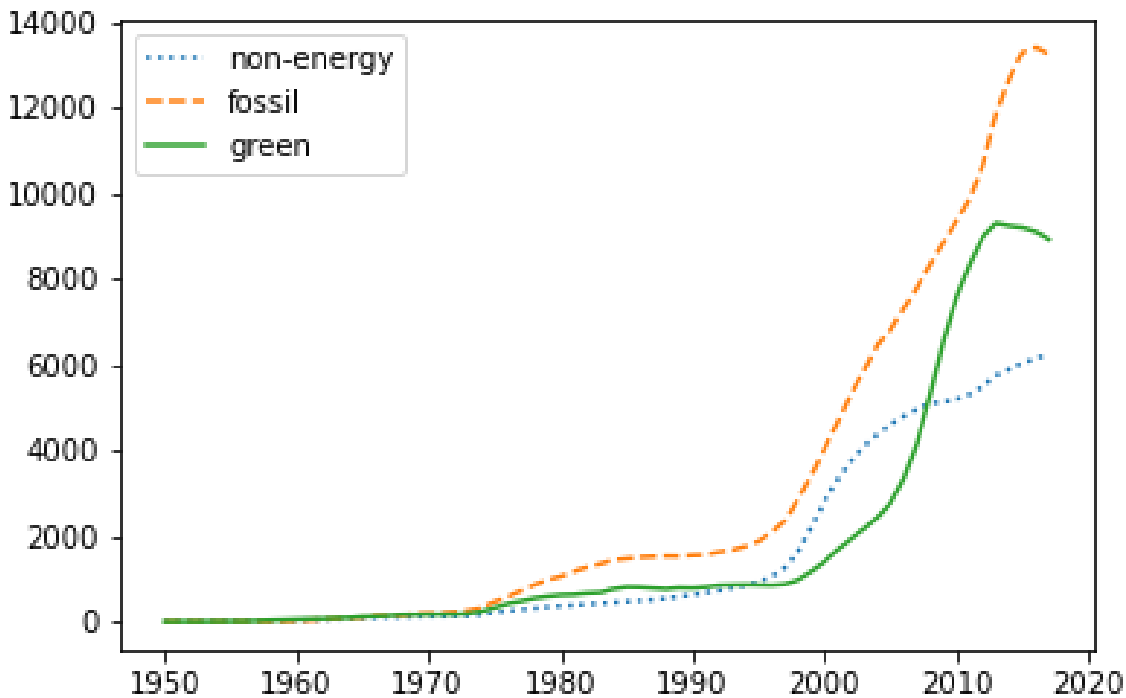
¹⁷Using this calibration approach, it is not ensured that the economy is on a balanced growth path. However, the goal of this paper is to study necessary interventions to meet an absolute emission limit. Therefore, it is important to capture whether the economy is transitioning, for example, to a higher fossil share. The optimal dynamic policy has to counteract these forces.

¹⁸These may be companies, individuals, or the government. I include government patent applicants because the innovation remains important for knowledge spillovers. Such patents, however, account only for 1.5% of all patents considered.

¹⁹The number of granted patents displays a sharp reduction after 2017 due to the time which may elapse from applying for protection to a patent being granted. The data on granted patents for more recent years, thus, underrates innovative activity.

²⁰The table of classifications of green technologies can be found here: https://link.epo.org/web/patents_and_the_energy_transition_study_en.pdf. The equivalent table for fossil-based technologies

Figure 1: Annual knowledge stock by sector



Notes: Knowledge stock per research process by sector in the US based on the number of granted patents by the US patent authority (USPTO). Only patents filed by US applicants are considered, the respective filing date is shown on the x-axis. Data comes from the EPO’s patent data bank PATSTAT. I classify patents by sector based on definitions derived by patent and energy experts discussed here: https://link.epo.org/web/patents_and_the_energy_transition_study_en.pdf. Non-energy knowledge is scaled by the relative number of research processes in that sector.

supply, exploration, processing, transport, and distribution of fossil fuels.²¹ To get an idea of *green* knowledge, I focus on *low-carbon energy* supply technologies.

Using the number of patents²² related to green, fossil, and non-energy technologies, I is given here: https://link.epo.org/web/patents_and_the_energy_transition_study_annex_en.pdf.

²¹These are technology advances which increase the output of fossil fuels from the same amount of inputs, hence, making fossil energy cheaper while emissions per unit of energy remain unchanged.

²²The number of patents may not be a good proxy for “knowledge”, as patents can differ in their quality. An alternative measure used in the literature are citation-weighted patents which gives an idea about the stimulating force of an innovation. The more frequent a patent is cited, so the logic, the more knowledge is conveyed in this innovation. However, citation data is confounded in that it depends on the structure of the economy and the green transition. A fossil-related innovation, for instance, may see less citations not because it is of lower quality, but because all innovation happens in the green sector due to political intervention. This would understate the potential of fossil knowledge. Underestimating fossil-based knowledge, in turn, would lower the need for policy intervention to counter path dependency of innovation. Using stock exchange information as used in Kogan et al. (2017) would also capture market expectations on policies and the

calculate a measure of the knowledge stock within sectors based on the *perpetual inventory method* which assumes that knowledge accumulates over time as follows:

$$K_{Jt} = (1 - \delta)K_{Jt-1} + R_{Jt},$$

where R_{Jt} stands in for new patents in sector J , and K_{Jt} is the knowledge stock. Knowledge depreciates at rate δ capturing that knowledge becomes obsolete overtime as it is overrun by new innovation. I assume a 15% annual depreciation rate as in [Noailly and Smeets \(2015\)](#). To make knowledge stocks comparable across sectors, I normalize the number of patents in a sector by the number of research processes of the sector, (ρ_F, ρ_G, ρ_N) , where I use the estimates of [Fried \(2018\)](#). Essentially, fossil and green sectors are of similar size.

[Figure 1](#) depicts the evolution of the annual knowledge stock by US sectors over time. The fossil-related knowledge stock exceeds green knowledge, albeit a catching up of green knowledge in the mid-2000's, the stock of fossil knowledge remained higher. In recent years, patenting in the energy sector reduced, and depreciation of knowledge caused a reduction of the knowledge stock in the green and the fossil sector. However, this drop is stronger in the green sector. As a result, the gap between fossil and green knowledge stocks widened in the late 2010's .

This graph stresses one argument for why a smoother transition of fossil to green research may be optimal: fossil research can build on a huge knowledge stock. This productive capital, knowledge, would quickly become unproductive when research rapidly transitions to the green sector.

As initial knowledge levels I use the average knowledge stock in the 2010-2014 period and normalize values by green knowledge in 2010-2014.: $K_{n0} = 0.64, K_{g0} = 1.00, K_{f0} = 1.30$.

[Acemoglu et al. \(2016\)](#) also estimate the knowledge gap between *clean* and *dirty* energy greening of the economy, thus most likely understating knowledge advances in the fossil sector. The number of patents as a measure of knowledge relies on the assumption that the quality of patents within sectors is equal on average.

sectors. The resulting gap equals $\frac{K_{f0}}{K_{g0}} = 1.48$.²³ Using more recent data, I find a smaller knowledge advantage in the fossil sector of 30%. Note that the higher the gap between knowledge in green and fossil sectors, the more beneficial it is to maintain some fossil scientists who can learn from fossil-based knowledge generated in the past. [Fried \(2018\)](#) who derives the initial distribution of knowledge from output data, finds a much higher knowledge advantage in the fossil sector of $\frac{K_{f0}}{K_{g0}} = 2.5$; a finding potentially affected by a lack of diffusion of green technology and policies in favor of fossil energy.

Innovation process To calibrate the remaining parameters governing the innovation process, $\{\gamma, \eta, \phi\}$, I combine information on the knowledge stock with information on R&D expenditures in the green, fossil, and non-energy (residually determined as total minus energy-specific R&D) sector from the National Center for Science and Engineering Statistics' (NCSES) Industrial Research and Development Information System (IRDIS).²⁴ I rationalize observed growth in knowledge stocks given R&D expenditures and the law of motion of knowledge in the model for distinct years from the 1980s; a time period potentially less affected by climate considerations than later periods. I use the average of parameter values to calibrate the model.

The resulting relative importance of cross-sectoral knowledge spillovers is $\phi = 0.43$, a value in line with the literature: [Hart \(2019\)](#) calibrates a value equivalent to $\phi = 0.1$, and [Fried \(2018\)](#) sets $\phi = 0.5$ based on theoretic considerations.²⁵ [Aghion et al. \(2016\)](#) estimate for the US automotive industry that clean innovation within a firm is comparably more important for clean patent growths than dirty knowledge. They estimate an elasticity of new clean innovation to past clean innovation of 0.306 compared to an elasticity of 0.139 with respect to past dirty innovation. Matching the relative importance of within- to cross-sectoral

²³This is the weighted average of knowledge stocks in clean and fossil sectors found in [Acemoglu et al. \(2016\)](#).

²⁴Tables can be found here: https://www.nsf.gov/statistics/iris/history_pub.cfm.

²⁵Note that the specification of the aggregate knowledge stock in [Fried \(2018\)](#) differs to my model which reduces comparability of the parameter values.

spillovers, I get that $\phi = 0.3124$.²⁶

Calibrated returns to research are decreasing at a value of $\eta = 0.38$. This value falls within the range of estimates used in the literature. [Acemoglu et al. \(2016\)](#) find a similar average value of $\eta = 0.37$ in a first-difference estimation based on micro-level data on the energy sector.²⁷ [Fried \(2018\)](#) estimates $\eta = 0.79$. The smaller value in my calibration implies that a more equal allocation of researchers per process across sectors is more productive motivating a higher fossil research subsidy to prevent the stepping-on-toes of researchers in the green sector. [Hart \(2019\)](#), in contrast, finds a value of $\eta = 0.19$.²⁸

3.2 Other parameters

To calibrate the rest of the model, I, first, set certain parameters to values found in the literature. Second, I calibrate the remaining variables requiring that targets from the data are model solutions. [Table 1](#) summarizes the parameter values.

In the first step, I set the parameters governing research processes, ρ_F, ρ_N, ρ_G , to the values in [Fried \(2018\)](#). The non-energy sector is the biggest research sector with $\rho_N = 1$ while $\rho_F = \rho_G = 0.01$. The parameters ι_K and δ_K are taken from [Fischer and Newell \(2008\)](#) and [Noailly and Smeets \(2015\)](#), respectively: $\iota_K = 0.15$ and $\delta_K = 0.55$ for a five year depreciation rate. The elasticity of substitution between energy and non-energy goods is set to $\varepsilon_y = 0.05$ following [Fried \(2018\)](#). As is supported by the empirical literature, energy and non-energy goods are complements ([Hassler et al., 2016](#)). I calibrate fossil and green energy as substitutes with $\varepsilon_e = 1.8$ based on [Papageorgiou et al. \(2017\)](#). As a result, fossil energy cannot be one-for-one substituted for by green energy without reductions in output. The

²⁶Note that they focus on the automotive industry and micro-level estimates. These estimates, hence, do not include spillovers across firms.

²⁷Since [Acemoglu et al. \(2016\)](#) do not account for the knowledge stock in their ordinary least square estimation results might be driven by firm-specific knowledge stocks. If firms with a higher knowledge stock, for which research is more productive, higher more researchers and have a higher patent output, the elasticity of patents to R&D increases. The more appropriate estimate for this paper's model which explicitly accounts for knowledge stocks, the estimates of the first difference equations which controls for firm fixed effects, are better suited.

²⁸Also compare [Hart \(2019\)](#) for a discussion of other values in the literature which range from 0.05 to 1 (the latter are models abstracting from the stepping-on-toes effect).

discount factor, β , is set to 0.985⁵ as in [Barrage \(2020\)](#). I set the business-as-usual policy to $\tau_{F0} = 0, \tau_{sF0} = 0, \tau_{sG0} = 0$, accounting for the missing climate policy in the US under President Trump.

In the second step, I calibrate remaining parameters so that a solution to the model rationalizes certain data targets. The weight on energy in final good production results from matching the average expenditure share on energy relative to GDP over the period from 2015 to 2019 which I take from the US Energy Information Administration ([EIA, 2023](#), Table 1.7). The expenditure share equals 6%. The resulting weight on energy is $\delta_y = 0.39$. Initial productivity levels, $\{A_F, A_G, A_N\}$, follow from normalizing output in the base period to $Y = 1$ and matching the ratio of fossil-to-green energy production over the years 2015-2019 which equals 3.7 according to ([EIA, 2023](#), Table 1.1). The relation of productivity and knowledge stocks, $\{\kappa_F, \kappa_G, \kappa_N\}$, follows from matching productivity levels with knowledge stocks which are projected by the model for the base period 2015-2019.

Capital shares in non-energy and fossil good production follow from the compensation of labor in value added from the BEA. I classify NAICS sectors 21 and 324 as fossil energy production. I derive an estimate of the capital share in the green energy sector from the green job tables of the BLS.²⁹ The model is calibrated to match the share of green energy employment to total employment of 0.48%. I find a green capital share of $\alpha_G = 0.87$ which is slightly lower than the high share found in [Fried \(2018\)](#) of 0.91.

Equipped with these parameters, I can calibrate the sink capacity to match the average difference between gross and net CO₂ emissions over the baseline period from 2015 to 2019. Information on emissions comes from the US Environmental Protection Agency ([EPA, 2022](#)). The resulting sink capacity per model period (5 years) is $\delta = 3.19\text{GtCO}_2$. The parameter relating CO₂ emissions and fossil energy in the base period equals $\omega = 211.37$.³⁰

²⁹Retrieved from <https://www.bls.gov/green/home.htm>, 06 September 2023. Unfortunately, these tables are only available for 2010 and 2011.

³⁰I perceive the fossil sector in the model as source of all CO₂ emissions including, for instance, non-energy use of fuels and incineration of waste. This is necessary as the emission target is expressed on an aggregate level.

Table 1: Calibration

Parameter	Target	Value
<i>Household</i>		
Discount factor β	Barrage (2020)	0.93
Working time endowment \bar{H}	14.5 hours per day (Jones et al., 1993)	1.00
S	Fried (2018)	0.01
<i>Research</i>		
Returns to research η	} growth in knowledge stocks and R&D	0.38
Knowledge spillovers ϕ		0.43
Scientists' productivity γ		2.27
Sector size (ρ_F, ρ_G, ρ_N)	Fried (2018)	(0.01, 0.01, 1.00)
Initial knowledge stock (K_{F0}, K_{G0}, K_{N0})	knowledge stock in 2010-2014	(1.30, 1.00, 0.64)
Learning $(\kappa_F, \kappa_G, \kappa_N)$	matching knowledge stock and output	(24.38, 0.85, 1.50)
Elasticity of productivity to knowledge ι_K	Fischer and Newell (2008)	0.15
Depreciation knowledge stock δ_K	Noailly and Smeets (2015)	0.55
<i>Production</i>		
Elasticities of substitution $(\varepsilon_y, \varepsilon_e)$	Fried (2018), Papageorgiou et al. (2017)	(0.05, 1.50)
Weight on energy in final good δ_y	expenditure share on energy (EIA, 2023)	0.39
Capital shares $(\alpha_F, \alpha_G, \alpha_N)$	BLS and Green Jobs and Compensation of employees	(0.75, 0.87, 0.36)
<i>Government</i>		
Policy instruments $(\tau_{F0}, \tau_{sF0}, \tau_{sG0})$	-	(0, 0, 0)
<i>Emissions</i>		
Carbon sinks δ	EPA (2022)	3.19
Emissions per fossil energy ω	EPA (2022)	211.37

3.3 Emission target

I consider CO₂ emissions only and abstract from other greenhouse gasses since carbon is the most important pollutant with the highest mitigation potential (IPCC, 2022, p.29). I use the estimated global CO₂ emission target from the latest IPCC assessment report (Van der Wijst et al., 2023, Figure SPM.5).³¹

To deduce an emission target for the US, further assumptions on the distribution of mitigation burdens have to be made. I use an *equal-per-capita* approach according to which emissions per capita shall be equalized across countries.³² To this end, I employ projected

³¹I abstract from slightly negative emission targets and set the goal to zero because the model abstract from carbon-capture technologies.

³²See Robiou Du Pont et al. (2017) for a discussion of five distinct principles of distributive burden sharing.

population shares from the [United Nations \(2022\)](#).

The reduction in net CO₂ emissions necessary to meet the emission limit relative to 2019 emissions in the US is substantial (also compare [Figure 2](#)). It amounts to around 63.47% in 2020 and increases to 81.22% in 2030. The result is not only explained by the global emission limit but also by the US emitting beyond its population share in 2019. In 2019, US emissions accounted for 10.44% of global net emissions while the population share of the US was 4.3%. Hence, even without an emission limit, the US would have to reduce emissions according to the *equal-per-capita* principle.

The necessary reduction in net CO₂ emissions found in this calibration exceeds political goals. On April 22, 2021, President Biden announced a 50-52% reduction in net greenhouse gas emissions relative to 2005 levels in 2030 and net-zero emissions no later than 2050.³³ However, relative to 2019, the planned reduction for 2030 corresponds to a 38% decline only. This is less than half the reduction required to meet the emission limit derived from the IPCC estimate used in the present paper.

3.4 Laissez-faire allocation

The model is not calibrated in the steady state in order to capture transitional dynamics which shape the optimal policy. To get an idea of the model dynamics and the sensibility of the calibration, this section briefly discusses the laissez-faire allocation.³⁴

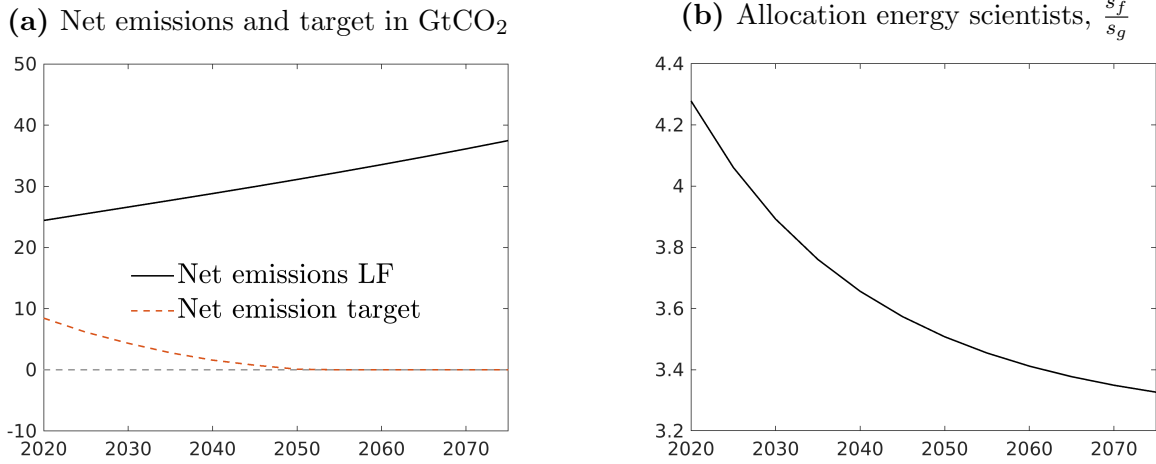
[Figure 2a](#) visualizes the resulting emission limit for the US starting from 2020; the orange-dashed graph. Each point corresponds to a five year period starting in the indicated year on the x-axis. The black graph shows net emissions under laissez-faire in the calibrated model. The model predicts a steadily increasing path of net emissions. Clearly, there is scope for government intervention.

In absence of any policy intervention (other than those correcting for monopolistic competition),

³³Source: <https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/22/>, retrieved 14 September 2022.

³⁴In my model, laissez-faire (including subsidies to correct for monopolistic competition) and BAU are equivalent since all policy instruments, research subsidies, and carbon taxes are set to zero.

Figure 2: Net emissions and allocations under laissez-faire



the share of fossil to green researchers reduces over time (Figure 2b). The number of fossil researchers is more than 4 times as big as in the green sector. The reduction in the share of fossil to green scientists is due to two forces. First, cross-sectoral knowledge spillovers imply that green research becomes more productive as fossil knowledge grows. Second, the marginal productivity gain from fossil research declines due to the concave relation of knowledge and productivity. Both mechanisms diminish the gains from fossil research relative to green research and scientists transition to the green sector. Nevertheless, the rise in fossil knowledge surpasses the growth in green knowledge which again mutes the reduction in fossil research due to within-sector knowledge spillovers reinforced by a higher demand for fossil goods, a market size effect. In the long run, though, cross-sectoral knowledge spillovers are strong enough so that both fossil and green knowledge grows.

The increase in fossil knowledge spurs fossil output and culminates in a rise in emissions. Albeit fossil knowledge raises exponentially, the rise in emissions is muted due to declining productivity returns to research. Nevertheless, the rise in net emissions widens the gap to the emission target which is zero starting from 2050.

4 Results

How to close the gap between emissions and the target without excessively lowering consumption?

This section discusses the answer to this question. To set the stage, I will first look at the first-best allocation in a model without emission target (subsection 4.1). In relation to this benchmark, I then study the first-best allocation to implement emission targets and the corresponding policy in subsection 4.2. I close this section by discussing results of counterfactual model calibrations in subsection 4.3.

4.1 First best without emission target

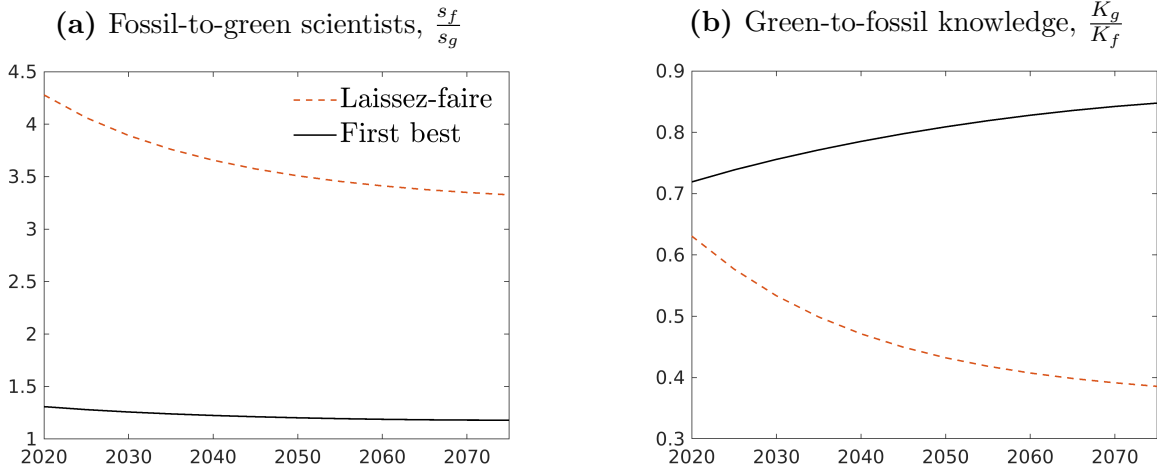
Figure 3 depicts the socially optimal allocation of key variables in comparison to the laissez-faire allocation. In the laissez-faire allocation absent emission target, the optimal allocation of researchers features more green researchers even though there is no limit on emissions. To understand this aspect, notice that gains from knowledge for new research within sectors is declining in knowledge, $1 - \phi < 1$. A more even allocation of knowledge, thus, enables to profit from stronger knowledge spillovers on aggregate. In a same spirit, cross-sectoral knowledge spillovers can be exploited by a more similar allocation of knowledge stocks. Having an uneven distribution of knowledge stocks makes knowledge less productive in stimulating new ideas. In the laissez-faire allocation, in contrast, knowledge is directed to the fossil sector since the within-sector knowledge spillovers make fossil research so profitable for firms (*path dependency*). Firms do not internalize that a more even allocation of knowledge stocks facilitates new innovation tomorrow.

To counter this mechanism, the government subsidizes the green relative to the fossil sector which reduces the costs of scientists for firms in the green relative to the fossil sector. Demand for scientists in the green sector increases. In the transition to the new equilibrium, the wage rate for green scientists rises and more scientists transition to the green sector until wages are equalized. In the new equilibrium, the private returns to research³⁵ (net of

³⁵By *returns to research* I refer to the private marginal product of scientists.

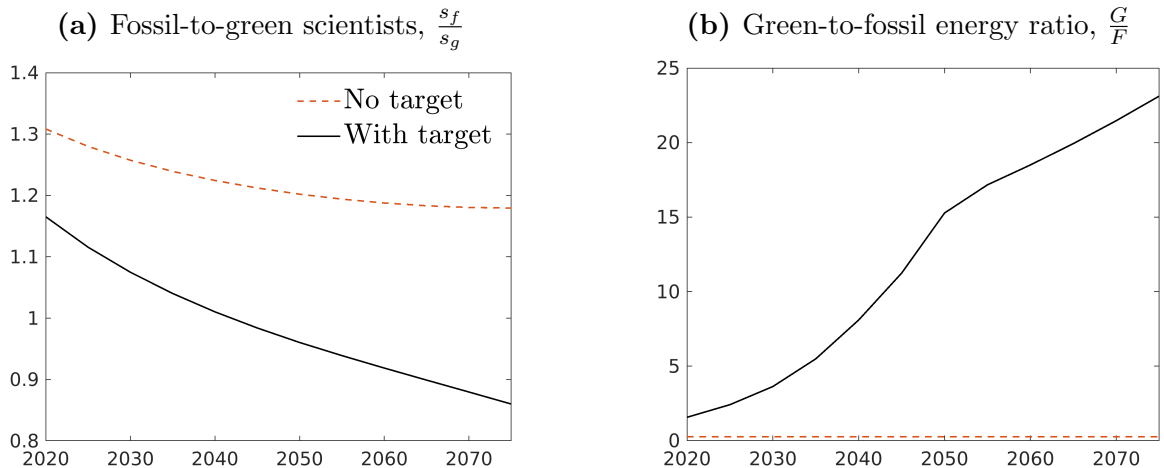
subsidies) in the subsidized sector fall below the returns to research in the non-subsidized sector. The research subsidy ensures that the gap in private marginal returns to research is maintained in the competitive equilibrium.

Figure 3: First best without emission target



4.2 First-best allocation and optimal policy to meet emission targets

Figure 4: First-best implementation of the emission target



Notes: The x-axis indicates the first year of the 5-year period to which the variable value corresponds.

When the planner has to satisfy an emission limit, the production of energy switches to green sources; compare [Figure 4b](#). To lower the costs of this transition, the efficient allocation

of researchers changes to more green research: [Figure 4a](#) shows a smaller share of fossil-to-green researchers than absent an emission limit. The economy builds up green relative to fossil knowledge which allows future green scientists to profit from a higher green knowledge stock. This result is in line with the findings in the literature ([Acemoglu et al., 2012, 2016](#); [Hart, 2019](#)): An efficient emission mitigation implies more green research today and in the future.

My main result stands in contrast to these papers: The social planner chooses a smooth transition of fossil to green R&D. Due to cross-sectoral knowledge spillovers the allocation of scientists can make use of the knowledge advantage in the fossil sector which makes fossil researchers relatively more productive and avoid costs from decreasing returns to research in the green sector.

The reduction in the share of fossil-to-green scientists accelerates in later years relative to the non-target allocation. In the future, when more green knowledge capital has been build, the profitability of green R&D investment rises.

How can the first-best allocation be implemented in a competitive equilibrium using tax instruments? A steadily increasing carbon tax, [Figure 5a](#), is set to meet the emission target optimally. It rises from roughly 50 US\$ in the period from 2020 to 2024 to slightly less than 350\$ in the late 2070s. The increasing pattern results from a tightening of the emission target until 2050 and the continued rise in fossil productivity due to the maintained research in this sector and knowledge spillovers to the fossil from other sectors.³⁶

To focus the analysis on optimal emission mitigation, [Figure 5b](#) presents research subsidies in addition to the optimal level without emission target.³⁷ Starting at a fossil research subsidy of roughly 50% of fossil R&D expenditures in 2020-2024, the subsidy approaches unity in

³⁶When only a carbon tax is available to meet emission targets, a continued rise in carbon taxes is necessary to counter increased profitability of fossil R&D.

³⁷Let $\hat{\tau}_{s,J}$ be these additional subsidies. Where they are defined in addition to subsidies to counter knowledge externalities in the world without emission target: $(1 - \tau_{s,J}^{\text{no target}})(1 - \hat{\tau}_{s,J}) = (1 - \tau_{s,J}^{\text{target}})$. [Figure 9](#) in [Appendix C](#) shows the level of the green and fossil research subsidy. Relative to green research, fossil research is subsidized since there is a higher subsidy on the latter sector. The high subsidies are mainly explained by the distortions in the allocation of knowledge due to knowledge spillovers that arise even absent an emission target.

later years and under the net-zero emission limit. The high value of the fossil research subsidy has to be understood in light of carbon taxes. The tax on carbon reduces research efforts in the fossil sector as the quantity and producer price of fossil machines declines. However, maintaining some fossil research is beneficial to increase the productivity of researchers: Fossil researchers can build on fossil-related knowledge and a smoother allocation of researchers mitigates the risk of duplicating ideas. Cross-sectoral knowledge spillovers ensure that the gains in fossil knowledge remain valuable for green productivity growth in the future.

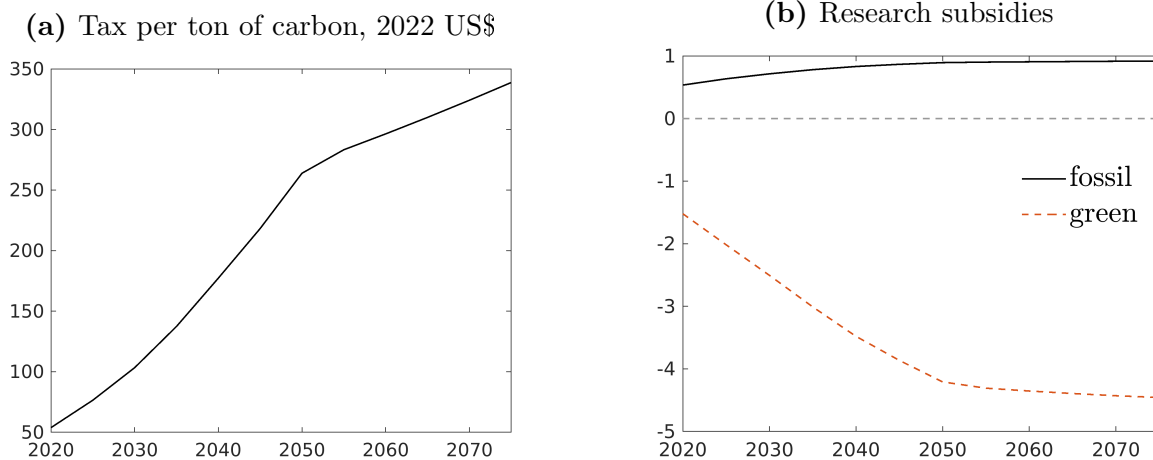
Relative to the benchmark without emission limit, the government chooses to tax green research (Figure 5b). This seems counterintuitive at first glance. Recall that the optimal emission mitigation is characterized by a rise in green research activity relative to fossil. Again, this instrument counters the rise in green research activity entailed by taxing carbon. This finding is in stark contrast to Acemoglu et al. (2016) who find that the optimal policy consists of initially high green research subsidies and small carbon taxes. They argue that relying on research subsidies initially without distorting the use of energy inputs in production too much via a carbon tax is less costly in terms of output. Accelerated green growth reduces the costs of reducing emissions today and in the future. As will become clearer in subsection 4.3, cross-sectoral knowledge spillovers explain the differences in results. Absent cross-sectoral knowledge spillovers³⁸, initially high green research subsidies characterize the optimal environmental policy. The reason is that knowledge spillovers to the fossil sector require a higher carbon tax to mitigate productivity rises in fossil energy stemming from spillovers from other sectors. A green research subsidy alone would be insufficient to meet emission targets.

In line with Acemoglu et al. (2016), dynamics are similar. I find that net green research “subsidies” relative to the fossil research subsidy are more pronounced in earlier years of the

³⁸In Acemoglu et al. (2016) cross-sectoral knowledge spillovers arise only for breakthrough innovation and not for incremental innovation which may reduce the strength of this force. Furthermore, the gains from knowledge spillovers are symmetric in their model while in the model studies here cross-sectoral knowledge spillovers are stronger the more backward a sector. As a result, in Acemoglu et al. (2016) clean innovation ceases and all research activity transitions to the polluting sector. For environmental policy this means that cross-sectoral knowledge spillovers do not necessitate a continued intervention.

transition. This observation can be rationalized by the idea to use green research subsidies today to promote green growth which achieves a shift to green energy sources (similar to a carbon tax) but it is less costly than a carbon tax as it does not distort the share of energy sources.³⁹

Figure 5: Optimal policy



Notes: The x-axis indicates the first year of the 5-year period to which the variable value corresponds. Depicted subsidies, $\hat{\tau}_{s,J}$, are in addition to subsidies to counter knowledge externalities in the world without emission target: $(1 - \tau_{s,J}^{\text{no target}})(1 - \hat{\tau}_{s,J}) = (1 - \tau_{s,J}^{\text{target}})$.

4.3 Discussion

This section serves to understand the importance of distinct channels in the model for the results. It looks at counterfactual calibrations where one parameter at a time is changed.

Cross-sectoral knowledge spillovers Cross-sectoral knowledge spillovers are the key driver which make sustained fossil research optimal. [Figure 6a](#) shows that when there are no cross-sectoral knowledge spillovers, the share of fossil research is reduced massively during the transition to net-zero emissions and approaches zero in the long run. To achieve this allocation, the government taxes fossil research ([Figure 6b](#)) in addition to the carbon tax and green research subsidies. Absent cross-sectoral knowledge spillovers, the optimal policy

³⁹On this point also compare [Figure 9](#) in [Appendix C](#) which shows the aggregate research subsidies. Green research subsidies are initially higher than in the long run.

is to use a front-loaded green research subsidy, similar to the result in [Acemoglu et al. \(2016\)](#); compare the dashed orange graph in [Figure 6c](#). Fostering green innovation today is part of efficient emission mitigation by making green energy cheaper. The tax on fossil research supports green innovation without discouraging non-energy research. With faster green growth today, the required carbon tax is smaller during the transition and in the long run ([Figure 6d](#)). The gap widens over time, as market mechanisms direct production to the relatively more productive green sector. Output costs today are diminished through the carbon tax.

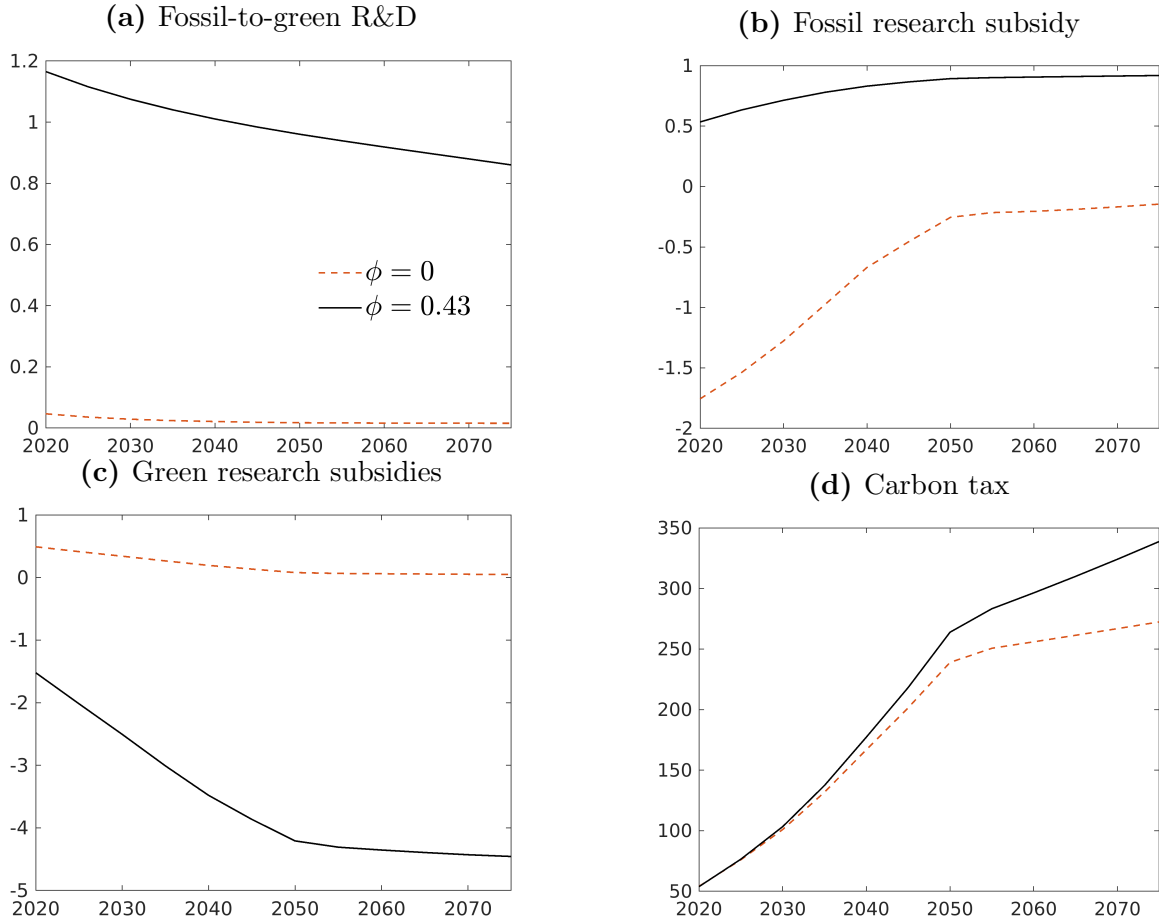
This observation highlights that with cross-sectoral knowledge spillovers to the fossil sector a high carbon tax is necessary to prevent rising fossil research productivity to boost demand for fossil goods. Hence, taken this aspect into account which is missing in [Acemoglu et al. \(2016\)](#) keeps the economy from profiting from green growth to meet emission targets.

In addition, the gains from more fossil research activity in the baseline calibration vanish. Even though the use of higher carbon taxes today is costly as it distorts production towards the less productive green alternative. The planner chooses an even higher carbon tax when knowledge spills across sectors because the gains from more fossil knowledge—which materialize in the future—outweigh these costs.⁴⁰

Stepping on toes Another aspect making a retarded transition to green research efficient are decreasing returns to research captured by the parameter η . The risks of duplicating ideas when working on the same research task makes a shift to green production costly. [Figure 7](#) contrasts the optimal policy for distinct values found in the literature for this parameter. Results remain unchanged when the risk of replicating ideas increases, $\eta = 0.19$ (the value found in [Hart \(2019\)](#)). A reduction in the risk, $\eta = 0.79$ (the value found in [Fried \(2018\)](#)), rationalizes a tax on fossil research relative to the non-target subsidy, and almost all energy scientists are allocated to the green sector ([Figure 7a](#)).

⁴⁰On this point compare the discussion in [Appendix C](#) where I show the optimal policy when (i) no fossil research subsidy or (ii) no subsidies are in the government’s toolkit to respond to climate change.

Figure 6: Counterfactual calibration: Knowledge spillovers

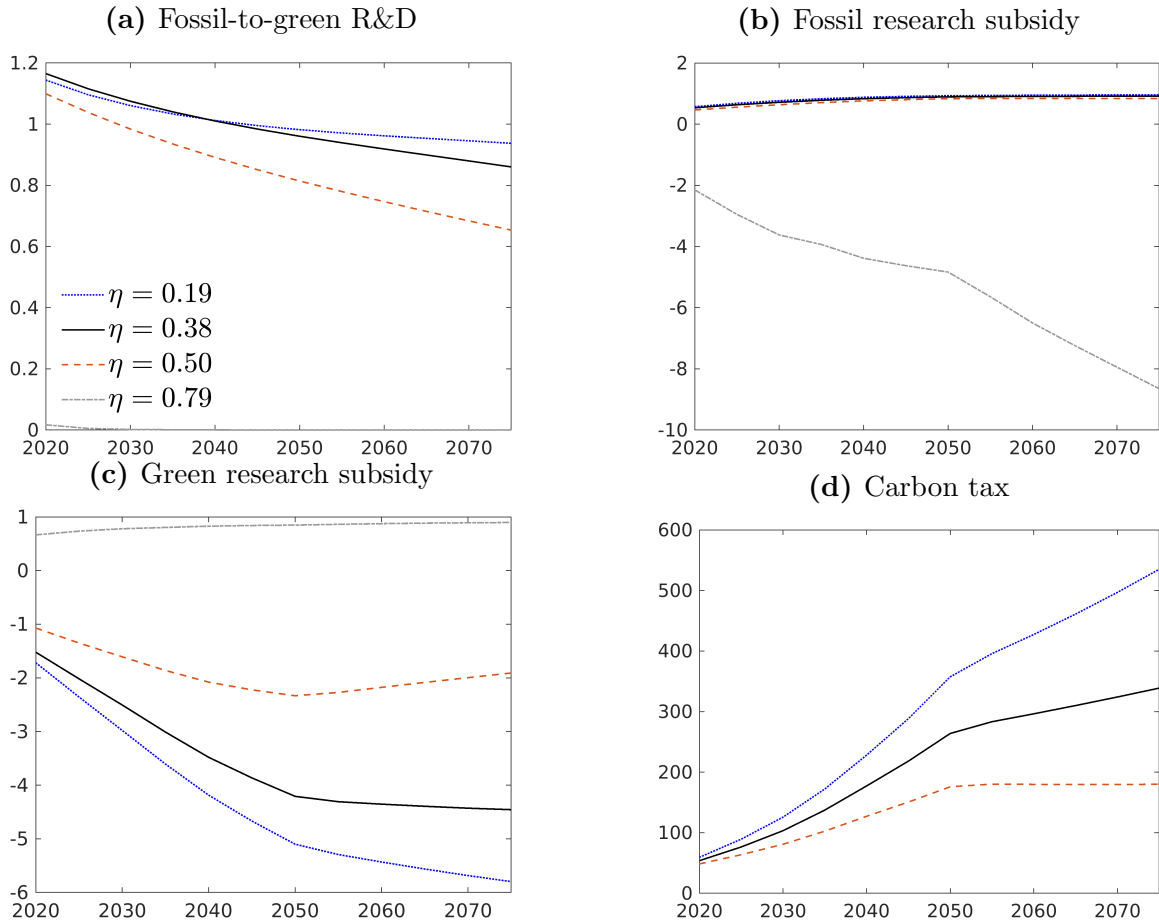


Notes: The x-axis indicates the first year of the 5-year period to which the variable value corresponds. Fossil research is taxes tend to minus infinity when there are no knowledge spillovers. They are not depicted.

When a transition to green research is less costly due to muted decreasing returns to research, the optimal policy stops all fossil research in the medium run. To achieve this, the government chooses a massive tax on fossil research while keeping the carbon tax constant. As is the case in [Acemoglu et al. \(2016\)](#), targeting the allocation of researchers is more efficient than targeting demand for fossil energy: The fossil research tax is preferred above rising carbon taxes. As fossil energy becomes less cost competitive, energy producer's demand redirects production to green goods.

Initial knowledge stocks The optimal environmental policy is largely unaffected by the distribution of initial knowledge stocks found in the literature.⁴¹ Overall, the reduction in fossil-to-green research is more pronounced in early years, and, over time, the decline becomes more linear. Since there are no gains from building on past fossil knowledge, a greener distribution of researchers becomes optimal. The reduction is not accelerated since there is no catching-up of the green sector.

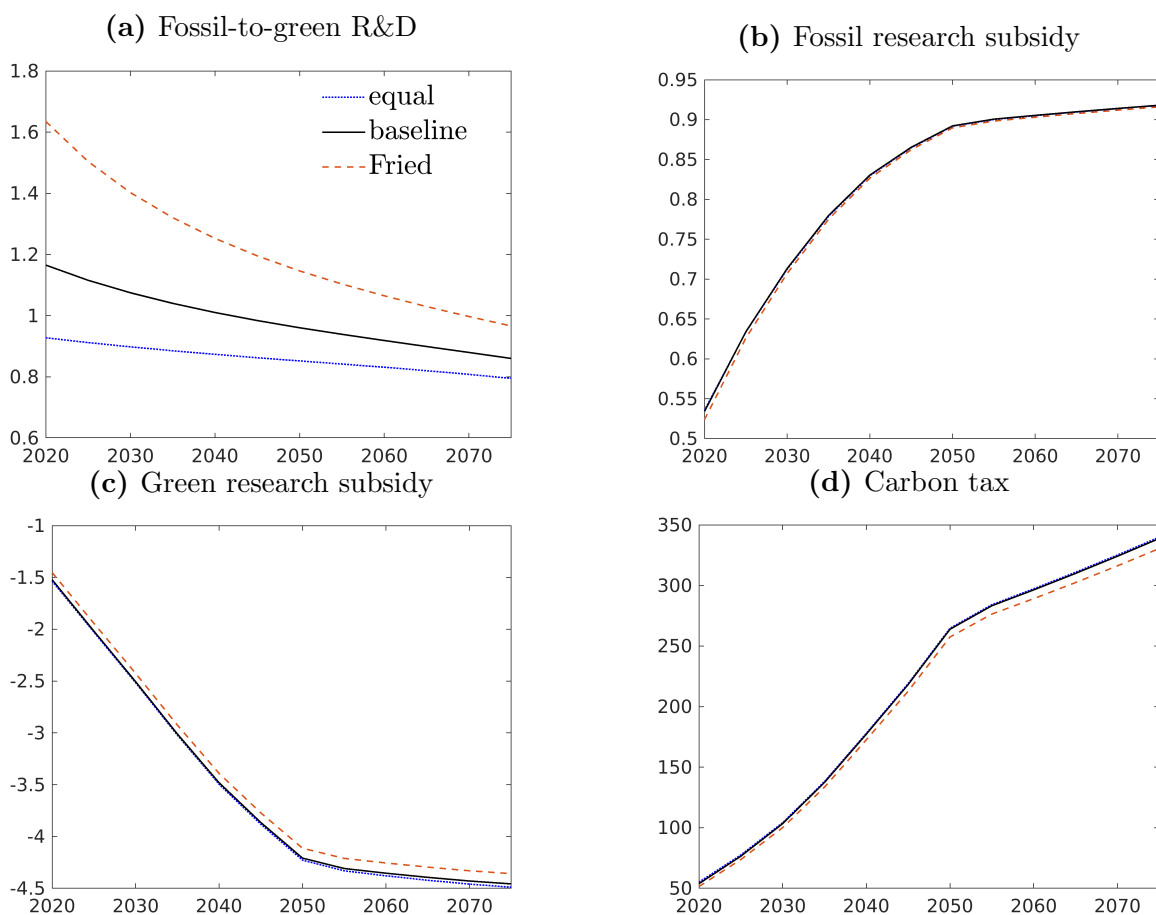
Figure 7: Counterfactual calibration: Returns to research



Notes: The x-axis indicates the first year of the 5-year period to which the variable value corresponds. Fossil research is taxes tend to minus infinity when there are no knowledge spillovers. They are not depicted.

⁴¹Total optimal research subsidies, i.e., those including the motive to deal with distortions other than the emission limit, are higher for the fossil sector the higher the knowledge advantage in the fossil sector. Conversely, the green sector's subsidy declines the more backward the green sector.

Figure 8: Counterfactual calibration: Initial knowledge stock



Notes: The x-axis indicates the first year of the 5-year period to which the variable value corresponds. Fossil research is taxes tend to minus infinity when there are no knowledge spillovers. They are not depicted.

5 Conclusion

The latest assessment report of the [IPCC \(2022\)](#) stresses the necessity to transition to net-zero emissions in order to meet climate goals. The economics literature has largely focused on the use of carbon taxes and green research subsidies to lower emissions. I argue that once research in non-energy sectors—which accounts for roughly 98% of R&D in the US—is included in the analysis, fossil research subsidies or taxes form part of optimal emission mitigation.

Whether subsidies or taxes on fossil research are optimal in a transition to net-zero emissions is a quantitative question. I analyze an endogenous growth model with three sectors in which an emission limit renders fossil energy socially costly. I find that during the transition and thereafter, the optimal policy subsidizes fossil research in combination with carbon taxes. This policy mix achieves a smoother transition in research while meeting emission limits. Even though, overall, the share of green research increases the stimulating effect of carbon taxes on green research is so high that fossil research subsidies and green research taxes are used to mitigate the shift to green research.

The rationale of this result is that fossil research can draw from a deep pool of knowledge generated in the past which raises research productivity in this sector. Furthermore, the risk of replicating ideas when too many scientists work on the same research topic makes a rapid shift to green research costly. Importantly, cross-sectoral knowledge spillovers to the green sector render fossil-related innovation productive in a green future.

An important aspect of a green transition is societal acceptance. However, subsidizing fossil research presumably is hard to motivate politically. Investigating alternative and potentially more accepted instruments to replicate the fossil research subsidy suggests to be an important avenue for future research. In addition, this paper assumes the availability of lump-sum taxes. In reality, this instrument, as well, is politically difficult to implement. Introducing labor income taxes as a source of government funding will enable a more comprehensive study of the use of fossil research subsidies.

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A Social planner

The solution to the social planner's problem is defined as an allocation

$\{L_{Ft}, L_{Gt}, L_{Nt}, x_{Ft}, x_{Gt}, x_{Nt}, C_t, s_{Ft}, s_{Gt}, s_{Nt}\}$ for each period which maximizes the social welfare function

$$\sum_{t=0}^T \beta^t u(C_t) + PV$$

s.t. $\omega F_t - \delta \leq \Omega_t$

$$C_t + x_{Ft} + x_{Gt} + x_{Nt} = Y_t$$

Law of Motion of knowledge and initial knowledge stocks

$$L_{Ft} + L_{Gt} + L_{Nt} \leq H,$$

$$s_{Ft} + s_{Gt} + s_{Nt} \leq S.$$

Production of Y_t is defined by the equations describing production in the model. It holds that $x_{Jt} = \int_0^1 x_{Jit} di$. PV stands in for the continuation value of the economy; see [Appendix B](#) for the derivation.

B Numerical appendix

Since I cannot solve explicitly for the optimal policy over an infinite horizon, I truncate the problem after period T . In the literature, utility in periods after T are approximated under the assumption that policy variables are fixed, and the economy reaches a balanced growth path ([Barrage, 2020](#); [Jones et al., 1993](#)). However, assuming a constant carbon tax would most likely violate the emission limit since the model is designed to reflect market forces describing an economy with green and fossil sectors operating in equilibrium.

I motivate the design of the continuation value by assuming the planner would hand over the economy to a successor after period T . A continuation value, PV , in the objective function captures that the planner cares about utility after period T . This set-up accounts

for concerns about economic well-being of future generations in a similar vein than the sustainability criterion proposed by the [World Commission on Environment and Development \(1987\)](#) by attaching some value to the final technology level.⁴² I approximate the value of future technology levels by assuming constant growth rates. To mitigate concerns that the choice of the continuation value drives the results, I experiment with the exact value of explicit optimization periods. I truncate the problem once explicitly adding a further period leaves the optimal allocation numerically unchanged. That is the case after $T = 42$, or 210 years. The planner’s objective function becomes:

$$\sum_{t=0}^T \beta^t u(C_t) + PV.$$

In more detail, I define the continuation value as the consumption utility over the infinite horizon starting from the last explicit maximization period:

$$PV = \sum_{s=T+1}^{\infty} \beta^s u(C_s).$$

I make two simplifying assumptions to derive the continuation value. First, I assume that the consumption share, c_s , with $C_s = c_s Y_s$, is constant from period $T + 1$ onward. Then, consumption grows at the same rate as output. Second, as an approximation to future growth, I assume the economy grows at the same rate as in the last explicit optimization period. Let $\gamma_{yT} = \frac{Y_T}{Y_{T-1}} - 1$. Under above assumptions, I can rewrite future consumption as

⁴²The sustainable development criterion reads “[...] to ensure that it meets the needs of the present without comprising the ability of future generations to meet their own needs.” (p.24). This is a vague definition. [Dasgupta \(2021\)](#) p.(332) interprets this criterion as meaning: “[...] each generation should bequeath to its successor at least as large a productive base as it had inherited from its predecessor.” However, this cannot be used to derive a sensible condition on the optimization in the present setting since there is no negative growth and technology is the only asset bequeathed to future generations. Thus, successors will always have at least as much productive resources as predecessors left. The relation to the future is instead approximated by a future potential to derive utility from consumption given bequeathed technology levels. Natural needs of the future are accounted for through the emission limit.

$C_s = (1 + \gamma_{yT})^{s-T} C_T$. Given the functional form

$$u(C_s) = \frac{C_s^{1-\theta}}{1-\theta},$$

the continuation value reduces to

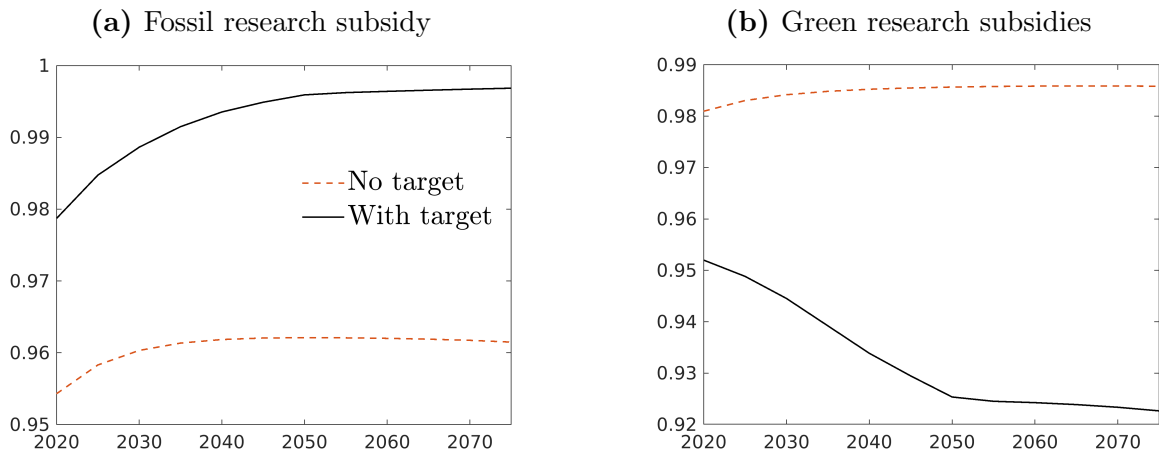
$$PV = \beta^T \left(\frac{1}{1 - \beta(1 + \gamma_{yT})^{1-\theta}} \frac{C_T^{1-\theta}}{1 - \theta} \right).$$

C Results

C.1 Optimal research subsidies in levels

In contrast to the presentation in the main text, the research subsidies presented here in [Figure 9](#) are the aggregate subsidies on the laissez-faire allocation. Their level is shaped by both knowledge externalities which are optimal absent an emission target and optimal emission mitigation.

Figure 9: Optimal policy relative to non-target optimal policy



Notes: The x-axis indicates the first year of the 5-year period to which the variable value corresponds.

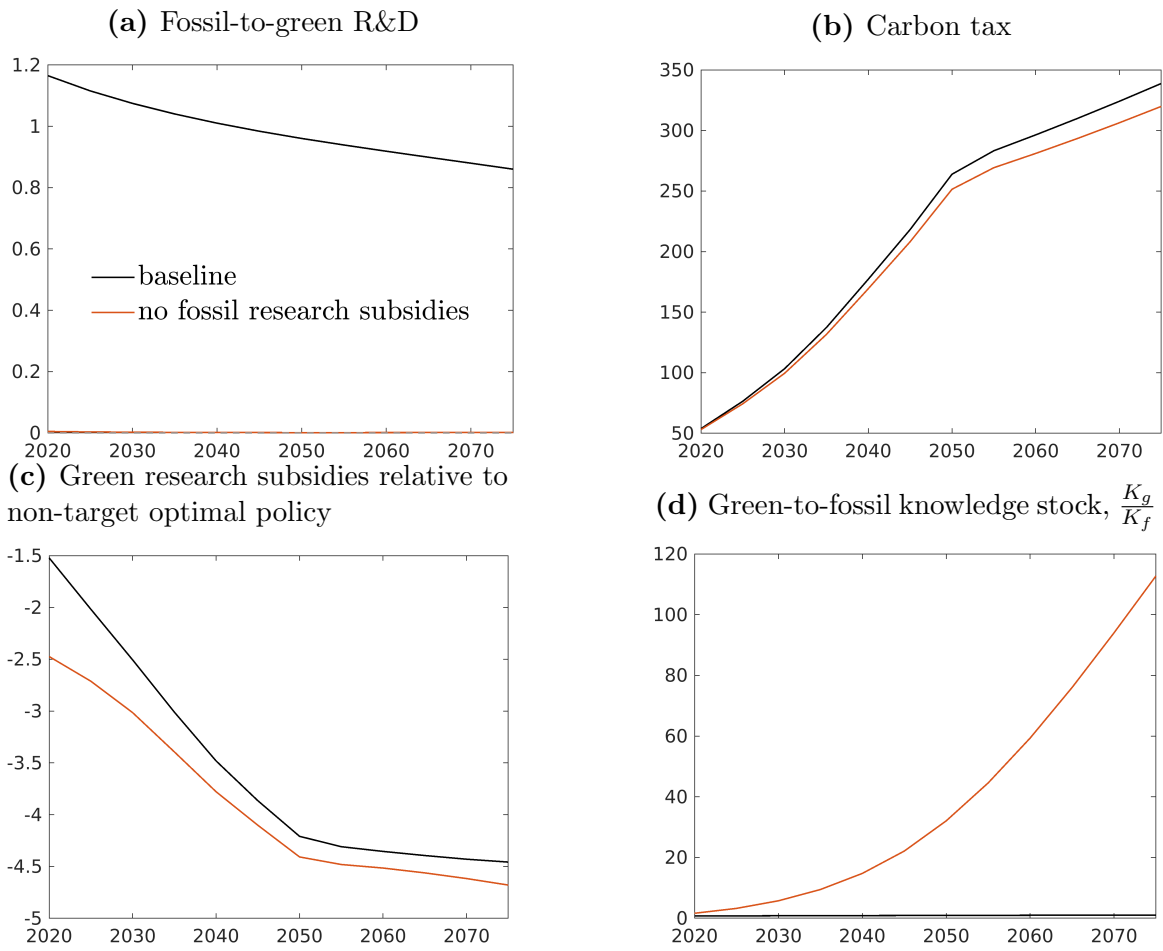
C.2 Constrained optimal policy when fossil research subsidy is fixed at non-target optimal level

To better understand the gains of targeting fossil research activity, I contrast the allocation under the baseline policy to a policy regime where the planner is constrained to a carbon tax and green research subsidies. [Figure 10a](#) depicts the optimal ratio of fossil-to-green R&D under the baseline regime and in the regime without fossil research taxes. The fossil research subsidy helps maintain a higher fossil research activity in early years thereby engineering a smoother transition towards green research.

When no fossil research subsidy is available, the government lacks the instrument to maintain fossil research. The optimal implementation of the emission target characterized by, on the one hand, rising green-to-fossil energy use and, on the other hand, fossil research activity poses a challenge to carbon taxes and green research subsidies alone. Both instruments direct research away from the fossil sector. Therefore, the optimal policy is to tax green research more to counter the reductive effect of the carbon tax on fossil research. However, such a policy also directs more scientists to the non-energy sector which is not desirable given the allocation of initial capital stocks.

Notice the reduction in carbon taxes when no fossil research subsidies can be adjusted relative to the baseline regime in [Figure 10b](#). The graph reveals that parts of the carbon tax are a reaction to higher fossil research subsidies to optimally meet emission targets. It is, hence, not the case that the higher fossil research subsidies are only a reaction to high carbon taxes, but, instead, they constitute an efficient way to foster more green growth in a green future. In the baseline policy regime, carbon taxes are higher to benefit from more fossil research while meeting emission limits.

Figure 10: Comparison to policy regime without fossil subsidy adjustment



Notes: The x-axis indicates the first year of the 5 year period to which the variable value corresponds.