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Mads Greaker, Tom-Reiel Heggedal and Knut Einar Rosendahl

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Mads Greaker, Tom-Reiel Heggedal and Knut Einar Rosendahl

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Abstract:
The "resource curse" is a potential threat to all countries relying on export income from abundant natural resources such as fossil fuels. The early literature hypothesized that easily accessible natural resources would lead to lack of technological progress. In this article we instead propose that abundance of fossil fuels can lead to the wrong type of technological progress. In order to inquire into our research question, we build a model of a small, open economy having specialized in export of fossil fuels. R&D in fossil fuel extraction technology competes with R&D in clean energy technologies. Moreover, technological progress is path dependent as current R&D within a technology type depends on past R&D within the same type. Finally, global climate policy may reduce the future value of fossil fuel export. We find that global climate policy may either lead to a resource curse or help the country escaping a potential resource curse. The ripeness of the clean energy technologies is essential for the outcomes: If the clean technology level is not too far beyond the fossil fuel technology, a shift to exporting clean energy is optimal independent of global climate policy and climate policy can accelerate this shift. While if the clean technology is far behind, a shift should only happen as a response to global climate policy, and the government should intervene to accelerate this shift.

Keywords: O30, O31, O33

JEL classification: Environment; Directed technological change; Innovation policy; Resource curse

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Address: Mads Greaker, Statistics Norway and OsloMet. E-mail: madsg@oslomet.no

Tom-Reiel Heggedal, BI, E-mail: Tom-Reiel.Heggedal@bi.no

Knut Einar Rosendahl, Statistics Norway and NMBU,
E-mail: knut.einar.rosendahl@nmbu.no

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Sammendrag

Ressursforbannelse er en potensiell trussel for alle land som baserer seg på eksportinntekter fra store mengder naturressurser slik som fossile brensler. Tidlig økonomisk litteratur kom fram til at lett tilgjengelige naturressurser ville lede til mangel på teknologisk framgang. I denne artikkelen undersøker vi om stor tilgang på fossile brensler kan føre til feil type teknologisk framgang. For å undersøke dette bygger vi en modell for en liten åpen økonomi som har spesialisert seg i eksport av fossile brensler. FoU innen teknologier for utvinning av fossile brensler konkurrerer med FoU innen klimavennlige energiteknologier. Vi legger til grunn at teknologisk framgang er stiavhengig, som betyr at dagens FoU innen en type teknologi bygger på tidligere FoU innen samme teknologitype. Vi antar også at global klimapolitikk kan redusere den framtidige verdien av eksport av fossile brensler.

Vi finner at global klimapolitikk kan føre til enten en ressursforbannelse eller hjelpe landet til å unngå en potensiell ressursforbannelse. Utfallet avhenger ikke minst av hvor utviklet den klimavennlige energiteknologien er. Hvis denne teknologien ikke er altfor langt bak den fossile teknologien, vil et skifte til eksport av klimavennlig energi være optimalt uavhengig av global klimapolitikk, men klimapolitikk kan akselerere skiftet. Hvis derimot den klimavennlige energiteknologien er langt bak den fossile, er det optimalt å skifte kun ved en global klimapolitikk, og myndighetene bør gripe inn for å framskynde skiftet.

1 Introduction

Many countries with abundant natural resources experience lower economic growth than countries with little or no natural resources. In the economics literature this is referred to as the "resource curse". Recent articles in this literature attribute the curse to political failures (Robinson et al. 2014), while previous literature hypothesized that easily accessible natural resources providing export income would lead to lack of technological progress (van der Ploeg, 2011). In this article we revisit the early explanations for the resource curse, but instead of explaining the curse by lack of technological progress, we investigate whether resource abundance can lead to the *wrong type* of technological progress.

Our focus is on countries having abundant fossil fuel resources providing them with a generous export income. Using fossil fuels to produce energy in any form implies greenhouse gas (GHG) emissions. The Paris agreement sets an ambitious target for the global reduction of GHG emissions, and a large share of discovered fossil fuel resources needs to be left in the ground (Welsby et al, 2021). Most countries, apart from the EU block, have so far been reluctant to implement ambitious climate policies, and hence, we have not yet seen a climate policy induced slump in global fossil fuel prices. This could, however, occur later in this or the next decade as the evidence for climate change caused by GHG emissions accumulates.

Although the current postponement of more stringent climate policies implies that fossil fuel exporting countries can continue to profit from their fossil fuel extraction, their prosperity may actually be hampered in the longer run. Recent economic theory has hypothesized that technological change within energy technologies may be path dependent (Acemoglu et al., 2012). Path dependency can only happen if there are separate innovation systems for clean and dirty energy technologies, see e.g. Greaker et al. (2018) which interprets "dirty technologies" as all technologies related to the extraction and usage of fossil fuels. A natural question thus arises: Will innovation markets in countries with fossil fuel resources induce a switch away from fossil fuel technologies to clean technologies in time, or will innovators' choices be locked in by history and result in a resource curse?

In order to shed light on this question, we build a model of an open economy having specialized in fossil fuel exports to an exogenous global price. In our model, even though fossil fuels are non-renewable resources, the country can continue exporting fossil fuels as long as it devotes enough resources to research and development (R&D) making fossil fuel extraction from more costly deposits profitable. In the business as usual scenario (BaU), the government only enacts a neutral R&D policy and does not tax fossil fuel extraction. On the contrary, in the optimal policy scenario, the government may use both an extraction tax and a directed subsidy to either clean or dirty innovation.

We first solve the model analytically. The relevant question when analyzing optimal subsides towards either of the two research sectors is how the market's valuation of clean versus dirty innovation evolves relative to the planner's valuation. We show that the optimal allocation of researchers depends on a *technology effect* and a *price effect*. The technology effect is treated in the earlier literature. Since the social value of the positive knowledge externality is larger when a certain technology is being more used in the future, R&D within this technology should be subsidized more (Gerlagh et al., 2014; Greaker et al., 2018). Hence, if clean technologies will be relatively more used in the future, the technology effect suggests giving a directed R&D subsidy to clean R&D.

The price effect is the isolated effect of fossil fuel prices on optimal R&D subsides. The effect was also present in the earlier literature, but by assuming that the fossil fuel price is exogenous to the economy under study, we can scrutinize the impact of price movements further. Clearly, since scientists discount the future harder than the planner, future changes in fossil fuel prices will not be properly taken into account by the scientists (in our model patent life-time is finite). Thus, we find that if fossil fuel prices fall with a constant rate or a higher rate in the future than today, the optimal R&D subsidies to clean technologies should be increased. Moreover, taken together the *technology effect* and the *price effect* could lead to a resource curse type of outcome if the R&D policy stays neutral.

Finally, as shown by Heal (1976), extraction paths are likely to be forward biased when extraction costs depend positively on accumulated extraction, i.e., there is too much extraction in early periods of the lifetime of the resource. Our model shares this feature, and a failure to correct for this dynamic cost-externality decreases the net present value of the resource sector. The dynamic cost-externality also implies that too many researchers are allocated to dirty energy research early along the extraction path. Thus, we find that introducing an extraction tax lowers the need for a dedicated R&D subsidy.

To complement our theoretical findings, we provide several numerical illustrations based on our model, comparing the BaU scenario with both first and second best policy scenarios. Depending on the future development in fossil fuel prices (influenced by global climate policy) and the current state of the clean technology alternative, the small, open economy may evolve according to the following three types of outcomes:

I Steady course: No intervention in redirecting R&D is needed since global climate policy stays weak and the initial gap between dirty and clean technology productivity is large.

II Resource curse due to global climate policy: R&D should be redirected since researchers do not sufficiently take into account the effects of future climate policy on fossil fuel prices.

III Resource curse with no global climate policy: R&D should be redirected even if fossil fuel prices stay constant, due to better prospects for clean technology.

Note that in II and III the government can improve the outcome by offering directed subsidies to clean R&D. Moreover, since extraction paths are forward biased, the R&D subsidy to clean R&D in these outcomes should be higher without an extraction tax. On the other hand, in our model simulations the extraction tax alone does too little to redirect R&D towards the clean sector.

The rest of the paper is laid out as follows: In the next section we briefly review the relevant literature. Then in Section 3 we present and solve the model for the *laissez fair* (BaU) solution. This solution is compared to the socially optimal solution in Section 4. Our results are then illustrated by a numerical example in Section 5. Finally, in Section 6 we conclude.

2 Literature

Our paper relates to the so-called "resource curse" literature which informs us that when a country is endowed with a valuable and tradable resource, the country may experience low or even negative economic growth. As mentioned in the introduction, several explanations for the resource curse have been discussed in the literature (e.g., van der Ploeg (2011); Robinson et al (2014)). In particular, the earlier literature emphasized lack of technological progress due to a down scaling of the traded good sector in which most of the technological progress happened (van der Ploeg, 2011).

In our paper, harvesting the resource requires a high level of technological skills. However, since technological change is directed, the country may be locked into developing a technology with poor possibilities in the future.

The literature on directed technological change and the environment is steadily expanding. Several papers modify and simulate the model from Acemoglu et al. (2012), though in different directions and analyzing other problems than in the present paper: Hourcade, Pottier, and Espagne (2011) discuss parameter choices related to the climate part of the model; Mattauch, Creutzig, and Edenhofer (2015) add learning-by-doing effects to the framework; Durmaz and Schroyen (2020) extend the model by adding abatement technology (carbon capture and storage); André and Smulders (2014) have either energy-saving R&D or labor-saving R&D; Hémous (2013) and van den Bijgaart (2015) extend the model to include more than one country and analyze unilateral environmental policies in a global context; Acemoglu, Akcigit, Hanley, and Kerr (2016) assume that clean and dirty machines within a product line are perfect substitutes, and hence a new clean machine must in most cases outcompete the dirty machine within the same product line, which only happens rarely; and finally Hart (2019) introduces deadweight losses from R&D subsidies.

In a more recent contribution, Lemoine (2020) studies whether a technological shift will happen by itself or whether the economy is locked-in to a certain technology for ever. Lemoine finds that this depends on the elasticity of substitution between resources and capital in the intermediate energy services production function. We consider the same question, but focus on whether global climate policy can induce a shift in due time.

Apart from Acemoglu et al (2012), none of the above mentioned papers include extraction of a non-renewable resource. And even more importantly for our contribution, none of the papers explore the implication of directed technical change for an open economy having specialized in export of a non-renewable resource. We are thus able to investigate the interplay between a possible cost externality in extraction with the knowledge externality in research. Such an investigation is to our knowledge new to the literature.

Hassler et al (2021) do consider non-renewable resources in a model with directed technical change, but they do not include a clean technology and hence deviate more from the literature building on Acemoglu et al (2012), where our paper belongs. They show that R&D effort will be allocated by the market, improving the effciency of resource use when the resource becomes scarce.

The same happens in our model; R&D can make up for higher prices of the resource, however, as there exists an alternative technolgical development path in our model economy, devoting more and more R&D effort to a dwindling non-renewable resource may be sub-optimal.

A key assumption in models of directed technical change is that innovation is path (state) dependent. A new innovation builds on past quality within a field and increases the productivity of future innovations within the same field. Aghion, Dechezlepretre, Hemous, Martin, and Van Reenen (2016) analyze clean and dirty technologies in the automotive industry. By using patent citations they find evidence for separate innovation systems within clean and dirty technologies. Further, they find that the productivity of innovation within a field depends positively on the accumulated innovation within the same field.

In most models of directed technical change, research opportunities in dirty and clean technologies are identical. Thus, the standing on shoulders effect dominates such that research in one area becomes ever more potent when knowledge accumulates. Popp et al. (2013), however, find that research opportunities in any one area of research may dry out. That is, the best ideas are taken first, and later ideas improve the state of the technology to a lesser degree. In the literature this is referred to as *fishing out*, see, e.g., Greaker and Pade (2009). Clearly, if *fishing out* occurs, path dependency may be less likely. Dechezleprêtre, Martin, and Mohnen (2013) find based on a patent citation analysis that spillovers are larger in clean than dirty technologies. The driving force behind the result seems to be that clean technologies are newer technologies than dirty, and that a new technology field has larger spillovers than an old technology field.

3 The model

3.1 Preliminaries

We set up an infinite-horizon, discrete-time, open-economy model with directed technical change and natural resources. We focus on the energy sector, and do not model other sectors of the economy. In each period t, the country in question produces dirty energy Y_{dt} based on extraction of fossil fuels and clean energy Y_{ct} from different kinds of renewable resources. Furthermore, we assume that the two types of energy (denoted by $j = d, c$) are freely traded, and that the country faces exogenous world market prices on the dirty and the clean energy good, P_{dt} and P_{ct}, respectively.

Consequently, the decision on how much to consume and how much to produce of the two energy goods are effectively separated. Furthermore, this implies that national wealth in our stripped down model is synonymous with the current net value of future energy production, and thus in our analysis we only focus on the production side. First, we start out by describing the *laissez faire* solution.

3.2 Production of the energy goods

In order to produce the two types of energy goods j, the open economy at time t uses machine variants i of different qualities A_{jit} in the amount x_{jit}, and natural resources R_{jt}. The production function is given by:[1]

$$Y_{jt} = R_{jt}^{\alpha_2} \int_0^1 A_{jit}^{1-\alpha_1} x_{jit}^{\alpha_1} di, \tag{1}$$

where α_1 and α_2 are parameters. Within each time period, we assume that there is decreasing returns to scale in energy goods production, and hence, $\alpha_1 + \alpha_2 < 1$. Every time a new innovation is made in one of the sectors, one particular machine type i is replaced by a better machine of the same type. The innovation is drastic, implying the older version of the machine type is no longer used in the market.

Production of dirty energy is based on fossil fuel resources of different accessibility. We assume that the most accessible resources are developed first, and hence, the unit extraction cost c_{dt} will tend to increase in accumulated extraction. Production of clean energy on the other hand, is based on setting aside dedicated areas (onshore, offshore and/or below ground), which is assumed to be in abundant supply and have constant unit costs $c_{ct} = \bar{c}$. The profits π_{jt} in each of the sectors are then given by:

$$\pi_{jt} = P_{jt} R_{jt}^{\alpha_2} \int_0^1 A_{jit}^{1-\alpha_1} x_{jit}^{\alpha_1} di - \int_0^1 p_{jit} x_{jit} di - (c_{jt} + \tau_{jt}) R_{jt}, \tag{2}$$

where p_{jit} is the price of machine type i , c_{jt} is the unit resource costs, and τ_{jt} is a potential extraction tax, which (if imposed) reflects the fossil resource constraint with the corresponding

[1] Without loss of generality, we disregard labour input in energy production.

scarcity rent μ_{jt}.[2] The representative producer maximizes profits π_{jt} with respect to R_{jt} and x_{jit}. The first order condition with respect to the optimal use of the resources is given by:

$$\alpha_2 P_{jt} R_{jt}^{\alpha_2 - 1} \int_0^1 A_{jit}^{1-\alpha_1} x_{jit}^{\alpha_1} di - c_{jt} - \tau_{jt} = 0, \tag{3}$$

yielding the resource use on reduced form:

$$R_{jt} = \left(\frac{\alpha_2 P_{jt} \int_0^1 A_{jit}^{1-\alpha_1} x_{jit}^{\alpha_1} di}{c_{jt} + \tau_{jt}} \right)^{\frac{1}{1-\alpha_2}}. \tag{4}$$

Or alternatively, using the definition of Y_{jt}, the resorce use can be written:

$$R_{jt} = \frac{\alpha_2 P_{jt} Y_{jt}}{c_{jt} + \tau_{jt}}. \tag{5}$$

In the BaU scenario we have $\tau_{jt} = 0 \ \forall t$. Note that higher unit extraction costs c_t will decrease the resource use, while higher average machine quality A_{jt} will increase it. That is, new innovations increase how much energy can be produced from a resource at a given cost.

As mentioned above, we assume that the unit extraction cost for the fossil resources c_{dt} is increasing in the accumulated amount of resources already extracted (there is no physical limit to the amount that can be extracted):

$$c_{dt} = c(Q_t),$$

where Q_t is accumulated extraction at time t ($Q_0 = 0$), and $c' > 0$, $c'' > 0$.[3] We assume that firms in the dirty sector do not take into account the development in c_{dt} when maximizing profits, for instance, because they do not have property rights of the resources but can apply for concessions issued by the government and have to start their activity within a certain time.[4]

In an alternative setting, we assume that firms face an extraction tax τ_{dt}, in which case the effective private cost per unit extracted is $c_{dt} + \tau_{dt}$. As indicated above, the extraction tax may be set equal to the scarcity rent μ_{dt}, which develops according to:

[2] Note that since $c_{ct} = \bar{c}$ and $\mu_{ct} = 0$ for all t, we set $\tau_{ct} = 0$ for all t.
[3] In the simulations later we use $c_{dt} = c_0(1 + \phi Q_t^2)$ where ϕ is a parameter.
[4] For more on our modelling of extraction, see the discussion section.

$$\mu_{dt} = (1+r)\mu_{dt-1} - c'(Q_t)R_{dt},$$

with $lim_{t\rightarrow\inf}(1+r)^{-t}\mu_{dt}Q_t = 0$, where r is the per period discount rate. The extraction tax τ_{jt} then would reflect that higher extraction today increases extraction costs in future periods.

Next, the first order condition with respect to the optimal use of machines is given by:

$$\alpha_1 P_{jt} R_{jt}^{\alpha_2} A_{jit}^{1-\alpha_1} x_{jit}^{\alpha_1 - 1} - p_{jit} = 0, \tag{6}$$

Rearranging (6) yields the demand function for machines in both sectors:

$$x_{jit} = \left(\frac{\alpha_1 P_{jt} R_{jt}^{\alpha_2}}{p_{jit}}\right)^{\frac{1}{1-\alpha_1}} A_{jit.} \tag{7}$$

The machine producers have a monpoly on their machine type i and maxmize profit with point of departure in (7). Lastly, note that the government may tax π_{jt} without changing the first order conditions (3) and (6). Resource rent taxation is however beyond the scope of the paper.

3.3 Supply of machines

A domestic producer with the highest quality machine type ji is in effect a monopolist and solves:

$$\max_{p_{jit}}[(p_{jit} - \psi(1-\sigma))x_{jit}], \tag{8}$$

where demand x_{jit} is given by (7) above, ψ is the unit cost of a machine, and σ is a subsidy to correct for the static monopoly distortion. The problem (8) yields:

$$p_{jit} = \frac{\psi(1-\sigma)}{\alpha_1} \tag{9}$$

Without loss of generality, costs are normalized to $\psi = \alpha_1^2$ (cf. Acemoglu et al., 2012), and the efficient subsidy rate that gives price equal to marginal cost is then $\sigma = 1 - \alpha_1$, which we assume is implemented for both machine types. The profit maximizing price on machines is then $p_{jit} = \psi = \alpha_1^2$. Inserting back into (8), we have: $\pi_{jit} = \alpha_1^2(1-\alpha_1)x_{jit}$. Further, using (7), we obtain for the per period profit π_{jit} of a machine producer:

$$\pi_{jit} = \bar{\alpha} \left(P_{jt} R_{jt}^{\alpha_2} \right)^{\frac{1}{1-\alpha_1}} A_{jit.}, \tag{10}$$

where $\bar{\alpha} = (1 - \alpha_1)\, \alpha_1^{\frac{1-2\alpha_1}{1-\alpha_1}}$.

3.4 Innovation and allocation of scientists

Average machine quality increases both due to successful innovation by domestic scientists and the arrival of foreign innovations. When a new innovation is made or imported of machine type i, A_{jit} bumps up to $(1+\gamma)A_{jit}$, where γ is the quality step.

We normalize the number of domestic scientists to one:

$$\ell_{ct} + \ell_{dt} = 1 \tag{11}$$

where the mass of scientists in one sector is given by ℓ_{jt}. A scientist can choose sector, but not target a specific machine type; instead a scientist is randomly allocated to a machine type in the specific sector. Thus, the scientist makes her decision based on the average machine quality in sector A_{jt} which is given by:

$$A_{jt} \equiv \int_0^1 A_{jit} di. \tag{12}$$

A scientist engaged in innovation in sector j then expects a quality $(1+\gamma)A_{jt}$ upon successful innovation. Further, we assume that there may be duplication by other scientists, i.e. more than one scientist may have the same successful innovation in a given period. We let the duplication effect be represented by decreasing returns to labor input on aggregate sector innovation given by the function $\ell_{jt}^{\varpi}$where $\varpi \in (0,1)$.[5] The probability of a successful domestic innovation in sector j is then given by $\eta_j \ell_{jt}^{\varpi}$, where η_j is a parameter.

Foreign innovations in sector j arrive with probability ν_j. The average quality of the machine types then develops according to:

[5] Jones and Williams (2000) refer to this as a *stepping on toes effect.*

$$A_{j,t} = \left(1 + (\eta_j \ell_{jt}^{\varpi} + \nu_j)\gamma\right) A_{jt-1}. \tag{13}$$

We will not analyze the effect of forreign innovation v_j analytically, but return to this in the numerical simulations. Moreover, we follow Acemoglu et al. (2012) and assume that scientists only earn profits on an innovation in the same period as they innovate.[6] Using (10), the expected profit Π_{jt} of a single scientist entering sector j at time t is then given by:

$$\Pi_{jt} = (1 + s_{jt})\eta_j \ell_{jt}^{(\varpi-1)} \bar{\alpha} \left(P_{jt} R_{jt}^{\alpha_2}\right)^{\frac{1}{1-\alpha_1}} (1+\gamma) A_{jt-1} \tag{14}$$

where $\ell_{jt}^{(\varpi-1)}$ is the average productivity of a scientist in sector j and s_{jt} is a potential subsidy to research in sector j. The allocation of scientists is then decided by the following arbitrage condition: $\Pi_{ct} = \Pi_{dt}$. By solving for ℓ_{ct}/ℓ_{dt} we obtain:

$$\frac{\ell_{ct}}{\ell_{dt}} = \left(\frac{(1 + s_{ct})\eta_c \left(P_{ct} R_{ct}^{\alpha_2}\right)^{\frac{1}{1-\alpha_1}} A_{ct-1}}{(1 + s_{dt})\eta_d \left(P_{dt} R_{dt}^{\alpha_2}\right)^{\frac{1}{1-\alpha_1}} A_{dt-1}} \right)^{\frac{1}{1-\varpi}}. \tag{15}$$

First, remember from (4) that, *ceteris paribus*, resource use will be higher, the lower the resource price. Second, implementing a neutral R&D policy, e.g., setting $s_{ct} = s_{dt}$ and assuming $\eta_c = \eta_d$, we observe from (15) that the allocation of scientists in the economy under study is governed by three factors:

Proposition 1 *More researchers will be allocated to a sector j i) the higher is the final product price P_{jt}, ii) the lower is the private resource cost $c_{jt} + \tau_{jt}$, and iii) the higher is the level of technology A_{jt-1}.*

If resource use is regulated by the state, e.g. through concessions, such that the first order condition (4) may not hold, the state will also (indirectly) influence the allocation of researchers by its concession policy.

The decentralized *laissez fair* equilibrium is now characterized. That is, for each period t (1), (3), (11), (13) and (15) constitute eight equations which together determine the eight variables

[6] Greaker et al. (2018) investigates the implication of short term patents in a model building on Acemoglu et. (2012). They introduce infinitely lived patents, but due to the creative destruction process a patent may lose its value in a later period if a new and better machine arrives. The effective discount rate of the researchers is therefore higher than the social discount rate. In Greaker et al. (2018) this makes researchers behave as if they are myopic.

$Y_{dt}, Y_{ct}, R_{dt}, R_{ct}, A_{dt}, A_{ct}, l_{ct}$ and l_{dt} given initial values A_{d0} and A_{c0}. Finally, the wealth W of the open economy in the *laissez fair* is given by:

$$W = \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} \left[\sum\nolimits_j P_{jt} Y_{jt} - \psi \left(\int_0^1 x_{cit} di + \int_0^1 x_{dit} di \right) - c_{dt} R_{dt} - \bar{c} R_{ct} \right], \tag{16}$$

where the terms in the brackets are the per period net value of the energy production. In the next section we compare the *laissez fair* with the first best.

4 First best and innovation subsides

4.1 The socially optimal allocation of researchers

The planner's problem is to maximize W in (16), that is, the present value of production, with technologies A_j and non-renewable resource Q as the stock variables:

$$\begin{aligned} \max_{\ell_{jt}, R_{jt}, Y_{jt}} \quad & \sum_{t=0}^{\infty} \tfrac{1}{(1+r)^t} \left[\sum\nolimits_j P_{jt} Y_{jt} - \psi \left(\int_0^1 x_{cit} di + \int_0^1 x_{dit} di \right) - c_{dt} R_{dt} - \bar{c} R_{ct} \right] \\ & Y_{jt} = R_{jt}^{\alpha_2} \int_0^1 A_{jit}^{1-\alpha_1} x_{jit}^{\alpha_1} di \\ s.t \quad & A_{jt} = [1 + (\eta_j \ell_{jt}^{\varpi} + \nu_j)\gamma] A_{jt-1} \\ & Q_t = Q_{t-1} + R_{d,t-1} \\ & \ell_{ct} + \ell_{dt} \leq 1, \end{aligned} \tag{17}$$

given $A_{c0} < A_{d0}$, Q_0, and $c_{dt} = c(Q_t)$.

Solving the problem (17) gives the following expression for the optimal allocation of scientists (where we have assumed $\eta_c = \eta_d$):

$$\frac{\ell_{ct}^S}{\ell_{dt}^S} = \left(\frac{\frac{A_{ct-1}}{A_{ct}} \sum\limits_{k=0}^{\infty} (\frac{1}{1+r})^k P_{c,t+k} Y_{c,t+k}}{\frac{A_{dt-1}}{A_{dt}} \sum\limits_{k=0}^{\infty} (\frac{1}{1+r})^k P_{d,t+k} Y_{d,t+k}} \right)^{\frac{1}{1-\varpi}}, \tag{18}$$

where ℓ_{jt}^S denotes the first best allocation of researchers at time t to innovation in sector j (see Appendix A.1 for derivation).

To compare the socially optimal allocation with the market allocation of researchers, we rewrite (15) and set $\eta_c = \eta_d$ and $s_{ct} = s_{dt}$. We then get the following expression for the decentralized allocation of scientists:[7]

$$\frac{\ell_{ct}^M}{\ell_{dt}^M} = \left(\frac{\frac{A_{ct-1}}{A_{ct}} P_{ct} Y_{ct}}{\frac{A_{dt-1}}{A_{dt}} P_{dt} Y_{dt}} \right)^{\frac{1}{1-\varpi}} \tag{19}$$

where ℓ_{jt}^M denotes the market allocation of researchers at time t to innovation in sector j.

Not surprisingly, the first best allocation of researchers given by (18) may depart from the market allocation of researchers given by (19). Along the socially optimal growth path, the social planner allocates more scientists to the innovation sector in which the net present value of the total future production is greater, while in the market allocation researchers are allocated to the sector in which today's value of production is greater.[8] This difference in allocation may lead to a (technology) resource curse:

Definition 1 *The economy is in a state of (technology) resource curse if along the* laissez fair *growth path, more researchers are allocated to dirty innovation than clean innovation in each period, i.e., $\ell_{dt}^M > \ell_{ct}^M$ $\forall t \in [0, T]$, while there exist alternative development paths that give higher wealth as given by (16) in which more researchers are allocated to clean innovation than dirty innovation for a prolonged period before T, i.e., $\ell_{dt} < \ell_{ct}$ $\forall t \in \left[\hat{t}, T\right]$.*

Our numerical analysis in Subsections 5.3-5.5 show examples of such a lock-in in technology, which we label as a resource curse. A resource curse is caused by the market misallocating researchers. One obvious reason is that fossil fuel prices in the future may fall relative to clean energy prices due to climate policy. Another reason is that future fossil fuel production will become more costly. As we will see, both factors may give rise to a resource curse.

4.2 Comparing allocations of scientists

We now want to inquire further into optimal policies for avoiding a resource curse as defined above. Consider the following ratio between the allocation of scientists in the decentralized market solution

[7] Inserting (7) and $p_{ijt} = \alpha_1^2$ into (1), we can substitute R_{jt} with Y_{jt} by using $R_{jt}^{\frac{\alpha_2}{1-\alpha_1}} = Y_{jt} A_{jt}^{-1} \left(\frac{P_{jt}}{\alpha_1}\right)^{\frac{-\alpha_1}{1-\alpha_1}}$. This is then inserted into (15).

[8] Assuming that scientists discount the future completely as in (19) is admittedly a strong assumption, which we have copied from Acemoglu et al (2012). We return to this issue in Section 6.

relative to the planner's solution:

$$\frac{\frac{\ell_{ct}^M}{1-\ell_{ct}^M}}{\frac{\ell_{ct}^S}{1-\ell_{ct}^S}} = \left(\frac{\frac{P_{ct}Y_{ct}}{P_{dt}Y_{dt}}}{\frac{\sum_{k=0}^{\infty}(\frac{1}{1+r})^k P_{c,t+k}Y_{c,t+k}}{\sum_{k=0}^{\infty}(\frac{1}{1+r})^k P_{d,t+k}Y_{d,t+k}}} \right)^{\frac{1}{1-\varpi}}. \tag{20}$$

We pose the following question: What innovation sector must be subsidized more in a given period in order to implement that period's efficient allocation of scientists when either resource market values or resource extraction policies change? Note that a subsidy to an innovation sector j will simply increase the value of doing research in sector j, see (14). For instance, a decline in the price P_{dt} will, ceteris paribus, reduce the allocation of scientists to dirty innovation *both* in the decentralized market and the socially optimal solution. However, the relevant question is not whether dirty innovation is reduced, but whether the relative change in allocations given by (20) is impacted such that a change in R&D policy is warranted.

This relative change in allocations depends on both the direct price effect and the indirect effects of changes in the development of technology $A_{j,t+k}$ and the private resource cost $c_{dt} + \tau_{dt}$, which determines the time path of Y_{jt} in (20). To simplify notation, we define the private resource costs $\chi_{dt} \equiv c_{dt} + \tau_{dt}$. In the following we develop three propositions focusing on the different effects *in isolation*. That is, in each proposition we take the paths of two of the three variables $A_{j,t+k}$, $P_{j,t+k}$ and $\chi_{d,t+k}$ as given, and examine the partial effects on optimal R&D subsidies of a change in the chosen variable.

Taking prices $P_{j,t+k}$ and resource costs $\chi_{d,t+k}$ as given, we first have a proposition on optimal subsides and the isolated *technology effect*:

Proposition 2 *Along an optimal subsidy path where the socially optimal $A_{j,t+k}$ are induced in the market, while the prices $P_{j,t+k}$ and the resource costs $\chi_{d,t+k}$ are given for all k, the optimal subsidy s_{ct}^* at time t is increasing in the socially optimal allocation of scientists $\ell_{c,t+k}^S$ for any $k > 0$.*

Proof. See Appendix $A.3$ ■

If the planner wants to increase the allocation of scientists to clean innovation in the future, the optimal subsides to clean innovation needs to increase today. The efficient allocation of scientists to dirty innovation may decline over time, and this *technology effect* in terms of reduced future dirty technology growth tends to push up the current need for clean innovation subsides. We demonstrate in the numerical illustrations that along an optimal growth path in which clean technology gradually substitutes for dirty technology, subsidies to clean energy should be higher at the start, but should never completely be removed.

Matters are, however, more complicated as this technology effect may be countervailed by the direct effect of fossil fuel prices on optimal subsides. Suppose the planner have set optimal subsides to induce technology paths $\hat{A}_{j,t+k}$ in the market. Then, taking these paths $\hat{A}_{j,t+k}$ and resource costs $\chi_{d,t+k}$ as given, we have the following proposition on the optimal subsides to clean R&D and the isolated *price effect*:

Proposition 3 *For given technologies $\hat{A}_{j,t+k}$ and resource costs $\chi_{d,t+k}$ for $j \in c, d$ for all k, the optimal subsidy s_{ct}^{*} at time t is:*

i) unchanged if the percentage fall in prices $P_{d,t+k}$ is the same for all k;

ii) higher (lower) if the percentage fall in prices $P_{d,t+k}$ is larger (smaller) than the price fall at time t for at least one $k > 0$ and equal for all other k.

Proof. See Appendix $A.4$ ■

The intuition is that when prices change, taking technology and resource costs paths as given, the planner's value of clean innovation changes relative to the market's valuation (as given by (20)). If this relative valuation increases (decreases), the planner wants to induce the market to increase (decrease) its relative allocation of scientists to clean innovation today. Last, as the relative allocations of scientists implied by the technology paths $\hat{A}_{j,t+k}$ was induced in the market by a subsidy that was optimal prior to the price change, the optimal subsidy s_{ct}^{*} must go up (down) to increase (decrease) the relative allocation of scientists.

Moreover, locking down technology and resource costs paths, whether the optimal subsidy increases or decreases depends on *when* the price change occurs. Focusing on lower fossil fuel prices, scientists today do not take into account a fall in future prices and thus provide too much dirty innovation today, which tends to push up the need for subsides to clean innovation. Contrary to this, if fossil fuel prices fall relatively more today than in the future, scientists reduce dirty innovation too much. Thus, less subsides to clean innovation is needed.

Proposition 3 together with Proposition 2, then, may inform us on the direction of optimal subsides of lower fossil fuel prices. Lower fossil prices reduce the allocation of scientists to dirty innovation, both by the market and the planner, and by Proposition 2 the technology effect is to push up subsidies to clean innovation. If fossil fuel prices fall with a constant or higher rate in the future than today, the price effect following from Proposition 3 pushes in the same direction as the technology effect from Proposition 2. Hence, we can surmise that the optimal subsidy to clean innovation increases (for given resource costs). However, if fossil fuel prices fall relatively more today than in the future, the technology effect and the price effect pull in opposite directions, and in sum optimal subsidies to clean innovation today may be positive or negative. In the numerical illustrations we focus on a gradual decline in fossil fuel prices, and show that this induces a large positive shift in the subsidy to clean R&D compared with a scenario in which fossil fuel prices stay constant.

We next turn to changes in the private resource cost $\chi_{d,t+k}$ and how this interacts with innovation incentives and optimal subsides. Recall that resource use in a period is given by (4), so resource use and costs are implicitly contained in (20) through the energy production market values $P_{jt}Y_{jt}$. Consider a market with resource extraction tax set lower than in an optimally regulated market, i.e. $0 \leq \tau_t < \mu_t$. The problem then is that firms do not sufficiently take into account that future costs are increasing in current resource extraction. The planner should raise the extraction tax τ_t such that $\tau_t = \mu_t$. Such a shift in policy would increase the net present value of fossil fuel production, which again would increase the socially optimal allocation of scientists to dirty innovation. From Proposition 2, then, we know that the technology effect in isolation would push down the need to subsidize clean innovation today.

However, as with the price effect, this technology effect may be countervailed by the direct effect of the resource extraction costs on optimal subsides. Taking prices $P_{j,t+k}$ and technology paths $\hat{A}_{j,t+k}$ as given, we have the following proposition on optimal subsides to dirty innovation and the isolated *resource costs effect:*

Proposition 4 *For given technologies $\hat{A}_{j,t+k}$ and prices $P_{j,t+k}$ for $j \in c, d$ for all k, the optimal subsidy s^*_{ct} at time t is:*

i) unchanged if the percentage rise in private resource costs $\chi_{d,t+k}$ is the same for all k;

ii) higher (lower) if the percentage rise in private resource costs $\chi_{d,t+k}$ is larger (smaller) than the cost rise at time t for at least one $k > 0$ and equal for all other k.

Proof. The proposition follows from Proposition 3 together with the fact that $\frac{\partial Y_{j,t+k}}{\partial(c_{d,,t+k}+\tau_{d,t+k})} < 0$ ■

That is, a change in the private resource cost that is the same across all periods does not directly impact on the optimal subsidy. However, as scientists only consider current incomes (as opposed to the planner), the time profile of a change in resource costs directly impacts on the optimal subsidy.

Perhaps more interestingly, a rise in the extraction tax τ_{dt} today dampens current extraction and thus leads to lower (or unchanged) unit costs $c_{d,t+k}$ in future periods (for given technology paths). Thus, taking prices $P_{j,t+k}$ and technology paths $\hat{A}_{j,t+k}$ as given, while allowing for changes in the unit costs $c_{d,t+k}$, we have the following corollary on optimal subsides to dirty innovation and the *extraction tax effect:*

Corollary 1 *For given technology $\hat{A}_{j,t+k}$ and prices $P_{j,t+k}$ for $j \in c, d$ for all k, the optimal subsidy s^*_{ct} at time t is lower if the percentage rise in the extraction tax $\tau_{d,t+k}$ is larger at time t than the rise for any $k > 0$.*

That is, a higher extraction tax today increases the net present value of fossil fuel production (given $\tau_{dt} < \mu_{dt}$ before the change) as unit resource costs are lower in the future. This increases both the planner's and the decentralized market's allocation of scientists to dirty innovation in future periods. However, the value of fossil fuel production today is lower, which reduces dirty innovation incentives in the market today, exacerbating the undersupply of dirty innovation that follows from the technology effect given by Proposition 2. Thus, a rise in the extraction tax today and *not* in the future, implies that the optimal subsidy to clean innovation decreases today.

5 Numerical simulations

5.1 Data input

In this section we illustrate our theoretical findings by a numerical simulation of the model. The length of each period is set to 5 years as in Acemoglu et al. (2012). We assume the annual (real) discount rate to be 0.04. Following Acemoglu et al. (2012), we further assume the annual probability of innovation to be 0.02, and the technology quality step to be one. In the main simulations, we disregard arrivals of foreign innovations, and focus on domestic innovations. The parameter ϖ, which determines decreasing returns to scale of scientists in each sector (dirty and clean innovations), is set equal to 0.5 based on Acemoglu et al. (2016). For the parameters in the Cobb-Douglas production function we have $\alpha_1 = 0.3$ and $\alpha_2 = 0.3$ yielding decreasing returns to scale for this small open economy. The parameter ϕ in the non-renewable resource extraction cost function is set to one, implying that unit costs double after 20 years in the BaU scenario.[9]

We consider four cases with different combinations of exogenous inputs. The initial level of the dirty technology A_{d0} is normalized to 1 in all cases. Moreover, we set the initial price of clean energy P_{c0} and dirty energy P_{d0} to 1. Then in two of the cases both prices are kept constant over time, while in the other two cases we let the market price of dirty energy fall by a constant rate equal to 5 percent each 5 years period. This may be interpreted as a gradually stronger climate policy, and according to Proposition 3 should tend to increase the subsidy to clean R&D.[10] The table below shows the essential parameter combinations in our four cases:

Table 1. The four cases

Case	1	2	3	4
A_{c0}	0.4	0.4	0.6	0.6
$\frac{\Delta P_{dt}}{P_{dt}}$	0%	-5%	0%	-5%

For all the four cases we simulate four scenarios: *laissez fair* (BaU), optimal policy which involves an extraction tax equal to μ_{dt} and a subsidy s_{ct} to clean R&D, a second best subsidy which only involves a subsidy to clean R&D, and finally, a second best tax, which only includes an extraction tax.[11]

As mentioned in the introduction, we obtain three types of outcomes:

[9] The model is simulated in GAMS for 30 periods, but only the first 20 periods are reported. The code is available from the authors upon request.

[10] Note that a constant decline rate for the price of dirty energy means that the price in period $t+k$ will decline relatively more (relative to the cases with constant price) than the price in period t for any positive k.

[11] The BaU scenario is simulated by solving for the unique decentralized laissez fair equilibrium as described at the end of Section 3, with taxes and subsidies set equal to zero. The policy scenarios are simulated by searching for the optimal level of taxes and/or subsidies, i.e., that maximizes welfare in equation (16).

I Steady course (Case 1): It is optimal to keep on extracting fossil fuels since the increasing extraction cost can be counteracted by focusing R&D effort in the dirty energy sector.

II Resource curse due to global climate policy (Case 2): Keeping on extracting fossil fuels is not optimal when the market price on fossil fuels decreases, but the private sector does not shift the R&D effort to the the clean energy sector and extraction continues for too long.

III Resource curse irrespective of global climate policy (Case 3 and 4): Keeping on extracting fossil fuels is not optimal even if the market price on fossil fuels stays constant, but the private sector does not shift the R&D effort to the clean energy sector and extraction continues for too long.

Clearly, the state of the clean technology is essential. If it is fairly developed (Case 3 and 4), a shift to this technology is optimal independent of global climate policy (Outcome III), while if it is underdeveloped (Case 1 and 2), a shift should only happen as a response to global climate policy (Outcome II).

The numerical results are shown in Figures 1-4, one figure for each case. In each figure there are four panels, showing respectively fossil fuel resource extraction, the relative contribution to national wealth of the clean technology, allocation of researchers to the dirty technology, and tax and subsidy levels.

5.2 Case 1: Steady course

Steady course is the outcome in the case with constant energy prices, and an underdeveloped clean energy sector. We see from Figure 1a) that fossil fuel resource extraction is initially too high without an extraction tax (the tax is implemented in "optimal" and "2nd best tax"), and that a clean R&D subsidy alone ("2nd best subs") plays no role in changing the extraction path, that is, the BaU path and the path with only a subsidy to clean R&D are almost identical.

Figure 1 to be placed here

From Panel b) we see that profits from dirty energy production (and hence contribution to national wealth) dominates clean energy throughout the whole time horizon, and moreover, that dirty energy's dominance is increasing irrespective of policy. The reason can be found in Panel c): The allocation of researchers is practically the same in all BaU/policy scenarios, with almost all researchers entering the dirty sector. Clearly, there is no resource curse induced by directed technical change in this case (according to our Definition 1). That is, reseachers should continue working on reducing the cost of dirty energy production.

Finally, we see from Panel d) that in order to accomplish an optimal extraction of the fossil fuel resource, the government should impose an extraction tax of 50-100% of the resource cost. This should be combined with a slightly negative subsidy to clean R&D. Since the government wants to continue resource extraction, knowledge spillovers from R&D are more valuable for dirty R&D. Without an extraction tax, however, there should be a positive subsidy to clean R&D initially to counteract the boosting effect on dirty R&D from a too high initial extraction.

5.3 Case 2: Resource curse due to global climate policy

In Case 2, the price on dirty energy declines over time, while we still have an underdeveloped clean energy sector initially. We see from Figure 2a) that resource extraction is continuously too high in BaU, and that, in particular, both the optimal extraction path and the second-best path with only an extraction tax involve lower extraction, especially in the beginning.

Figure 2 to be placed here

Panel b) now shows another picture than in Case 1: In all four BaU/policy scenarios clean energy will eventually dominate dirty energy with respect to profits and wealth creation. This, however, happens far later in BaU and with only an extraction tax ("2nd best tax"). In fact, with an optimal policy or with a clean R&D subsidy alone, the value of the clean sector will trump the value of dirty after 20-30 years, while without the R&D subsidy this will happen after 60-70 years.

From Panel c) we note that the BaU and the second best tax both involve a far too slow redirection of R&D. Thus, we have a resource curse according to our Definition 1. Both with the opimal policy mix and with only a clean R&D subsidy, researchers are rather quickly moved to clean R&D. Thus, these results suggest that governments cannot look at current profitability for a sector when deciding how to prioritize R&D.

Finally, in Panel d) we see that a redirection of researchers is resolved by substantial subsidies to clean R&D, both in the optimal policy scenario and in the scenario without an extraction tax (subsidy rates of 500-700% of the expected private profit initially). Obviously, the clean R&D subsidy needs to be even higher if the government for some reason does not tax extraction.

5.4 Case 3: Resource curse due to fairly developed clean technology

In this case the price on dirty energy stays constant, but compared to Case 1, we initially have a more developed clean energy sector. As for Case 2, we see from Figure 3a) that resource extraction is continuously too high compared with the optimal extraction path and the extraction path with only an extraction tax. In Panel b) we see that with an optimal policy or with a clean R&D subsidy alone, the value of the clean sector will trump the value of dirty after 20 years, while without the R&D subsidy this might never happen (BaU) or happen after more than 80 years ("2nd best tax").

Figure 3 to be placed here

Furthermore, as for Case 2 we see from Panel c) that the BaU involves a far too slow redirection of R&D. Both for the optimal set of taxes and the second best R&D subsidy, researchers are even more quickly moved away from dirty R&D than in Case 2. Thus, we have a resource curse according to our Definition 1. This happens even if fossil fuel prices do not decline relative to clean energy prices. The reason is of course the future increasing cost of extraction, and that clean energy is a relatively low hanging fruit in this case, which the private R&D sector misses out on.

Finally, in Panel d) we see that a redirection of researchers is resolved by substantial subsidies to clean R&D in both the policy scenarios with and without an extraction tax. Again, the clean R&D subsidy needs to be even higher if the government cannot tax extraction.

5.5 Case 4: Resource curse due to global climate policy and fairly developed clean technology

In the final case, the price on dirty energy declines over time (as in Case 2), and we initially have a more developed clean energy sector (as in Case 3). Seemingly, the declining dirty energy price partly resolves the resource curse situation we observed in Case 3: Note from Figure 4a) that the extraction paths in all four BaU/policy scenarios nearly merge after six periods. Thus, in Case 4 resource extraction is too high only in the first 30 years. However, from Panel c), we see that a lack of appropriate policies will still postpone redirection of R&D. While with an optimal policy mix almost all researchers should be moved to clean R&D initially, in the BaU, more than half of the researchers stay in dirty R&D for 30-35 years. Thus, even with declining fossil fuel prices relative to clean energy prices and a relatively developed clean sector, we may experience a resource curse according to Definition 1.

Figure 4 to be placed here

As can be seen from Panel b), a redirection of researchers quickly makes the clean energy sector more profitable than dirty; it happens in about 10-15 years time. While in the BaU, dirty energy stays more profitable for another 15 years.

Finally, in Panel d), as in Case 2 and 3, we see that a redirection of researchers is resolved by substantial subsidies to clean R&D (whether or not an extraction tax is imposed), with the highest subsidy when the government does not tax extraction.

5.6 Wealth effects

In our model, national wealth is given from equation (16). For each of the BaU/policy scenarios in each of the Cases 1-4, we can calculate the value of the discounted stream of net profits from energy production over the time horizon of the model. In Table 2 we have the four cases in the columns from left to right and the four BaU/policy scenarios in the rows from top to bottom.

Table 2. Wealth comparison

Cases	1	2	3	4
BaU	3.52	2.40	4.17	3.65
Optimal	3.96	2.89	5.00	4.43
2nd best subsidy	3.53	2.82	4.84	4.37
2nd best tax	3.95	2.56	4.59	3.91
(Optimal-BaU)/BaU	12.5%	20.4%	20.0%	21.4%
(2nd subsidy-BaU)/(optimal-BaU)	0.3%	85.6%	80.5%	92.6%
(2nd tax-BaU)/(optimal-BaU)	97.9%	31.3%	50.7%	33.4%

In the row "(Optimal-BaU)/BaU" we measure the relative difference in total discounted wealth between the optimal policy mix and the BaU. As discussed above, in Cases 2-4 the researchers should be shifted swiftly to the clean technology, but without a policy this may never happen or it happens too late. In all these three cases it leads to a loss in wealth by approximatly 20%. In Case 1 the welfare difference is smaller (12%), but not insignificant since with dirty energy production far into the future, the lack of an extraction tax matters quite a lot.

In the next row "(2nd subsidy-BaU)/(optimal-BaU)", we measure how close a stand alone subsidy to clean R&D can take us from BaU towards the optimal solution. We see that for the three Cases 2-4, more than 80 percent of the gap is closed. Hence, prioritizing clean R&D seems to be crucial.

Then, in the last row we measure how close a stand alone extraction tax can take us towards the optimal solution. We note that the tax is insufficient for the two Cases 2 and 4, but that it takes us nearly all the way in Case 1 (in which case R&D policies are less needed) and half the way in Case 3 in which a redirection of R&D is desirable. Hence, an extraction tax could be important also for redirecting R&D effort whenever for some reason a directed R&D subsidy is not available.

5.7 Spillovers between research areas

A key assumption in models of directed technical change is that a new innovation builds on past quality within a field and only increases the productivity of future innovations *within the same field*. We now want to relax this assumption and introduce technology spillovers between dirty and clean technology research. Clean machine quality then develops according to:

$$A_{c,t} = A_{c,t-1} + (1-\vartheta)(\eta \ell_{ct}^{\varpi})\gamma A_{c,t-1} + \vartheta(\eta \ell_{dt}^{\varpi})\gamma A_{d,t-1} \tag{21}$$

where ϑ is the spillover rate which we have set to 0.25 as in Greaker et al. (2018). Note that due to the initial conditions implying $A_{c0} < A_{d0}$ and decreasing returns to R&D ($\varpi < 1$), it no longer pays to shift all research to clean technology to boost this technology as much as possible. In fact with $A_{c0} = 0.4$ (and $A_{d0} = 1$), the largest advancement in clean technology happens when $\ell_{ct} = 0.6$ (and $\ell_{dt} = 0.4$) suggesting that a spillover rate of 0.25 might be too high. Here, we focus on the parameter combination in Case 2, which produces the "resource curse due to global climate policy" outcome.

First, even with the high spillover, we find that the allocation of researchers to dirty R&D in the BaU is too high. The share of researchers working at improving dirty energy technologies should start at $\ell_{d0} = 0.8$ compared to $\ell_{d0} = 0.95$ in BaU.[12] Consequently, clean R&D should be subsidized initially. Both with and without an extraction tax, the subsidy starts at around the level of the expected R&D profits (higher without an extraction tax).

Second, the share of researchers working at improving dirty energy technologies should steadily decline over the period since research within this area becomes less profitable when dirty energy prices decline and extraction costs increase. However, due to the decreasing returns to research within an area, the government should strive to keep researchers in both areas. Hence, after approximatly 30 years of clean R&D subsidies, dirty R&D should be subsidized instead.

Finally, there is no qualitative change in the conclusion regarding the extraction tax. Also in the other three cases (even Case 1), we find that there should be a subsidy to clean R&D initially and an extraction tax over the whole period. A failure to implement the extraction tax requires a higher clean R&D subsidy. Hence, for the first periods, the high spillover rate does not alter our conclusions regarding the clean R&D subsidy.

[12] See the figures in the the Appendix. Note also that due to the spillover, this allocation of researchers imply a larger initial advancement in clean technologies than if all researchers worked with clean technologies.

5.8 Arrival of foreign innovation

In the model set up we allowed for the arrival of foreign innovation, but then disregarded this possibility in both the theoretical and numerical analysis. Here we briefly report the results of incorporating foreign innovation in the numerical model. To better compare with the main results (with only domestic innovation), domestic productivity has been halved for both clean and dirty whereas the exogenous arrival of foreign innovation ($\nu_c = \nu_d$) is set equal to the productivity of domestic innovation when R&D activity is equally shared between clean and dirty.

One important implication of having more of the innovation coming from abroad is that it is no longer optimal with more dirty R&D than in BaU in Case 1, and hence subsidies to clean innovation is positive also in this case (but still much smaller than in the other cases). The domestic innovation effect is smaller than before, and hence the future cost increase for the non-renewable resource becomes more important, and the clean transition should take place (although very slowly).

Second, R&D subsidies are less important than before, which is as expected when domestic R&D is less productive. The subsidy is still more important than the extraction tax in Case 4 (when a rapid switch to clean R&D is warranted), but in Case 3 the extraction tax is more important (in which case a gradual clean transition is optimal due to lax global climate policy).

6 Discussion and conclusion

In this paper we follow Acemoglu et al (2012) and let patents only last for one period. Hence, a future slump in fossil fuel prices will not redirect private research from dirty to clean energy. Furthermore, since extraction paths are forward biased, the tendency for the market to allocate too many researchers to fossil fuel technology, is exacerbated. We show that the government should counteract these effects by giving a higher subsidy to clean energy research. Admittingly, assuming that researchers only look one period ahead may seem unrealistic. The important assumption for our purpose, however, is that researchers put less weight on future periods than the planner. This is the case in Greaker et. (2018), in which researchers have complete and perfect foresight. A crucial insight from Greaker et al (2018) is that the results from Acemoglu et al (2012) are robust to changing from myopic researchers to farsighted researchers.

A unique feature of our paper is that we investigate the interconnection between postive knowledge spillovers in R&D and the cost externality in extraction. Modelling extraction of a non-renewable resource with stock dependent extraction costs seem to be standard in empirical investigations of non-renewable resource markets, see, e.g., Livernois (2009). We furthermore assume that extracters do not internalize the cost externality. This would be the case if firms develop low-cost deposits first and at the same time only have short-term concessions on the deposits. It is then up to the country owning the deposits to control the rate of extraction. This can be done by a strict consession policy or by an extraction tax of which we look at the latter.

In our model the country in question faces an exogenous price on dirty energy, and this price either stays constant or declines relative to clean energy. The Hotelling rule would predict that the price should increase since we are dealing with a non-renewable resource. The evidence for the Hotelling rule is however scarce, see Livernois (2009). One possible explanation is that technological change and increasing stock dependent extraction costs outweigh each other (as they can do in our paper). When facing a backstop in abundant supply, theory also predicts that the non-renewable price could stay constant, see e.g. Salant (1979). In order to keep our model simple, we have not model the global market for the dirty energy resource. However, we belive that a more or less stringent climate policy in all cases would affect its relative price to the clean energy resource.

In our paper, R&D in dirty technology only competes with R&D in clean technology. Clearly, "clean technology" could be any new emerging field of technology; the only essential aspect of the alternative technology is that its relative price will with some probability increase *vis-a-vis* the price of fossil fuels. We have chosen to stay within the dirty and clean technology dichtonomy from Acemoglu et al. (2012). One example of a country that fits with this dichtonomy could be Algeria, which currently exports oil and gas but could potentiallly produce solar energy both for electricity export and green hydrogen export. The same may be relevant for Middle Eastern countries. Another example could be Norway, which so far has escaped the resource curse, but still uses a lion's share of its R&D resources on improving oil and gas extraction techniques, while having great opportunities for offshore wind development.

Surprisingly, we find that global climate policy may both lead to a resource curse or help the country escaping a potential resource curse. The ripeness of the clean technology is essential for the outcomes: If the clean technology is not too far beyond the dirty technology, a shift to this technology is optimal independent of global climate policy, and climate policy can induce this shift.

While if the clean technology is underdeveloped, a shift should only happen as a responce to global climate policy, and the government must intervene to make it happen. Our paper could thus have policy implications for fossil fuel exporting countries that employs a major share of their high skilled workers in developing new technologies for fossil fuel exploration and extraction.

References

Acemoglu, D., P. Aghion, L. Bursztyn and D. Hémous. 2012. The Environment and Directed Technical Change. *American Economic Review* 102, 131-166.

Acemoglu, D., U. Akcigit, D. Hanley and W. Kerr. 2016. Transition to clean technology, *Journal of Political Economy*, 124(1), 52-104.

Aghion, P., A. Dechezleprêtre, D. Hémous, R. Martin and J. Van Reenen. 2016. Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry. *Journal of Political Economy* 124(1), 1-51.

André F. J. and S. Smulders. 2014. Fueling growth when oil peaks: Directed technological change and the limits to efficiency. *European Economic Review* 69, 18-39.

Dechezleprêtre, A., R. Martin and M. Mohnen. 2013. Knowledge spillovers from clean and dirty technologies: A patent citation analysis. Grantham Research Institute on Climate Change and the Environment Working Paper 135.

Durmaz, T. and F. Schroyen. 2020. Evaluating Carbon Capture and Storage in a Climate Model with Induced Technical Change. *Climate Change Economics* 11 (01), 2050003.

Gerlagh, R., S. Kverndokk and K.E. Rosendahl. 2014. The optimal time path of clean energy R&D policy when patents have finite lifetime. *Journal of Environmental Economics and Management*, 67(1), 2-19.

Greaker M., T.R. Heggedal and K.E. Rosendahl. 2018. On the rationale for directing R&D to zero emission technologies, *Scandinavian J. of Economics* 120:4.

Greaker M. and L. Pade. 2009. Optimal CO2 abatement and technological change: Should emission taxes start high in order to spur R&D? *Climatic Change* 96, 335-355.

Hart R. 2019. To everything there is a season: Carbon pricing, research subsidies, and the transition to fossil-free energy, *J. of Association of Environmental and Resource Economists* 6, 349-389.

Hassler J.,P. Krusell and C. Olovsson. 2021. Directed technical change as a response to resource scaricity, *Journal of Political Economy* 129, number 11.

Heal, G. 1976. The Relationship between Price and Extraction Cost for a Resource with a Backstop Technology, *The Bell Journal of Economics* 7 (2), 371-378.

Hémous, D. 2013. The dynamic impact of unilateral environmental policies, *Journal of International Economics* 103, 80-95.

Hourcade, J.C, A. Pottier and E. Espagne. 2011. The Environment and Directed Technical Change: Comment. *FEEM Working paper* 95/2011.

Jones, C.I. and J.C. Williams. 2000. Too Much of a Good Thing? The Economics of Investment in R&D, *Journal of Economic Growth* 5, 65-85.

Lemoine D. 2020. Innovation led transition in energy supply. University of Arizona Working Paper 17-10.

Livernois, J. 2009. On the empirical significance of the Hotelling rule. *Review of Environmental Economics and Policy* 3, 22-41.

Mattauch, L., F, Creutzig and O. Edenhofer. 2015. Avoiding carbon lock-in: Policy options for advancing structural change. *Economic Modelling* 50, 49-63.

Popp, D., N. Santen, K. Fisher-Vanden and M. Webster. 2013. Technology Variation vs. R&D Uncertainty: What Matters Most for Energy Patent Success? *Resources and Energy Economics* 35, 505-533.

Robinson, J. A., R. Torvik and T. Verdier. 2014. Political foundations of the resource curse: A simplification and a comment. *Journal of Development Economics* 106, 194-198.

Salant S. 1979. Staving of the back-stop: Dynamic limit pricing with a kinked demand curve. *Advances in the economics of energy and resources : a research annual* 2, 187-204.

van den Bijgaart, I. 2015. The Unilateral Implementation of a Sustainable Growth Path with Directed Technical Change. *FEEM Working Paper* No. 11.2015.

van der Ploeg, F. 2011. Natural Resources: Curse or Blessing? *Journal of Economic Literature* 49(2), 366-420.

Welsby, D., J. Price, S. Pye et al. 2021. Unextractable fossil fuels in a 1.5 °C world. *Nature* 597, 230-234.

Appendix

Appendix A: Theoretical model

A.1 Derivation of First-best

The Lagrangian given by problem 17 is:

$$
\begin{aligned}
\mathbf{L} \;=\; & \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} \left[\sum\nolimits_j P_{jt} R_{jt}^{\alpha_2} \int_0^1 A_{jit}^{1-\alpha_1} x_{jit}^{\alpha_1} di - \psi \left(\int_0^1 x_{cit} di + \int_0^1 x_{dit} di \right) - c_{dt} R_{dt} - \bar{c} R_{ct} \right] \\
& - \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} \lambda_{ct} (A_{ct} - (1 + \gamma(\eta_c \ell_{ct}^{\varpi} + \nu_c)) A_{c,t-1}) \\
& - \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} \lambda_{dt} (A_{dt} - (1 + \gamma(\eta_d (1-\ell_{dt})^{\varpi} + \nu_d)) A_{d,t-1}) \\
& + \sum_{t=0}^{\infty} \frac{1}{(1+r)^t} \mu_t (Q_{t+1} - Q_t - R_{d,t}),
\end{aligned}
$$

where λ_{jt} is the shadow value of energy good $j \in \{c, d\}$, ω_{jt} is the shadow value of the average machine quality (the technology stock) in $j \in \{c, d\}$, and μ_t is the shadow cost of the extraction. Note that we set $\ell_{ct} + \ell_{dt} = 1$.

The first order condition wrt machines x_{jit} is

$$
P_{jt} R_{jt}^{\alpha_2} A_{jit}^{1-\alpha_1} \alpha_1 x_{jit}^{\alpha_1 - 1} - \psi = 0,
$$

which using the fact $\psi = \alpha_1^2$ can be written

$$
x_{jit} = \left(\frac{1}{\alpha_1} P_{jt} R_{jt}^{\alpha_2} L_{jt}^{\alpha_3} \right)^{\frac{1}{1-\alpha_1}} A_{jit},
$$

which is the same as the market solution, when $\sigma = 1 - \alpha_1$.

The first order conditions wrt resources R_{ct} and R_{ct} are

$$
\begin{aligned}
\alpha_2 P_{ct} R_{ct}^{\alpha_2 - 1} L_{ct}^{\alpha_3} \int_0^1 A_{cit}^{1-\alpha_1} x_{cit}^{\alpha_1} di - \bar{c} &= 0 \\
\alpha_2 P_{dt} R_{dt}^{\alpha_2 - 1} L_{dt}^{\alpha_3} \int_0^1 A_{dit}^{1-\alpha_1} x_{dit}^{\alpha_1} di - c_{dt} + \mu_t &= 0,
\end{aligned}
$$

which using the definition of Y_{jt} can be rewritten

$$\begin{aligned} R_{ct} &= \alpha_2 \frac{P_{ct} Y_{ct}}{\bar{c}} \\ R_{dt} &= \alpha_2 \frac{P_{dt} Y_{dt}}{c_{dt} + \mu_t}. \end{aligned} \tag{22}$$

Comparing he first best resource use (22) with the market solution (5) we see that they are the same as long as the firms face the scarcity rent μ_t. The development of the scarcity rent over time is given by the first order condition wrt Q_t which can be written

$$\mu_t = (1+r)\mu_{t-1} - \frac{\partial c_{dt}}{\partial Q_t} R_t.$$

The relevant first order condition for the allocation of scientist is

$$\begin{aligned} \varpi \lambda_{ct} \gamma \eta_c \ell_{ct}^{\varpi-1} A_{c,t-1} - \varpi \lambda_{dt} \gamma \eta_d (1-\ell_{ct})^{\varpi-1} A_{d,t-1} &= 0 \\ &\Leftrightarrow \\ \left(\frac{\lambda_{ct} \eta_c A_{c,t-1}}{\lambda_{dt} \eta_d A_{d,t-1}} \right)^{\frac{1}{1-\varpi}} &= \frac{\ell_{ct}}{1-\ell_{ct}}. \end{aligned} \tag{23}$$

Now we want to substitute out the $\lambda' s$ in (23). To this end, note that the first order condition wrt average quality A_{jt} is

$$P_{jt} R_{jt}^{\alpha_2} L_{jt}^{\alpha_3} (1-\alpha_1) \textstyle\int_0^1 A_{jit}^{-\alpha_1} x_{jit}^{\alpha} di - \lambda_{jt} + (\frac{1}{1+r}) \lambda_{j,t+1} (1 + \gamma(\eta_c \ell_{c,t+1}^{\varpi} + \nu_c)) = 0. \tag{24}$$

Next we use $A_{jt} \equiv \int_0^1 A_{jit} di$ and the definition of Y_{jt} to rewrite equation (24)

$$P_{jt}(1-\alpha_1) \frac{Y_{jt}}{A_{jt}} - \lambda_{jt} + (\frac{1}{1+r}) \lambda_{j,t+1} (1 + \gamma(\eta_c \ell_{c,t+1}^{\varpi} + \nu_c)) = 0. \tag{25}$$

Then we use equation (13) to rewrite equation (25):

$$\lambda_{jt} = P_{jt}(1-\alpha_1) \frac{Y_{jt}}{A_{jt}} + (\frac{1}{1+r}) \lambda_{jt+1} \frac{A_{j,t+1}}{A_{jt}}. \tag{26}$$

Note that equation (26) can be expanded

$$
\begin{aligned}
\lambda_{jt} &= P_{jt}(1-\alpha_1)\frac{Y_{jt}}{A_{jt}} + (\frac{1}{1+r})(P_{jt+1}(1-\alpha_1)\frac{Y_{j,t+1}}{A_{j,t+1}}\frac{A_{j,t+1}}{A_{jt}} \\
&\quad +(\frac{1}{1+r})^2\lambda_{jt+2}\frac{A_{j,t+2}}{A_{j,t+1}}\frac{A_{j,t+1}}{A_{jt}}) \\
&= P_{jt}(1-\alpha_1)\frac{Y_{jt}}{A_{jt}} + (\frac{1}{1+r})(P_{jt+1}(1-\alpha_1)\frac{Y_{j,t+1}}{A_{j,t+1}}\frac{A_{j,t+1}}{A_{jt}} \\
&\quad +(\frac{1}{1+r})^2 P_{jt+2}(1-\alpha_1)\frac{Y_{j,t+2}}{A_{j,t+2}}\frac{A_{j,t+2}}{A_{j,t+1}}\frac{A_{j,t+1}}{A_{j,t}} + (\frac{1}{1+r})^3\lambda_{jt+3}\frac{A_{j,t+3}}{A_{j,t+2}}\frac{A_{j,t+2}}{A_{j,t+1}}\frac{A_{j,t+1}}{A_{jt}},
\end{aligned}
$$

and so forth. We use this to obtain

$$
\lambda_{jt} = (1-\alpha_1)\frac{1}{A_{jt}}\sum\nolimits_{v\geq t}(\frac{1}{1+r})^{v-t}P_{jv}Y_{jv}. \tag{27}
$$

Then, combining equations (23) and (27), the optimal allocation of scientists is given by (18)

A.2 Partial derivatives of Y_{jt}

In (1) we substitute out R_{jt} using (5) and x_{jit} using (7) to rewrite Y_{jt} as a function of A_{jt}, $\tau_{jt}$and parameters:

$$
\begin{aligned}
Y_{jt} &= \left(\frac{\alpha_2 P_{jt} Y_{jt}}{c_{jt}+\tau_{jt}}\right)^{\alpha_2} \int_0^1 A_{jit}^{1-\alpha_1}\left[\left(\frac{P_{jt}\left(\frac{\alpha_2 P_{jt} Y_{jt}}{c_{jt}+\tau_{jt}}\right)^{\alpha_2}}{\alpha_1}\right)^{\frac{1}{1-\alpha_1}} A_{jit.}\right]^{\alpha_1} di \qquad (28) \\
Y_{jt} &= \left(\frac{\alpha_2 P_{jt} Y_{jt}}{c_{jt}+\tau_{jt}}\right)^{\alpha_2} A_{jt}\left[\left(\frac{P_{jt}\left(\frac{\alpha_2 P_{jt} Y_{jt}}{c_{jt}+\tau_{jt}}\right)^{\alpha_2}}{\alpha_1}\right)^{\frac{1}{1-\alpha_1}}\right]^{\alpha_1} \\
Y_{jt} &= A_{jt}^{\frac{1-\alpha_1}{(1-\alpha_2-\alpha_1)}} P_{jt}^{\frac{\alpha_2+\alpha_1}{(1-\alpha_2-\alpha_1)}}\left(\frac{1}{c_{jt}+\tau_{jt}}\right)^{\frac{\alpha_2}{(1-\alpha_2-\alpha_1)}} \alpha_2^{\alpha_2}\left(\frac{\alpha_2^{\alpha_2}}{\alpha_1}\right)^{\frac{\alpha_1}{(1-\alpha_2-\alpha_1)}}.
\end{aligned}
$$

Clearly $\frac{\partial Y_{jt}}{\partial A_{jt}} > 0$ and$\frac{\partial Y_{jt}}{\partial P_{jt}} > 0$. For future reference note that $\frac{\partial Y_{jt}}{\partial c_{jt}} < 0$, $\frac{\partial Y_{jt}}{\partial \tau_{jt}} < 0$, and, since $\frac{1-\alpha_1}{(1-\alpha_2-\alpha_1)} > 1$, we have $\frac{\partial Y_{jt}}{\partial A_{jt}} > 1$. That is Y_j grows by a factor higher than the growth rate of A_j.

A.3 Proof Proposition 2

First we analyze an increase in the allocation to the clean sector keeping $A_{d,t+k}$ unchanged for all k. Note that the optimal subsidy is set so that the right hand side of (20) is equal to one so that $\ell_{c,t+k} = \ell^M_{c,t+k} = \ell^S_{c,t+k}$ for all k. That is the optimal subsidy is implemented and $A_{c,t+k}$ is at the socially optimal level also in the decentralized equilibrium. Then, to show that s^*_{ct} needs to go up at time t when $\ell_{c,t+k}$ increases it is sufficient to show that

$$\frac{P_{ct}Y_{ct}}{\sum\limits_{k=0}^{\infty}(\frac{1}{1+r})^k P_{c,t+k}Y_{c,t+k}}, \tag{29}$$

goes down when $\ell_{c,t+k}$ increases. To this end we rewrite the problem slightly, using (28) to get

$$\frac{P_{ct}A^{\beta}_{ct}H_{ct}}{\sum\limits_{k=0}^{\infty}(\frac{1}{1+r})^k P_{c,t+k}A^{\beta}_{c,t+k}H_{c,t+k}},$$

where $\beta = \frac{1-\alpha_1}{1-\alpha_2-\alpha_2}$ and $H_{jt} \equiv P_{jt}^{\frac{\alpha_2+\alpha_1}{1-\alpha_2-\alpha_1}}\left(\frac{1}{c_{jt}+\tau_{jt}}\right)^{\frac{\alpha_2}{1-\alpha_2-\alpha_1}}\alpha_2^{\alpha_2}\left(\frac{\alpha_2^{\alpha_2}}{\alpha_1}\right)^{\frac{\alpha_1}{1-\alpha_2-\alpha_1}}$. Showing that (29) goes down is equivalent to showing that

$$\frac{\sum\limits_{k=0}^{\infty}(\frac{1}{1+r})^k P_{c,t+k}A^{\beta}_{c,t+k}H_{c,t+k}}{P_{ct}A^{\beta}_{ct}H_{ct}} = \frac{\sum\limits_{k=0}^{\infty}(\frac{1}{1+r})^k P_{c,t+k}[\Big(1+(\eta_c\ell^{\varpi}_{c,t+k}+\nu_c)\gamma\Big)A_{c,t+k-1}]^{\beta}H_{c,t+k}}{P_{ct}[(1+(\eta_c\ell^{\varpi}_{ct}+\nu_c)\gamma)A_{ct-1}]^{\beta}H_{ct}}, \tag{30}$$

goes up, where we have used the fact that $A_{c,t+k} = \Big(1+(\eta_c\ell^{\varpi}_{c,t+k}+\nu_c)\gamma\Big)A_{c,t+k-1}$. Noticing the compounding feature of innovation on A_c, we can cancel out $(1+(\eta_c\ell^{\varpi}_{ct}+\nu_c)\gamma)A_{ct-1}$ as it is present in all elements of the sum in the numerator, and write (30) as

$$\frac{\sum\limits_{k=0}^{\infty}(\frac{1}{1+r})^k P_{c,t+k}[\prod\limits_{v=1}^{k}\Big(1+(\eta_c\ell^{\varpi}_{c,t+k}+\nu_c)\gamma\Big)]^{\beta}H_{c,t+k}}{P_{ct}H_{ct}}. \tag{31}$$

Then we have

$$\frac{\partial\left(\frac{\sum_{k=0}^{\infty}(\frac{1}{1+r})^k P_{c,t+k}[\prod_{v=1}^{k}\left(1+(\eta_c\ell_{c,t+k}^{\varpi}+\nu_c)\gamma\right)]^{\beta}H_{c,t+k}}{P_{ct}H_{ct}}\right)}{\partial\ell_{c,t+k}} > 0 \text{ for any } k>0, \tag{32}$$

and we have thus established our result.

Next, we also consider that impact of changing $A_{d,t+k}$. When $\ell_{c,t+k}$ increase for some k, $\ell_{d,t+k}$ must decrease with the same amount as $\ell_{c,t+k}+\ell_{d,t+k}=1$. Due to symmetry in (20) this exacerbates the problem and further enhances the need for s_{ct} to go up at time t when $\ell_{c,t+k}$ increase for some $k>0$.

Last, for completeness, notice that the derivative given by (32) is equal to zero for $k=0$, since $\ell_{c,t}$ is canceled out from the fraction.

A.4 Proof of Proposition 3

Similarly to the proof of Proposition 2, showing that the optimal subsidy s^*_{jt} at time t needs to go up (down) to get the right hand side of (20) equal to one amounts to showing that

$$\frac{P_{jt}Y_{jt}}{\sum_{k=0}^{\infty}(\frac{1}{1+r})^k P_{j,t+k}Y_{_{j,t+k}}}, \tag{33}$$

goes down (up). Note that we here analyse the change in (33) of a change in $P_{j,t+k}$, holding both $\hat{A}_{j,t+k}$ and $\chi_{_{d,t+k}}$ fixed for $j\in c,d$ for all k.

First consider the case where prices $P_{j,t+k}$ changes by the same percentage for all k. This does not impact on (33) as the price changes cancel out of the fraction.

Next, having established part $i)$ of the proposition, it is sufficient to show that s^*_{jt} goes down (up) when the prices $P_{j,t+k}$ decreases (increases) for any $k>0$. Recall that in Appendix $A.2$ we established $\frac{\partial Y_{jt}}{\partial P_{jt}}>0$. It follows that $\frac{\partial(P_{j,t+k}Y_{j,t+k})}{\partial P_{j,t+k}}>0$. Then, for any $k>0$ we have

$$\frac{\partial\left(\frac{P_{jt}Y_{jt}}{\sum_{k=0}^{\infty}(\frac{1}{1+r})^k P_{j,t+k}Y_{_{j,t+k}}}\right)}{\partial P_{j,t+k}}<0,$$

and thus (33) goes up (down) when $P_{j,t+k}$ decreases (increases), and consequently s^*_{jt} must go down (up).

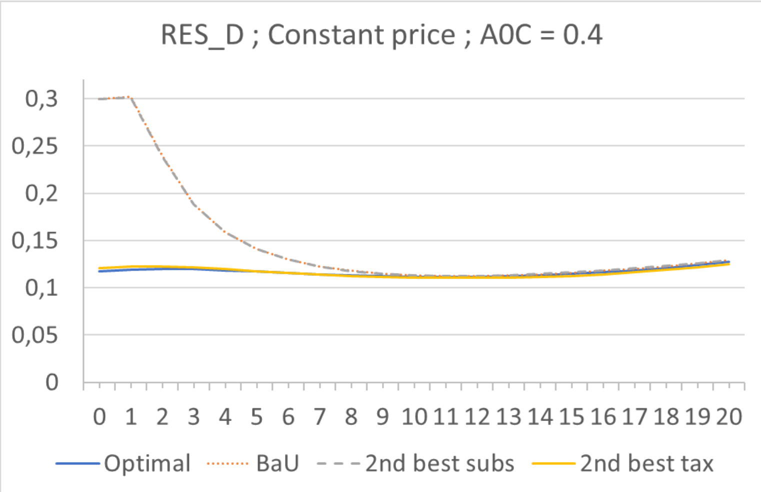
Last, consider the case when prices $P_{j,t+k}$ decreases (increases) only at $k=0$. For $k=0$,

$$\frac{\partial\left(\frac{P_{jt}Y_{jt}}{\sum\limits_{k=0}^{\infty}(\frac{1}{1+r})^k P_{j,t+k}Y_{j,t+k}}\right)}{\partial P_{jt}} = \frac{\frac{\partial(P_{jt}Y_{jt})}{\partial P_{jt}}\left(\sum\limits_{k=0}^{\infty}(\frac{1}{1+r})^k P_{j,t+k}Y_{j,t+k} - P_{jt}Y_{jt}\right)}{\left(\sum\limits_{k=0}^{\infty}(\frac{1}{1+r})^k P_{j,t+k}Y_{j,t+k}\right)^2} > 0,$$

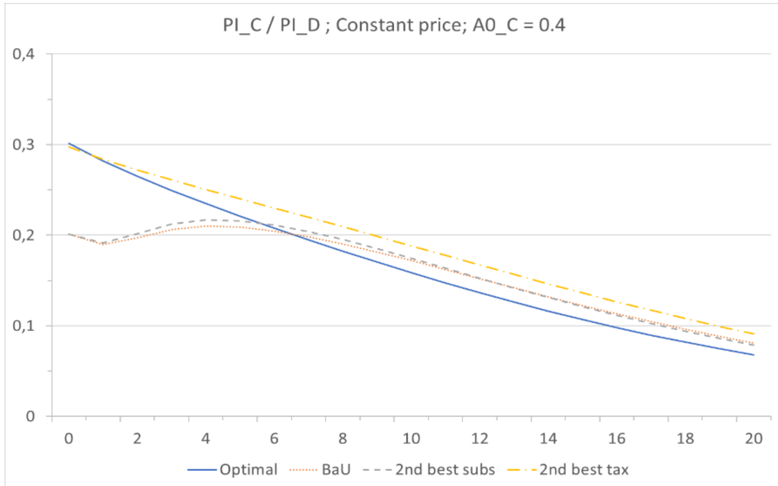
and thus (29) goes down (up) when P_{jt} decreases (increases) and consequently s^*_{jt} must go up (down).

Figure 1 “Constant energy prices and underdeveloped clean sector”

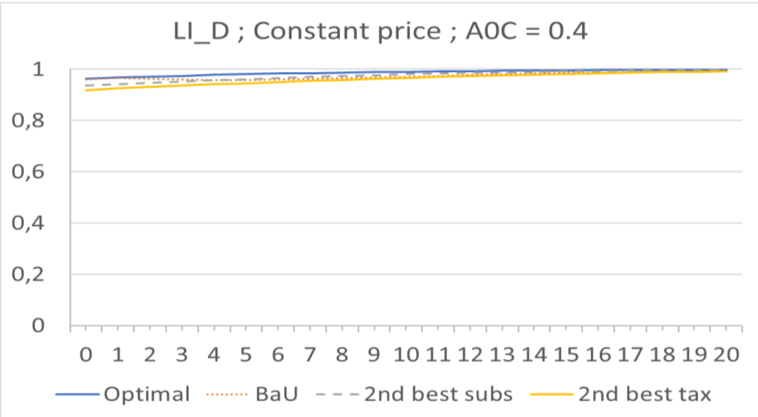
Panel a) Petroleum resource extraction



Panel b) Relative profits in clean versus dirty energy production



Panel c) Allocation of researchers to dirty R&D



Panel d) Tax and subsidy levels (as shares of resource costs and expected R&D profits, respectively)

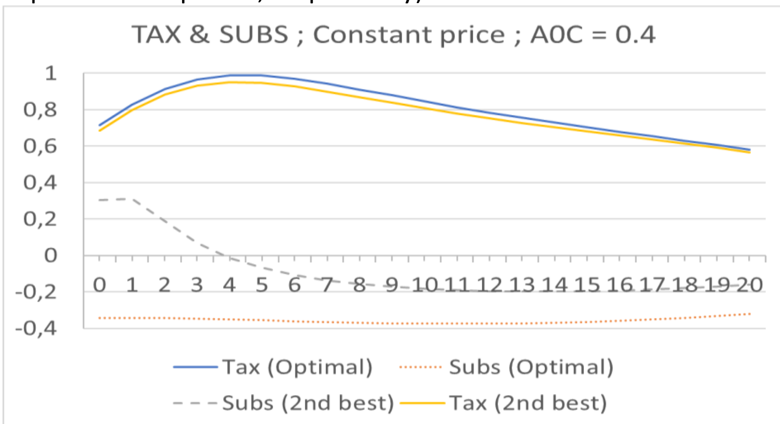
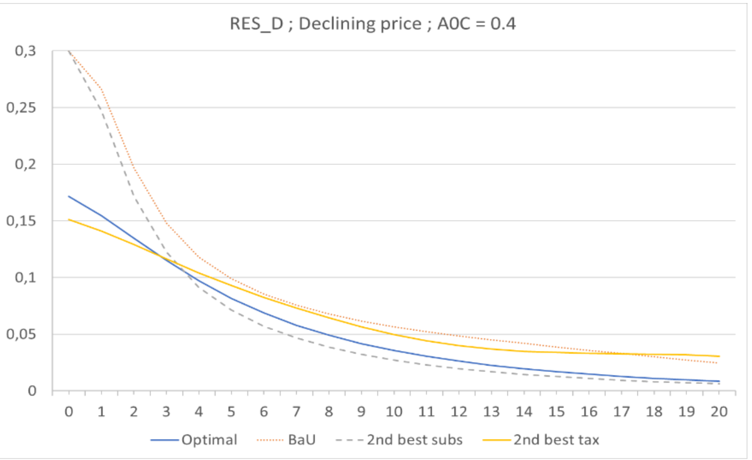
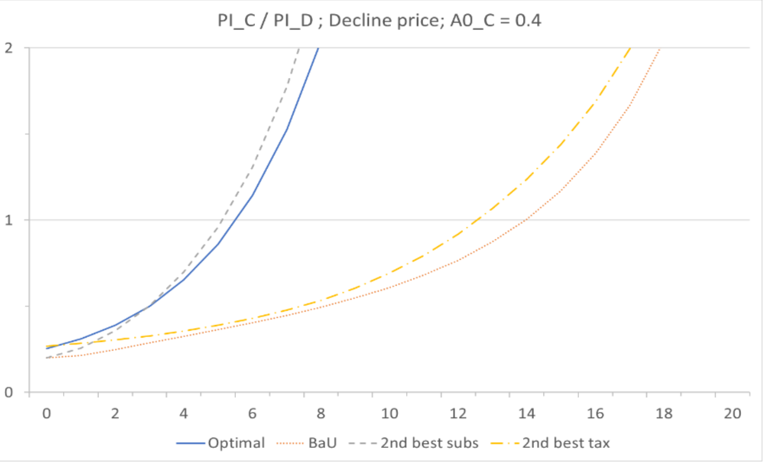


Figure 2 "Declining petroleum prices and underdeveloped clean sector"

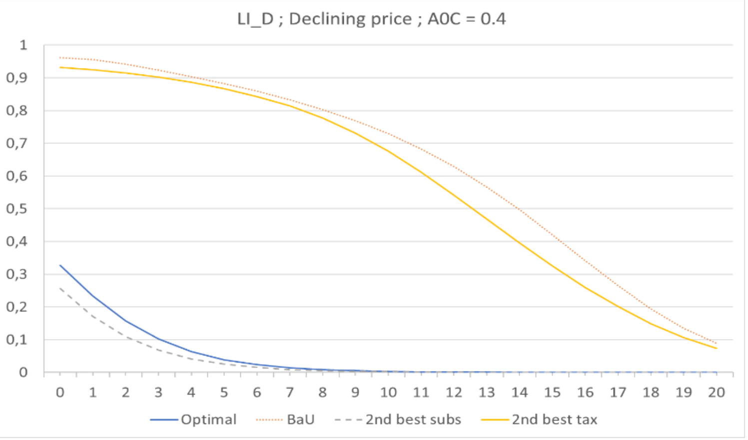
Panel a) Petroleum resource extraction



Panel b) Relative profits in clean versus dirty energy production



Panel c) Allocation of researchers to dirty R&D



Panel d) Tax and subsidy levels (as shares of resource costs and expected R&D profits, respectively)

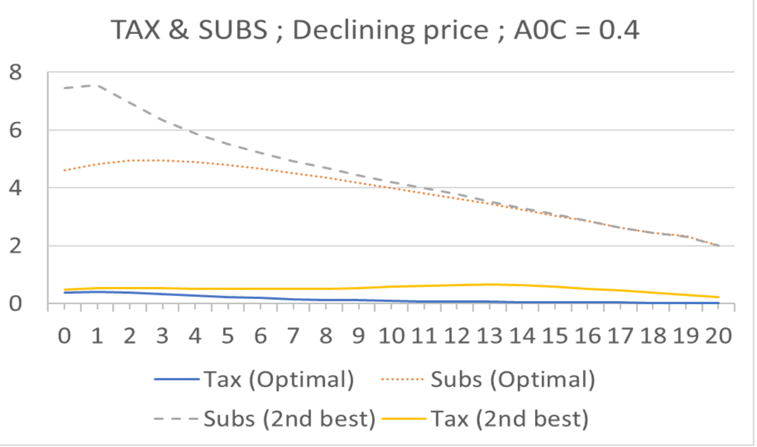
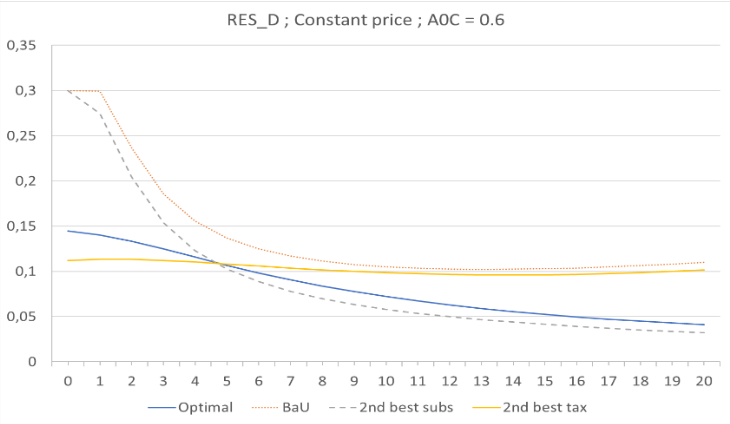
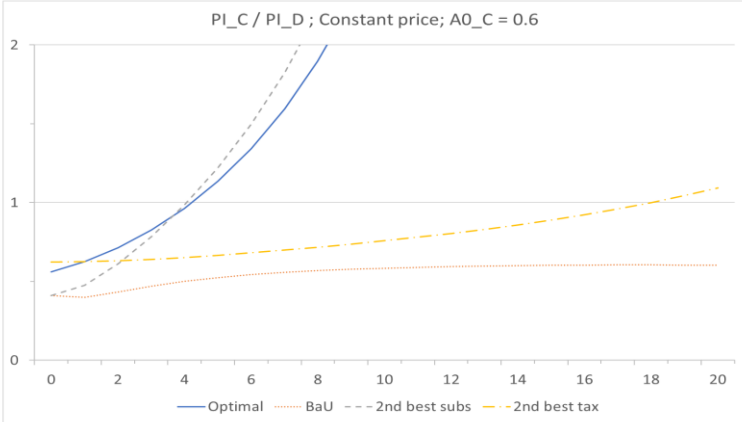


Figure 3 “Constant energy prices and developed clean sector”

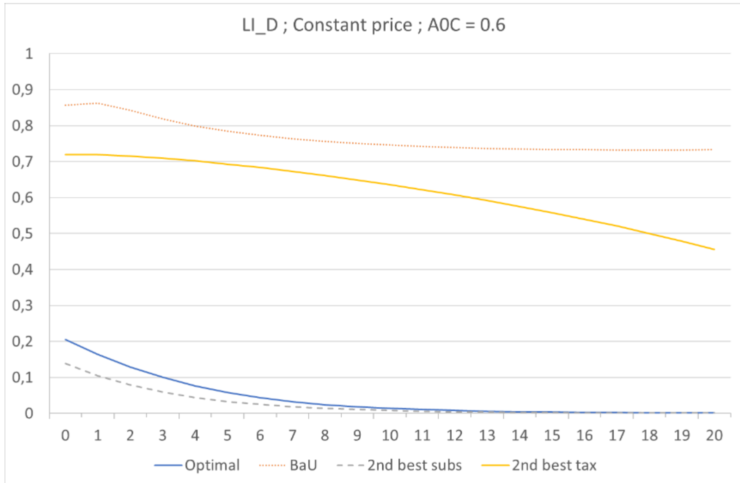
Panel a) Petroleum resource extraction



Panel b) Relative profits in clean versus dirty energy production



Panel c) Allocation of researchers to dirty R&D



Panel d) Tax and subsidy levels (as shares of resource costs and expected R&D profits, respectively)

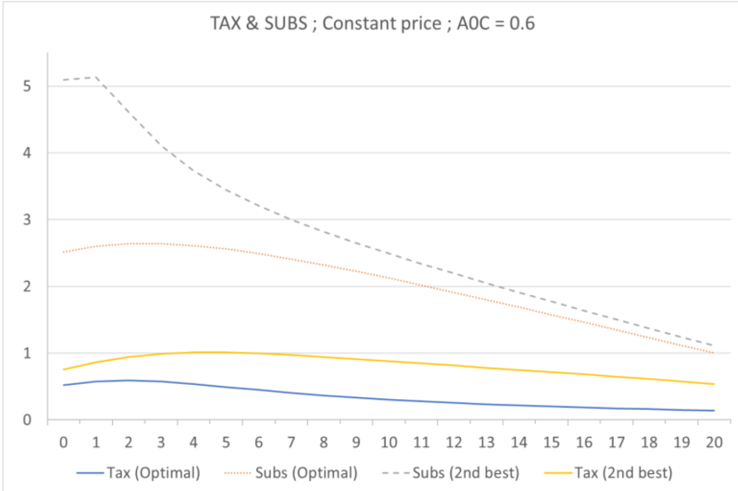
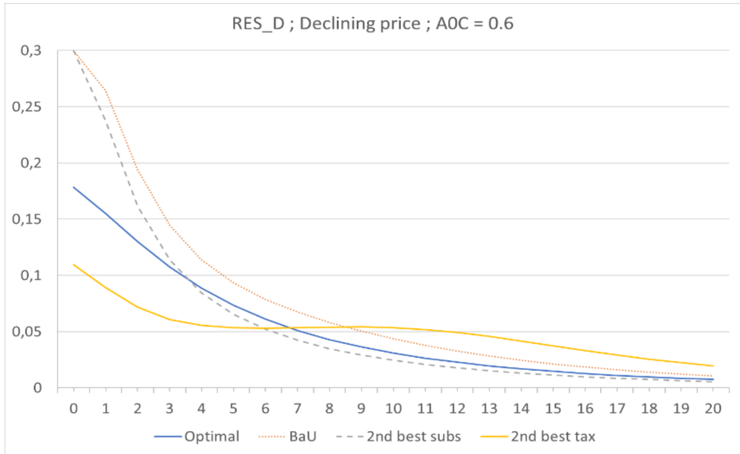
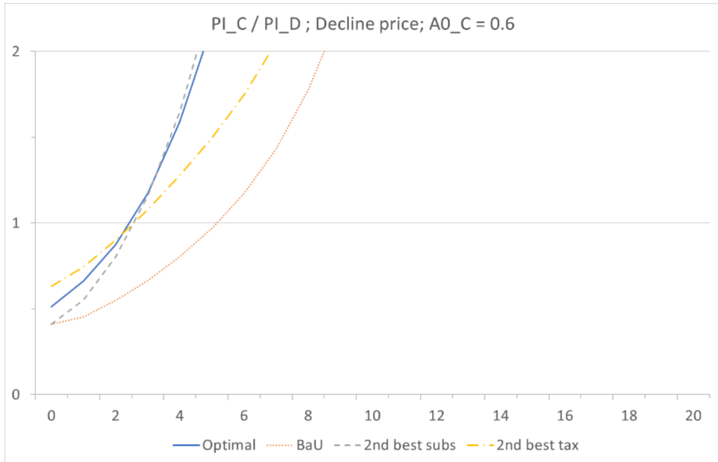


Figure 4 “Declining petroleum prices and developed clean sector”

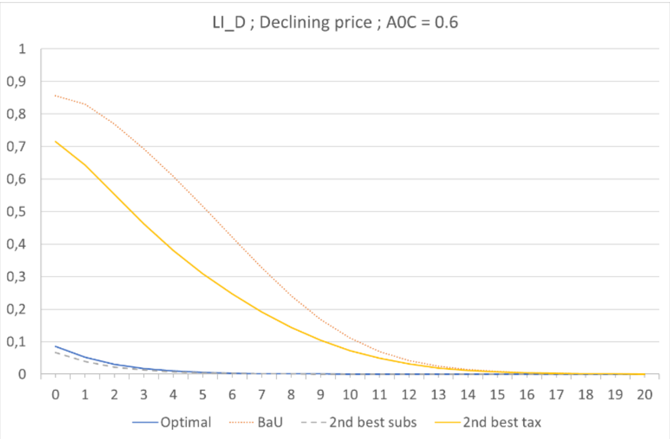
Panel a) Petroleum resource extraction



Panel b) Relative profits in clean versus dirty energy production



Panel c) Allocation of researchers to dirty R&D



Panel d) Tax and subsidy levels (as shares of resource costs and expected R&D profits, respectively)

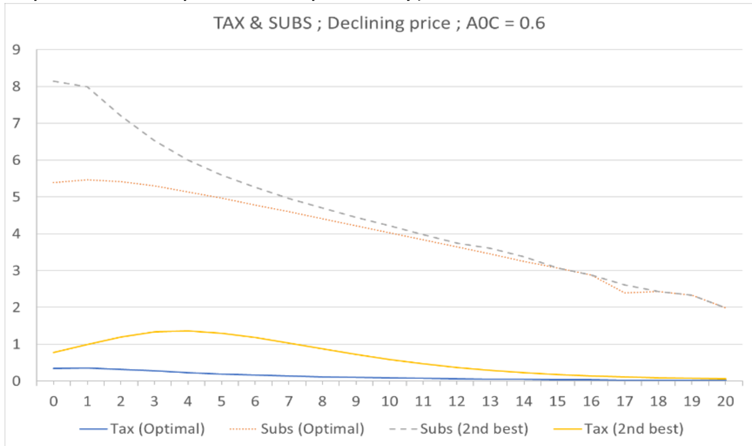
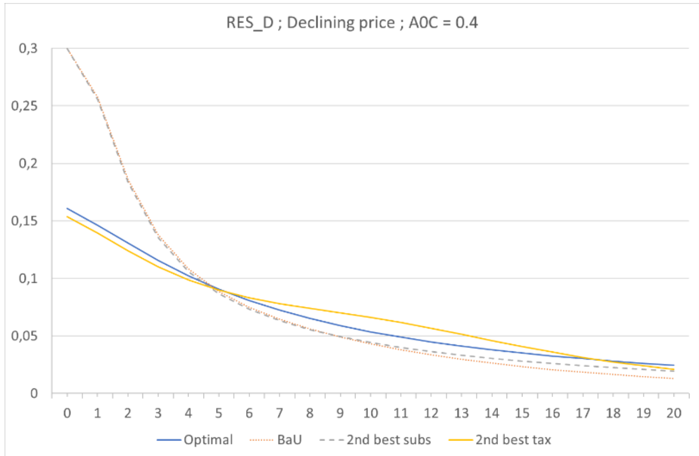
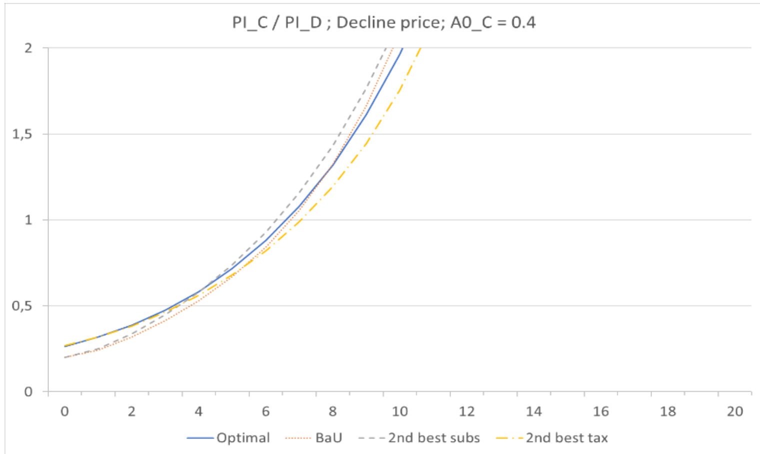


Figure AI “Declining petroleum prices and underdeveloped clean sector with knowledge spill-overs”

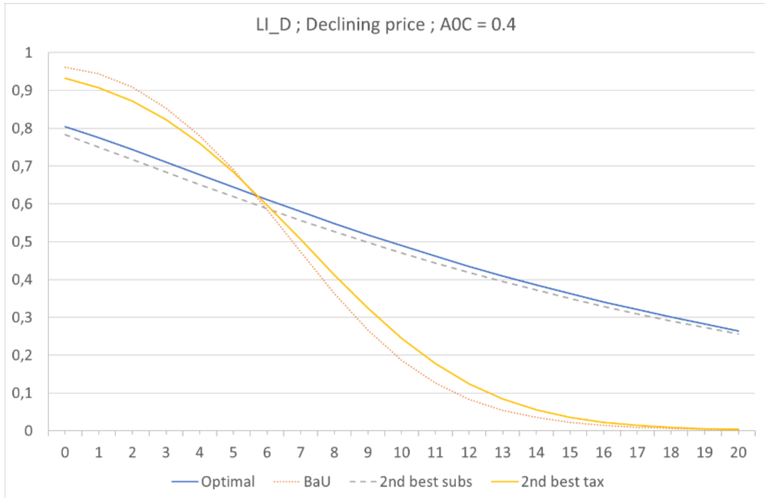
Panel a) Petroleum resource extraction



Panel b) Relative profits in clean versus dirty energy production



Panel c) Allocation of researchers to dirty R&D



Panel d) Tax and subsidy levels (as shares of resource costs and expected R&D profits)