Meeting Climate Targets:
The Optimal Fiscal Policy Mix

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Abstract How to optimally finance research subsidies in the transition to net-zero emissions? I study a model of directed technical change and learning-by-doing in which an emission limit renders the use of fossil energy socially costly. In a calibration to the US, I quantify the optimal mix of carbon taxes, research subsidies, and distortionary labor income taxes. I find that a labor tax of up to 2.5% should complement carbon tax revenues to finance research subsidies. This policy is optimal even though the government would like to spur learning by subsidizing labor. Research subsidies adjust to engineer the same ratio of fossil-to-green R&D as with lump-sum financed subsidies. This result changes sharply when the government is constrained to use carbon tax revenues to finance subsidies. Carbon taxes are excessively costly so the optimal policy is to reduce research subsidies, implying an inefficiently high ratio of fossil-to-green R&D.

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1 Introduction

The transition to net-zero emissions means a massive shift in how we produce, and around the globe, research subsidies are a prominent tool to tackle the green transition. However, little is known about how these instruments should be set and financed within a distortionary fiscal environment.[1] In this paper, I depart from the assumption of the feasibility of lump-sum taxes to finance research subsides, instead, the government has to revert to distortionary labor income taxes. In contrast to lump-sum taxes, these instruments lower labor efforts and, thus, slow down learning about how to use new technologies. This implication becomes especially costly during a green transition when learning to work with new green technologies is essential. On the other hand, a higher carbon tax to finance subsidies would entail more green learning and research; a potential double dividend of carbon taxes arises.

Taking seriously fiscal constraints to generate funds, I revisit the question of the optimal dynamic mix between carbon taxes and research subsidies. The government chooses the dynamic path of carbon taxes, green, and fossil research subsidies, and labor income 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. Calibrating the model to the US economy in the period from 2015 to 2019, I can characterize the optimal policy mix during the transition toward net-zero emissions and thereafter.

Results unfold in three steps. First, I find that labor taxes are less costly to finance research subsidies than carbon taxes. There is hence no strong double dividend of the latter. A finding confirming results in the literature on optimal climate policies in distortionary fiscal settings in a model of directed technical change. Second, the rise in the labor tax diminishes output, thereby, allowing for a smaller tax on carbon while emission targets are met. Research subsidies adjust to design the same allocation of researchers as with lump-sum financed subsidies. Thirdly, when no labor income taxes are available and carbon tax

[1] The literature by and large has focused on optimal climate policies in non-distortionary fiscal settings, i.e., lump-sum taxes are available. On this point see, for instance, Fischer and Newell (2008); Acemoglu et al. (2012, 2016); Hart (2019).

revenues are the only source of funding, the optimal policy is to reduce research subsidies. This policy comes at the cost of inefficiently high fossil R&D‘ yet safeguarding consumption today.

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. Machines are used in the intermediate sectors: non-energy, fossil, and green energy. The model builds on the directed technical change framework developed in Acemoglu et al. (2012), where innovation profits from past technology levels within a sector (*within-sector knowledge spillovers*). In addition to their model, returns to research decrease in the number of scientists employed within a sector (*stepping-on-toes effect*), and some knowledge spills across sectors (*cross-sectoral knowledge spillovers*).

The calibration of initial knowledge stocks are key to determine optimal policies. Therefore, I refine the process of knowledge generation in two main ways. First, I differentiate 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. Second, I extend the model to feature some notion of learning-by-doing following Fischer and Newell (2008). It implies that new technologies are adopted more efficiently the more workers gain experience by working with the technologies. Hence, similar to technology stocks, learning builds on know-how that has been accumulated in the past. I introduce this aspect of productivity to capture potential bottle necks due to labor shortage observed in today's economies. Furthermore, it creates additional lock-in effects[2]: as economies are experienced in using fossil fuels, transitioning to green energy sources becomes more costly. A quick transition may seem desirable to avoid such lock-in. Learning generates an additional source of inefficiencies in the model since workers and firms do not internalize that a higher work effort today increases productivity tomorrow. The government, therefore, wishes to increase labor effort.

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). To derive a national emission target for the US, I use an *equal-per-capita* approach that allocates emissions in proportion to population shares.

I find that a labor tax of up to 2.5% should complement carbon tax revenues to finance research subsidies. This policy is optimal even though the government would like to spur learning by subsidizing labor. The lower level of output—relative to a policy regime with non-distorting fiscal instruments—allows to reduce the carbon tax. The lower carbon tax, in turn, implies that R&D in the fossil sector becomes more profitable as more fossil energy is produced and more fossil expertise is generated. Subsidies adjust to boost research on green technologies. This finding is interesting since the green transition under the distortionary fiscal regime is characterized by a higher share of fossil fuel consumption. Nevertheless, the same allocation of researchers remains optimal.

When the government is constrained to using carbon tax revenues to finance research subsidies, expenditures are cut to meet carbon tax revenues from exactly implementing the emission target. This result highlights the high costs associated with carbon taxes: lower work effort and a less productive composition of energy. For these reasons, the optimal policy forfeits future higher green technology growth and accepts inefficiently high fossil-related R&D which will become worthless in a green future.

[2] Path-dependency in innovation are another form of lock-in in the model.

Literature The paper contributes to three strands of the literature: (i) the literature on optimal climate policies in endogenous growth models, (ii) the literature studying the interaction of fiscal and climate policies, and (iii) the literature on public finance.

I complement the first literature (e.g. Fischer and Newell, 2008; Acemoglu et al., 2012, 2016; Hart, 2019) by adding a more realistic fiscal side. When distortionary fiscal instruments have to be used to finance subsidies, the optimal policy is characterized by lower carbon taxes and higher green research subsidies. The reason is that the emission target is implemented at a lower level of output and a higher share of fossil energy in a distortionary fiscal setting. A higher share of fossil energy in production entails lower green energy demand and learning. Which directs research to the fossil sector. The rise in green-to-fossil research subsidies counters this effect.

A central question of this literature concerns the relative importance of research subsidies versus carbon taxes in a green transition. My findings highlight that carbon taxes are the instrument of choice to implement the emission target, and that research subsidies are of subordinate importance. When no other fiscal instrument is available, the carbon tax is not used in excess of implementing the emission target to generate funds. Instead, research subsidies reduce which comes at the expense of inefficiently high R&D investment on fossil-based technologies.

Second, my paper contributes to the literature on optimal climate policies in distortionary fiscal settings. This literature originated from the question whether environmental, corrective taxes entail a double dividend by not only correcting for an externality but also generating government funds (e.g. Bovenberg and De Mooij, 1994), a so-called *strong double dividend*. In its simplest form, this literature attests no strong double dividend of carbon taxes.[3] Instead, the optimal environmental tax may even lie below the social cost of the externality, hence, deviating from the Pigou principle, as it reduces labor supply thereby aggravating the fiscal burden to generate funds. Recently, the question of how the optimal environmental tax

[3]Since the carbon tax not only distorts labor supply but also the composition of goods consumed, it is more costly than a labor income tax.

deviates from the Pigou principle has been revisited in dynamic settings (Barrage, 2020), with inequality (Jacobs and van der Ploeg, 2019), or both (Douenne et al., 2022).

The present paper contributes by adding an endogenous growth perspective which motivates the use of labor income taxes to finance research subsidies. My results suggest that there is neither a strong double dividend to finance research subsidies. This result holds even though carbon taxes have the additional advantage to foster learning and R&D in the green sector. To the contrary, though, the government uses labor income taxes and lowers expenditures on research subsidies.

Another question relevant for the interaction of optimal environmental and fiscal policies is how to best recycle carbon tax revenues. Early papers on this topic take a fiscal perspective and find a *weak double dividend*: Given an exogenous government funding constraint, it is cost saving to recycle environmental tax revenues to lower distortionary labor income taxes as opposed to higher lump-sum transfers (e.g. Goulder, 1995; Bovenberg and Goulder, 2002). The latter decreases labor supply through an income effect thereby lowering the tax base of the labor income tax. Since then a broad literature investigating how to best use carbon tax revenues emerged: for example in economies with inequality, in multi-period problems, or accounting for the acceptance of climate policies (Carattini et al., 2018; Goulder et al., 2019; van der Ploeg et al., 2022; Kotlikoff et al., 2021; Fried et al., 2018; Carbone et al., 2013). I confirm the weak double dividend when research subsidies have to be financed using distortionary instruments: Carbon tax revenues are optimally used to lower the fiscal burden to finance subsidies. The labor income tax only finances research subsidies in excess of carbon tax revenues.

Thirdly, the paper connects to the literature on public policy. Central to this literature is an efficiency-equity trade-off which shapes the optimal use of distortionary taxes (e.g. Domeij and Heathcote, 2004; Conesa et al., 2009; Heathcote et al., 2017; Loebbing, 2019).[4]

[4] With concave utility specifications an equal distribution of income is efficient. However, the optimal tax system does not feature full redistribution when labor supply is elastic. Instead, redistribution is traded off against aggregate output as individuals alter their labor supply and skill investment as the labor tax reduces the after-tax returns to labor.

In the present paper, instead, the labor income tax is used to finance research subsidies, i.e. to implement a more productive allocation of researchers during a green transition. Efficiency costs are intensified with slower learning as labor effort declines: A trade-off between innovation and learning arises shaping the optimal labor income tax.

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. I add learning-by-doing to capture the relation of technology and total factor productivity. Finally, to account for distortions from labor income taxation, labor supply is elastic.

Households A representative household describes the household side. The household chooses consumption, C_t, and the share of hours spent working, H_t, taking prices as given. The household owns machine producing firms from which it receives profits, Π_t[5]. It also supplies scientific work in a fixed amount: S.[6] The household behaves according to solving the problem below each period:

$$\begin{aligned} &\max_{C_t, H_t} \quad \log(C_t) - \chi \frac{H_t^{1+\sigma}}{1+\sigma} \\ &s.t. \quad p_t C_t \leq w_t(1-\tau_{lt})H + w_{st}S + T_t + \Pi_t. \end{aligned}$$

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

[6]These 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. On the downside, it implies that increasing research in one sector translates to a crowding-out of research in other sectors (compare Hémous and Olsen, 2021).

The variables w_t and p_t indicate prices for labor and the final consumption good. Lump-sum transfers from the carbon tax, the labor income tax, and subsidies for machine producers and research are denoted by T_t. Labor income is taxed at a linear rate τ_{lt}.[7]

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

[7] Since this paper focuses on the effects of labor income taxes through generating funds and affecting the level of production, redistributive effects of non-linear labor taxes can be neglected. A recent literature studies the effects of labor taxation and redistribution on the direction of research through a labor supply, or market size, effect. See for instance, Loebbing (2019).

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

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

The government subsidizes machine production by ζ_{Jt} financed by lump-sum taxes on the household to correct for the monopolistic structure.[8] 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.

Research and knowledge I differentiate between knowledge, K_{Jt}, and productivity, A_{Jt}. This allows to distinguish two functions of knowledge: first, it makes labor more productive in working with machines as it spurs technology growth, and, second, it facilitates the generation of new ideas 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

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

not modeled to shape sector-specific knowledge stocks.[9] A more reasonable level of initial knowledge stocks is measured from patent data.[10]

Innovation originates from researchers, whose productivity, in turn, is shaped by past knowledge advances. The law of motion of the knowledge stock from firm i in sector J is modeled as

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

The parameter γ governs the productivity of researchers, δ_K the depreciation of knowledge adding the notion of creative destruction to my model, and η governs returns to scale of research.[11] 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 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

[9]Compare, for example, the discussion in Kogan et al. (2017).

[10]A 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).

[11]The decreasing returns to research governed by η capture a "stepping-on-toes" effect arising from the duplication of ideas. They are important to ensure no increasing returns to research and that the equilibrium is unique (compare Wiskich, 2021). The decreasing returns to knowledge in generating productivity, governed by ι_K, similarly diminish the returns to research.

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^{ϕ}_{-Jt-1}. The parameter ϕ governs the relative importance of cross-sectoral and within-sector knowledge spillovers. There are no cross-sectoral knowledge spillovers when $\phi = 0$.

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

$$A_{Jt}^{1-\alpha_J} = Q_{Jt}^{\iota_L} K_{Jt}^{\iota_K},$$

where $Q_{Jt} = Q_{Jt-1} + J_t$ is the proxy for know-how or experience which is assumed a one-to-one relationship with cumulative past and present production. The baseline level of know-how per sector, Q_{J0}, are calibrated when fitting the model. Since workers are assumed to move freely across firms, I model experience as sector and not firm specific. Notice that these initial levels of know-how will be affected by market distortions which imply deviations of production across sectors. The parameter ι_K captures the elasticity of productivity to innovation, and ι_L similarly governs the elasticity with respect to learning.[12]

These two ingredients of the relation of productivity and knowledge determine the marginal (private) product of research which determines the amount of researchers employed in a sector. It equals the competitive wage for scientists given by

$$w_{st}(1 - \tau_{sJt}) = \frac{J_t p_{jt} \iota_K}{K_{Jt}} \times \gamma \eta \rho_J^{-\eta} K_{t-1}^{\phi} K_{J_t-1}^{1-\phi} (s_{Jit})^{\eta-1}.$$

Today's knowledge stock, K_{Jt}, shows up in the first fraction because the higher the knowledge

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

stock, the smaller the marginal effect of new knowledge on productivity due to decreasing productivity returns to knowledge.

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

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

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, labor income taxes and research subsidies to solve:

$$\max_{\{\tau_{lt}\}_{t=0}^{\infty},\{\tau_{Ft}\}_{t=0}^{\infty},\{\tau_{sFt}\}_{t=0}^{\infty},\{\tau_{sGt}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \log(C_t) - \chi \frac{H_{ft}^{1+\sigma_s}}{1+\sigma_s}$$

$$s.t. \quad \omega F_t - \delta \leq \Omega_t, \tag{1}$$

$$\tau_{Ft} F_t + \tau_{lt} w_t H_t + T_{xt} - T_{Rt} = T_t, \tag{2}$$

$$T_{Rt} = \tau_{sFt} w_{st} s_{Ft} + \tau_{sGt} w_{st} s_{Gt}, \tag{3}$$

$$\tau_{lt} w_t H_t \geq 0 \tag{4}$$

subject to the behavior of firms and households, and feasibility.[13] Constraint (1) is the emission limit. The parameter δ captures the capacity of the environment to reduce emitted CO_2 through natural sinks, such as forests and moors. The parameter ω determines CO_2 emissions per unit of fossil energy produced.

Revenues from the carbon tax are rebated lump sum, eq. (2), if not used to finance research subsidies.[14] Depending on the policy regime studied, the government can choose negative lump-sum transfers. In the counterfactual version of the model, negative lump-sum transfers are feasible replicating the standard assumption in the literature. That is, the government may finance research subsidies lump-sum and choose negative taxes on labor income and fossil energy. Equipped with these instruments, the government would implements the first-best or social planner allocation, defined in Appendix B, if learning would not introduce an additional externality of labor. With learning-by-doing, however, implementing the first-best allocation necessitates additional instruments so that intermediate good producers internalize the positive spillovers of their production on workers' expertise. In the benchmark policy regime, lump-sum transfers and transfers from the labor income tax have to be non-negative.[15]

3 Calibration

This section describes the calibration of the model. Special emphasis is given to the measurement of initial knowledge stocks subsection 3.1. Parameter calibration is depicted in subsection 3.2. Finally, I turn to calibrate the emission target in subsection 3.3.

I calibrate the model to the US in the baseline period from 2015 to 2019. Using 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

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

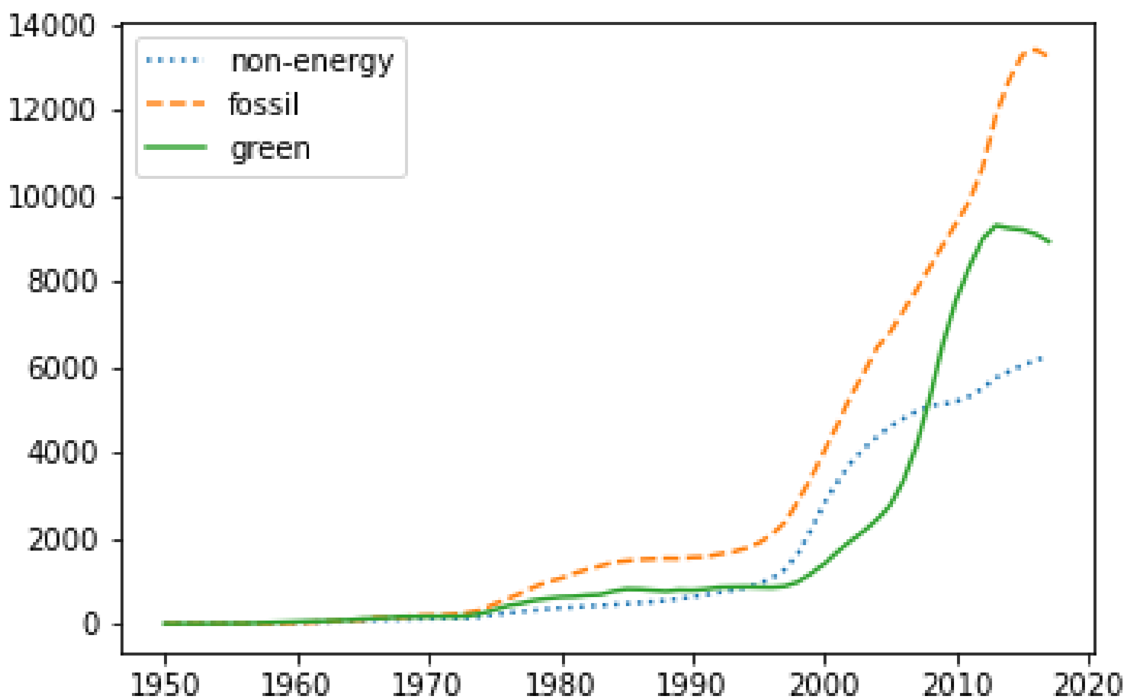
[14] Subsidies to machine producers are financed lump-sum, T_{xt}, as they are only in the model to allow to abstract monopolistic competition to affect results.

[15] Only transfers to finance subsidies of machine-producing monopolists are admitted.

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 counter these forces.

3.1 Research

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 as described here: https://link.epo.org/web/patents_and_the_energy_transition_study_en.pdf.

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 applicants[16] from the European Patent Office (EPO)'s database PATSTAT. I consider patents filed between 1950 to 2017.[17] 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.[18] Fossil energy patents relate to the supply, exploration, processing, transport, and distribution of fossil fuels.[19] To get an idea of "green" knowledge, I focus on the "low-carbon energy" supply technologies.

Using the number of patents[20] related to green, fossil, and non-energy technologies, I calculate a measure of the knowledge stock within sectors based on the "perpetual inventory method" which assumes that knowledge accumulates over time and depreciates. More precisely, I calculate sector-specific knowledge, K_{Jt}, as:

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

where R_{Jt} stands in for new patents in sector J. Depreciation of knowledge captures that knowledge becomes obsolete overtime as it is overrun by new innovation. To achieve consistency with the model, one period in the perpetual inventory model is set to 5 years.

[16] These 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.

[17] The number of granted patents displays a sharp reduction after this year 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 is, thus, not complete.

[18] The 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 is given here: https://link.epo.org/web/patents_and_the_energy_transition_study_annex_en.pdf

[19] These 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.

[20] The 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, the more important the knowledge conveyed in this innovation. However, citation data is flawed 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, for example. Using stock exchange information as used in Kogan et al. (2017) would also capture market expectations on policies and the 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.

Following the literature, I set the 5-year depreciation rate to $\delta = 0.55$.[21] 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).

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 the huge knowledge stock. This productive capital, knowledge, would become unproductive when all research transitions to the green sector rapidly.

3.2 Model parameters

To calibrate the rest of the model, I proceed in three steps. First, I set certain parameters to values found in the literature. Second, I calibrate the remaining variables requiring that targets from the data are model solutions. Third, I calibrate the research and the emission side. Table 1 summarizes the parameter values.

I set the elasticity of substitution between energy and non-energy goods, ε_y to the values in 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 $\varepsilon_e = 1.8$ following Papageorgiou et al. (2017). As a result, fossil energy cannot be one-for-one substituted for by green energy without reductions in output. The utility parameters, β is set to 0.985^5 following Barrage (2020). The business-as-usual carbon tax is set to $\tau_{F0} = 0$,

[21] This corresponds to a 15% annual depreciation rate as in Noailly and Smeets (2015). The depreciation rate of knowledge is

accounting for the missing climate policy in the US under President Trump. The linear labor tax amounts to $\tau_{l0} = 0.24$, as in Barrage (2020). Finally, I set the parameters governing the number of research processes per sector, ρ_F, ρ_N, ρ_G to the values found by Fried (2018): $\rho_N = 1$ and $\rho_F = \rho_G = 0.01$. The parameters ι_K, ι_L and δ_K are taken from the literature: $\iota_K = \iota_L = 0.15$ following the discussion in Fischer and Newell (2008), and $\delta_K = 0.15$ as in Noailly and Smeets (2015).

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 by matching the average expenditure share on energy relative to GDP over the period from 2015 to 2019 taken from the US Energy Information Administration (EIA, 2023, Table 1.7). The expenditure share equals 6%. The resulting weight on energy is $\delta_y = 0.14$.[22] Initial productivity levels 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).

Labor shares in non-energy and fossil good production follow from the compensation of labor in value added from the BEA. As in Fried (2018), I classify NAICS sectors 21 and 324 as fossil energy production. I derive an estimate of the labor share in the green energy sector from the green job tables of the BLS.[23] 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.

In a third step, I match parameters governing the generation and role of knowledge: $\{\gamma, \eta, \phi, K_{n0}, K_{g0}, K_{f0}, Q_{n0}, Q_{g0}, Q_{f0}\}$. As initial knowledge levels, I use the knowledge stock derived from patent data in the 2010-2014 period: $K_{n0} = 0.64, K_{g0} = 1.00, K_{f0} = 1.30$ (subsection 3.1). Knowledge stocks are normalized by green knowledge in 2010-2014. Acemoglu et al. (2016) also estimate the knowledge gap between "clean" and "dirty" energy sectors.

[22] Note that δ_y qualifies as a measure of energy efficiency in the economy.

[23] Retrieved from https://www.bls.gov/green/home.htm, 06 September 2023.

The resulting gap equals $\frac{K_{f0}}{K_{g0}} = 1.48$.[24] 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.

To calibrate the generation of knowledge governed by γ, η, ϕ, I combine information on the knowledge stock with information on R&D expenditures in green, fossil, and non-energy (residually determined as total minus energy-specific R&D) from the National Center for Science and Engineering Statistics' (NCSES) Industrial Research and Development Information System (IRDIS). [25] 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. I also allow for research subsidies to shape the allocation of R&D, the base year research subsidies are $\tau_{sF0} = 0.53$, and $\tau_{sG0} = 0.32$, suggesting that given the model a net-subsidy of fossil research in the base year rationalizes the observed allocation of R&D. Finally, to get estimates for Q_{n0}, Q_{g0}, and Q_{f0}, I match knowledge stocks simulated by the model for the base period, 2015 to 2019, to productivity levels found in the calibration of the producing sector. I find a massive learning advantage in the fossil sector: $Q_{n0}^{\iota L} = 1.20, Q_{f0}^{\iota L} = 2.11$, and $Q_{g0}^{\iota L} = 0.85$. That means that fossil technology can be translated into productive use more than twice as well as in the green sector.

The resulting relative importance of cross-sectoral knowledge spillovers is $\phi = 0.43$, a value in line with the literature. Aghion et al. (2016) estimate for the US automotive industry that

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

[25] Tables can be found here: `https://www.nsf.gov/statistics/iris/history_pub.cfm`. The data does not contain R&D subsidies. Compare comment in table from 1999: " The company R&D in this table is the industrial R&D performed within company facilities funded from all sources except the Federal Government."

clean innovation within a firm is comparably more important for clean patent growths than dirty knowledge.[26] Hart (2019) calibrates a value equivalent to $\phi = 0.1$, and Fried (2018) sets $\phi = 0.5$ based on theoretic considerations.[27]

I find a value of $\eta = 0.38$. The value below unity can be explained by the probability of duplicating results the more researchers work on the same research process. 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.[28] Fried (2018) estimates $\eta = 0.79$. The smaller value 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 $\eta = 0.19$.[29]

Having specified the full economic side of the model, I turn to emissions. I define the sink capacity to match the total difference between gros emissions from energy and net CO_2 emissions from all sources over the baseline period from 2015 to 2019.[30] Information on emissions comes from the US Environmental Protection Agency (EPA, 2022). The resulting sink capacity per model period (5 years) is $\delta = 3.19\text{GtCO}_2$.[31] To find the parameter relating CO_2 emissions from energy and fossil energy use in the model, I reduce the distance between

[26]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 spillovers, I get that $\phi = 0.3124$. But note that they focus on the automotive industry and micro-level estimates. These estimates, hence, do not include spillovers across firms.

[27]Note, that the specification of the aggregate knowledge stock differs to my model which reduces comparability of the parameter values.

[28]Since 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 effe'cts, are better suited.

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

[30]Because the model abstracts from CO_2 sources other than energy, I define the sink capacity as net of emissions from agriculture and industry; i.e., matching total observed net emissions in the data: Net emissions=Energy +Industry+Agriculture-Natural sinks $\Leftrightarrow$ Net emissions=Energy -δ.

[31]I consider this capacity to be constant as it relates to natural sinks. Carbon capture and storage technologies are not considered in the model for simplicity.

Table 1: Calibration

Parameter	Target	Value
Household		
σ	Chetty et al. (2011)	1.33
χ	average hours worked per economic time endowment by worker: 0.34 (OECD, 2021)	9.66
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
Research		
Returns to research η	growth in knowledge stocks and R&D	0.38
Knowledge spillovers ϕ	growth in knowledge stocks and R&D	0.43
Scientists' productivity γ	growth in knowledge stocks and R&D	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)
Initial know-how ($Q^{\iota_L}_{F0}, Q^{\iota_L}_{G0}, Q^{\iota_L}_{N0}$)	matching knowledge stock and output	(2.11, 0.85, 1.2)
Elasticity of productivity to knowledge ι_K	Fischer and Newell (2008)	0.15
Depreciation knowledge stock δ_K	Noailly and Smeets (2015)	0.55
Production		
Elasticities of substitution (ε_y, ε_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 (α_F, α_G, α_N)	BLS and Green Jobs and Compensation of employees	(0.75, 0.87, 0.36)
Government		
Policy instruments ($\tau_{F0}, \tau_{sF0}, \tau_{sG0}, \tau_{l0}$)	Barrage (2020) and knowledge stocks and R&D distribution	(0, 0.53, 0.32, 0.24)
Emissions		
Carbon sinks δ	EPA (2022)	3.19
Emissions per fossil energy ω	EPA (2022)	211.37

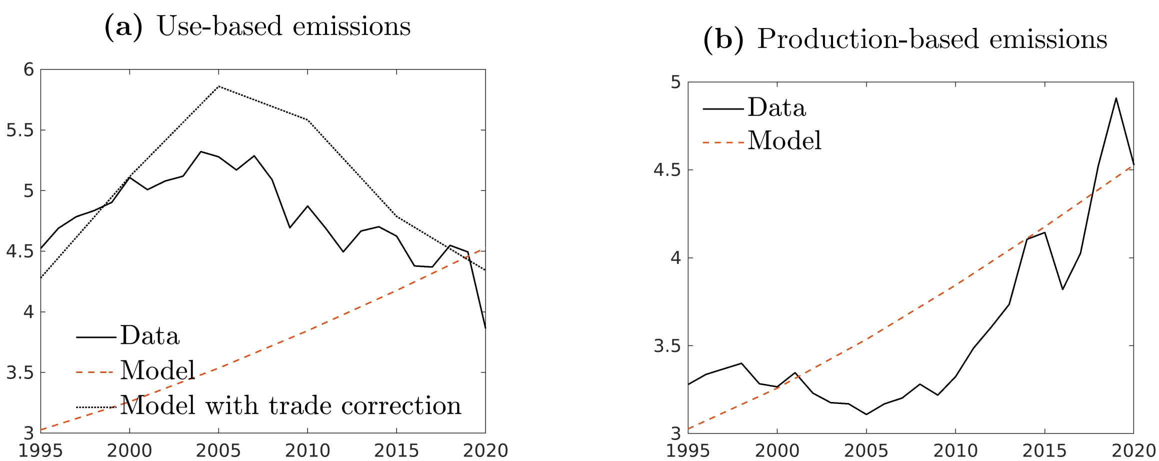
projected values of fossil production in the model to observed energy emissions. One difficulty is that the assessment of country-specific emissions: What emissions are relevant, those arising during consumption or those arising from the fuels produced in a country—which ultimately count to a country's GDP? The EPA's Inventory Greenhouse Gas Emissions and Sinks dataset contains emissions associated with the use of polluting products. This is the emissions information which is subject to regulation.[32] The production of fossil-fuel energy per se is not reflected in these emissions data when it is exported. In the present model, I abstract from trade and focus on matching the production side which is closer to the invention of new technologies than consumption. The underlying assumption being that all energy that is produced in the US is also consumed in the US. To calibrate the carbon intensity of fossil

[32] For an overview see here: https://www.epa.gov/climate-indicators/greenhouse-gases#sources-of-data.

fuels, however, I match use-based emissions with *consumed* fossil fuels. This is more accurate in capturing the pollution content of fossil-fuels than using produced fuels since net exports, for instance, would bias the emission content of burning fossil-fuels downwards. The emissions arising from the model, thus, can be interpreted as emissions that results from the level of fossil-fuels produced in the US. Emission intensity of fossil-fuel production is $\omega = 96.49$.

This approach understates observed use-based emissions from 1990 until the mid-2010s, compare Figure 2a. Most f the gap can be explained by the US importing fossil fuels; compare the dotted graph in Figure 2a—showing a trade-corrected level of fossil-fuel production from the data—which tracks the pattern of emissions fairly well. In the second half of the 2000s, emissions started to reduce, which can be explained by a drop in consumption of fossil fuels while production of fossil-fuels increased. When contrasting emissions predicted from the model to a proxy of production-based emissions, Figure 2b, the model matches the trend in the data well.

Figure 2: Net Emissions Data and Model



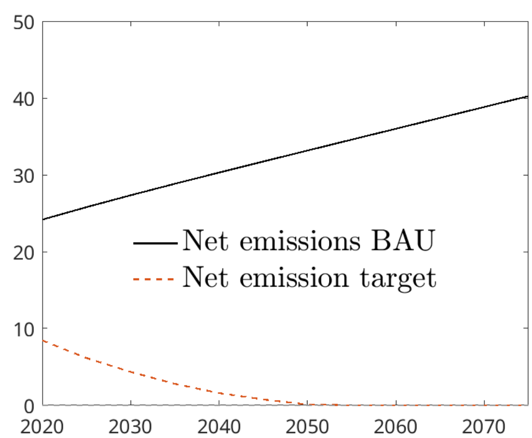
Notes: Annual Net-CO_2 emissions in Gigatonnes.

3.3 Emission target

I consider CO_2 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 CO_2 emission target from the latest IPCC assessment report (Van der Wijst et al., 2023, Figure SPM.5).

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.[33] I use projected population shares from the United Nations (2022). Figure 3 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 the business-as-usual policy in the calibrated model. Clearly, there is scope for government intervention.

Figure 3: Emission target and net CO_2 emissions in model periods (5 years) under business as usual in Gt



Notes: The x-axis indicates the first year of the 5 year period to which the variable value corresponds. Emissions are given in sum over the five years used as a model period. US net-CO_2 emissions in Gigatonnes in 2019 amounted to 4.66 (where I deducted emissions from other greenhouse gases).

The reduction in net CO_2 emissions necessary to meet the emission limit relative to 2019 emissions in the US is substantial. 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%

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

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 CO_2 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.[34] 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.

4 Results

This section presents the results. First, I turn to the first-best implementation of the emission target in subsection 4.1. Relative to this benchmark, second, subsection 4.2 discusses the optimal implementation of the emission target for different policy regimes. Finally, subsection 4.3 analyzes optimal policies when either only carbon tax revenues or labor income taxes are available to finance subsidies.

4.1 First-best implementation of the emission target

The first thing to note is that the social planner completely exhausts admissible emissions; Figure 4a. This allows the economy to profit from very productive fossil energy and knowledge generation in this sector. This is efficient despite lock-in effects of fossil production through learning-by-doing and path-dependency of innovation.

The production of energy switches to green sources; compare Figure 4c. To lower the costs of this transition, the efficient allocation of researchers changes to more green research. Figure 4b shows a smaller share of fossil-to-green researchers than absent an emission limit.

[34] Source: https://www.whitehouse.gov/briefing-room/statements-releases/2021/04/22/, retrieved 14 September 2022.

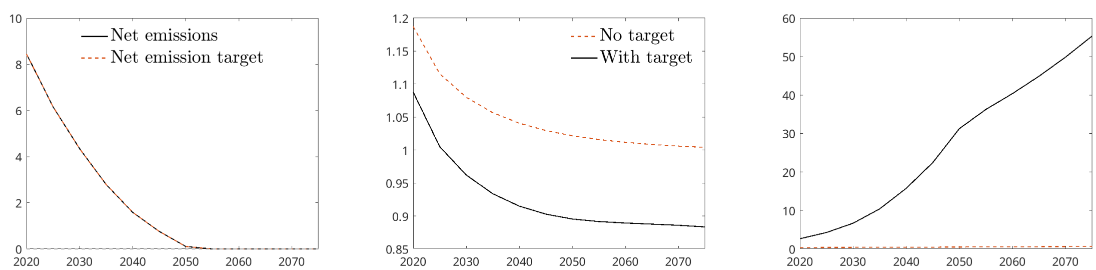
The economy builds up green relative to fossil knowledge which allows future green scientists to profit from a higher green knowledge stock. This result is in line with the findings in the literature (Acemoglu et al., 2012, 2016; Hart, 2019): An efficient emission mitigation implies more green research starting today.

However, the social planner chooses to only reduce the share of fossil to green R&D smoothly over time, and some fossil research activity is maintained over the full horizon considered. Nevertheless, 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 built, the profitability of green R&D investment rises.

What explains the maintained investment in fossil knowledge? 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. Furthermore, this allocation avoids costs from decreasing returns to research when too many scientists work on the same process in the green sector.

Figure 4: First-best implementation of emission limit

(a) Net emissions and target **(b)** Fossil-to-green scientists **(c)** Green-to-fossil energy



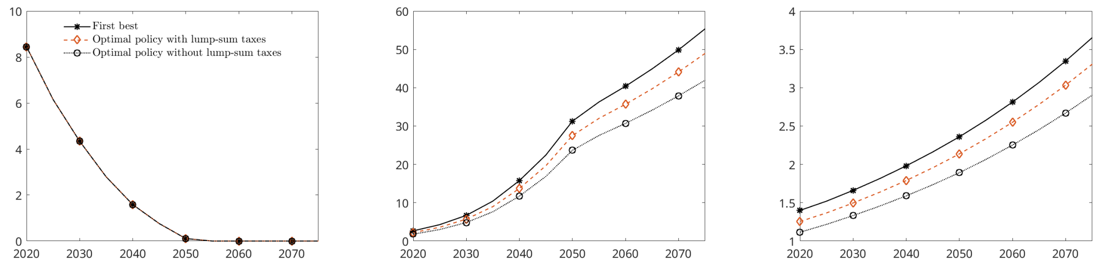
Notes: The x-axis indicates the first year of the 5-year period to which the variable value corresponds.

4.2 Optimal allocation and policy

With the set of available instruments, carbon taxes, labor income taxes, and research subsidies the first-best allocation is infeasible given the spillovers from learning-by-doing. The dashed-diamond graphs in Figure 5 show that the optimal policy implements the emission limit at a

Figure 5: Optimal allocation

(a) Fossil-to-green scientists (b) Green-to-fossil energy (c) Output



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

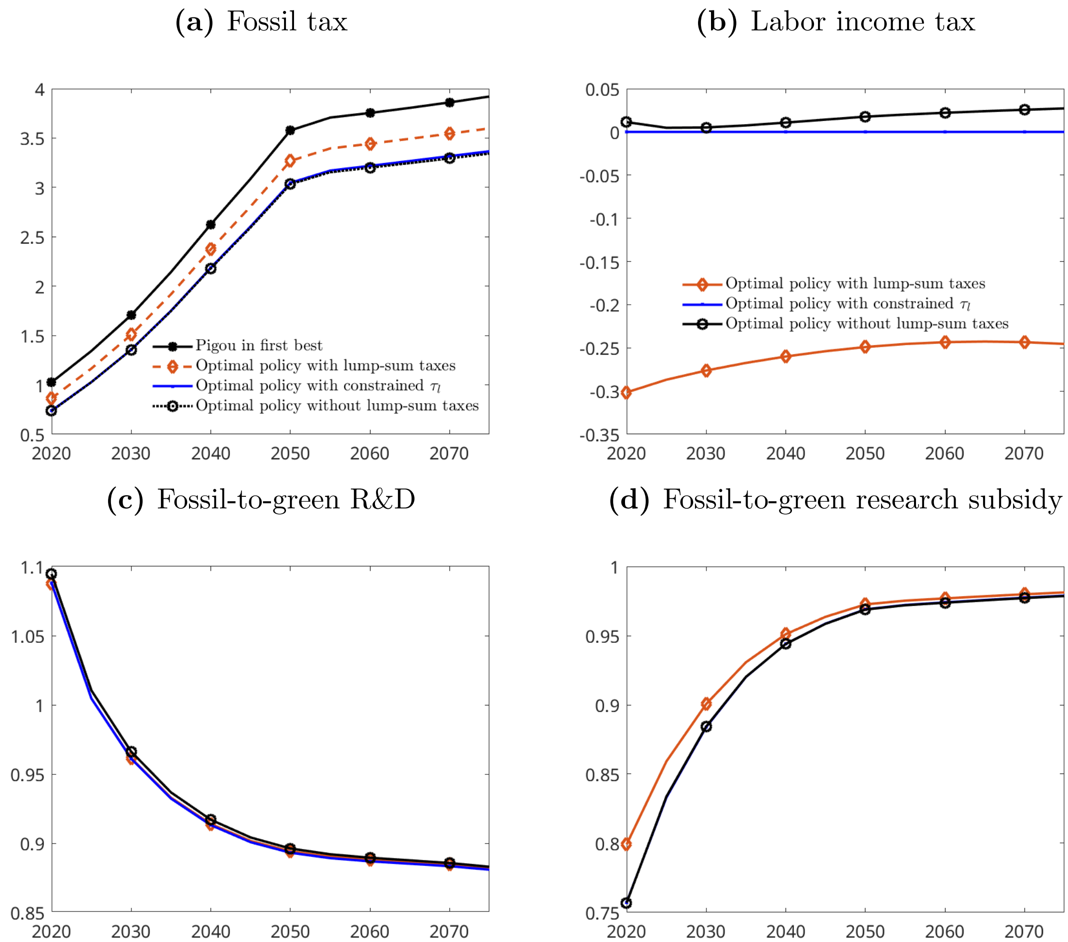
smaller output level (Figure 5c) and a lower ratio of green-to-fossil energy (Figure 5b). The reason is that the government lacks an instrument to target sector-specific output to foster learning. Output is lower than what the social planner would choose. However, the lower output level allows to consume a higher fossil energy share.

When, in addition, distortionary fiscal policies have to finance research subsidies, the gap between optimal and efficient allocation widens since tax instruments distort households' labor supply decisions further. The emission target is implemented at an even lower output level and higher fossil-to-green energy ratio. In all scenarios, the emission limit is met exactly (Figure 5a) pointing to no additional benefits, no strong double dividend, of carbon taxes. This observation is confirmed by the optimal policy mix which implements the emission limit and is discussed next.

Figure 6 displays the optimal policy under distinct regimes in comparison to the first-best Pigouvian tax which would be set in a scenario with lump-sum taxes and additional instruments to target learning. Consider first the dashed-diamond graph which depicts the optimal carbon tax with lump-sum taxes. It is lower than the Pigouvian rate since labor effort is inefficiently low in the Ramsey allocation and a lower carbon tax suffices to meet emission limits. This is so despite labor subsidies: The labor income tax is set to between -30% and -24% over the horizon considered.

When lump-sum taxes are no longer feasible, i.e., research subsidies have to be financed

Figure 6: Deviation from First-best by Policy Regime



with distortionary fiscal instruments and labor cannot be subsidized, the optimal labor tax becomes positive ranging between 1% and 2.5%. The optimal carbon tax declines. It is hence not the case that carbon taxes are set higher to finance research subsidies. Instead, the government reverts to labor taxes. The rationale has been discussed in the literature: Carbon taxes not only lower labor supply but also distort the consumption basket which makes them more costly than labor taxes to generate funds (e.g. Jacobs and van der Ploeg, 2019). My findings confirm this logic even if carbon taxes have the additional benefit of directing labor and scientists to the green sector thereby accelerating innovation and know-how about how to use these new green technologies.

Carbon tax revenues are optimally used to finance research subsidies as opposed to redistributing them lump-sum. This finding is analogous to the weak double dividend result from the literature that looks at exogenous financing constraints. Recycling carbon tax revenues as lump-sum transfers would lower the tax base for the income tax thereby aggravating distortions to generate funds.

Figure 6c and Figure 6d depict how research and subsidies respond to the changes in the policy regime. First, expenditures on subsidies decline which lowers the fiscal burden. In addition, the composition of fossil-to-green research taxes adjusts: First, as labor cannot be subsidized anymore, the carbon tax declines, and more research is allocated to the fossil sector as fossil-based research becomes more profitable. A smaller ratio of fossil-to-green subsidies balances this effect of the carbon tax.

Second, when research subsidies in addition have to be financed with distortionary taxes, the carbon tax remains largely unaffected (compare the black and blue graph). It appears that labor taxes are used to finance the gap between carbon tax revenues and expenditures for research subsidies. Since the carbon tax does not change much, the relation of fossil to green research subsidies remains unaffected (Figure 6d). Overall, the ratio of fossil-to-green R&D engineered during the green transition remains relatively stable with a negligibly small rise in the ratio of fossil-to-green R&D.[35]

4.3 Constrained Policy Regimes

To further shed light on the motives behind the optimal financing mix, Figure 7 contrasts the optimal policy under a joint budget, i.e. subsidies can be financed either by carbon tax or labor tax revenues, earmarking, i.e. only carbon tax revenues can be used to finance subsidies, and income-tax-financed research subsidies.

In the earmarking scenario, when the government cannot use labor income taxes to finance research subsidies, the optimal carbon tax increases to counter the rise in emissions as the labor tax is lowered; compare the orange line with diamonds to the circled-black graph. But,

[35] An increase explained by the smaller carbon tax. It is optimal because learning and production of the fossil sector rises, too.

there is no increase of the carbon tax that would lower emissions beyond the target. Instead, research subsidy expenditures are lowered to ease the financial burden. These results further support the observation that there is no strong double dividend of carbon taxes to finance research subsidies. Rather, too high carbon taxes are extremely costly and the government accepts a higher share of non-energy scientists (Figure 7d). Furthermore, relative subsidies are altered substantially. The fossil-to-green research subsidy increases not only to balance the effect of the carbon tax to direct research to the green sector: It even engineers a higher ratio of fossil-to-green R&D (Figure 7c). Note that this latter observation is irrespective of financing constraints.

It would be desirable to increase energy research, but the government is financially constrained. Therefore, the optimal policy balances the misallocation of researchers and accepts too high a ratio of fossil-to-green scientists. Indeed, a lower ratio of fossil-to-green R&D could be designed with a lower subsidy on fossil and a higher subsidy on green scientists without increasing financing needs. However, such an expenditure-neutral policy amendment would entail an even lower ratio of fossil-to-non-energy R&D.[36]

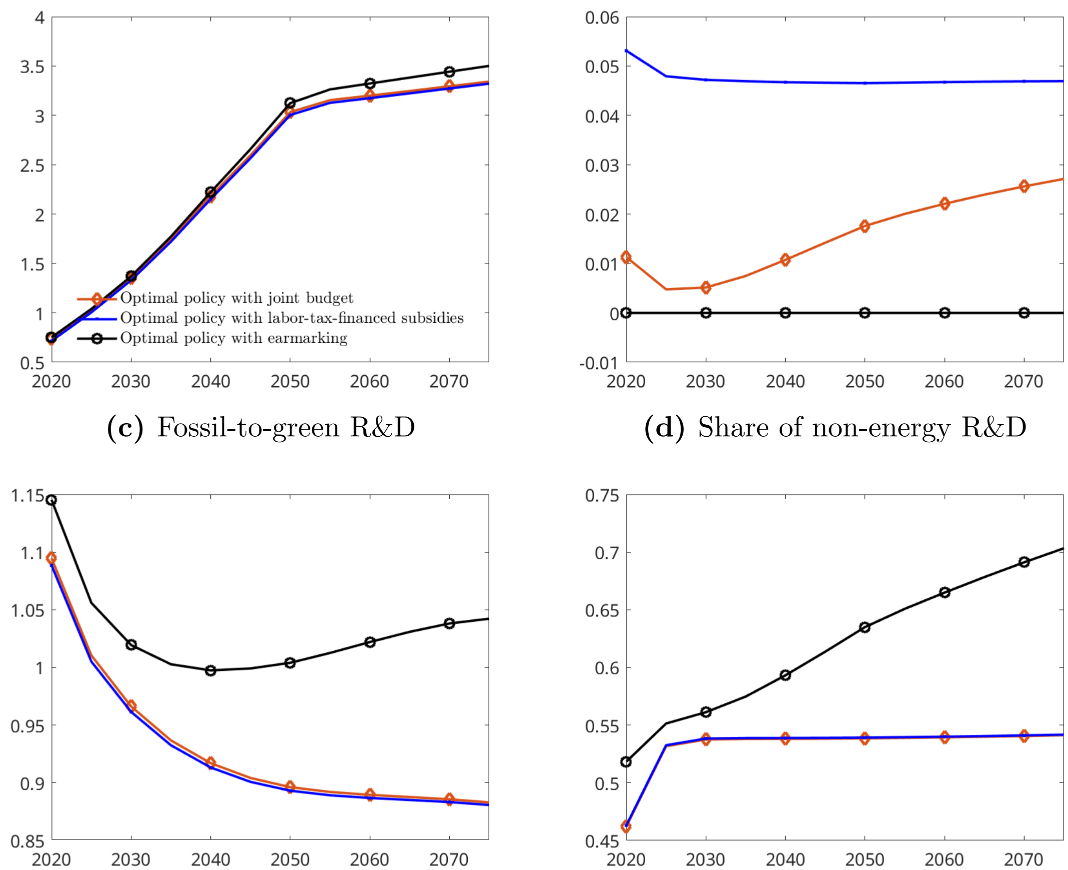
When constraining the government to finance research subsidies with the labor income tax (the solid-blue graphs), research subsidies are not adjusted. The labor income tax is raised sufficiently to finance subsidies. The carbon tax only reduces minimally as much as the emission target admits. This result underlines the financing advantage of the labor tax relative to carbon taxes.

5 Conclusion

The transition to net-zero emissions means a massive shift in how we produce, and around the globe, research subsidies are a prominent tool to tackle the green transition. However, little is known about how these instruments should be set and financed within a distortionary

[36]Some fossil-related innovation remains valuable in a green future due to cross-sectoral knowledge spillovers. Such spillovers allow the economy to profit from a more productive smoother allocation of scientists.

Figure 7: Joint budget versus earmarking and income-tax-financed subsidies



(a) Fossil tax

(b) Labor income tax

(c) Fossil-to-green R&D

(d) Share of non-energy R&D

fiscal environment.

In this paper, I depart from the assumption of the feasibility of lump-sum taxes to finance research subsides. The government has to revert to distortionary labor income taxes or carbon tax revenues. In contrast to lump-sum taxes, these instruments lower labor efforts and thus slow down learning about how to use new technologies. This implication becomes especially costly during a green transition when learning to work with new green technologies is crucial. On the other hand, a higher carbon tax to finance subsidies would entail more green learning and research.

I find that labor taxes are less costly to finance research subsidies than carbon taxes. There is hence no strong double dividend of the latter. The rise in the labor tax diminishes output thereby allowing for a smaller tax on carbon. The reduction in the carbon tax entails a shift in R&D towards the fossil sector. Therefore, green research subsidies increase to counter the effect of the lowered carbon tax to direct research to the green sector.

When the government is constrained to using carbon tax revenues to finance research subsidies, expenditures are cut to meet carbon tax revenues from exactly implementing the emission target. This result highlights the high costs associated with carbon taxes: lower work effort and a less productive composition of energy production. For these reasons, the optimal policy forfeits future higher green technology growth and accepts inefficiently high fossil R&D which will become worthless in a green future.

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A Model equations

Household and Government Budget, January 2025. To clearly separate the different functions of the government, I model one budget as follows

Government: With Lump-sum taxes

$$
\begin{aligned}
\text{Labor Income Taxation} \quad & \tau_{lt} w_t H_t = T_{lt} + G_t \\
\text{Environmental Policy} \quad & \tau_{Ft} F_t = T_{Ft} \\
\text{Research Subsidization} \quad & T_{Rt} = w_{st}(\tau_{sFt} s_{Ft} + \tau_{sGt} s_{Gt}) \\
\text{Monopoly Correction} \quad & T_{xt} = \int_0^1 (p_{Fit}\zeta_t x_{Fit} + p_{Nit}\zeta_t x_{Nit} + p_{Git}\zeta_t x_{Git}) di \\
\text{Lump Sum Transfers} \quad & T_{Ft} + T_{Lt} - T_{Rt} - T_{xt} = T_t
\end{aligned}
$$

The household receives income from working, from engaging in science, from owning machine producing firms, and lump sum transfers from the government:

Household

$$
\begin{aligned}
\text{Income} \quad & (1 - \tau_{lt}) w_t H_t + w_{st} S + \Pi_t + T_t \\
\text{where} \quad & \Pi_t = \int_0^1 (\pi_{Fit} + \pi_{Git} + \pi_{Nit})\, di \\
\text{with} \quad & \pi_{Jit} = p_{Jit}(1 + \zeta_{Jt}) x_{Jit} - x_{Jit} - w_{st} s_{Jit} \;\; \forall J
\end{aligned}
$$

Notice that the household budget simplifies extensively as firm profits, income from science, and subsidies to firms and research cancel. This observation holds in both cases: when research subsidies are financed lump-sum or with the linear labor tax. The budget becomes:

$$(1 - \tau_{lt}) w_t H_t + T_{Ft} + T_{lt}$$

I assume the existence of interior solutions for labor supply.

B 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 C for the derivation.

C 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.[37] 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

[37] The 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

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