Meeting Climate Targets: The Optimal Fiscal Policy Mix

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Abstract This paper studies the optimal fiscal policy mix for the green transition under realistic fiscal constraints. I develop a model with directed technical change and learning-by-doing, where an emission target renders fossil energy use socially costly. In a calibration to the US, I quantify the optimal mix of carbon taxes, research subsidies, and distortionary labor income taxes. The central insight is that the optimal fiscal mix internalizes its impact on R&D investment and learning-by-doing. Carbon taxes encourage both green R&D and learning, justifying rates above the social cost of carbon. In contrast, labor income taxes suppress learning-by-doing, especially in the green sector, where experience is initially scarce. Throughout the transition, labor taxes are lower than absent learning-by-doing. In a more constrained regime where carbon tax revenues are rebated lump-sum, the government insufficiently subsidizes research on energy-related technologies to preserve green learning-by-doing.

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1 Introduction

The transition to net-zero emissions requires a profound transformation in how we produce. Around the globe, research subsidies are a central policy tool to support this shift. At the same time, public budgets are already under pressure, with growing demands to finance climate adaptation, social security in aging societies, and aforesaid research subsidies. Yet little is known about the fiscal mix that best supports a green transition when growth is endogenous.[1]

In this paper, I depart from the common assumption that lump-sum taxes are available to fund the government. Instead, I study an environment where the government must rely on distortionary labor income taxes or carbon taxes to raise funds and, in particular, to finance research subsidies. Unlike lump-sum taxes, these distortionary labor taxes reduce labor effort and thereby slow learning-by-doing—an especially costly distortion during a green transition when building expertise in green technologies is essential. By contrast, raising revenues through higher carbon taxes may an additional benefit: supporting green innovation and learning-by-doing.

I quantify the optimal dynamic policy mix of carbon taxes, labor income taxes, and research subsidies in a model featuring both directed technical change and learning-by-doing calibrated to the US economy. The government faces an exogenous revenue constraint and an emission target, anticipating that net emissions must decline in the near term and reach zero in the long run.

The results show that the optimal fiscal mix supports an advantageous allocation of researchers and boosts learning-by-doing which is especially important during a green transition. Carbon taxes exceed the social cost of carbon to spur innovation and learning in the green sector. In contrast, the labor tax is on average eight percentage points lower than absent learning-by-doing. In a more fiscally constrained regime, when carbon tax revenues must

[1] The literature studying optimal environmental policies in directed-technical-change settings has largely abstracted from fiscal distortions, i.e., lump-sum taxes are available. On this point see, for instance, Fischer and Newell (2008); Acemoglu et al. (2012, 2016); Hart (2019).

be redistributed lump-sum, the planner insufficiently subsidizes research to preserve green learning-by-doing.

In more detail, I build a model characterized by three crucial ingredients of a green transition: learning-by-doing, research, and elastic labor supply. The basic structure of the model is similar to Fried (2018). Final output 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*).

Workers' expertise to work with machines is sector specific and accumulates over time as a function of past output in the spirit of learning-by-doing. I introduce this aspect to capture potential bottle necks due to labor shortage observed in today's economies during a green transition. Furthermore, it creates additional lock-in effects[2]: as economies become more experienced in using fossil fuels, transitioning to green energy sources becomes more costly.

Learning-by-doing gives an additional externality to labor which the government would like to correct with targeted labor subsidies. However, the government lacks such a tool. Then, a subsidy on labor is favorable to steer learning-by-doing in all sectors. A trade-off between subsidizing research on the one hand, and boosting learning-by-doing arises. This innovation-learning dilemma gets an additional bite during the green transition. A concave relation between a sector's total factor productivity and workers' expertise means that productivity gains due to learning in a younger sector are higher. On the flip side, a

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

reduction in learning hits less mature sectors more severely. Taxing labor, thus, implies a more adverse negative effect on the green sector's productivity that spills over into the future.

The calibration of initial knowledge stocks are key to determine optimal policies. Therefore, 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 25 percent higher than in the green sector over the 2010-2014 period.

The key qualitative result is that the optimal fiscal mix internalizes its effects on the allocation of R&D and learning-by-doing. On the one hand, because learning-by-doing cannot be targeted and more subtly, on the other hand, fiscal constraints on the funding of research subsidies make a fiscal combination that directs research to the sector with the highest social benefit preferable.

More precisely, during the green transition the motives shaping the optimal fiscal mix play out differently. While initially, at lower productivity levels, generating government funds is more difficult, the government relies on taxing labor heavily and the carbon tax is set below the social costs of carbon to ease fiscal distortions. At the beginning of the green transition, using carbon taxes in excess of the social costs of carbon would be very costly since productivity in the green sector is too far behind the fossil sector.[3] In the long run, however, the additional benefit of motivating green research and learning outweigh the additional output loss of a carbon tax, and the carbon tax is set higher than the social cost of carbon.

[3] Carbon taxes are extremely expensive to finance the government as opposed to labor income taxes since they not only alter labor supply but also reduce the composition of goods produced. This additional distortion makes carbon taxes especially costly from a fiscal perspective.

I show that learning-by-doing has an important effect on the optimal choice of fiscal instruments. Absent learning-by-doing labor income taxes are less distortive justifying taxing labor more heavily, by roughly eight percentage points on average, and the carbon tax never exceeds the social costs of carbon during the green transition. Nevertheless, the carbon tax more and more internalizes the social costs of carbon as the economy grows and fiscal constraints loosen with economic productivity.

As a final exercise, I compare my main results where the government runs a joint budget, i.e., labor and carbon tax revenues both finance the government, to a more restrictive regime where carbon tax revenues are redistributed lump sum. Such a policy has gained a lot of attention in the political and academic debate. When accounting for learning-by-doing and directed technical change, though, this policy becomes costly. Higher labor taxes are required to fund government expenditures thereby slowing learning-by-doing. Furthermore, subsidizing research becomes more costly as it adds to the revenues that have to be generated. Under such a regime, carbon taxes raise beyond the social cost of carbon in the long run despite no additional revenues that can be generated. One reason are gains from green learning-by-doing. Another is that a higher carbon tax fosters more green research. Hence, carbon taxes may be preferred to research subsidies when the latter have to be financed with distortionary instruments. A quick transition may seem desirable to avoid fossil lock-in. Perhaps surprisingly, the results suggest that maintaining fossil fuel production as high as admitted by the emission target is optimal. Knowledge spillovers from the fossil sector and diminishing returns to research explain this result.

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.

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.[4] 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 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 distortionary instruments and endogenizes part of government expenditures. My results suggest that optimal carbon taxes may exceed the social costs of carbon to cope inefficiencies arising from learning-by-doing and knowledge spillovers. But only in the long run, when the green sector has become more productive. The optimal fiscal mix features higher carbon taxes and lower labor taxes due to learning-by-doing.

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).

[4]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.

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 in a setting with learning-by-doing and directed technical change. Carbon tax revenues are optimally used to lower labor taxes which has the additional benefit of spurring labor and thus learning-by-doing. An effect that is especially beneficial during a green transition.

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).[5] 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 that shapes 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

[5] 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.

stocks. Second, 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[6]. It also supplies scientific work in a fixed amount: S.[7] The household behaves according to solving the problem below each period:

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

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}.[8]

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:

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

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

[7]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).

[8]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).

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

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

The government subsidizes machine production by ζ_{Jt} financed by lump-sum taxes on the household to correct for the monopolistic structure.[9] 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.[10]

Research and knowledge 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

$$K_{Jt} = \int_0^1 K_{Jit}di,$$
$$K_{-J,t} = \frac{\sum_{j\in\{-J\}}\rho_j K_{jt}}{\sum_{j\in\{-J\}}\rho_j},$$

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

[10]The choice of the normalization sector is not innocuous as soon as research subsidies have to be financed by use of distortionary instruments. Taxing non-energy becomes fiscally expensive since it necessitates a subsidy on energy research. A more symmetric approach could be to allow a subsidy in all sectors that is constrained to be positive.

[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.

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 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 $Q_{Jt} = Q_{Jt-1} + J_{t-1}$ 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 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:

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

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

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

research subsidies to solve:

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

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

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

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

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

$$T_t \geq Trans_{min,t} \tag{5}$$

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.

In the baseline regime, the government runs a joint budget meaning that both carbon taxes and labor income taxes finance government expenditures: transfer to households and government consumption, G_t^C.[14] Transfers have to be higher than a minimum transfer level, $Trans_{min,t}$, which represents government transfers such as social security benefits. 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 expenditures lump sum. Negative taxes on labor income become feasible. Equipped with these instruments, the government would implement 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'

[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.

expertise. As we will see, the labor tax is then used to subsidize labor.

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 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

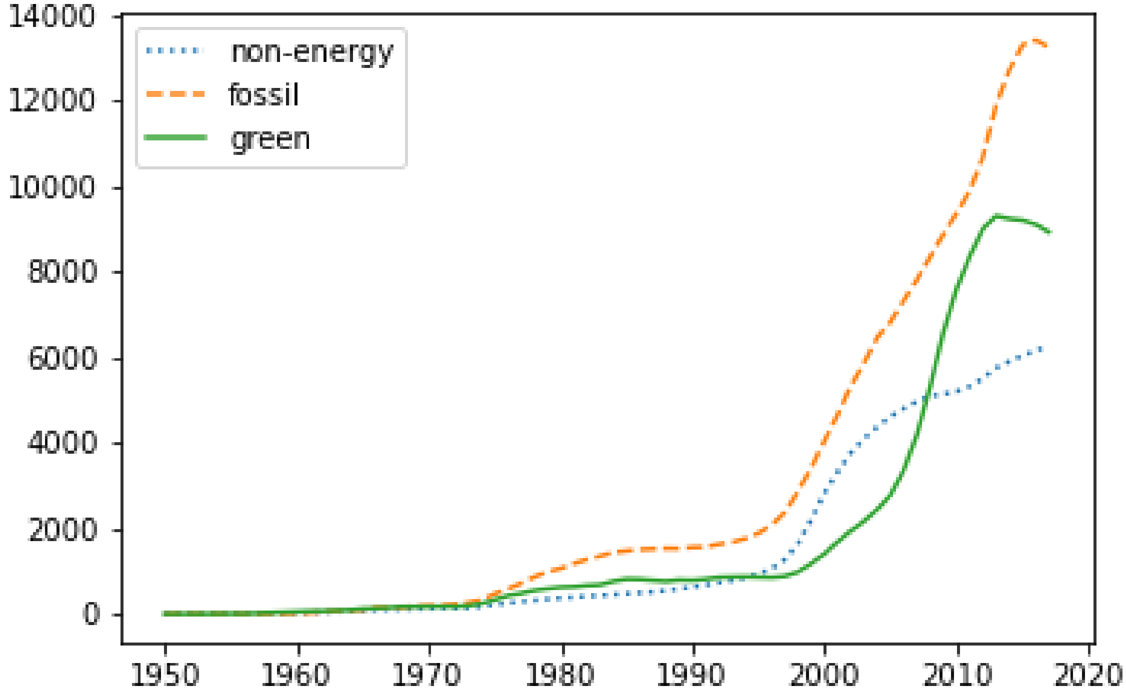
Initial knowledge stocks The distribution of initial knowledge stocks is a crucial driver of the optimal environmental policy, as it determines the relative productivity of researchers across sectors through within sectoral knowledge spillovers. To measure sectoral knowledge stocks, I use the universe of patents granted by the United States Patent and Trademark Office (USPTO) and filed by US applicants[15] from the European Patent Office (EPO)'s database PATSTAT. I consider patents filed between 1950 to 2017.[16] 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.[17] Fossil energy patents relate to the

[15] 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.

[16] 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.

[17] 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

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.

supply, exploration, processing, transport, and distribution of fossil fuels.[18] To get an idea of "green" knowledge, I focus on the "low-carbon energy" supply technologies.

Using the number of patents[19] related to green, fossil, and non-energy technologies, I

[18]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.

[19]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

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. Following the literature, I set the 5-year depreciation rate to $\delta = 0.55$.[20] 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.

sectors is equal on average.

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

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 to the values in Fried (2018): $\varepsilon_y = 0.05$. 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 $\tau_{F0} = 0$, accounting for the missing climate policy in the US under President Trump. The linear labor tax amounts to $\tau_{l0} = 0.42$ to satisfy the exogenous government budget constraint with observed government expenditures relative to GDP in 2015-2019.[21] 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 $\delta_y = 0.21$.[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

[21] The data comes from the Federal reserve Bank of St. Louis found here `https://fred.stlouisfed.org/series/W068RCQ027SBEA`

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

(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 $\alpha_G = 0.86$ 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: $K_{n0} = 63.60, K_{g0} = 100, K_{f0} = 125.38$ (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. 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 25%. 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

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

[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."

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 $\tau_{sG0} = 0.32$. That means that according to the model the observed high expenditures on fossil R&D are only rational under a net-subsidy on fossil R&D. 19 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 green sector is relatively backwards. Given the concave relationship between learning and total factor productivity, the green sector is more adversely affected by a reduction in overall labor supply.

The resulting relative importance of cross-sectoral knowledge spillovers is $\phi = 0.62$, a value slightly higher than counterparts found in the literature. 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.[26] Since they focus on the automotive industry and micro-level estimates, these estimates do not include spillovers across firms. Hart (2019) calibrates a value equivalent to $\phi = 0.1$, and Fried (2018) sets $\phi = 0.5$ based on theoretic considerations.[27] High cross-sectoral knowledge spillovers ensure that a balanced growth path exists. Which is also why too low cross-sectoral spillovers would cause unstable solutions in my model.

I find a value of $\eta = 0.41$. 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

[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 $\phi = 0.3124$.

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

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.Fried (2018) estimates $\eta = 0.79$. The higher 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 $\eta = 0.19$.[28]

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

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.[29] Information on

[28]Also 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).

[29]Because the model abstracts from CO_2 sources other than energy, I define the sink capacity as net

emissions comes from the US Environmental Protection Agency (EPA, 2022). The resulting sink capacity per model period (5 years) is $\delta = 3.19\text{GtCO}_2$.[30] To find the parameter relating CO_2 emissions from energy and fossil energy use in the model, I reduce the distance between 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.[31] 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 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 result from the level of fossil-fuels produced in the US. Emission intensity of fossil-fuel production is $\omega = 308.56$.

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).

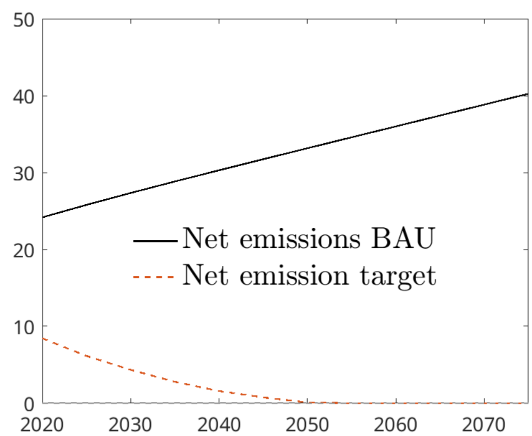
of emissions from agriculture and industry; i.e., matching total observed net emissions in the data: Net emissions=Energy +Industry+Agriculture-Natural sinks $\Leftrightarrow$ Net emissions=Energy -δ.

[30] 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.

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

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] I use projected population shares from the United Nations (2022). Figure 2 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 2: Emission target and net CO_2 emissions in model periods (5 years) under business as usual in gigatonnes



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% 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*

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

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.[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.

4 Results

This section presents the results. First, I present and discuss the results on the optimal allocation and policy in subsection 4.1 and compare them to the first-best allocation. Second, I discuss the optimal policy when carbon tax revenues are redistributed lump-sum in subsection 4.2.

4.1 Implementation of the emission target: The optimal fiscal mix

4.1.1 The ideal transition: Social planner allocation

The first thing to note is that the social planner completely exhausts admissible emissions; Figure 3a. This allows the economy to profit from very productive fossil energy and knowledge generation. This is efficient despite lock-in effects of fossil production through learning-by-doing and path-dependency of innovation.

Nevertheless, there is a strong rise in the share of green energy used in energy production; compare Figure 3b. To lower the costs of the transition, the efficient allocation of researchers changes to more green research and expertise. The economy builds up green relative to fossil knowledge which allows future green scientists to profit from a higher green knowledge stock.

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

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.

The reason is that 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.

4.1.2 Optimal allocation and policy

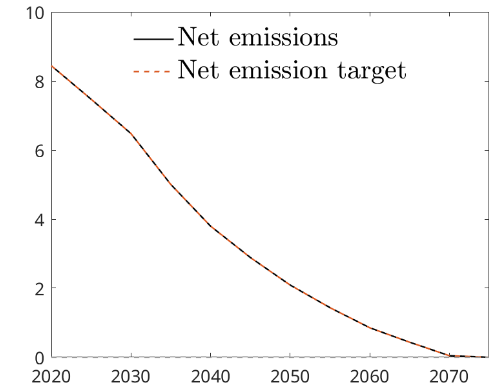
With the set of available instruments, carbon taxes, labor income taxes, and research subsidies the first-best allocation is infeasible given the spillovers from learning-by-doing even with lump-sum taxes.

Allocation Figure 4 shows the optimal allocation when lump-sum taxes are available and in the distortionary setting. In all cases, the optimal policy exactly implements the emission limit (Figure 4a) at a lower ratio of green-to-fossil energy (Figure 4b). The reason is that output is lower in the Ramsey allocation as the government lacks an instrument to target sector-specific output to foster learning. The lower output level allows to consume a higher fossil energy share.

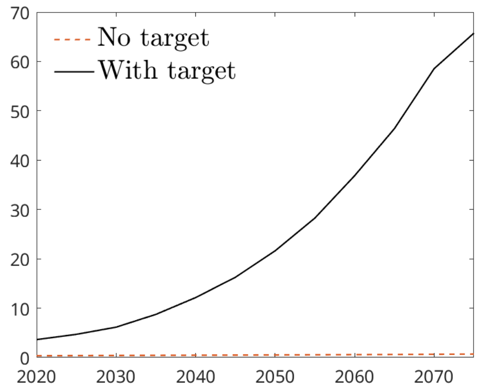
When distortionary fiscal policies have to fund the government, the gap between optimal and efficient allocation widens since tax instruments distort households' labor supply decisions further. The emission target is implemented at an even lower output level and higher fossil-to-green energy ratio. The gap between the first-best allocation and second-best widens over time.

Figure 3: Social planner's implementation of emission limit

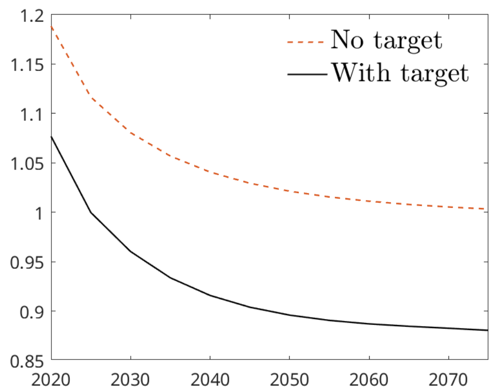
(a) Net emissions and target



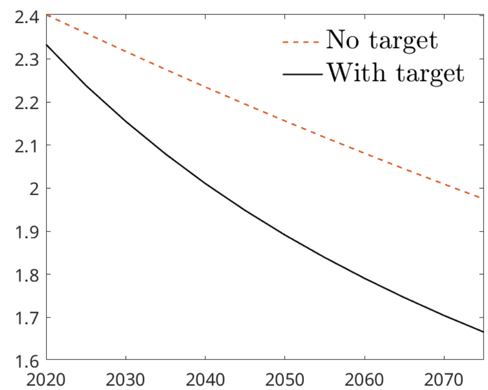
(b) Green-to-fossil energy



(c) Fossil-to-green scientists



(d) Fossil-to-green expertise

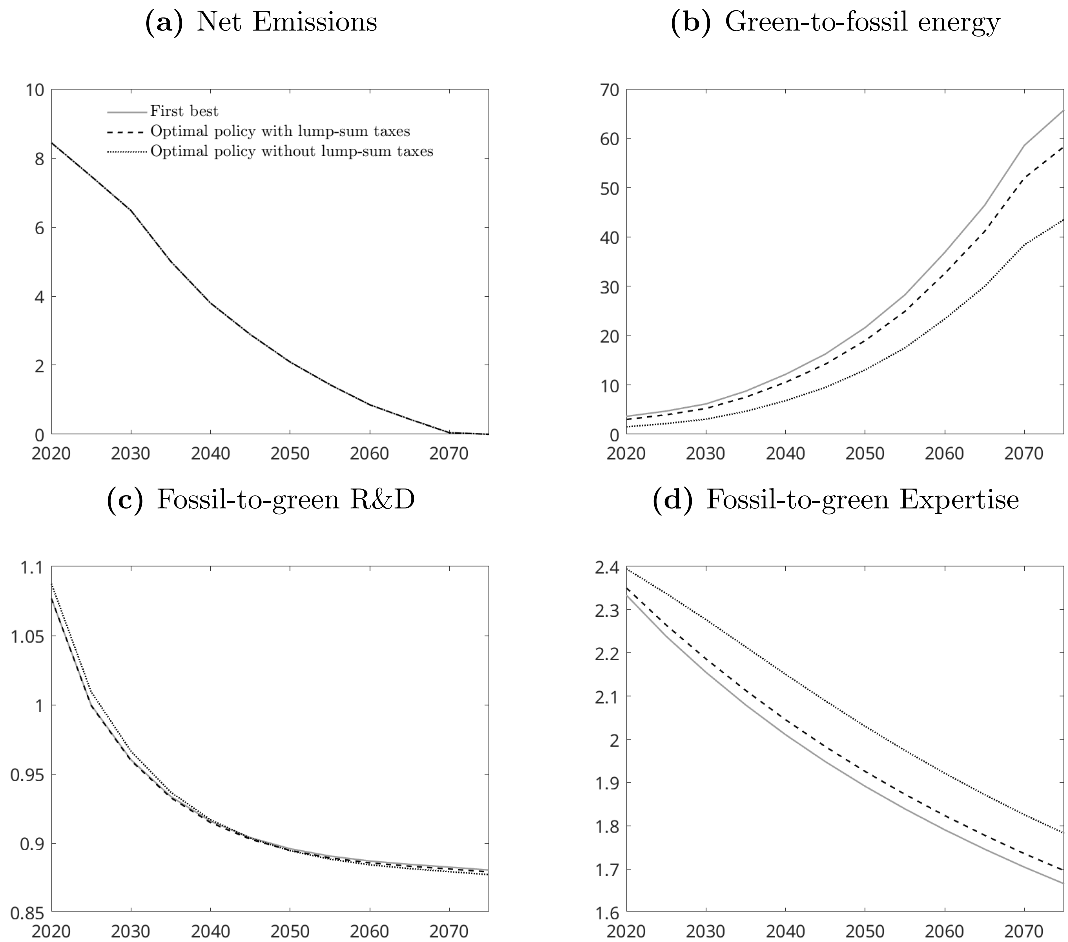


Notes: The x-axis indicates the first year of the 5-year period to which the variable value corresponds.

The allocation of researchers seems largely unaffected by the unavailability of lump-sum taxes (Figure 4c). This indicates that optimal research subsidies are chosen to counter the adverse effect of labor income taxes and lower green carbon taxes on green research. In contrast, expertise in the green sector declines which is mainly due to the lack of an adequate instrument. An additional decline arises from distortionary income taxes. This observation underscores the government's dilemma of a green transition: raising revenues directs learning efforts away from the green sector towards outdated fossil ones.

Optimal policy Figure 5 summarizes the optimal environmental policy. To discuss the optimal policy, I start by comparing the carbon tax to the social cost of carbon. This

Figure 4: Optimal allocation with joint budget



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

comparison is informative on how additional distortions form the optimal environmental policy beyond making energy producers internalize the social costs of using fossil energy. Figure 5a depicts the ratio of the carbon tax to the social cost of carbon.

In the baseline model with learning-by-doing, the optimal carbon tax raises above the social cost of carbon shortly after 2034, and continues to rise thereafter albeit slowly (black-solid graph in Figure 5a). When dropping learning-by-doing from the model, the carbon tax never exceeds th Pigouvian rate indicating that it is learning-by-doing which urges the planner to tax carbon massively. This logic also applies when lump-sum taxes are available: the carbon tax exceeds the Pigouvian rate by roughly 5 percent in all periods while it is exactly the same absent learning-by-doing (dashed versus solid line with asterisks).

In the early years of the transition, the carbon tax, however, is below the social costs of carbon, even though green expertise is too low, indicating that fiscal distortions are more important. As the economy grows and the tax base of the labor tax increases, fiscal constraints become less important and the additional distortionary effects of a higher carbon tax vanish.[34]

To focus the discussion of other policy instruments on the green transition, the following refers to changes in policy instruments relative to the non-target optimal policy measured in percentage points. Figure 5c illustrates the optimal adjustment of the labor income tax relative to its optimal level in the non-target optimal policy (solid graph). The labor income tax is reduced relative to the non-target value. Hence, carbon tax revenues are optimally used to lower the labor tax. It is the case that all carbon tax revenues are recycled in this way, and the level of transfers to households exactly matches the minimum transfers the government has to provide. This finding is analogous to the weak double dividend result from the literature that looks at exogenous financing constraints. In section subsection 4.2, I quantify the costs of a green transition rebating carbon tax revenues lump-sum relative to the joint budget.

Learning-by-doing makes a stronger reduction in the labor tax optimal (Figure 5c). Thus, the optimal fiscal mix features a higher carbon tax and a lower labor tax to boost learning-by-doing in the green sector. This adjustement in the fiscal mix becomes relevant to adjust the change in research subsidies.

The optimal environmental policy features a subsidy on fossil research throughout the transition (again measured as change relative to the no-target optimal policy in percentage points). The fossil research subsidy is a by-product of the carbon tax. Implementing the emission target requires a massive tax on carbon to redirect demand to green energy. Such a high tax also fosters a reallocation of researchers towards green technologies. This additional

[34] An equally rising pattern is visible from the optimal carbon tax absent learning-by-doing affirming this interpretation.

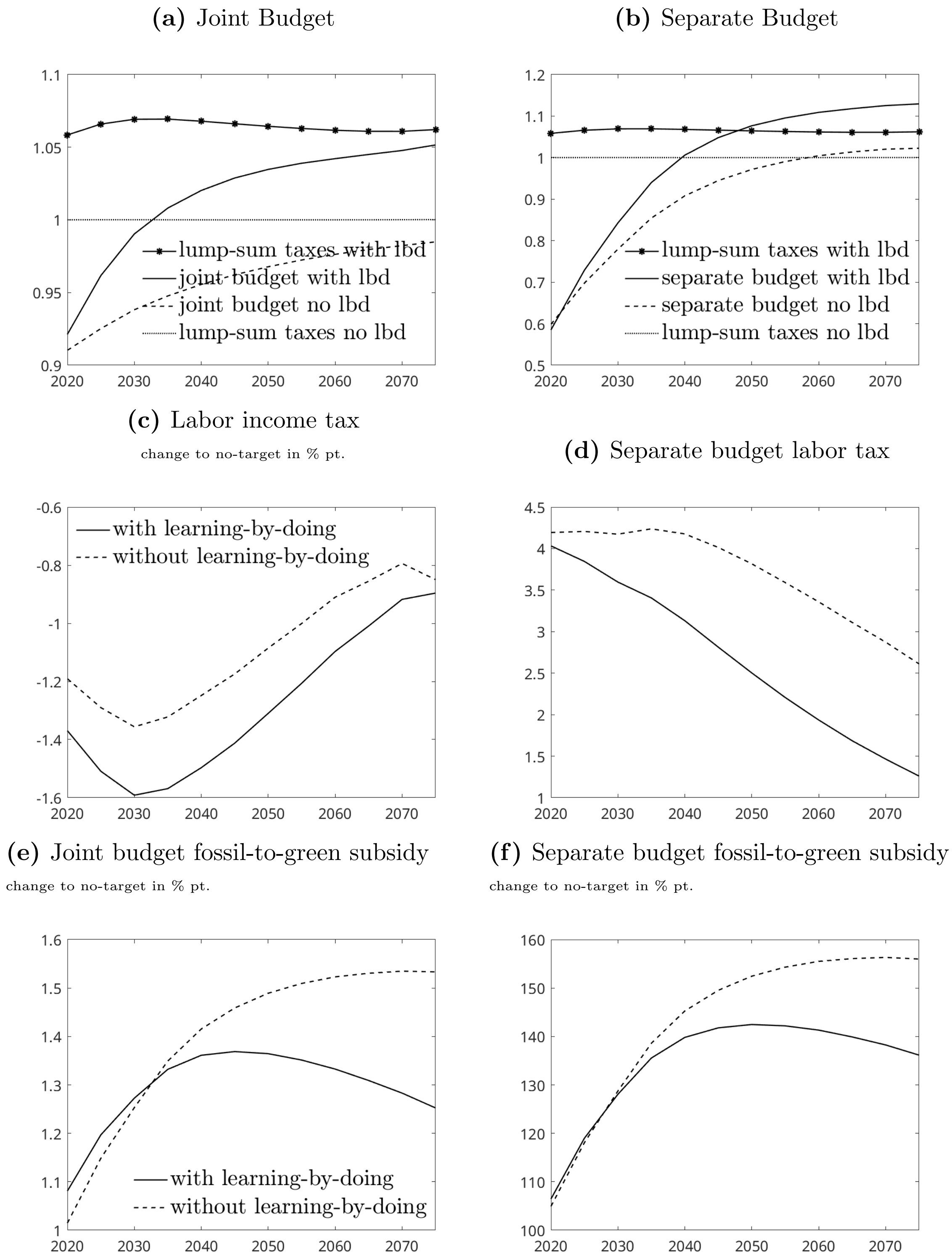
contribution of the carbon tax, on the one hand, makes a smaller carbon tax necessary to implement a target (Fried, 2018). However, given the strength of the intervention and that knowledge spillovers allow fossil knowledge to remain valuable in a green future call for a smoother reallocation of researchers than what the necessary carbon tax would implement. As shown by Figure 4c, a smooth transition to green research is optimal. As a result, the optimal carbon tax is best accompanied with a net-subsidy on fossil-based R&D. This result suggests that it is not the case that green subsidies are more important than carbon taxes to implement a green transition. To the contrary, the carbon tax is so important to implement the emission target that green research would grow too quickly in light of stepping-on-toes effects and cross-sectoral knowledge spillovers.

Carbon tax revenues are optimally used to finance research subsidies as opposed to redistributing them lump-sum: under the baseline fiscal regime with a joint budget, the optimal level of transfers exactly meets the minimum level of transfers the government has to finance. This finding is analogous to the weak double dividend result from the literature. Recycling carbon tax revenues as lump-sum transfers would lower the tax base for the income tax thereby aggravating distortions to generate funds. This finding becomes even more apparent when studying a more restrictive fiscal regime in which carbon tax revenues are redistributed lump-sum. The next section discusses the optimal policy and compares the costs of a transition under the two regimes.

4.2 Comparison of regimes and welfare analysis

The optimal policy under a *separate budget* regime, that is, with carbon tax revenues being redistributed lump sum, is depicted in the right-hand column of Figure 5. What stands out is that the carbon tax exceeds the Pigouvian tax more under the distortionary regime than with lump-sum taxes (solid and graph with asterisks in Figure 5b). This finding is surprising since carbon tax revenues are not an additional source of government revenues. In contrast, a higher carbon tax intensifies fiscal distortions. The excessively high carbon

Figure 5: Optimal Policy



tax originates (i) from lower learning in the green sector due to a higher labor tax, and (ii) from the difficulty to finance research subsidies. The latter urges the planner to cut back on the amount spent on research subsidies which in turn means that the optimal allocation of researchers between energy (fossil and green) and non-energy cannot be achieved.[35] This interpretation that solely focuses on research is supported by the carbon tax in the model without learning-by-doing without lump-sum taxes, which rises above unity in the long run. In the short run, though, the optimal carbon tax deviates more negatively from the social costs of carbon due to the tighter government budget.

Finally, I calculate the costs of running a separate budget as opposed to a joint budget, i.e., the baseline regime. More precisely, I compare the costs of implementing the emission target under the separate and the joint budget regime measured in consumption equivalence variation.[36] The green transition costs 4.8% under the joint budget and 5.9% under a separate budget; a gain of 23% of financing the green transition in a distortionary fiscal setting with a joint budget.

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 fiscal environment.

In this paper, I depart from the assumption of the feasibility of lump-sum taxes to finance research subsides and government expenditures in general. 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

[35]This result is due to the choice to normalize subsidies on the non-energy sector. A way to model research subsidies more symmetrically would be to allow for a subsidy in all sectors and constraining them at zero.

[36]This measure is informative on the welfare costs of the green transition. It measures the percentage change in life-time consumption the representative household requires to be compensated for the green transition. Importantly, the two regimes deviate only negligibly in terms of welfare under the non-target optimal policy. Households value a joint budget equivalently to a 0.002% rise in lifetime consumption above a separate budget.

learning to work with new green technologies is crucial. On the other hand, a higher carbon tax would entail more green learning and research.

In my model, the optimal carbon tax exceeds the social cost of carbon because it also corrects for dynamic inefficiencies arising from underinvestment in green technologies. But only in the long run, when fiscal constraints loosen due to productivity growth. The labor tax is lowered to avoid disproportionately low expertise in the green sector.

Redistributing carbon tax revenues lump-sum instead of using them to lower labor taxes raises the costs of a green transition measured in consumption equivalence variation by 23 percent. To set this number into context, the presented model abstracts from important aspects that determine the optimal use of carbon tax revenues. Recent work integrating inequality into the analysis find that some lump-sum redistribution of carbon tax revenues is optimal.[37]

[37] See for instance Douenne et al. (2022).

References

Acemoglu, D., Aghion, P., Bursztyn, L., and Hemous, D. (2012). The environment and directed technical change. American Economic Review, 102(1):131–166.

Acemoglu, D., Akcigit, U., Hanley, D., and Kerr, W. (2016). Transition to Clean Technology. Journal of Political Economy.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R., and Van Reenen, J. (2016). Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry. Journal of Political Economy, 124(1).

Barrage, L. (2020). Optimal Dynamic Carbon Taxes in a Climate-Economy Model with Distortionary Fiscal Policy. Review of Economic Studies, 124(2):1–39.

Bovenberg, A. L. and De Mooij, R. A. (1994). Environmental Levies and Distortionary Taxation. American Economic Review, 84(4):1085–1089.

Bovenberg, A. L. and Goulder, L. H. (2002). Environmental Taxation and Regulation. In Auerbach, A. J. and Feldstein, M., editors, Handbook of Public Economics, volume 3, chapter 23, pages 1471–1545. Elsevier Science B.V.

Carattini, S., Carvalho, M., and Fankhauser, S. (2018). Overcoming public resistance to carbon taxes. WIREs Climate Change, 9(5):e531.

Carbone, J. C., Morgenstern, R. D., Williams III, R. C., and Burtraw, D. (2013). Deficit Reduction and Carbon Taxes: Budgetary, Economic, and Distributional Impacts. Technical report, Resources for the Future.

Chetty, R., Guren, A., Manoli, D., and Weber, A. (2011). Are micro and macro labor supply elasticities consistent? A review of evidence on the intensive and extensive margins. American Economic Review, 101(3):471–475.

Conesa, J. C., Kitao, S., and Krueger, D. (2009). Taxing capital? not a bad idea after all! American Economic Review, 99(1):25–48.

Dasgupta, P. (2021). The Economics of Biodiversity: The Dasgupta Review. Technical report, London: HM Treasury.

Domeij, D. and Heathcote, J. (2004). On the Distributional Effects of Reducing Capital Taxes. International Economic Review, 45(2):523–554.

Douenne, T., Hummel, J. A., and Pedroni, M. (2022). Optimal Fiscal Policy in a Climate-Economy Model with Heterogeneous Households.

Fischer, C. and Newell, R. G. (2008). Environmental and technology policies for climate mitigation. Journal of Environmental Economics and Management, 55(2):142–162.

Fried, S. (2018). Climate policy and innovation: A quantitative macroeconomic analysis. American Economic Journal: Macroeconomics, 10(1):90–118.

Fried, S., Novan, K., and Peterman, W. B. (2018). The distributional effects of a carbon tax on current and future generations. Review of Economic Dynamics, 30:30–46.

Goulder, L. H. (1995). Environmental Taxation and the Double Dividend: A Reader's Guide. International Tax and Public Finance, 2:157–183.

Goulder, L. H., Hafstead, M. A. C., Kim, G., and Long, X. (2019). Impacts of a carbon tax across US household income groups: What are the equity-efficiency trade-offs? Journal of Public Economics, 175:44–64.

Hart, R. (2019). To Everything There Is a Season: Carbon Pricing, Research Subsidies, and the Transition to Fossil-Free Energy. The Association of Environmental and Resource Economists, 6:135–175.

Hassler, J., Krusell, P., and Smith, A. A. (2016). Environmental Macroeconomics. In Handbook of Macroeconomics, volume 2, pages 1893–2008. Elsevier B.V.

Heathcote, J., Storesletten, K., and Violante, G. L. (2017). Optimal tax progressivity: An analytical framework. Quarterly Journal of Economics, 132(4):1693–1754.

Hémous, D. and Olsen, M. (2021). Directed Technical Change in Labor and Environmental Economics. Annual Review of Economics, 13:571–597.

IPCC (2022). *Climate Change 2022: Mitigation of Climate Change. Contribution of Working Group III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* [P.R. Shukla, J. Skea, R. Slade, A. Al Khourdajie, R. van Diemen, D. McCollum, M. Pathak, S. Some, P. Vyas, R. Fradera, M. Belkacemi, A. Hasija, G. Lisboa, S. Luz, J. Malley, (eds.)]. Cambridge University Press, Cambridge, UK and New York, NY, USA. doi:10.1017/9781009157926.

Jacobs, B. and van der Ploeg, F. (2019). Redistribution and pollution taxes with non-linear Engel curves. Journal of Environmental Economics and Management, 95:198–226.

Jones, C. I. and Williams, J. C. (1998). Measuring the Social Return to R&D. The Quarterly Journal of Economics, 113(4):1119–1135.

Jones, L. E., Manuelli, R. E., and Rossi, P. E. (1993). Optimal Taxation in Models of Endogenous Growth. Journal of Political Economy, 101(3):485–517.

Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. Quarterly Journal of Economics, 132(2):665–712.

Kotlikoff, L., Kubler, F., Polbin, A., Sachs, J., and Scheidegger, S. (2021). Making Carbon Taxation a Generational Win Win. International Economic Review, 62(1):3–46.

Loebbing, J. (2019). National Tax Association Redistributive Income Taxation with Directed Technical Change. 112:1–97.

Noailly, J. and Smeets, R. (2015). Directing technical change from fossil-fuel to renewable energy innovation: An application using firm-level patent data. Journal of Environmental Economics and Management, 72:15–37.

OECD (2021). Average annual hours actually worked per worker. https://stats.oecd.org/Index.aspx?DataSetCode=ANHRS, (Accessed on 11 February 2021).

Papageorgiou, C., Saam, M., and Schulte, P. (2017). Substitution between Clean and Dirty Energy Inputs: A macroeconomic perspective. The Review of Economics and Statistics, 99(2):281–290.

Robiou Du Pont, Y., Jeffery, M. L., Gütschow, J., Rogelj, J., Christoff, P., and Meinshausen, M. (2017). Equitable mitigation to achieve the Paris Agreement goals. Nature Climate Change, 7(1):38–43.

United Nations Department of Economic and Social Affairs, Population Division (United Nations) (2022). World Population Prospects: The 2022 Revision. https://population.un.org/dataportal/data/indicators/49/locations/900,840/start/2010/end/2100/table/pivotbylocation (Accessed on 04 August 2022).

United States Environmental Protection Agency (EPA) (2022). Trends in Greenhouse Gas Emissions. https://nepis.epa.gov/Exe/ZyPDF.cgi/P1011XV3.PDF?Dockey=P1011XV3.PDF (Accessed on 02 February 2022).

US Energy Information Administration (EIA) (2023). Monthly Energy Review August 2023. https://www.eia.gov/totalenergy/data/monthly/, (Accessed on 06 September 2023).

van der Ploeg, F., Rezai, A., and Tovar Reanos, M. (2022). Gathering support for green tax reform: Evidence from german household surveys. European Economic Review, 141:103966.

Van der Wijst, K., Byers, E., Riahi, K., Schaeffer, R., and Van Vuuren, D. (2023). Data for Figure SPM.5 of Summary for Policymakers of the Synthesis report of the Sixth Assessment Report, MetadataWorks.

Wiskich, A. (2021). A comment on innovation with multiple equilibria and “The environment and directed technical change”. Energy Economics, 94.

World Commission on Environment and Development (1987). *Our Common Future*. New York: Oxford University Press.

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.[38] 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

[38] 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

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

D Results

This section presents additional results. Figure 6 confirms that without learning-by-doing the labor income tax only affects the level of production leaving the ratio of green-to-fossil energy use and R&D spending unchanged.

Figure 6: Effect of a Labor income tax on the allocation of research: Distinct Parameters

Without Learning-by-doing

(a) Green-to-fossil energy ratio **(b)** Fossil-to-green R&D