Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

Clean Innovation, Heterogeneous Financing Costs, and the Optimal Climate Policy Mix

CAMA Working Paper 25/2023 (Earlier versions are available as 25a&25b/2023)
May 2024

Emanuele Campiglio
University of Bologna
RFF-CMCC European Institute on Economics and the Environment (EIEE)
LSE Grantham Research Institute on Climate Change and the Environment

Alessandro Spiganti
Ca' Foscari University of Venice
RFF-CMCC European Institute on Economics and the Environment (EIEE)

Anthony Wiskich
Centre for Applied Macroeconomic Analysis, ANU

Abstract

Access to finance is a major barrier to clean innovation. We incorporate a financial sector in a directed technological change model, where research firms working on different technologies raise funding from financial intermediaries at potentially different costs. We show that, in addition to a rising carbon tax and a generous but short-lived clean research subsidy, optimal climate policies include a clean finance subsidy directly aimed at reducing the financing cost differential across technologies. The presence of an endogenous financing experience effect induces stronger mitigation efforts in the short-term to accelerate the convergence of heterogeneous financing costs. This is achieved primarily through a carbon price premium of 39% in 2025, relative to a case with no financing costs.

Keywords

carbon tax, endogenous growth, innovation policy, green financial policy, low-carbon transition, optimal climate policy, sustainable finance

JEL Classification

H23, O31, O44, Q55, Q58, G18

Address for correspondence:

(E) cama.admin@anu.edu.au

ISSN 2206-0332

Clean innovation, heterogeneous financing costs, and the optimal climate policy mix*

Emanuele Campiglio[a,b,c], Alessandro Spiganti[b,d], and Anthony Wiskich[e]

[a] *Department of Economics, University of Bologna, Bologna, Italy*
[b] *RFF-CMCC European Institute on Economics and the Environment (EIEE), Milan, Italy*
[c] *LSE Grantham Research Institute on Climate Change and the Environment, London, UK*
[d] *Department of Economics, Ca' Foscari University of Venice, Venice, Italy*
[e] *Centre for Applied Macroeconomic Analysis, Australian National University, Canberra, Australia*

Abstract

Access to finance is a major barrier to clean innovation. We incorporate a financial sector in a directed technological change model, where research firms working on different technologies raise funding from financial intermediaries at potentially different costs. We show that, in addition to a rising carbon tax and a generous but short-lived clean research subsidy, optimal climate policies include a clean finance subsidy directly aimed at reducing the financing cost differential across technologies. The presence of an endogenous financing experience effect induces stronger mitigation efforts in the short-term to accelerate the convergence of heterogeneous financing costs. This is achieved primarily through a carbon price premium of 39% in 2025, relative to a case with no financing costs.

Keywords: carbon tax, endogenous growth, innovation policy, green financial policy, low-carbon transition, optimal climate policy, sustainable finance
JEL codes: H23, O31, O44, Q55, Q58, G18

*Emails: emanuele.campiglio@unibo.it alessandro.spiganti@unive.it, twiskich@googlemail.com. Corresponding author: Alessandro Spiganti. We thank Nadia Ameli, Louis Daumas, Stephie Fried, Claudia Ghisetti, Christian Haas, Karol Kempa, Sumit Kothari, Francesco Lamperti, Francesca Larosa, Hubert Massoni, Joëlle Noailly, Laura Nowzohour, Dongyang Pan, Francesco Ricci, Esther Shears, Bjarne Steffen, Roberta Terranova, and audiences at the 2022 conferences of the Italian Association of Environmental and Resource Economists (IAERE) and the European Association of Environmental and Resource Economists (EAERE), the 2022 Monte Verità Conference on Sustainable Resource Use and Economic Dynamics (SURED), the 2022 Environmental Protection and Sustainability Forum (EPSF), and the 2023 conference of the Italian Economics Society (SIE), for useful comments and suggestions. The research leading to these results has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 Research and Innovation Programme (Grant agreement No 853050 - SMOOTH).

1 Introduction

Mitigating climate change requires an unprecedented technological transition to carbon-free productive processes (IPCC, 2023). However, despite rapid recent advancement in some areas, low-carbon technologies are often still less competitive than their carbon-intensive counterparts, especially in the so-called 'hard-to-abate' sectors (IEA, 2022a, IPCC, 2022). A large-scale innovation effort is thus needed to develop the technologies capable of replacing polluting incumbents (Cervantes et al., 2023).

The role of innovation in the transition to a sustainable economy has been thoroughly studied in recent decades (Popp, 2019, Grubb et al., 2021). Innovation in itself is subject to a market failure stemming from the public good nature of knowledge - i.e. innovators are not fully able to reap the benefits of their inventions. In the case of 'clean' innovation, a second market failure emerges from the environmental externality, as individuals do not fully internalise the net social benefits of using technologies that reduce emissions (Popp, 2010, Fischer et al., 2017, Howell, 2017). The canonical answer of economic theory to these issues is to introduce policies able to correct market failures. More precisely, the seminal work by Acemoglu et al. (2012), as well as the subsequent literature on clean directed technical change (e.g. Acemoglu et al., 2016, Greaker et al., 2018, Hart, 2019, Lemoine, 2024), identifies two key policy interventions to achieve an optimal low-carbon transition: a rising carbon tax to internalise the climate externality and a generous but temporary clean research subsidy, which helps direct a higher share of research efforts towards clean technological development.

So far, however, the modelling literature on the topic has typically abstracted from a crucial dimension of innovation: access to finance. Indeed, access to finance is one of the major barriers to firms' innovative activity (e.g. Hall and Lerner, 2010, Brown et al., 2012, Hottenrott and Peters, 2012, Kerr and Nanda, 2015). Firms with little experience, in emerging sectors, or requiring more upfront capital, are found to be particularly financially constrained (Howell, 2017). It is not surprising then that access to finance for innovative activities is particularly problematic for clean sectors. First, innovative clean firms tend to be rather small and lack long-standing relationships with banks, which renders securing debt financing more difficult (Noailly and Smeets, 2015). Second, it is costlier for investors to run risk assessments and due diligence processes for novel and immature technologies, for which performance data is scarcely available and standardised investment structures, frame contracts, and partner networks are lacking (Egli et al., 2018). Third, there is evidence of lenders' technological conservatism, whereby financial institutions deter lending for new technologies when their information on the existing technology is not transferable (Minetti, 2011). Finally, clean innovations are characterised by higher technical risks, longer payback periods, and more uncertainty on the appropriability of private rents, all characteristics that increase the probability of experiencing barriers to access financing (Ghisetti et al., 2017). The above mechanisms have two main implications: i) financing clean technologies is subject to more uncertainty and ii) it demands additional costs, such as risk assessments, to mitigate this uncertainty.

While financing clean innovation can be harder than for other technologies, access conditions to external finance can improve via learning and experience effects. Experience curves have been observed in several productive sectors, including clean technology ones, with a general interpretation that costs decline as cumulative production increases (e.g. Boston Consulting Group, 1970, Yelle, 1979, Weiss et al., 2010, Rubin et al., 2015). A similar 'learning-by-lending' effect has been investigated for financing activities, where lenders are able to offer more and better directed funding as their knowledge of firms and industries improves (Botsch and Vanasco, 2019, Degryse et al., 2022, Jiang and Li, 2022). There is also empirical evidence of an experience effect among debt providers in the specific case of renewable energy technologies: financing conditions improve as lenders become acquainted with novel technologies and growing markets trigger the formation of in-house project finance teams specialised in renewable technologies, allowing for more accurate technology assessments and better due diligence processes (Egli et al., 2018, Polzin et al., 2021, IRENA, 2023).

In addition, policy-makers can design and implement strategies aimed at facilitating the access to finance for firms investing in clean technologies. For instance, public development financial institutions have often supported sustainable investments by offering loans at lower-than-market interest rates (EIB, 2023). The role of development banks is particularly crucial for technologies in need of innovation finance and characterised by high risk perceptions and technological immaturity (Geddes et al., 2018, Mazzucato and Semieniuk, 2018, Geddes and Schmidt, 2020). Alternatively, governments can support the mobilisation of private finance flows towards low-carbon technologies by mitigating risks through guarantees, insurance products, public-private partnerships, and technical assistance (Prasad et al., 2022). More recently, central banks and financial regulators have also explored strategies to directly incentivise bank lending towards sustainable activities, through either monetary or prudential policies (D'Orazio and Popoyan, 2019, Boneva et al., 2022). These policy tools are likely to be complementary to carbon pricing, clean technology subsidies, and other traditional mitigation strategies, as they address additional market failures specific to the financial sector.

Therefore, abstracting from the financial-related dimensions of innovation might lead to partially incorrect policy conclusions and leave many relevant questions unanswered. For example, are climate policies sufficient to incentivise lenders to redirect funds towards innovations in emission-free products and industries? How quickly should emissions be reduced, given the existence of these financing barriers? Is a policy specifically targeting the financial sector needed for the transition? And what is the optimal mix of policies to ensure a low-carbon transition in the presence of financing experience effects?

In this paper, we begin to answer these questions by embedding a financial sector into an endogenous growth model where innovation can be directed to high-carbon (dirty) and low-carbon (clean) inputs. In our economy: i) a manufacturing sector produces a homogeneous final good using clean and dirty intermediate inputs; ii) two (clean and dirty) intermediate sectors produce the required inputs using labour and a continuum of machines;[1] iii) two capital good sectors produce (clean and dirty) machines; iv) two (clean and dirty) research sectors employ scientists to improve the productivity of machines; and v) a financial sector provides funds to research firms at a cost.

Research firms require external finance to cover the flow mismatch between the payments to input factors and revenue realisation, and thus enter into contracts with financial intermediaries outlining the advancement of funds from the intermediary to the firm and the payment from the firm back to the intermediary. In the stochastic innovation process à la Acemoglu et al. (2012), research firms have a positive probability of failing, in which case they are unable to repay their loan. The financial sector demands a higher interest rate to clean firms due to greater fundamental risks of such innovative projects succeeding, and to cover direct economic costs that help to mitigate these risks. Indeed, while the probability of success of an individual firm is unobservable, an intermediary can choose to assess – at a cost – the project proposed by a research firm, thereby increasing the odds of financing a successful project and getting repaid.[2]

We first show that our theoretical model is characterised by a laissez-faire equilibrium in which research and production are pursued in both technologies. In addition to the effects already outlined by the literature on directed technical change,[3] we highlight a novel *financing experience effect*, which directs innovation towards the sector characterised by lower auditing, monitoring and screening costs; more advanced risk assessments and due diligence processes; more standardised contracts and investment structures; or by intangible assets more easily valued. Since financial intermediaries ignore the social benefits linked to the financing of clean innovative firms, the amount of funds going to clean in-

[1] Clean intermediate inputs can narrowly be intended as low-carbon energy (as in Acemoglu et al., 2012, Fried, 2018, Greaker et al., 2018, Hart, 2019) or more broadly as any input that could substitute for polluting ones (as in Hémous, 2016).

[2] The assessment, whose cost is increasing and convex in these odds, can be interpreted as a combination of screening (King and Levine, 1993), monitoring (Townsend, 1979, Gale and Hellwig, 1985, Williamson, 1986, Cole et al., 2016), and redeployability potential assessment (Shleifer and Vishny, 1992). For example, this process can be thought of as the financial intermediary requesting external technical expertise to better understand the prospects of different technologies – e.g. the likelihood of low-carbon vehicles being based on electric batteries rather than hydrogen fuel cells or biofuels (Dugoua and Dumas, 2021, 2023) – or the relative expected performance of different firms within the same technological space – see for instance the failure of Solyndra in an otherwise florid solar energy market (Caprotti, 2017).

[3] The literature usually distinguishes: i) a direct productivity effect, which directs innovation to the relatively more advanced sector; ii) a price effect, which directs innovation towards the more backward sector commanding a higher price; iii) a market size effect, incentivising innovation in the larger sector (see e.g. Acemoglu et al., 2012).

novations in any given period is sub-optimal. Across periods, this has an intertemporal externality, as it translates in too little research and production in the clean sectors and financing costs that are persistently higher for clean research firms, since these depend on cumulative outputs in each technology. Our theoretical results underline that heterogeneous access conditions to external finance stifle innovation and thus production in the relatively novel sector: unless policy takes account of the differential in financing costs, this leads to a delay in the low-carbon transition. The optimal climate policy mix involves a carbon tax, a clean research subsidy, and a subsidy dedicated to facilitate clean financing. While the first two policy tools are already discussed in the related literature on clean technical change, the presence of a financial subsidy in the optimal policy mix is a novel result of this paper.

To study the dynamic interactions between climate policy, clean innovation, and financing costs, we then calibrate and numerically simulate our model, under a constraint on cumulative emissions compatible with a 2°C limit in global temperatures. We highlight two main sets of findings. First, we show that the optimal low-carbon transition path involves a diversified and evolving portfolio of climate policies. While the endogenous financing experience effect helps the transition even without policies, this is by no means sufficient in reaching mitigation objectives. In line with the directed technical change literature, we find an optimal transition to require a steeply rising carbon tax and a generous but temporary clean research subsidy, which help induce a higher clean research share in the near term. In our main scenario, the optimal carbon price starts at \$205 per tonne of CO_2 in 2025 and later grows at an annual rate between 4% and 5%, while the optimal clean research subsidy jumps to 0.23% of GDP in 2025, before being phased out by 2050. However, our modelling framework also allows us to reach a key additional novel result: in an optimal transition, the social planner must also introduce a 'clean finance subsidy', aimed at supporting intermediaries that provide innovation finance to clean research firms. In our numerical simulations, this subsidy is approximately equal to 0.08% of GDP in 2025, before slowly decreasing and disappearing in the second half of the century. Not allowing for this third policy – as customary in the large majority of related models – leads to a sub-optimal outcome. Our results indicate that, while abstracting from clean finance subsidies has an effect on the optimal values of both the carbon tax and the clean research subsidy, these are unable to compensate for the absence of an additional dedicated policy, as the financial market failure remains partially unaddressed.

Second, the presence of endogenous financing costs affects the time profile of optimal climate policies, pushing for an earlier effort. While heterogeneous access to finance poses a substantial threat to the low-carbon transition as it creates path dependency and stifles innovation in the clean sector, the endogenous reaction of financing costs to technological evolution enhances the efficacy of climate policies. Endogenous clean financing costs decline more rapidly as output becomes cleaner, winning reluctance of the financial sector and triggering a stronger redirection of funds to clean technologies, further speeding up the transition in a virtuous decarbonisation cycle. A key consequence of this link is that it becomes optimal for the policy-maker to strengthen climate policy and decrease emissions more rapidly in the near-term. Our benchmark scenario finds a premium in optimal carbon price of 39% in 2025 (then decreasing over time towards zero), relative to a case without financing costs. We also show that the optimal policy mix depends on the nature of the financing experience effect, i.e. on which indicators financial intermediaries build to update their financing conditions. If the financial sector reacts to relative cumulative sector outputs, the endogeneity of this experience effect leads to a higher carbon tax, since this is a more effective instrument at targeting outputs than the clean research subsidy. Conversely, if the experience effect is linked to research, the policy ambition translates into a higher initial clean research subsidy (higher by 29%, or 0.11% of GDP). In both cases, a clean finance subsidy between 0.04% and 0.08% of GDP is needed. Therefore, the choice of optimal climate policies will differ across markets, technologies, and geographical areas if the nature of this experience effect differs, possibly due to different lending environments and institutions (see for instance Aghion et al., 2022).

We build on and contribute to three main streams of literature. First, we closely connect to the modelling literature examining clean directed technical change in an endogenous growth setting, originating from Acemoglu et al. (2012). While this framework has been extended in many directions,[4] our main novelty is that we add a financial sector and a specific policy tool aimed at promoting access to finance by clean innovators.

Second, we relate to the literature pointing out the importance of finance for growth. Among the seminal papers, we are particularly close to King and Levine (1993), where financial intermediaries strengthen the rate of technological progress by identifying the projects that are most likely to succeed, and Greenwood and Jovanovic (1990), where they enhance growth by funding more promising firms, while producing valuable information on them. For more recent contributions, see e.g. Buera et al. (2011), Greenwood et al. (2010), and Cole et al. (2016). Our novelty is to focus on an environmental setting, with clean and dirty sectors.

Third, we build on the (mostly) empirical literature on clean innovation and financing constraints. Contributions in this area usually find that environmental innovations face

[4]For example, Acemoglu et al. (2016) provide a micro-founded quantitative version of the model; Hémous (2016) adds a second country to examine whether unilateral environmental policies can ensure sustainable growth; Lennox and Witajewski-Baltvilks (2017) adds slowly depreciating capital; Greaker et al. (2018) consider long-lasting patents and decreasing returns to research; Fried (2018) and Hart (2019) introduce technology spillovers across sectors; in Stern et al. (2019), both intermediate sectors use energy inputs; Wiskich (2021) analyses the presence of multiple equilibria; Nowzohour (2021) adds adjustment costs; Smulders and Zhou (2022) add expectations about the future path of innovation; Kruse-Andersen (2023) adds population growth; Lemoine (2024) adds complementarities between innovations and energy resources; Wiskich (2024) considers clean production subsidies.

more hindrances than traditional innovations when it comes to the financing process (Howell, 2017, Jensen et al., 2019, Noailly and Smeets, 2021).[5] This is in line with the empirical evidence suggesting that access to debt is more difficult in the case of new and immature technologies than for incumbent and widely-known technologies – see Lahr and Mina (2021) for a general analysis and Kempa et al. (2021) for a focus on energy firms.

To the best of our knowledge, only two other recent articles try to combine these streams of work, as we do: Pan et al. (2022) and Aghion et al. (2022).[6] While these authors also add financing costs to a model of clean directed technical change, our focus substantially differs from theirs. Pan et al. (2022) discuss the role of clean innovation in the recovery period after the COVID-19 pandemic, whereas Aghion et al. (2022) analyses differences in the long-run rate of patenting of clean technologies between the EU and selected peers and across EU member states, and how these relates to cross-country differences in venture capital investments. From a modelling perspective, both papers consider financing conditions to be exogenous and time-independent, and abstract from targeted policies. We move beyond these assumptions by i) considering dynamic and endogenous financing costs and ii) introducing the possibility for the policy-maker to implement endogenous clean finance subsidies. Our framework thus allows for a richer set of policy-relevant results.

The remainder of this paper is organised as follows. Section 2 formalises the model and Section 3 describes its balanced growth path. Section 4 presents our calibration strategy. Section 5 provides numerical analyses and policy experiments. Finally, Section 6 concludes.

2 The Model

We consider an infinite-horizon economy in discrete time. This is inhabited by a continuum of infinitely-lived households comprising a constant mass L of workers and a constant mass H of scientists. As summarised in Figure 1, our economy features several sectors: i) a manufacturing sector producing a homogeneous final good using a clean intermediate input and a dirty intermediate input, ii) two intermediate sectors, producing differentiated intermediate inputs (one clean and one dirty) using labour and

[5] Related are also the findings by Ghisetti et al. (2017) and Cecere et al. (2020) that enterprises involved in eco-innovation activities in Europe struggle in getting external sources of finance due to the perception of uncertainties in the clean innovation returns, mainly related to their long payback period. Olmos et al. (2012) reviews policy instruments to overcome these challenges.

[6] Other authors have tried to link financial and transition dynamics using alternative modelling approaches (see for instance Hoffmann et al., 2017, Kotchen and Costello, 2018, D'Orazio and Valente, 2019, Diluiso et al., 2021, Haas and Kempa, 2023, Lessmann and Kalkuhl, 2023); however, most of these papers do not allow for innovation investments. Empirically, De Haas and Popov (2023) shows that better functioning stock markets facilitate the development of cleaner technologies by polluting industries, while also redirecting investments towards more carbon-efficient sectors.

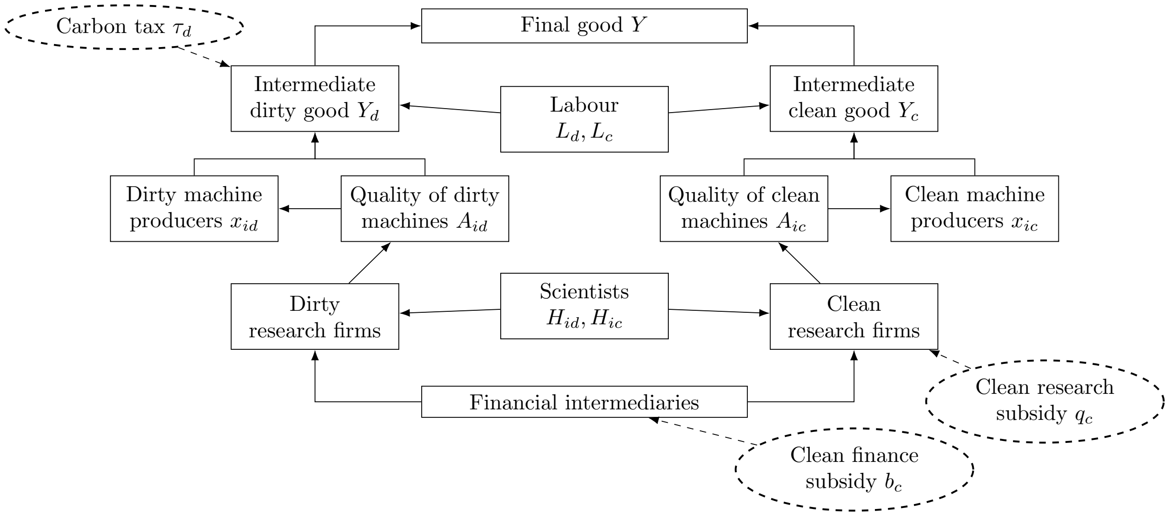


Figure 1: Overview of the model

a continuum of machines, iii) two machine sectors producing machines (some clean and some dirty) using the final good and patents, iv) two research sectors producing patents by employing scientists, and v) a financial sector providing funds to research firms. Workers and scientists are free to move across sectors, with the decision to move only hinging on wage rates.

2.1 Final Good Production

Households consume a unique final good, Y_t. This is produced competitively by a representative firm combining clean and dirty inputs, Y_{ct} and Y_{dt}, according to the following constant elasticity of substitution technology,

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

where ϵ is the elasticity of substitution between the two intermediate inputs. We focus on the more empirically relevant case in which the two intermediate inputs are substitutes (see Section 4), as we expect clean technologies to replace dirty technologies.

Assumption 1. *The intermediate inputs are (gross) substitutes, i.e.* $\epsilon > 1$.

2.2 Intermediate Inputs Production

The production function for each intermediate input $j \in \{c, d\}$ has constant returns to scale in labour and a unit mass of sector-specific machines,

$$Y_{jt} = L_{jt}^{1-\alpha} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha} \, di, \quad \forall j = \{c, d\}, \tag{2}$$

where L_{jt} is labour demand in sector j at time t, $\alpha \in (0,1)$, A_{jit} is the quality of machine $i \in [0,1]$ in sector j at time t, and x_{jit} is the quantity demanded of this machine. The Cobb-Douglas formulation of the production function in (2) leads to the following iso-elastic demands for inputs,

$$L_{jt} = \left[\frac{(1-\alpha)\, p_{jt}}{w_{jt}\,(1+\tau_{jt})} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha}\, di \right]^{\frac{1}{\alpha}} \tag{3a}$$

$$x_{jit} = \left[\frac{\alpha p_{jt}}{p_{jit}\,(1+\tau_{jt})} \right]^{\frac{1}{1-\alpha}} A_{jit} L_{jt}, \tag{3b}$$

where p_{jt} is the price of the intermediate good Y_{jt}, τ_{jt} is a tax (or subsidy) rate on the production of intermediate good Y_{jt} as in Acemoglu et al. (2012), w_{jt} is the wage in sector j at time t, and p_{jit} is the price of machine i in sector j at time t. In equilibrium, labour market clearing requires that $L_{ct} + L_{dt} = L$.

The first order conditions of the final good producer imply that the relative demands for the intermediate inputs are inversely related to their prices,

$$\frac{Y_{ct}}{Y_{dt}} = \left(\frac{p_{dt}}{p_{ct}} \right)^{\epsilon}. \tag{4}$$

Without loss of generality, we normalise the price of the final good in each period to one, $\left(p_{ct}^{1-\epsilon} + p_{dt}^{1-\epsilon}\right)^{1/(1-\epsilon)} \equiv 1$.

While clean intermediate production does not create carbon emission, dirty production emits κ units of carbon per intermediate input, i.e. emissions at time t are κY_{dt}. Cumulative emissions at time t are given by[7]

$$S_t = \sum_{\tau=-\infty}^{t} \kappa Y_{d\tau}. \tag{5}$$

In this context, optimal climate policy takes the form of a carbon budget $\bar{S}$ for cumulative future emissions.

2.3 Production of Machines

Machines are produced by two machine producing sectors, each with a continuum of firms of mass one. In line with the endogenous growth literature, each machine producer in a sector acts as a monopolist in the production of its particular machine. In particular, each of these firms has purchased a one-period patent from a research firm in the corre-

[7] We do not incorporate a carbon cycle following insights in atmospheric science (e.g. Allen et al., 2009, Matthews et al., 2009) arguing that warming is linear in cumulative carbon emissions. This has already been assimilated in the economics literature, see e.g. van der Ploeg (2018), Dietz and Venmans (2019), Dietz et al. (2021), van der Ploeg and Rezai (2021), and Comerford and Spiganti (2023).

sponding research sector and can then produce the related machine at marginal cost equal to ψ units of the final good; the machine is then sold to the intermediate goods producers in the relevant sector j at price p_{jit}. As common in this literature (e.g. Acemoglu et al., 2012, Fried, 2018), machines fully depreciate after use.

Formally, the maximisation problem of the producer of machine i in sector j is, once acquired a patent,

$$\pi_{jit} \equiv \max_{p_{jit}, x_{jit}} \left[p_{jit} - \psi \left(1 - s\right)\right] x_{jit}, \qquad \text{s.t. (3b)}, \tag{6}$$

where s is a subsidy rate that the social planner can use to correct for the static and symmetric monopoly distortion (see e.g. Acemoglu et al., 2012). Without loss of generality, we normalise $\psi \equiv \alpha^2$ (as in Acemoglu et al., 2012, Aghion et al., 2022, Lemoine, 2024). Each machine producer faces the demand x_{jit} in (3b): since the demand is iso-elastic, the monopoly price is a constant mark-up over the marginal cost, i.e. $p_{jit} = \psi(1 - s)/\alpha = \alpha(1 - s)$, thus unique across the economy. Substituting this price into the equilibrium demand function (3b) shows that the demand for a machine i within sector j and the subsequent profits of its producer are, respectively,

$$x_{jit} = \left[\frac{p_{jt}}{\left(1 - s\right)\left(1 + \tau_{jt}\right)}\right]^{1/(1-\alpha)} A_{jit} L_{jt} \tag{7a}$$

$$\pi_{jit} = \alpha(1 - \alpha) \left[\frac{p_{jt}}{\left(1 - s\right)^{\alpha}\left(1 + \tau_{jt}\right)}\right]^{1/(1-\alpha)} A_{jit} L_{jt}. \tag{7b}$$

2.4 The Innovation Process

Following the large literature originated from Romer (1990a,b), there is a continuum of firms of mass one in each research sector aiming to produce knowledge using scientists and existing knowledge. At the beginning of each period, a research firm hires scientists to try innovating, i.e. to increase the quality of its machine. As in Acemoglu et al. (2012), innovation is stochastic: a research firm is successful in the innovation process with probability $\lambda_j \in [0, 1]$, in which case the quality of the machine increases and the research firm can sell the patent to a machine producer in the corresponding sector. Conversely, with the remaining probability $1 - \lambda_j$, the innovation process is unsuccessful and the quality of the machine does not increase; as in Aghion and Howitt (2009), Acemoglu et al. (2012), and Aghion et al. (2022), the patent for this machine with the old quality is then allocated randomly to a research firm drawn from the pool of failed innovators.[8]

Following Fried (2018), the evolution of the machine's quality for research firm i in

[8]This assumption is taken for simplicity, but Acemoglu et al. (2012) show that the qualitative results are identical with free entry for old machines.

sector j is

$$A_{jit} = \begin{cases} A_{jt-1}\left(1+\gamma H_{jit}^{\eta}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}\right), & \text{with probability } \lambda_j \\ A_{jt-1}, & \text{with probability } 1-\lambda_j, \end{cases} \tag{8}$$

where H_{jit} is the number of scientists hired by firm i in sector j at time t, the parameter $0 \leq \eta < 1$ induces decreasing marginal returns in research (the so-called 'stepping on toes' feature, introduced by Kortum, 1993, Jones, 1995), $\gamma > 0$ measures the efficiency with which new innovations are produced by scientists, $A_{jt} \equiv \int_0^1 A_{jit} di$ is the average quality of the machines in sector j at the end of period t, $A_t \equiv A_{ct} + A_{dt}$ is aggregate technology,[9] and $0 \leq \phi \leq 1$ determines the strength of the cross-sector spillovers. Let H_{jt} represent the total number of scientists employed in sector j: in equilibrium, labour market clearing for scientists requires that $H_{ct} + H_{dt} = H$.

This form of the innovation possibility frontier is quite general and encompasses several characteristics that may be important for the financing conditions of these technologies. First, in line with the baseline model by Acemoglu et al. (2012), it allows for the possibility of failure in the innovation process, thus underlining that innovation is a risky business. We show below that, in our model, this will also impact the financing conditions set by financial intermediaries, as interest rates charged on loans must consider the probability that these will not get repaid.

Second, there are technology spillovers within a sector after one period, when discoveries are observed by other machine producers in the same sector and can be incorporated into their own innovation processes. This represents the 'standing on shoulders' feature of innovation, which characterises many endogenous growth models.[10] In our model, this also introduces a positive externality in terms of financing conditions within sectors: when the level of a technology increases faster than the competing one, its relative output increases, which may lead to a change in the relative financing conditions, as explained below.

Finally, there are technology spillovers across different sectors as in Fried (2018) and Hart (2019), among others. In particular, a relatively backward sector j has a productiv-

[9]The qualitative results are unaffected as long as the economy technology frontier is a linearly homogeneous function of the knowledge in the two intermediate sectors.

[10]We follow Fried (2018) in assuming that the initial quality of each machine in a period depends on the average quality of all the machines in a sector at the end of the previous period. An alternative approach (used in e.g. Acemoglu et al., 2012, Greaker et al., 2018, Lemoine, 2024) would be to assume that an innovator is randomly allocated to at most one machine in the chosen sector. Yet another approach is to add knowledge spillovers across machines within the same sector, as in Hémous (2016). These alternative assumptions, which allow one to focus on the evolution of average technologies rather than keeping track of the entire distribution of machine qualities, lead to the same results.

ity advantage equal to the catch-up ratio $(A_{t-1}/A_{jt-1})^{\phi}$.[11] Indeed, it seems reasonable to assume that some improvements in the technology of one sector may increase the productivity of innovation in the other sector (see e.g. Barbieri et al., 2023). If these spillovers are sufficiently strong, then innovation occurs in both sectors along the balanced growth path, matching empirical evidences on the amount of innovation in both fossil and clean technologies since at least the 1970s (Fried, 2018). In our setting, this means that both technologies may require access to finance at the same time along the balanced growth path; still, financing conditions may be different across different sectors.

2.5 The Financial Contract

In each period, there are several intermediaries in a competitive financial sector, each owned equally by all agents. Each intermediary has access to international capital markets and enters into financial contracts with research firms to provide funds; without loss of generality, we normalise the cost of raising funds for financial intermediaries to zero. A financial contract lasts one period and specifies the amount of funds that the intermediary will lend to the research firm and the unit repayment $1 + r_{jit}$ that the firm will make to the intermediary. The repayment is contingent on the outcome of the innovation process, which is publicly observable. Research firms are protected by limited liability, which means that the debt of an unsuccessful firm is never repaid.

To introduce heterogeneous financing costs into the model, we follow the basic idea that working capital is required to cover the flow mismatch between the payments to the factors of production made at the beginning of the period and the realisation of revenues at the end of the period (Mendoza, 2010, Jermann and Quadrini, 2012). For this reason, research firms need intra-period loans from financial intermediaries, with the expected revenues serving as collateral for the credit.

Moreover, we follow King and Levine (1993) and suppose that, in addition to the research firms presented in the previous subsection, there are some other firms seeking to finance innovative projects that are in fact not feasible under any circumstances.[12] In particular, let $1 - \theta_{jt}$ be the probability that a borrower in sector j coming to a financial intermediary has an infeasible project; with the remaining probability θ_{jt}, the borrower is a research firm capable of carrying an innovative project, on which it will succeed with probability λ_j.

[11] If $\phi = 0$, there are no cross-sector spillovers, there is full path dependence, and in equilibrium innovation occurs in only one sector if $\epsilon > 1$; if $\phi = 1$ there is no path dependence, and a stable balanced growth path equilibrium exists in which innovation occurs in both sectors. In general, see Acemoglu (2002), Hart (2013), and Fried (2018) for the relationship between the stability of the interior balanced growth path and the strength of the cross-sector spillovers.

[12] This is for ease of exposition, but results are the same if research firms have some probability of drawing infeasible projects.

The main friction in the financial sector is that the feasibility of a project is unobservable by financial intermediaries. However, this friction weakens as the financial sector accumulates experience with a particular technology. First, the financial sector as a whole 'learns-by-lending' about how to discriminate between feasible and unfeasible projects in a given research sector (similarly to Botsch and Vanasco, 2019, Degryse et al., 2022, Jiang and Li, 2022). To model this, let $\nu_{jt} \in [0, 1]$ indicate *financing experience*, a continuous, differentiable, and weakly increasing function of the cumulative output of the corresponding intermediate input.[13] Then, we assume θ_{jt} to be a continuous, differentiable, and weakly increasing function of financing experience. In other words, the more prominent is a technology in production, the more financing this technology receives, and thus the more information is spread throughout the financial sector on how to discern a feasible project within this technology class.

Second, financial intermediaries can decide to embark on costly activities to better understand the feasibility and promises of a project before agreeing on a financial contact, like running risk assessments, due diligence processes, and creating in-house project finance teams specialised in a given technology (Egli et al., 2018, Polzin et al., 2021). To model this, we follow Cole et al. (2016), where an intermediary can decide to run a costly assessment that results in the odds μ_{jit} of financing a feasible project, with the cost of assessment formalised as follows.

Assumption 2. *For each unit lent to firm i in sector j at time t, the cost of assessment is $c(\mu_{jit}, \nu_{jt})$, with i) $c_\mu(\mu_{jit}, \nu_{jt}) \geq 0$ and $c_{\mu\mu}(\mu_{jit}, \nu_{jt}) \geq 0$; ii) for all $\mu_{jit} \leq \theta_{jt}$, $c(\mu_{jit}, \nu_{jt}) = 0$ and $c_\mu(\mu_{jit}, \nu_{jt}) \leq 1/\theta_{jt}$; iii) there exists $\bar{\mu}_t \in (\theta_{jt}, 1]$ such that, as $\mu_{jit} \to \bar{\mu}_t$, both $c(\mu_{jit}, \nu_{jt}) \to \infty$ and $c_\mu(\mu_{jit}, \nu_{jt}) \to \infty$; and iv) $c_\nu(\mu_{jit}, \nu_{jt}) \leq 0$.*

The cost function has four desirable properties. First, it is increasing and convex in the odds μ_{jit}, as usual in this literature. Second, the intermediary can decide not to run the assessment, and this costs nothing; if it then decides to start the assessment, the marginal cost is initially low. Third, full assessment is prohibitively costly, and may not be able to fully remove the risk that an unfeasible project is chosen. Fourth, the cost is decreasing in financing experience. When the financial sector is faced with a technology which it has never financed before, the cost faced by intermediaries is high; however, as this technology is financed and thus used in production, the financial sector accumulates experience with it, allowing intermediaries to investigate a project's quality at a lower cost.

[13] To ensure the stability of the balanced growth path, the limit of the first derivative of this function is zero as cumulative output approaches infinity. Whereas theoretical results are unchanged if experience depends on cumulative sectoral output, research, productivity, labour, or loans, quantitative results may differ: in Section 5.2, we compare simulations where these effects depend on cumulative output versus research.

Because there are several competitive intermediaries seeking to lend to each research firm, the optimal financial contract will maximise the expected payoff of the research firm, subject to an expected non-negative profit constraint for the intermediary, and taking as given current financing experience and technology levels. As a consequence, the contract problem between a research firm and an intermediary is

$$\Pi_{jit} = \max_{H_{jit}, r_{jit}, \mu_{jit}} \lambda_j \left[\pi_{jit} - w^s_{jit} H_{jit} \left(1 + r_{jit}\right)\right], \tag{9a}$$

$$\text{s.t. (7b) and (8)} \tag{9b}$$

$$\pi_{jit} - w^s_{jit} H_{jit} \left(1 + r_{jit}\right) \geq 0, \tag{9c}$$

$$\left[\mu_{jit} \lambda_j \left(1 + r_{jit}\right) - c\left(\mu_{jit}, \nu_{jt}\right)\left(1 - b_{jt}\right) - 1\right] H_{jit} w^s_{jit} \geq 0, \tag{9d}$$

where the objective function Π_{jit} represents the research firm's expected profits, which is simply the expected value of the monopoly profits from selling the patent for the production of the new machine $\lambda_j \pi_{jit}$,[14] net of the expected repayment of principal and interest to the intermediary $\lambda_j w^s_{jit} H_{jit}(1 + r_{jit})$. Constraint (9b) reports the profits of the machine producers and the evolution of machine quality. Equation (9c) is the limited liability constraint for the research firm, specifying that the intermediary cannot take more than what the firm obtains in case of success. Finally, equation (9d) is the participation constraint of the intermediary, stipulating that it expects to earn non-negative profits from the financial contract, given the expected repayment, the cost of assessment, the need to raise funds from international capital markets, and a subsidy (or tax) with rate b_{jt} that the social planner can use to alleviate financial intermediaries' cost of assessment.

The solution to this maximisation problem is a triplet of policy functions specifying the number of scientists hired H_{jit} (and thus the size of the loan), the unit repayment requested by the intermediary $1 + r_{jit}$, and the odds from the assessment μ_{jit}; these will be functions of prices, the states of the technologies, financing experience, and policies. In equilibrium, $H_{jit} = H_{jt}$, $r_{jit} = r_{jt}$, and $\mu_{jit} = \mu_{jt}$ $\forall i$ since research firms in the same sector are ex-ante homogeneous; similarly, $w^s_{jit} = w^s_{jt}$ $\forall i$, since scientists are free to move across firms. Moreover, competition drives financing costs down, and the financial sector breaks-even in equilibrium.

Lemma 1. *The financing cost r_{jt} of technology j in period t is inversely related to the amount of financing experience ν_{jt} accumulated by the financial sector with that technology.*

Proof. See Appendix A.1. □

[14] Note that, from the point of view of a machine producer, the decision to undertake the production of a machine is taken comparing profits in (7b) to the cost of the initial investment in acquiring a patent from the research sector. With this knowledge, each patent holder sets the price of patent i in sector j at time t equal to the profits of the matched machine producer, π_{jit}.

2.6 Households

The representative household is inhabited by a unit mass of machine producers and research firms in each sector, L workers, and H scientists. It maximises the following instantaneous iso-elastic utility function,

$$\sum_{t=0}^{\infty}\left[\frac{1}{(1+\rho)^t}\left(\frac{C_t^{1-\sigma}-1}{1-\sigma}\right)\right], \tag{10}$$

where C_t is household consumption at time t, $\rho > 0$ is the discount rate, and $1/\sigma > 0$ measures the willingness to substitute intertemporally. The budget constraint is $C_t = w_{ct}L_{ct} + w_{dt}L_{dt} + w^s_{ct}H_{ct} + w^s_{dt}H_{dt} + \pi_{ct} + \pi_{dt} + g_t$, where g_t is a lump-sum tax (or transfer). As common in the directed technological change literature since e.g. Acemoglu (2002), households consume their entire income.

At the aggregate level, the final good can be used for consumption, machine production, or to pay the financing costs. Therefore, the aggregate resource constraint is $Y_t = C_t + X_{ct} + X_{dt} + M_{ct} + M_{dt}$, where $X_{jt} = \psi \int_0^1 (x_{jit})\, di$ is total expenditure on machines in sector j and $M_{jt} = c(\mu_{jt}, \nu_{jt})\, w^s_{jt}H_{jt}$ is total financing costs in sector j.

3 The Equilibrium

In this section, we characterise the equilibrium of the model and discuss how externalities can be corrected with policy (proofs are formally given in Appendix A.1). An equilibrium is defined by time paths of wages $[w_{ct}, w_{dt}, w^s_{ct}, w^s_{dt}]_{t=0}^{\infty}$, prices for inputs $[p_{ct}, p_{dt}]_{t=0}^{\infty}$, prices for each machine $[p_{cit}, p_{dit}]_{t=0}^{\infty}$, prices of patents $[\pi_{cit}, \pi_{dit}]_{t=0}^{\infty}$, financing costs $[r_{ct}, r_{dt}]_{t=0}^{\infty}$, policy rates $[\tau_{ct}, \tau_{dt}, s, q_{ct}, q_{dt}, b_{ct}, b_{dt}]_{t=0}^{\infty}$, assessment odds $[\mu_{ct}, \mu_{dt}]_{t=0}^{\infty}$, financing experiences $[\nu_{ct}, \nu_{dt}]_{t=0}^{\infty}$, intermediate inputs production $[Y_{ct}, Y_{dt}]_{t=0}^{\infty}$, labour allocations $[L_{ct}, L_{dt}, H_{ct}, H_{dt}]_{t=0}^{\infty}$, quantities of each machines $[x_{ct}, x_{dt}]_{t=0}^{\infty}$, and cumulative carbon emissions $[S_t]_{t=0}^{\infty}$, such that, in each period t, final good producers, intermediate good producers, machine producers, research firms, and financial intermediaries choose, respectively, (Y_{ct}, Y_{dt}), $(L_{ct}, L_{dt}, x_{ct}, x_{dt})$, $(x_{ct}, x_{dt}, p_{cit}, p_{dit})$, $(H_{ct}, H_{dt}, \pi_{cit}, \pi_{dit})$, and $(\mu_{ct}, \mu_{dt}, r_{ct}, r_{dt})$ to maximise profits, the social planner chooses $(\tau_{ct}, \tau_{dt}, s, q_{ct}, q_{dt}, b_{ct}, b_{dt})$ to maximise the net present value of the representative household's utility given $\bar{S}$, the evolution of wages $(w_{ct}, w_{dt}, w^s_{ct}, w^s_{dt})$ and prices $(p_{ct}, p_{dt}, p_{cit}, p_{dit}, \pi_{cit}, \pi_{dit})$ is consistent with market clearing, and the evolution of S_t is given by (5). In particular, we focus on a balanced growth path, i.e. an equilibrium in which aggregate output and consumption grow at the same constant rate as aggregate technology, $(A_{t+1} - A_t)/A_t$ for all t.

3.1 The Equilibrium Allocation of Workers

Combining the demand functions in (3), the equilibrium wage rate of a worker in sector j can be expressed as $w_{jt} = (1-\alpha) A_{jt} \left[p_{jt} (1+\tau_{jt})^{-1} (1-s)^{-\alpha}\right]^{1/(1-\alpha)}$. Since workers are free to move across sectors, in equilibrium they must receive the same compensation in the two sectors, i.e. $w_{dt} = w_{ct} \equiv w_t$. This implies

$$\frac{p_{dt}(1+\tau_{ct})}{p_{ct}(1+\tau_{dt})} = \left(\frac{A_{dt}}{A_{ct}}\right)^{-(1-\alpha)}, \tag{11}$$

which formalises the natural ideas that the input produced with more productive machines will have a relatively lower pre-tax price.

Inserting the equilibrium demand function for machines in (7a) into the intermediate input production function in (2) leads to $Y_{jt} = L_{jt} \left[p_{jt} (1+\tau_{jt})^{-1} (1-s)^{-1}\right]^{\alpha/(1-\alpha)} A_{jt}$. Therefore, the relative production of intermediate goods is

$$\frac{Y_{dt}}{Y_{ct}} = \frac{L_{dt}}{L_{ct}} \left[\frac{p_{dt}(1+\tau_{ct})}{p_{ct}(1+\tau_{dt})}\right]^{\alpha/(1-\alpha)} \frac{A_{dt}}{A_{ct}}. \tag{12}$$

Combining (4), (11), and (12) leads to the following relationship between the equilibrium ratio of labour demands from the two sectors and the relative productivity,

$$\frac{L_{dt}}{L_{ct}} = \left(\frac{A_{dt}}{A_{ct}}\right)^{-\varphi} \left(\frac{1+\tau_{ct}}{1+\tau_{dt}}\right)^{\epsilon}, \tag{13}$$

where $\varphi \equiv (1-\alpha)(1-\epsilon) < 0$ since the intermediate goods are gross substitutes by assumption.

3.2 The Equilibrium Allocation of Scientists

The social planner can use a research subsidy (or tax) at rate q_{jt} to (dis)incentivise scientists to move to a research sector.[15] Since scientists are free to move across sectors, in equilibrium they must receive the same net compensation, $w^s_{dt}(1+q_{dt}) = w^s_{ct}(1+q_{ct}) \equiv w^s_t$. The following relative equilibrium allocation of scientists ensues

$$\frac{H_{dt}}{H_{ct}} = \left[\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi} \left(\frac{p_{dt}}{p_{ct}}\frac{1+\tau_{ct}}{1+\tau_{dt}}\right)^{\frac{1}{1-\alpha}} \left(\frac{L_{dt}}{L_{ct}}\right) \left(\frac{1+q_{dt}}{1+q_{ct}}\right) \left(\frac{1+r_{ct}}{1+r_{dt}}\right)\right]^{\frac{1}{1-\eta}}. \tag{14}$$

[15] For simplicity, the research subsidy is paid directly to scientists (as in Hémous, 2016), but the equilibrium allocation of scientists would be identical if the subsidy was paid to the research firms. In Acemoglu et al. (2012) and Greaker et al. (2018), each research firm is composed of only one scientist, so the two policy approaches coincide.

Equation (14) summarises the three forces that commonly shape the incentives to innovate in the directed technological change literature: i) the direct productivity effect, captured by the term $(A_{dt-1}/A_{ct-1})^{1-\phi}$, which directs innovation to the relatively more advanced sector, ii) the price effect, captured by the term $(p_{dt}/p_{ct})^{1/(1-\alpha)}$, which directs innovation towards the more backward sector commanding a higher pre-tax price, and iii) the market size effect, captured by the term L_{dt}/L_{ct}, incentivising innovation in the sector with the largest market for machines. Equation (14) also highlights that a social planner can use a carbon tax ($\tau_{dt} > 0$ and $\tau_{ct} = 0$) and a clean research subsidy ($q_{dt} = 0$ and $q_{ct} > 0$) to incentivise research in the clean sector.

In our model, there is an additional financing experience effect, captured by the term

$$\frac{1+r_{ct}}{1+r_{dt}} = \left[\frac{1+c\left(\mu_{ct},\nu_{ct}\right)\left(1-b_{ct}\right)}{1+c\left(\mu_{dt},\nu_{dt}\right)\left(1-b_{dt}\right)}\right]\left(\frac{\mu_{dt}\lambda_{d}}{\mu_{ct}\lambda_{c}}\right), \tag{15}$$

that directs innovation towards the sector with the lower cost of external finance (an effect also stressed in the contemporaneuos paper by Aghion et al., 2022). In our equilibrium, this comprises of two terms. The first, in square brackets, captures the direction of scientists towards the sector with e.g. lower auditing, monitoring, and screening costs, with more advanced risk assessments and due diligence processes, more standardised contracts and investment structures, with intangible assets more easily valued. Within the first term, there are also the subsidies b_{jt} targeting assessment costs in the financial sector. The second term, in parentheses, directly depends on the success probabilities of the two research sectors and thus redirects scientists towards the safer, less likely to fail, sector. This effect has a direct link to productivity, as (given a fixed number of scientists) a lower chance of success reduces the aggregate increase in that technology.

3.3 The Laissez-Faire Equilibrium

We start by describing the laissez-faire equilibrium, i.e. the decentralised outcome without policies. First, note that, absent policies, the equilibrium ratios (11), (12), and (13) suggest that, if the ratios of the productivities of the technologies are constant, the amounts of intermediate inputs produced and workers' wage must grow at the same rate across sectors; conversely, labour demands and the prices of the intermediate inputs are constant. Moreover, if technologies grow at the same rate and the relative financing conditions are stable, the effects identified in (14) are constant over time, and so is the allocation of scientists across sectors, whereas a scientist's wage grows at the same rate across sectors.

It is then clear from the technology possibility frontier in (8) that there are two possible types of balanced growth path: a corner solution in which all the scientists are employed in the initially more advanced sector, whose technology grows at a constant rate whereas the other stagnates, and a stable interior path in which scientists are employed in both sectors and the ratio of dirty to clean technology is constant. *Ceteris paribus*, the relative allocation of scientists in the laissez-faire equilibrium depends on the strength of the cross-sector spillovers, ϕ: if these are relatively weak, the economy converges to the former; if they are relatively strong, then it converges to the latter.[16] We focus on the latter, which we consider more realistic and more interesting, by means of the following assumption.

Assumption 3. *The cross-sector spillovers ϕ are strong enough to ensure a stable interior laissez-faire equilibrium.*

In the long-run, the laissez-faire system is characterised by a constant allocation of workers and scientists across sectors. Since such a constant allocation exists, the laissez-faire economy exhibits a unique balanced growth path where innovation is pursued in both sectors under Assumptions 1, 2, and 3.

Proposition 1. *The laissez-faire economy exhibits a unique and globally stable balanced growth path equilibrium in which final output, intermediate inputs, consumption, aggregate technology, technology in each sector, and wages grow at the same constant rate. Along the balanced growth path, the price of a patent, the price of each intermediate input, the price of the final good, the financing costs and experiences, and the labour and scientists allocations across sectors are constant.*

Proof. See Appendix A.1. □

3.4 The Socially Optimal Allocation

In the socially optimal allocation, several market failures that are present in the laissez-faire equilibrium are internalised. The complete planner problem is in Appendix A.1; here, we discuss conditions that are directly relevant to optimal policy.

Let ζ_t and ζ_{jt} be the shadow values of one unit of the final good (which corresponds to the discounted marginal utility of consumption) and of the intermediate input, respectively; then, $\hat{p}_{jt} \equiv \zeta_{jt}/\zeta_t$ is the shadow price (relative to the price of the final good) of intermediate input j at time t. Additionally, let χ_t denote the Lagrange multiplier associated with the evolution of cumulative carbon emissions in (5) and v_{jt} the one associated with the evolution of financing experience in sector j. The socially optimal choices of

[16] An interested reader can find analytical expressions for the relative share of scientists across sectors and the required strength of the cross-sector spillovers for our framework in Appendix A.1.

intermediate input production satisfy

$$\hat{p}_{dt} = Y_{dt}^{-1/\epsilon}\left(Y_{ct}^{(\epsilon-1)/\epsilon} + Y_{dt}^{(\epsilon-1)/\epsilon}\right)^{1/(\epsilon-1)} - \frac{\kappa\chi_{t+1}}{\zeta_t} + \frac{\upsilon_{dt}}{\zeta_t}\frac{\partial\nu_{dt}}{\partial Y_{dt}} \tag{16a}$$

$$\hat{p}_{ct} = Y_{ct}^{-1/\epsilon}\left(Y_{ct}^{(\epsilon-1)/\epsilon} + Y_{dt}^{(\epsilon-1)/\epsilon}\right)^{1/(\epsilon-1)} + \frac{\upsilon_{ct}}{\zeta_t}\frac{\partial\nu_{ct}}{\partial Y_{ct}}. \tag{16b}$$

Compared to the laissez-faire allocation, the social optimum includes a wedge $\kappa\chi_{t+1}/\zeta_t$ representing the cost of an additional unit of the dirty input in terms of cumulative emissions, and a wedge $(\upsilon_{jt}/\zeta_t)\,(\partial\nu_{jt}/\partial Y_{jt})$ representing the external value of an additional unit of the intermediate input Y_{jt} in terms of the financial experience that it generates. Since the relative allocation of resources towards intermediate input production in the decentralised economy is pinned down by the ratio of their net prices, the social planner can simultaneously correct the financial experience and the environmental externalities with a tax on the production of the input with the lower social value; since this is the dirty input in our framework, we refer to this unique tool as 'carbon tax' hereafter.

The social planner must also correct for the knowledge externalities in the evolution of the technologies, as research firms do not internalise the external value of their innovations, which include increased utility (as the rise in average productivity boosts intermediate input production and thus total output), a positive knowledge spillovers across sectors, and the enabling of further productivity gains in the same sector in the future. As a consequence, the socially optimal allocation of scientists depends on all future shadow values of both average productivities. The social planner must then grant a subsidy q_{jt} for innovators in the sector with the higher social benefit.[17]

Further, the laissez-faire equilibrium suffers from under-utilisation of machines due to monopoly pricing. Since the social marginal cost of producing one machine is $\psi \equiv \alpha^2$ whereas the price set by the monopolistic machine producers is $\alpha(1-s)$, the social planner can correct this inefficiency by paying a subsidy $s = 1 - \alpha$ for each machine produced. This subsidy to the supply of all machines is symmetric across sectors, and thus it does not change the relative production of intermediate goods; as a consequence, it is not a focus of this paper and we assume it is corrected with this subsidy in all our simulations in Section 5.

Finally, in the laissez-faire equilibrium, financial intermediaries choose the assessment odds to equalise marginal costs with private marginal benefits, thus disregarding that these assessments reduce the risk of pursuing unfeasible projects and thus have positive externality in terms of long-term productivity gains for the economy at large. The social planner must thus incentivise more intense assessments by financial intermediaries via a

[17]In the absence of a climate constraint, the social planner will use a research subsidy to direct research either towards dominance of one technology if spillovers are low, or towards an interior solution if spillovers are high. Our choice of spillover parameter is made to ensure our scenario without financing costs starts on an interior balanced growth path, which then implies the latter.

positive subsidy b_{jt}.

Proposition 2. *There exists a unique socially optimal allocation that can be implemented using a subsidy for the use of all machines, a tax on dirty intermediate input production, a subsidy to clean innovation, and a subsidy to costly financial assessments.*

Proof. See Appendix A.1. □

4 Calibration

In this section, we discuss our calibration strategy. Calibrated parameters are in Table 1. Robustness checks are provided in Appendix A.2. Our initial period is calibrated to 2020, and our simulations run for 40 periods, with each period representing five years. The full span of our simulations thus goes from 2025 to 2220, although we will limit our analysis to the end of the century. The discount rate is 1.5% per annum, consistent with Acemoglu et al. (2012) and Nordhaus (2017).[18] The constant relative risk aversion parameter is taken to be $\sigma = 1.5$, close to the value of 1.45 assumed in Nordhaus (2017) and the value of 2 that is commonly found in the empirical literature (see e.g. Kaplow, 2005). We take $\alpha = 1/3$, so that the share of machines in production is approximately equal to the share of capital. We set the elasticity of substitution between clean and dirty inputs to $\epsilon = 3$.[19]

Patents last one period, as in many directed technological change models (e.g. Acemoglu et al., 2012, Fried, 2018). Fried (2018) also argues that five years (i.e. the length of our time step) is a reasonable time span for the occurrence of within-sector spillovers in clean and fossil technologies. We set the diminishing returns to research parameter to $\eta = 0.7$, close to the values of 0.7 and 0.79 used in Greaker et al. (2018) and Fried (2018), respectively. The strength of the cross-sector spillovers is set such that the economy starts from the interior balanced growth path in our symmetric scenario (discussed below), i.e. $\phi = -(1-\alpha)(1-\epsilon)\eta$ which equals 0.933 given our parameter values.[20] We set a research firm's probability of success in both sectors and in each period to $\lambda_c = \lambda_d = 2\%$ and

[18] Whereas Acemoglu et al. (2012) also consider a low value of 0.1%, here the discount rate does not control the extent of action on climate, as we assume cumulative emissions are constrained to keep warming to below 2°C.

[19] Elasticities used in integrated assessment and macroeconomic models have ranged between 1 and 10. For example, Acemoglu et al. (2012) provide simulations for elasticities equal to 3 and 10, Golosov et al. (2014) set it to approximately 1, Hart (2019) to 4, Greaker et al. (2018) use both 1.5 and 3, and Lemoine (2024) uses 1.8. Most empirical estimates range between 0.5 and 3 (e.g. Stern, 2012, Papageorgiou et al., 2017), although higher substitutability has been found in the electricity sector (Stöckl and Zerrahn, 2020, Wiskich, 2021). In Section A.2, we provide results with a lower elasticity.

[20] The equation fixing spillovers ϕ follows easily from (A.14). Our spillover parameter is high relative to the value of 0.5 used by Fried (2018), but we also consider results with a low elasticity of $\epsilon = 1.5$ in Section A.2 in which our spillover parameter is reduced to 0.233.

Table 1: Parameter Values

Description	Parameter	Value	Source
Annual discount rate	ρ	1.5	Nordhaus (2017)
Relative risk aversion	σ	1.5	Nordhaus (2017)
Elasticity of substitution	ϵ	3	Acemoglu et al. (2012)
Machines share	α	1/3	Capital's share
Number of workers	L	1	Normalisation
Initial global GDP	Y_0	\$85 trillion	World Bank
Initial clean energy share	$Y_{c0}/(Y_{d0}+Y_{c0})$	20%	EIA (2021)
Initial cumulative clean energy	$Ycum_{c0}$	$2Y_{c0}$	Energy Institute (2023)
Number of scientists	H	1	Normalisation
Scientist efficiency	γ	1	Acemoglu et al. (2012)
Scientist long-run chance of success	$\lambda_d = \lambda_c$	2%	Acemoglu et al. (2012)
Returns in research	η	0.7	Greaker et al. (2018)
Cross-sector spillovers	ϕ	0.933	Own calibration
2020 carbon emissions ($GtCO_2$)	Y_{d0}, S_0	37	Climate Watch (2022)
Emission Intensity	κ	1	Normalisation
Cumulative emissions limit ($GtCO_2$)	$\bar{S}$	1350	IPCC (2021)
Clean financing experience	ν_{c0}	92.97%	Ameli et al. (2021)
Dirty financing experience	ν_d	100%	Normalisation
Experience parameter	ω	1.32	Ameli et al. (2021)
Maximum assessment odds	$\bar{\mu}_t$	$0.2 + 0.8\nu_{jt}$	Own calibration

let the efficiency parameter $\gamma = 1$ so that the long-run annual growth rate is equal to 2% under a low-carbon transition (as in Acemoglu et al., 2012), i.e. as clean output and research shares approach 100%. Without loss of generality, we normalise the number of workers and scientists each to unity, i.e. $L = H = 1$.[21]

The initial relative level of the two technologies, A_{d0}/A_{c0}, is determined by the initial ratio of the dirty and clean inputs used in the final good sector, Y_{d0}/Y_{c0}. We set an initial clean share of intermediate production equal to 20%, since fossil fuels represent around 79% of energy generation in the US (EIA, 2021, Table 1.1) and 82% in the world (BP, 2022). The initial share of research in clean technology, 20% in our benchmark scenario, also follows from our assumptions of the initial output ratio and clean financing costs.[22] Total output Y_0 is set to the 2020 global GDP using data from the World Bank (2023).

[21] An alternative approach would be to calibrate the number of scientists to e.g. the percent of workers engaged in R&D in the US, as in Fried (2018). Our normalisation is without loss of generality, as this change would be completely compensated by a change in the efficiency parameter γ.

[22] For comparison, Acemoglu et al. (2012) and Greaker et al. (2018) assume clean energy initially makes up 18% and 20% of total energy, respectively, whereas Hart (2019) assumes an initial clean share of 5%. Acemoglu et al. (2016) reports a share of innovative firms in the US energy-sector classified as clean of 11%, and a share of energy-sector patents classified as clean energy of 14%; Aghion et al. (2016), who focus on automotive patents taken out in the patent offices in the US, Europe, and Japan, classify 25.6% of them as clean; Greaker et al. (2018) uses 18% as the initial share of research in clean technology; Lemoine (2024) has 23% of scientists initially working on clean innovation.

We normalise the emission intensity parameter to $\kappa = 1$. Global CO_2 emissions were approximately 37GtCO_2 in the latest available year of 2019 (Climate Watch, 2022), which we use to calibrate initial dirty intermediate production Y_{d0} and thus initial cumulative emissions S_0. In our policy experiments below, we apply a constraint on future cumulative CO_2 emissions equal to 1350GtCO_2, which is the estimated remaining carbon budget calculated from the beginning of 2020 to achieve a warming of 2°C with a 50% probability (IPCC, 2021, Table 5.8).[23]

We parametrize the intermediary's probability of drawing an infeasible project to $\theta_{jt} = \nu_{jt}$ and, incorporating this, the cost function for assessment to

$$c(\mu_{jt}, \nu_{jt}) = \left\{ \left[\frac{\delta(1-\nu_{jt})}{\delta + (1-\delta)\nu_{jt} - \mu_{jt}} \right]^{\delta} - 1 \right\} \left(\frac{1-\nu_{jt}}{\nu_{jt}} \right) \tag{17}$$

where we set $\delta = (\bar{\mu}_t - \nu_{jt}) / (1 - \nu_{jt}) = 0.2$, so that financial intermediaries can reduce the likelihood of choosing unfeasible projects by 20% at most: we consider a sensitivity with higher assessment power in Appendix A.2. These functional forms respect Assumption 2, while also delivering equilibrium outcomes which are analytically simple: the resulting optimal assessment odds, assessment costs, and financing costs in the laissez-faire equilibrium are $\mu_{jt} = \nu_{jt}$, $c(\mu_{jt}, \nu_{jt}) = 0$, and $1 + r_{jt} = (\nu_{jt}\lambda_j)^{-1}$, respectively. In other words, lenders optimally choose not to conduct any costly assessment in the laissez-faire equilibrium, which simplifies the analysis, but still allows the extent and determinants of the optimal subsidy to financial assessment to be investigated.

We normalise $\nu_d = 100\%$ and set $\nu_{c0} = 84.3\%$, which means that the initial gap in the financing costs for clean innovative projects is 15.7% (Ameli et al., 2021).[24] Following Rubin et al. (2015), Egli et al. (2018), and Polzin et al. (2021), we calibrate the evolution of clean financing experience ν_{ct} as to impose a 'one-factor experience curve' where financing costs decrease by a constant percentage for each doubling in the cumulative output of

---

[23] As in Ameli et al. (2021), we choose to focus on the 2°C target, rather than the 1.5°C one, because of its low reliance on negative emissions technologies, around which there is still large uncertainty.

[24] One simple interpretation of $\nu_d = 100\%$ is that dirty technologies are already mature and so no learning is possible; in our calibration, however, ν_{ct} increasing over time captures that there is relatively more learning in the green sector, while excluding the possibility that financing costs for dirty technologies will increase under a clean transition, reflecting e.g. asset stranding risks. Note that our calibration is likely to underestimate the true financing cost gap for innovative projects, as it is based on Ameli et al.'s (2021) estimates for mean global values for weighted average cost of capital (WACC), weighted by GDP, for low-carbon and high-carbon electricity generation (5.9% and 5.1%, respectively). If the clean innovative sector involves relatively backward and riskier technologies, the clean financing cost gap may better reflect part of the difference in WACC between commercial (e.g. combined cycle power plant, solar photovoltaic, onshore wind) and upcoming energy technologies (e.g. offshore wind, tidal and wave power, green hydrogen): for example, NERA (2015, Table 5.1) reports hurdle rates of around 8% for solar and wind and 12% for tidal and wave power, whereas IRENA's (2020) scenarios distinguish between a commercial WACC of 6% and a high risk one of 10%. We provide a sensitivity analysis in Appendix A.2.

clean technologies, i.e.

$$\frac{1}{\nu_{ct}} - 1 = \left(\frac{1}{\nu_{c0}} - 1\right)\left(\frac{Ycum_{c0}}{Ycum_{c0} + \sum_{\tau=1}^{t} Y_{c\tau}}\right)^{\omega}. \tag{18}$$

We impose cumulative output at the start of the simulation to equal twice the output value in 2020, $Ycum_{c0} = 2Y_{c0}$, since the combined output of wind, solar, and other renewable over the 5-year period from 2018 to 2022 is about equal to the output in all previous years (Energy Institute, 2023); a higher value is considered in Appendix A.2. We let the experience parameter $\omega = 1.32$ (i.e. the relative financing costs of clean to dirty technology decreases by $1 - 2^{-\omega} \approx 60\%$ for each doubling of clean cumulative output) so that the clean financing costs gap basically disappear by 2050 as in Ameli et al. (2021).[25]

5 Policy Experiments

In this section, we present a numerical analysis that builds on the calibration of our theoretical model and underlines the interactions between climate policy, innovation, and financing costs. We first show our *full* model, which includes optimal climate policy and endogenous financing experience effect for clean technology. As explained in Section 3.4 and given the calibration in Section 4, optimal policy is the combination of a carbon tax, a clean research subsidy, and a subsidy to clean lenders maximising households' lifetime utility while keeping cumulative emissions below the exogenous limit. The endogenous experience effect is modelled through clean financing costs which fall over time with cumulative clean output according to the experience curve in (18).

In the first subsection, we compare this scenario with i) a *laissez-faire* economy, i.e. an economy with no climate policy but with the endogenous experience effect, with the aim of drawing out the consequences of policy, and ii) a *symmetric* scenario, i.e. an economy with optimal climate policy but without a financing cost gap (i.e. where both the clean and dirty sector financing costs are constant at the level for the dirty technology), to draw out effects from heterogeneous financing costs. In the second subsection, we show, as deviations from the *symmetric* scenario, results from i) the *full* model, highlighting more clearly the consequences of heterogeneous and endogenous financing costs on optimal policy; ii) a *second-best* scenario, where the social planner cannot subsidise financial

[25] Egli et al. (2018, Supplementary Table 7) provide estimate for this experience effect across countries and technologies, with values ranging from 10% to 16% for clean investments in energy generation. However, their estimates represent absolute changes in the WACC for these technologies, whereas our parameter captures a relative change in the cost of external finance for clean innovation with respect to dirty investments. Although 60% may seem high, it leads to clean financing costs falling to low levels (1.4%) by 2040 in our benchmark scenario, when clean output overtakes dirty, which seems reasonable in principle and is in line with Ameli et al. (2021). Note that Ameli et al. (2021) also consider a scenario with slower learning, where the clean financing cost gap disappears only by 2100: we consider this as a sensitivity in Appendix A.2.

Table 2: Scenario overview

Scenario	Carbon tax	Research subsidy	Finance subsidy	Heterogeneous costs	Endogenous experience
Full	✓	✓	✓	✓	✓(output)
Laissez-faire	✗	✗	✗	✓	✓(output)
Symmetric	✓	✓	✗	✗	✗
Second best	✓	✓	✗	✓	✓(output)
Research	✓	✓	✓	✓	✓(research)

intermediaries and thus can only use the carbon tax and research subsidy; and iii) a *research* scenario, showing how the optimal policy mix changes when the experience effect depends on cumulative clean research (rather than cumulative clean output). Table 2 summarises the characteristics of the scenarios we look at. Robustness checks and sensitivity analyses are in Appendix A.2.

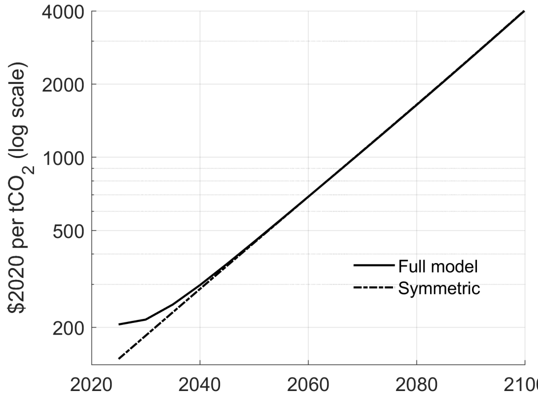
5.1 Optimal Climate Policy Mix

Figure 2 reports, for the *full* (solid line) and *symmetric* (dash-dot line) scenarios, the socially optimal paths of: 2a) the carbon tax in \$2020 per tonne CO_2, $\tau_t p_{dt}/(1+\tau_t)$; 2b) positive clean research subsidies as a share of GDP, $q_t w_{ct}^s H_{ct}/Y_t$; and 2c) clean finance subsidies as a share of GDP, $b_{ct} M_{ct}/Y_t$.[26]

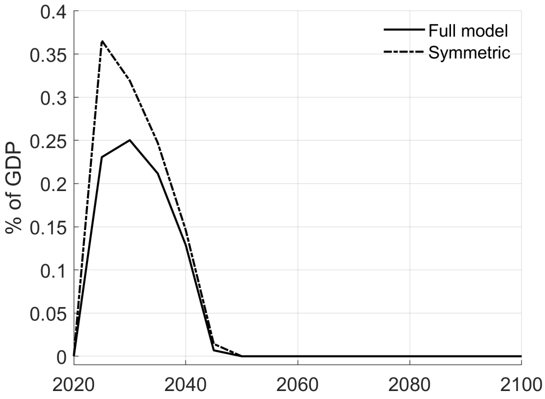
We start by focusing on the *full* model. Aside for the finance subsidy, optimal policy results are qualitatively in line with the the initial contribution by Acemoglu et al. (2012), with both a carbon tax and clean research subsidy needed. The carbon tax, shown in Panel 2a, starts at \$205 in 2025, grows slowly initially, before accelerating to grow at the social discount rate in the long-run; in 2050, it is equal to \$449. The clean research subsidy in Panel 2b jumps to 0.23% of GDP in the first period and to 0.25% in the second one, before dropping progressively to zero by 2050.[27] The novelty with respect to the associated literature – traditionally abstracting from the financial system – is that a

[26]Our model is discrete with five-year periods. In the figures, the value of a variable in a given period is in its first year, e.g. in 2025 for the second period (2025-2029), and we linearly interpolate them across periods. Within a period, timing is as follows: i) policies are implemented; ii) research firms innovate; iii) machines are produced; and iv) intermediate and final goods are produced. Whereas the two policy scenarios are identical in the first period (2020-2024) in Figure 2, the effect of policies implemented in the second period are already evident in that period.

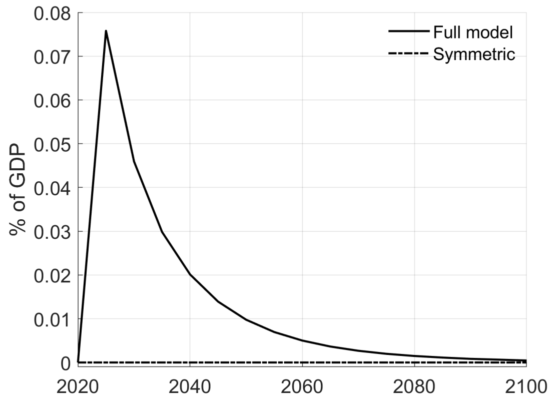
[27]As the timing of emissions does not enter our climate constraint, the optimal tax rises at the interest rate $\rho + g * \sigma$ in the long run. The subsidy becomes negative after 2050, as the model exhibits higher private clean returns (pre-subsidy) to research than is socially optimal. Without a climate constraint, the value of spillovers we adopt keeps research shares constant under laissez-faire without financing costs, and means optimal policy leads towards interior technology levels in the long run. Thus, with high clean share, optimal policy would gradually encourage greater dirty research (a negative clean research subsidy), and the presence of a carbon tax amplifies this effect. We do not consider this effect conveys any economic insight and thus exclude negative subsidy values (or equivalently a positive dirty research subsidy) ex-post in the figures. Doing so numerically (ex-ante) is more challenging computationally and does not change the key insights discussed (results are available upon request).



(a) Carbon tax



(b) Clean research subsidy



(c) Clean finance subsidy

Figure 2: Optimal policies in the *full* and *symmetric* scenarios

Notes. The *full* scenario includes heterogeneous financing costs and optimal policy from 2025. The *symmetric* scenario comprises optimal policy with homogeneous and constant financing costs. The deviation between scenarios prior to 2025 is due to linear interpolation (see footnote 26).

clean finance subsidy is now also needed (Panel 2c): this jumps to 0.08% of GDP in the first period, before decreasing slowly towards zero. By comparing the *full* model with the *symmetric* scenario, we see that the presence of an endogenous clean financing cost gap leads to a higher carbon tax (Panel 2a) and a lower clean research subsidy (Panel 2b): we investigate why in the next subsection.

Whereas our focus is on the time paths of policies rather than their levels at any given time, it is worth discussing the initial levels of the carbon tax and subsidies. In monetary terms, the initial carbon tax from the *full* model is four times greater than the US government's mean value of the social cost of carbon of $51 per tonne CO_2 (IWG, 2021), 48% higher than the $112 found in Lemoine (2024), and approximately 10% higher than Rennert et al.'s (2022) recent comprehensive mean social cost of carbon estimate of $185.[28] In relative terms, it adds approximately 13% to the price of the dirty intermediate

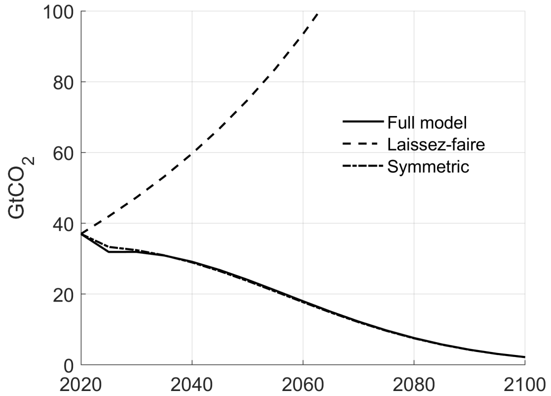
[28] Our carbon tax, which starts in 2025, would be approximately equal to Rennert et al.'s (2022) value when adjusted for the reference year.

input, which sits between the value of approximately 2-2.5% found by Acemoglu et al. (2012, 2016) and values around 15-25% found by Greaker et al. (2018), Hart (2019), and Wiskich (2024).

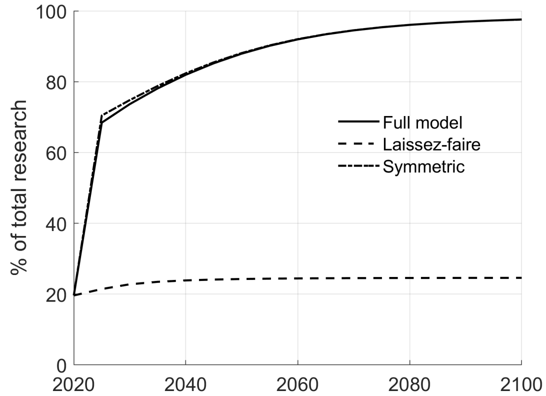
The clean research and finance subsidies in our *full* model are also likely to be quite high vis-à-vis current efforts. For comparison, IEA (2022b) estimates that direct global government spending (thus excluding tax reliefs) for research and development in clean and dirty energy was approximately 0.04% of global GDP in 2021, almost six times smaller than our initial clean research subsidy. The importance of clean research subsidies vary a lot in models of climate policy that endogenise innovation: while the initial clean research subsidy in our *full* model – which corresponds to approximately 16% of the private returns from research – is close to the value of approximately 10% found by Lemoine (2024), other papers have found values between 90% and 200% (Acemoglu et al., 2012, 2016, Wiskich, 2024) and up to 2500% (Greaker et al., 2018). Finally, our clean finance subsidy of 0.08% of global GDP in 2025 may seem small, but it roughly corresponds in relative terms to the entire $20 billion 10-year budget (0.07% of US GDP in 2023) of the National Clean Investment Fund and the Clean Communities Investment Accelerator, first-of-its-kind lending facilities dedicated to deliver accessible and affordable financing for clean technology projects nationwide (White House, 2024).

Figure 3 reports the optimal paths for a set of key variables for the *full* (solid line), *symmetric* (dash-dot line), and *laissez-faire* (dashed line) scenarios: 3a) $GtCO_2$ emissions, κY_{dt}; 3b) the share of scientists working on clean technologies, H_{ct}/H; 3c) clean output share, $Y_{ct}/(Y_{ct}+Y_{dt})$; and 3d) proportional clean financing cost gap, $(r_{ct}-r_d)/(1+r_d)$. By construction, all scenarios start from the same point, broadly calibrated to world economy outputs in 2020. Policy scenarios are then shocked by policy starting from 2025, whereas the *laissez-faire* one is undisturbed. Under optimal policy, the share of research dedicated to clean technologies (Panel 3b) rises from 20% in 2020 to 68% in 2025 and continues to climb, reaching 88% in 2050 and 98% in 2100. The share of clean output (Panel 3c) rises more slowly, as clean technology takes time to advance. Influenced by the acceleration in clean output share and the presence of the finance subsidy, the clean financing cost gap falls from 15.7% in 2020 to 7.6% in 2025 and 1% in 2050, and then continues to fall (Panel 3d). Panel 3a shows that the combination of policies is successful in dropping emissions by 35% below 2020 levels in 2050 and by 94% in 2100.

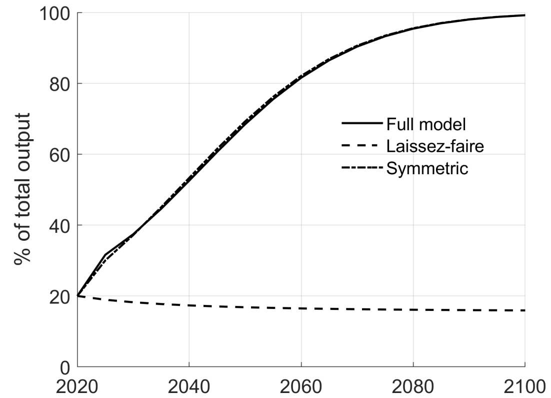
Since the economy is calibrated such that its laissez-faire balanced growth path is an interior equilibrium, clean research and production is pursued even without policy, which means that the cumulative output of the clean technologies progressively increases under the *laissez-faire* scenario, resulting in clean financing costs decreasing over time from 15.7% in 2020 to 10.6% in 2025 and 2.3% in 2050, as shown by the dashed line in Panel 3d; eventually, they tend to the same level of dirty technology costs. This incentivises scientists to slowly move from dirty to clean research, but at a much lower pace and



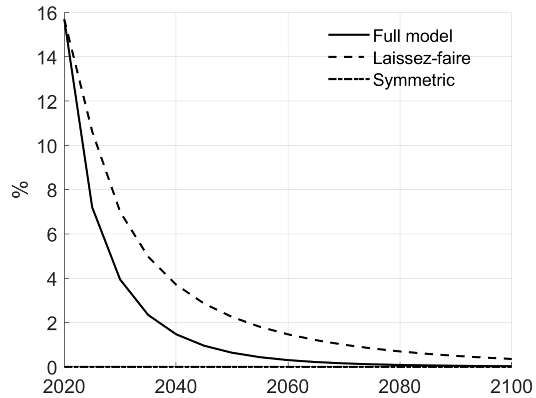
(a) Annual emissions



(b) Clean research share



(c) Clean output share



(d) Clean Financing Cost Gap

Figure 3: *Full*, *symmetric*, and *laissez-faire* scenarios

Notes. The *full* scenario includes heterogeneous financing costs and optimal policy from 2025. The *symmetric* scenario comprises optimal policy with homogeneous and constant financing costs. The *laissez-faire* scenario comprises financing costs but no policy. The deviation between scenarios prior to 2025 is due to linear interpolation (see footnote 26).

magnitude than with policy: indeed, the share of scientists in the clean research sector and the proportion of clean output stabilises in the long-run on a balanced growth path of 25% (Panel 3b) and 16% (Panel 3c), respectively. Under laissez-faire, there are no policies constraining carbon emissions (Panel 3a), which thus grow almost exponentially with dirty output (as we assume no change in emission intensity).

Thus, the comparison between the *full* and the *laissez-faire* scenarios highlights that the endogenous financing experience effect helps the low-carbon transition by itself, but is by no means sufficient in reaching the restricting climate objective. Indeed, an optimal low-carbon transition includes a steeply rising carbon tax complemented with a clean research subsidy and a long-lived finance subsidy. The evolution of emissions, clean research and clean output shares are similar between the *full* and the *symmetric* scenarios. However, the presence of a clean financing cost gap and endogenous link with technological evolution leads to a stronger carbon tax initially: \$205 versus \$148. This results as redirecting production towards the clean sector helps the financial sector accumulate clean financing experience, so that funds are more easily redirected to clean innovation, leading to a virtuous decarbonisation cycle. The next subsection investigates this effect in more depth.

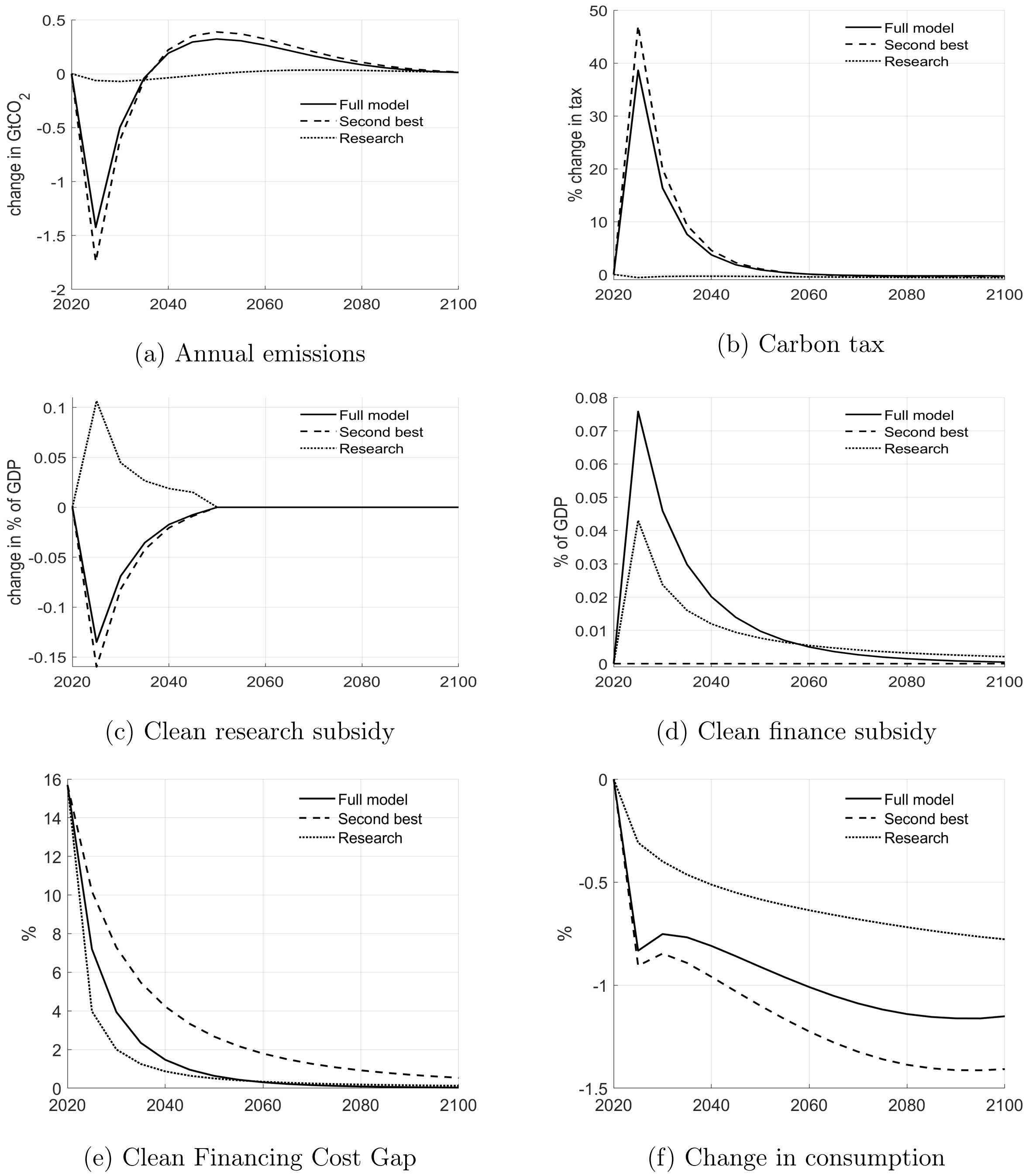
5.2 Clean Financing Effects

To delve deeper into the effects of an endogenous financing experience effect on optimal policy and the emission transition path, the solid line in Figure 4 shows results for our *full* model relative to the *symmetric* scenario. By definition, the *symmetric* scenario does not include a clean finance subsidy, so the solid line in Panel 4d is the same as in Panel 2c. Moreover, the policy mix in the *full* scenario needs to be more aggressive than in the *symmetric* scenario, as the presence of a clean financing cost gap means that transitioning to clean technology is costlier for a fixed emissions constraint; since more resources must be dedicated to policy, consumption is lower in the *full* model than in the *symmetric* scenario (Panel 4f). As partially explored in the previous subsection, the solid line in Panel 4b highlights that an endogenous experience effect makes the carbon tax more aggressive initially (it increases by 39% in the first period relative to the *symmetric* scenario); as the higher tax itself and the finance subsidy both induce more clean research, the clean research subsidy is instead lower (Panel 4c).

Our *full* model exhibits lower initial emissions than in the *symmetric* scenario (Panel 4a), which might appear counter-intuitive: one may expect that decreasing clean financing costs would lead to higher emissions in the near term, when credit to clean innovators is more expensive, and lower long-term emissions, once financial intermediaries are willing to finance clean research firms at progressively lower costs. The reason initial emissions are lower is due to endogeneity, i.e. the feedback between policy and the evolution of clean financing costs. Indeed, in our *full* model, financing experience is endogenously driven by increasing cumulative clean output: the presence of this positive spillover from output to the financial sector induces stricter policy in the near-term and, as a result, emissions fall in the near-term relative to the *symmetric* scenario. As highlighted in (16), the preferred instrument for this increased policy is the carbon tax, rather than the research subsidy, since financing experience depends on intermediate input production.[29]

To delve deeper on this point, the dotted lines in Figure 4 show results, relative to the *symmetric* scenario, of a *research* scenario, where the financing experience effect is

[29]This increase in initial (tax) policy stringency is due to a positive but sluggish feedback from policy to financing experience: if there was no such feedback (and experience was independent of policy) we would have higher emissions initially; if the feedback approached infinity, so experience was immediate, then we would obtain the *symmetric* scenario.



(a) Annual emissions

(b) Carbon tax

(c) Clean research subsidy

(d) Clean finance subsidy

(e) Clean Financing Cost Gap

(f) Change in consumption

Figure 4: Clean financing effects

Notes. Lines represent changes relative to the *symmetric* scenario, i.e. with optimal policy but with homogeneous and constant financing costs. The *full* scenario includes heterogeneous financing costs and optimal policy from 2025. The *second-best* scenario comprises heterogeneous financing costs and constrained optimal policy (without a clean finance subsidy). The *research* scenario comprises optimal policy and experience effect based on cumulative research.

linked to clean research, rather than clean output.[30] In particular, the *research* scenario is identical to the *full* model apart from the fact that we recast the one-factor experience curve in (18) as a function of cumulative clean research, i.e.

$$\frac{1}{\nu_{ct}} - 1 = \left(\frac{1}{\nu_{c0}} - 1\right)\left(\frac{\hat{H}_{c0}}{\hat{H}_{c0} + \sum_{\tau=1}^{t} H_{c\tau}}\right)^{\omega}, \tag{19}$$

where, for ease of comparison, the initial cumulative value of research is rescaled as to be equivalent to the benchmark case, $\hat{H}_{c0} \equiv Y_{c0}H_{c0}/(Y_{c0} + Y_{d0})$.

Panels 4b, 4c, and 4d show that the optimal policy mix is sensitive to whether the experience effect is based on output or research: indeed, as the clean research subsidy is a more effective instrument at internalising the financing experience externality when this depends on research, the policy stringency from endogeneity translates into much higher clean research subsidy in 2025 than in the benchmark case, while the carbon tax begins lower. Since the high clean research subsidy is able to shift researchers to the clean sector at greater speed than the one at which a carbon tax can move production towards clean output, financial learning occurs faster in the *research* scenario than in the *full* model, and thus a lower finance subsidy is needed (Panel 4d), with households able to afford higher long-run consumption (Panel 4f). Conversely, the effect on the emissions path is to reduce near-term emissions much less (Panel 4a).

Thus, the source of the financing experience effect drives the optimal level of a policy instrument. If experience is linked to production, then the policy instrument linked to production (carbon tax) is stringent. Instead, if learning effects are coming from research directly, then the research subsidy should be high. We find this policy-dependence on our assumption of how clean financing experience occurs an interesting insight, as it emphasises that the effectiveness of different climate policies in promoting the low-carbon transition may differ depending on how financial conditions respond endogenously to the development and deployment of new technologies. Indeed, if the nature of financing experience effects differs across markets, technologies, and geographical areas, due perhaps to different lending environments and institutions (as documented by Aghion et al., 2022, in the context of venture capital financing and clean investments across EU

[30]Indeed, there is evidence suggesting that institutions which provide funding to core or frontier research, including governments and venture capitalists, tend to fund startups which show promise, rather than following more ‘backward-looking’ measures, like market share of output. For example, Akcigit et al. (2022) find that the probability of venture capital funding is much higher for startups that already have a patent, and conditional on having a patent, it increases in the quality of the patents (as proxied by citations). Within government programs, Howell (2017) analyses the US Department of Energy’s Small Business Innovation Research Program, where the competition for funding is based on the strength of the scientific/technical approach, the ability to carry out the project in a cost effective manner, and the perceived commercialisation impact. Note that the theoretical results are obtained with a focus on the balanced growth path and thus are unaffected by whether experience depends on cumulative output or research, since the relative number of scientists and the relative share of output co-move with the relative level of the technology.

countries and between EU and US), then optimal climate policies will also differ across these environments.

Aghion et al. (2022) argue that carbon tax and research subsidies clearly fall in the realm of government policies, whereas climate actions on financial market may pertain to central banks. As a consequence, a tool targeting the financial intermediaries might face obstacles from both a legal and an economic perspective (Campiglio et al., 2018, NGFS, 2021). The dashed lines in Figure 4 shows results, relative to the *symmetric* scenario, of a *second-best* scenario, which is identical to the *full* model apart for the fact that the social planner can only use a carbon tax and a clean research subsidy. In this case, the social planner uses the carbon tax more aggressively (Panel 4b), but she is unable to induce a decrease in clean financing costs as fast as in the *full* model (Panel 4e). Since the social planner only has two instruments to target three market failures, the equilibrium is second best and involves a loss in consumption (Panel 4f).

6 Conclusions

In this paper, we enhance an environmental directed technical change model by introducing some novel elements capturing key real-world dimensions: i) research firms require access to external finance; ii) the costs of accessing innovation finance are heterogeneous across sectors, with novel clean technologies being disfavoured compared to incumbent polluting ones; iii) financing costs can endogenously decrease through an 'experience effect', by which lenders become more accustomed to clean technologies and to distinguish promising projects; and iv) policy-makers can accelerate the decline in clean financing costs by subsidising clean innovation finance.

We then use this model to derive analytical and numerical conclusions on optimal transition paths and associated climate mitigation policies. Our key results are the following. First, along a low-carbon transition, it is optimal to implement three concurrent policies: i) a high carbon tax (equal to $205 in 2025 in our full model numerical simulation), increasing at a long-run growth rate equal to the social discount rate, i.e. 4.5%; ii) a temporary subsidy to clean innovators, peaking at 0.25% of GDP in 2030 and dropping to zero by 2050; and iii) a subsidy to financial intermediaries providing clean innovation finance, immediately jumping to approximately 0.08% of GDP and gradually phasing out entirely in the second half of the century. While the environmental economics literature on directed technical change has already acknowledged the first two results (see Acemoglu et al., 2012, and subsequent contributions), the presence of a clean financial policy tool is a novelty of our paper. We show that, in a second-best scenario where a clean financial subsidy cannot be deployed, carbon taxes and clean research subsides are not able to compensate for its absence.

Second, the presence of an endogenous 'learning-by-lending' effect alters the effectiveness and time profile of optimal climate policies. More specifically, it provides an incentive to increase *short-term* climate policy effort. Compared to a 'symmetric' case without financing costs, our full model suggests a much stronger decline rate of carbon emissions until approximately 2035, which can then be partially relaxed afterwards. This is primarily achieved by a higher carbon tax: we find a carbon price premium in 2025 of almost 40%. This allows the clean research subsidy to actually be slightly lower than in the symmetric case for the whole transition. If, on the other hand, the financial experience effect depended on cumulative clean research – rather than output – the favourite policy tool is a larger clean research subsidy. In all cases, a significant subsidy to clean innovation finance remains necessary.

Our model could be improved in a number of ways. For example, we consider lenders always willing to provide funds to both types of firms; at the cost of added complication, one could instead incorporate a variety of different financial actors (as in Aghion et al., 2022) and the possibility that some firms do not receive credit (as in Haas and Kempa, 2023). Further, our global approach to the modelling and calibration disregards technological and geographical differences (as highlighted by e.g. Aghion and Jaravel, 2015, Steffen, 2020) that may have an impact on optimal policy. Finally, our model abstracts from political economy considerations (e.g. Fuest and Meier, 2023) and the social acceptability of the optimal climate policy mix: in reality, carbon taxes still face resistance (e.g. Anderson et al., 2023, Crowley, 2017, Douenne and Fabre, 2020) and a subsidy towards financial intermediaries may prove unpopular.

While we leave these interesting avenues open for future research, we expect the main take-away messages of our paper to remain the same. Including a key real-world dimension, such as the need for innovation to have access to finance, clearly highlights the importance of introducing a specific policy targeting financing conditions, which, together with stronger mitigation policies, is able to close the financing cost gap across technology and make the low-carbon transition happen.

References

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

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*, 124(1):52–104.

Aghion, P., Boneva, L., Breckenfelder, J., Laeven, L., Olovsson, C., Popov, A., and Rancoita, E. (2022). Financial markets and green innovation. European Central Bank Discussion Papers N. 2686.

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):1–51.

Aghion, P. and Howitt, P. (2009). *The Economics of Growth*. The MIT Press, Cambridge.

Aghion, P. and Jaravel, X. (2015). Knowledge spillovers, innovation and growth. *Economic Journal*, 125(583):533–573.

Akcigit, U., Dinlersoz, E., Greenwood, J., and Penciakova, V. (2022). Synergizing ventures. *Journal of Economic Dynamics and Control*, 143:104427.

Allen, M. R., Frame, D. J., Huntingford, C., Jones, C. D., Lowe, J. A., Meinshausen, M., and Meinshausen, N. (2009). Warming caused by cumulative carbon emissions towards the trillionth tonne. *Nature*, 458:1163–1166.

Ameli, N., Dessens, O., Winning, M., Cronin, J., Chenet, H., Drummond, P., Calzadilla, A., Anandarajah, G., and Grubb, M. (2021). Higher cost of finance exacerbates a climate investment trap in developing economies. *Nature Communications*, 12(1):4046.

Anderson, S., Marinescu, I., and Shor, B. (2023). Can Pigou at the polls stop us melting the poles? *Journal of the Association of Environmental and Resource Economists*, 10(4):903–945.

Barbieri, N., Marzucchi, A., and Rizzo, U. (2023). Green technologies, interdependencies, and policy. *Journal of Environmental Economics and Management*, 118:102791.

Boneva, L., Ferrucci, G., and Mongelli, F. P. (2022). Climate change and central banks: What role for monetary policy? *Climate Policy*, 22(6):770–787.

Boston Consulting Group (1970). Perspectives on experience. Technical report, Boston Consulting Group.

Botsch, M. and Vanasco, V. (2019). Learning by lending. *Journal of Financial Intermediation*, 37:1–14.

BP (2022). BP statistical review of world energy 2022. Technical report, BP.

Brown, J. R., Martinsson, G., and Petersen, B. C. (2012). Do financing constraints matter for R&D? *European Economic Review*, 56(8):1512–1529.

Buera, F. J., Kaboski, J. P., and Shin, Y. (2011). Finance and development: A tale of two sectors. *American Economic Review*, 101(5):1964–2002.

Campiglio, E., Dafermos, Y., Monnin, P., Ryan-Collins, J., Schotten, G., and Tanaka, M. (2018). Climate change challenges for central banks and financial regulators. *Nature Climate Change*, 8:462–468.

Caprotti, F. (2017). Protecting innovative niches in the green economy: Investigating the rise and fall of Solyndra, 2005–2011. *GeoJournal*, 82:937–955.

Cecere, G., Corrocher, N., and Mancusi, M. L. (2020). Financial constraints and public funding of eco-innovation: Empirical evidence from European SMEs. *Small Business Economics*, 54(1):285–302.

Cervantes, M., Criscuolo, C., Dechezleprêtre, A., and Pilat, D. (2023). Driving low-carbon innovations for climate neutrality. OECD Science, Technology and Industry Policy Papers 123, OECD.

Climate Watch (2022). Historical GHG emissions. Technical report, World Resources Institute.

Cole, H. L., Greenwood, J., and Sanchez, J. M. (2016). Why doesn't technology flow from rich to poor countries? *Econometrica*, 84(4):1477–1521.

Comerford, D. and Spiganti, A. (2023). The carbon bubble: Climate policy in a fire-sale model of deleveraging. *Scandinavian Journal of Economics*, 125(3):655–687.

Crowley, K. (2017). Up and down with climate politics 2013–2016: The repeal of carbon pricing in Australia. *WIREs Climate Change*, 8(3):e458.

De Haas, R. and Popov, A. (2023). Finance and green growth. *Economic Journal*, 133(650):637–668.

Degryse, H., Kokas, S., and Minetti, R. (2022). Banking on experience. Available at SSRN: `https://ssrn.com/abstract=4224476`.

Dietz, S., van der Ploeg, F., Rezai, A., and Venmans, F. (2021). Are economists getting climate dynamics right and does it matter? *Journal of the Association of Environmental and Resource Economists*, 8(5):895–921.

Dietz, S. and Venmans, F. (2019). Cumulative carbon emissions and economic policy: In search of general principles. *Journal of Environmental Economics and Management*, 96:108–129.

Diluiso, F., Annicchiarico, B., Kalkuhl, M., and Minx, J. C. (2021). Climate actions and macro-financial stability: The role of central banks. *Journal of Environmental Economics and Management*, 110:102548.

D'Orazio, P. and Valente, M. (2019). The role of finance in environmental innovation diffusion: An evolutionary modeling approach. *Journal of Economic Behavior and Organization*, 162:417–439.

Douenne, T. and Fabre, A. (2020). French attitudes on climate change, carbon taxation and other climate policies. *Ecological Economics*, 169:106496.

Dugoua, E. and Dumas, M. (2021). Green product innovation in industrial networks: A theoretical model. *Journal of Environmental Economics and Management*, 107:102420.

Dugoua, E. and Dumas, M. (2023). Global coordination challenges in the transition to clean technology: Lessons from automotive innovation. SSRN Working Paper 4620155.

D'Orazio, P. and Popoyan, L. (2019). Fostering green investments and tackling climate-related financial risks: Which role for macroprudential policies? *Ecological Economics*, 160:25–37.

Egli, F., Steffen, B., and Schmidt, T. S. (2018). A dynamic analysis of financing conditions for renewable energy technologies. *Nature Energy*, 3(12):1084–1092.

EIA (2021). Monthly energy review. Technical report, U.S. Energy Information Administration.

EIB (2023). Joint report on multilateral development banks' climate finance. Technical report, European Investment Bank.

Energy Institute (2023). Statistical review of world energy (2023). Technical report, Energy Institute. Other renewables (including geothermal and biomass) [dataset] - with major processing by Our World in Data, `https://ourworldindata.org/renewable-energy`.

Fischer, C., Preonas, L., and Newell, R. G. (2017). Environmental and technology policy options in the electricity sector: Are we deploying too many? *Journal of the Association of Environmental and Resource Economists*, 4(4):959–984.

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

Fuest, C. and Meier, V. (2023). Sustainable finance and climate change: Wasteful but a political commitment device? *Journal of Environmental Economics and Management*, 118:102795.

Gale, D. and Hellwig, M. (1985). Incentive-compatible debt contracts: The one-period problem. *Review of Economic Studies*, 52(4):647–663.

Geddes, A. and Schmidt, T. S. (2020). Integrating finance into the multi-level perspective: Technology niche-finance regime interactions and financial policy interventions. *Research Policy*, 49(6):103985.

Geddes, A., Schmidt, T. S., and Steffen, B. (2018). The multiple roles of state investment banks in low-carbon energy finance: An analysis of Australia, the UK and Germany. *Energy Policy*, 115(December 2017):158–170.

Ghisetti, C., Mancinelli, S., Mazzanti, M., and Zoli, M. (2017). Financial barriers and environmental innovations: Evidence from EU manufacturing firms. *Climate Policy*, 17(sup1):S131–S147.

Golosov, M., Hassler, J., Krusell, P., and Tsyvinski, A. (2014). Optimal taxes on fossil fuel in general equilibrium. *Econometrica*, 82(1):41–88.

Greaker, M., Heggedal, T. R., and Rosendahl, K. E. (2018). Environmental policy and the direction of technical change. *Scandinavian Journal of Economics*, 120(4):1100–1138.

Greenwood, J. and Jovanovic, B. (1990). Financial development, growth, and the distribution of income. *Journal of Political Economy*, 98(5):1076–1107.

Greenwood, J., Sanchez, J. M., and Wang, C. (2010). Financing development: The role of information costs. *American Economic Review*, 100(4):1875–1891.

Grubb, M., Drummond, P., Poncia, A., McDowall, W., Popp, D., Samadi, S., Peñasco, C., Gillingham, K., Smulders, S., Glachant, M., Hassall, G., Mizuno, E., Rubin, E. S., Dechezlepretre, A., and Pavan, G. (2021). Induced innovation in energy technologies and systems: A review of evidence and potential implications for CO2 mitigation. *Environmental Research Letters*, 16:043007.

Haas, C. and Kempa, K. (2023). Low-carbon investment and credit rationing. *Environmental and Resource Economics*, 86:109–145.

Hall, B. H. and Lerner, J. (2010). The financing of R&D and innovation. *Handbook of the Economics of Innovation, Volume 1*, 1(10):609–639.

Hart, R. (2013). Directed technological change and factor shares. *Economics Letters*, 119(1):77–80.

Hart, R. (2019). To everything there is a season: Carbon pricing, research subsidies, and the transition to fossil-free energy. *Journal of the Association of Environmental and Resource Economists*, 6(2):349–389.

Hémous, D. (2016). The dynamic impact of unilateral environmental policies. *Journal of International Economics*, 103:80–95.

Hoffmann, F., Inderst, R., and Moslener, U. (2017). Taxing externalities under financing constraints. *Economic Journal*, 127(606):2478–2503.

Hottenrott, H. and Peters, B. (2012). Innovative capability and financing constraints for innovation: More money, more innovation? *Review of Economics and Statistics*, 94(4):1126–1142.

Howell, S. T. (2017). Financing innovation: Evidence from R&D grants. *American Economic Review*, 107(4):1136–1164.

IEA (2022a). Clean energy technology innovation. Technical report, International Energy Agency.

IEA (2022b). Tracking clean energy innovation in the business sector: An overview. Technical report, International Energy Agency.

IPCC (2021). Climate change 2021: The physical science basis. Contribution of working group I to the sixth assessment report of the Intergovernmental Panel on Climate Change. Technical report, The Intergovernmental Panel on Climate Change, Geneva, Switzerland.

IPCC (2022). Climate change 2022: Mitigation of climate change. Working group III contribution to the sixth assessment report of the Intergovernmental Panel on Climate Change. Technical report, The Intergovernmental Panel on Climate Change, Geneva, Switzerland.

IPCC (2023). Climate change 2023: Synthesis report. Contribution of Working Group I, II, and III to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change. Technical report, The Intergovernmental Panel on Climate Change, Geneva, Switzerland.

IRENA (2020). Green hydrogen cost reduction: Scaling up electrolysers to meet the 1.5C climate goal. Technical report, International Renewable Energy Agency, Abu Dhabi, United Arab Emirates.

IRENA (2023). The cost of financing for renewable power. Technical report, International Renewable Energy Agency, Abu Dhabi.

IWG (2021). Social cost of carbon, methane, and nitrous oxide: Interim estimates under executive order 13990. Technical report, Interagency Working Group on Social Cost of Greenhouse Gases.

Jensen, F., Schäfer, D., and Stephan, A. (2019). Financial constraints of firms with environmental innovation. *Quarterly Journal of Economic Research (Vierteljahrshefte zur Wirtschaftsforschung)*, 88(3):43–65.

Jermann, U. and Quadrini, V. (2012). Macroeconomic effects of financial shocks. *American Economic Review*, 102(1):238–271.

Jiang, S. and Li, J. Y. (2022). He who lends knows. *Journal of Banking & Finance*, 138:106412.

Jones, C. I. (1995). R&D-based models of economic growth. *Journal of Political Economy*, 103(4):759–784.

Kaplow, L. (2005). The value of a statistical life and the coefficient of relative risk aversion. *Journal of Risk and Uncertainty*, 31(1):23–34.

Kempa, K., Moslener, U., and Schenker, O. (2021). The cost of debt of renewable and non-renewable energy firms. *Nature Energy*, 6(2):135–142.

Kerr, W. R. and Nanda, R. (2015). Financing innovation. *Annual Review of Financial Economics*, 7(1):445–462.

King, R. G. and Levine, R. (1993). Finance, entrepreneurship and growth: Theory and evidence. *Journal of Monetary Economics*, 32(3):513–542.

Kortum, S. (1993). Equilibrium R&D and the patent–R&D ratio: U.S. evidence. *American Economic Review*, 83(2):450–457.

Kotchen, M. J. and Costello, C. (2018). Maximizing the impact of climate finance: Funding projects or pilot projects? *Journal of Environmental Economics and Management*, 92:270–281.

Kruse-Andersen, P. K. (2023). Directed technical change, environmental sustainability, and population growth. *Journal of Environmental Economics and Management*, 122:102885.

Lahr, H. and Mina, A. (2021). Endogenous financial constraints and innovation. *Industrial and Corporate Change*, 30(3):587–621.

Lemoine, D. (2024). Innovation-led transitions in energy supply. *American Economic Journal: Macroeconomics*, 16(1):29–65.

Lennox, J. A. and Witajewski-Baltvilks, J. (2017). Directed technical change with capital-embodied technologies: Implications for climate policy. *Energy Economics*, 67:400–409.

Lessmann, K. and Kalkuhl, M. (2023). Climate finance intermediation: Interest spread effects in a climate policy model. *Journal of the Association of Environmental and Resource Economists*.

Matthews, H. D., Gillett, N. P., Stott, P. A., and Zickfeld, K. (2009). The proportionality of global warming to cumulative carbon emissions. *Nature*, 459:829–832.

Mazzucato, M. and Semieniuk, G. (2018). Financing renewable energy: Who is financing what and why it matters. *Technological Forecasting and Social Change*, 127:8–22.

Mendoza, E. G. (2010). Sudden stops, financial crises, and leverage. *American Economic Review*, 100(5):1941–1966.

Minetti, R. (2011). Informed finance and technological conservatism. *Review of Finance*, 15(3):633–692.

NERA (2015). Electricity generation costs and hurdle rates. Technical report, NERA Economic Consulting, London, UK.

NGFS (2021). Adapting central bank operations to a hotter world: Reviewing some options. Technical report, The Central Banks and Supervisors Network for Greening the Financial System, Paris, France.

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.

Noailly, J. and Smeets, R. (2021). Financing energy innovation: Internal finance and the direction of technical change. *Environmental and Resource Economics*, 83:145—-169.

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences of the United States of America*, 114(7):1518–1523.

Nowzohour, L. (2021). Can adjustments costs in research derail the transition to green growth? CIES Research Paper Series 67-2021.

Olmos, L., Ruester, S., and Liong, S.-J. (2012). On the selection of financing instruments to push the development of new technologies: Application to clean energy technologies. *Energy Policy*, 43:252–266.

Pan, D., Chen, C., Grubb, M., and Wang, Y. (2022). Financial policy, green transition and recovery after the COVID-19. Available at SSRN: `https://ssrn.com/abstract=3719695`.

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

Polzin, F., Sanders, M., Steffen, B., Egli, F., Schmidt, T. S., Karkatsoulis, P., Fragkos, P., and Paroussos, L. (2021). The effect of differentiating costs of capital by country and technology on the European energy transition. *Climatic Change*, 167(1-2):26.

Popp, D. (2010). Innovation and climate policy. *Annual Review of Resource Economics*, 2(C1):275–298.

Popp, D. (2019). Environmental policy and innovation: A decade of research. NBER Working Paper 25631.

Prasad, M. A., Loukoianova, M. E., Feng, A. X., and Oman, W. (2022). Mobilizing private climate financing in emerging market and developing economies. IMF Staff Climate Note 2022/007.

Rennert, K., Errickson, F., Prest, B. C., Rennels, L., Newell, R. G., Pizer, W., Kingdon, C., Wingenroth, J., Cooke, R., Parthum, B., Smith, D., Cromar, K., Diaz, D., Moore, F. C., Müller, U. K., Plevin, R. J., Raftery, A. E., Ševčíková, H., Sheets, H., Stock, J. H., Tan, T., Watson, M., Wong, T. E., and Anthoff, D. (2022). Comprehensive evidence implies a higher social cost of CO2. *Nature*, 610(7933):687—-692.

Romer, P. M. (1990a). Capital, labor, and productivity. *Brookings Papers on Economic Activity. Microeconomics*, pages 337–367.

Romer, P. M. (1990b). Endogenous technological change. *Journal of Political Economy*, 98(5):71–102.

Rubin, E. S., Azevedo, I. M., Jaramillo, P., and Yeh, S. (2015). A review of learning rates for electricity supply technologies. *Energy Policy*, 86:198–218.

Shleifer, A. and Vishny, R. W. (1992). Liquidation values and debt capacity: A market equilibrium approach. *Journal of Finance*, 47(4):1343–1366.

Smulders, S. and Zhou, S. (2022). Self-fulfilling prophecies in directed technical change. Mimeo.

Steffen, B. (2020). Estimating the cost of capital for renewable energy projects. *Energy Economics*, 88:104783.

Stern, D. I. (2012). Interfuel substitution: A meta-analysis. *Journal of Economic Surveys*, 26(2):307–331.

Stern, D. I., Pezzey, J. C. V., and Lu, Y. (2019). Directed technical change and the British industrial revolution. *Journal of the Association of Environmental and Resource Economists*, 8(6):1079–1114.

Stöckl, F. and Zerrahn, A. (2020). Substituting clean for dirty energy: A bottom-up analysis. DIW Discussion Paper No. 1885.

Townsend, R. M. (1979). Optimal contracts and competitive markets with costly state verification. *Journal of Economic Theory*, 21(2):265–293.

van der Ploeg, F. (2018). The safe carbon budget. *Climatic Change*, 147:47–59.

van der Ploeg, F. and Rezai, A. (2021). Optimal carbon pricing in general equilibrium: Temperature caps and stranded assets in an extended annual DSGE model. *Journal of Environmental Economics and Management*, 110(1):102522.

Weiss, M., Junginger, M., Patel, M. K., and Blok, K. (2010). A review of experience curve analyses for energy demand technologies. *Technological Forecasting and Social Change*, 77(3):411–428.

White House (2024). Biden-Harris administration announces historic $20 billion in awards to expand access to clean energy and climate solutions and lower energy costs for communities across the nation. Briefing Room's Statements and Releases.

Williamson, S. D. (1986). Costly monitoring, financial intermediation, and equilibrium credit rationing. *Journal of Monetary Economics*, 18(2):159–179.

Wiskich, A. (2021). A comment on innovation with multiple equilibria and 'The environment and directed technical change'. *Energy Economics*, 94(C):105077.

Wiskich, A. (2024). A carbon tax versus clean subsidies: Optimal and suboptimal policies for the clean transition. *Energy Economics*, 132(C):107410.

World Bank (2023). Databank: World Development Indicators. Economic Policy & Debt: National accounts: US$ at current prices: Aggregate indicators.

Yelle, L. E. (1979). The learning curve: Historical review and comprehensive survey. *Decision Science*, 10:302–328.

A Appendix

A.1 Proofs

Proof of Proposition 1. Competition among intermediaries drives financing costs down, until an intermediary break-even on expectation and (9d) holds with equality, i.e.

$$1 + r_{jt} = \frac{1 + c(\mu_{jt}, \nu_{jt})\,(1 - b_{jt})}{\mu_{jt}\lambda_j}. \tag{A.1}$$

Combining this with the first order condition with respect to μ_{jt}, the private optimal odds are the solution to

$$\frac{1 + c(\mu_{jt}, \nu_{jt})\,(1 - b_{jt})}{\mu_{jt}} = c_\mu(\mu_{jt}, \nu_{jt})\,(1 - b_{jt})\,. \tag{A.2}$$

The left-hand side of (A.2) represents average cost of the intermediary, whereas the right-hand side is the marginal cost. Given Assumption 2, there is an unique intersection between these two that happens at the minimum of the average cost curve. Since the left-hand side is decreasing in financing experience for a given subsidy b_{jt}, average costs decrease with financing experience, and thus the equilibrium interest rate in one sector also decreases with financing experience in that sector. □

Derivation of Equation (14). Taking as given the unit cost of the loan r_{jit} and the odds of a successful audit μ_{jit}, the maximisation problem of a research firm is to decide how many scientists to hire, given the probability of innovating, the innovation possibility frontier, and the price of the patent π_{jit}. Formally,

$$\max_{H_{jit}\geq 0} \quad \lambda_j\left[\pi_{jit} - w^s_{jit}H_{jit}\,(1 + r_{jit})\right] \tag{A.3a}$$

$$\text{s.t. } \pi_{jit} = \alpha(1-\alpha)\left[\frac{p_{jt}}{(1-s)^\alpha\,(1+\tau_{jt})}\right]^{1/(1-\alpha)} A_{jit}L_{jt} \tag{A.3b}$$

$$A_{jit} = A_{jt-1}\left(1 + \gamma H^\eta_{jit}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^\phi\right) \tag{A.3c}$$

This can be simplified to

$$\max_{H_{jit}\geq 0} \quad \lambda_j\alpha(1-\alpha)\left[\frac{p_{jt}}{(1-s)^\alpha\,(1+\tau_{jt})}\right]^{1/(1-\alpha)} A_{jit}L_{jt} + \\ - \lambda_j w^s_{jit}H_{jit}\,(1 + r_{jit}) \quad \text{s.t. (A.3c)}. \tag{A.4}$$

The first order condition then is

$$w^s_{jit} = \frac{\alpha(1-\alpha)\left[\frac{p_{jt}}{(1-s)^\alpha(1+\tau_{jt})}\right]^{\frac{1}{1-\alpha}} A_{jt-1}\gamma\eta H^{\eta-1}_{jit}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^\phi L_{jt}}{(1 + r_{jit})}. \tag{A.5}$$

Note that, since research firms are ex-ante identical within sectors, $r_{jit} = r_{jt}\ \forall i$ and

$H_{jit} = H_{jt}\ \forall i$. We then use (A.5) to obtain

$$\frac{w^s_{dit}}{w^s_{cit}} = \frac{(1+r_{ct})\left[p_{dt}\left(1+\tau_{ct}\right)\right]^{1/(1-\alpha)} A^{1-\phi}_{dt-1} L_{dt}}{(1+r_{dt})\left[p_{ct}\left(1+\tau_{dt}\right)\right]^{1/(1-\alpha)} A^{1-\phi}_{ct-1} L_{ct}} \left(\frac{H_{ct}}{H_{dt}}\right)^{1-\eta}. \tag{A.6}$$

Since scientists are free to move across sectors and firms, they all must receive the same wage after research subsidies, $w^s_{dit}(1+q_{dt}) = w^s_{cit}(1+q_{ct})\ \forall i$, which means that

$$\left(\frac{H_{dt}}{H_{ct}}\right)^{1-\eta} = \frac{(1+r_{ct})\left(1+q_{dt}\right)\left[p_{dt}\left(1+\tau_{ct}\right)\right]^{1/(1-\alpha)} A^{1-\phi}_{dt-1} L_{dt}}{(1+r_{dt})\left(1+q_{ct}\right)\left[p_{ct}\left(1+\tau_{dt}\right)\right]^{1/(1-\alpha)} A^{1-\phi}_{ct-1} L_{ct}}. \tag{A.7}$$

Rearranging, one obtains equation (14) in the text. □

Analytical Expression for the Relative Share of Scientists. Substituting the expressions for the ratios of prices from (11) and labour demands from (13) in the equilibrium condition (14), one obtains

$$\frac{H_{dt}}{H_{ct}} = \left[\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\left(\frac{A_{dt}}{A_{ct}}\right)^{-\varphi-1}\left(\frac{1+\tau_{ct}}{1+\tau_{dt}}\right)^{\epsilon}\left(\frac{1+q_{dt}}{1+q_{ct}}\right)\left(\frac{1+r_{ct}}{1+r_{dt}}\right)\right]^{\frac{1}{1-\eta}}. \tag{A.8}$$

To obtain an implicit form for the equilibrium ratio is enough to combine this with the innovation possibility frontier in (8) and rearrange to

$$\begin{aligned}\frac{H_{dt}}{H_{ct}} = &\left[\left(\frac{\mu_{dt}\lambda_d A_{dt-1}\left(1+\gamma H^{\eta}_{dt}\left(\frac{A_{t-1}}{A_{dt-1}}\right)^{\phi}\right)+(1-\mu_{dt}\lambda_d)A_{dt-1}}{\mu_{ct}\lambda_c A_{ct-1}\left(1+\gamma H^{\eta}_{ct}\left(\frac{A_{t-1}}{A_{ct-1}}\right)^{\phi}\right)+(1-\mu_{ct}\lambda_c)A_{ct-1}}\right)^{-\varphi-1}\right]^{\frac{1}{1-\eta}} \times \\ &\times\left[\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\left(\frac{1+\tau_{ct}}{1+\tau_{dt}}\right)^{\epsilon}\left(\frac{1+q_{dt}}{1+q_{ct}}\right)\left(\frac{1+r_{ct}}{1+r_{dt}}\right)\right]^{\frac{1}{1-\eta}}.\end{aligned} \tag{A.9}$$

□

Proof of Proposition 1. In an interior balanced growth path, the ratio of the two technologies is constant over time, i.e. $A_{dt}/A_{ct} = A_{dt-1}/A_{ct-1}$. From (A.8), this implies that, in absence of policies,

$$\frac{H_{dt}}{H_{ct}} = \left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{-\phi-\varphi}{1-\eta}}\left(\frac{1+r_{ct}}{1+r_{dt}}\right)^{\frac{1}{1-\eta}}. \tag{A.10}$$

At the same time, the growth rate of the two technologies must be the same. From (8), the growth rate of technology j is

$$\frac{A_{jt}-A_{jt-1}}{A_{jt-1}} = \mu_{jt}\lambda_j\gamma H^{\eta}_{jt}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}. \tag{A.11}$$

Therefore, we need to impose that, in the interior laissez-faire equilibrium,

$$\frac{H_{dt}}{H_{ct}} = \left(\frac{\mu_{ct}\lambda_c}{\mu_{dt}\lambda_d}\right)^{\frac{1}{\eta}} \left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{\phi}{\eta}}. \tag{A.12}$$

Combining (A.1), (A.10) and (A.12), one obtains that a condition for an interior laissez-faire steady-state is

$$\left(\frac{1+c(\mu_{ct},\nu_{ct})}{1+c(\mu_{dt},\nu_{dt})}\right) \left(\frac{\mu_{dt}\lambda_d}{\mu_{ct}\lambda_c}\right)^{\frac{1}{\eta}} = \left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{\phi+\varphi\eta}{\eta}}. \tag{A.13}$$

Solving equation (A.13) for ϕ defines the threshold value for the strength of the cross-sector spillovers above which the economy converges to a stable interior balanced growth path,

$$\phi \geq \eta \left[\frac{\ln\left(\frac{1+c(\mu_{ct},\nu_{ct})}{1+c(\mu_{dt},\nu_{dt})}\right) + \frac{1}{\eta}\ln\left(\frac{\mu_{dt}\lambda_d}{\mu_{ct}\lambda_c}\right)}{\ln\left(\frac{A_{d0}}{A_{c0}}\right)} - \varphi\right] \equiv \bar{\phi}. \tag{A.14}$$

□

Proof of Proposition 2. Here, we characterise the optimal allocation of resources and discuss how it can be decentralised by a social planner through taxes and subsidies. An optimal allocation of resources is the solution to

$$\max \quad \sum_{t=0}^{\infty}\left[\frac{1}{(1+\rho)^t}\left(\frac{C_t^{1-\sigma}-1}{1-\sigma}\right)\right] \tag{A.15a}$$

$$\text{s.t.} \quad C_t = Y_t - X_{ct} - X_{dt} - M_{ct} - M_{dt} \tag{A.15b}$$

$$Y_t = \left(Y_{ct}^{(\epsilon-1)/\epsilon} + Y_{dt}^{(\epsilon-1)/\epsilon}\right)^{\epsilon/(\epsilon-1)} \tag{A.15c}$$

$$Y_{jt} = L_{jt}^{1-\alpha}\int_0^1 A_{jit}^{1-\alpha}x_{jit}^{\alpha}\,di \tag{A.15d}$$

$$X_{jt} = \psi\int_0^1 x_{jit}di \tag{A.15e}$$

$$M_{jt} = \hat{c}\left(\mu_{jt},\nu_{jt},H_{jt}\right) \tag{A.15f}$$

$$A_{jt} = A_{jt-1}\left[1+\mu_{jt}\lambda_j\gamma H_{jt}^{\eta}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}\right] \tag{A.15g}$$

$$A_t = A_{ct} + A_{dt} \tag{A.15h}$$

$$S_t = \sum_{\tau=0}^{t}\kappa Y_{d\tau} = S_{t-1} + \kappa Y_{dt} \leq \bar{S} \tag{A.15i}$$

$$\nu_{jt} = \nu\left(\sum_{\tau=0}^{t} Y_{j\tau}\right) \tag{A.15j}$$

$$H_{ct} + H_{dt} = H \tag{A.15k}$$

$$L_{ct} + L_{dt} = L, \tag{A.15l}$$

where X_{jt} is total expenditure on machines, $M_{jt} = \hat{c}(\mu_{jt}, \nu_{jt}, H_{jt})$ is the total cost of assessments (i.e. unfeasible projects exists and must be screened out), and $\nu()$ is a continuous, differentiable, and weakly increasing function.

There are several market failures in the laissez-faire equilibrium. First, there is an environmental externality to the production of the dirty intermediate input, as dirty production emits κ units of carbon per intermediate input. While this is not internalised by markets, dirty production contributes to cumulative emissions S_t and thus to shrink the remaining carbon budget at time t. Letting χ_t denote the Lagrange multiplier associated with the evolution of cumulative carbon emissions in (A.15i), the first-order condition with respect to S_t gives $\chi_t = \chi_{t+1}$. Let ζ_t be the shadow value of one unit of the final good or, equivalently, the Lagrange multiplier associated with (A.15c). Since ζ_t is also the Lagrange multiplier for (A.15b), it equals the shadow value of one unit of consumption; then, the first-order condition with respect to C_t yields $\zeta_t = (1+\rho)^{-t} C_t^{-\sigma}$, which means that the shadow value of the final good is equal to the discounted marginal utility of consumption. Moreover, letting ζ_{jt} be the Lagrange multiplier associated with the intermediate input productions in (A.15d), the ratio $\hat{p}_{jt} \equiv \zeta_{jt}/\zeta_t$ is the shadow price (relative to the price of the final good) of intermediate input j at time t (in the laissez-faire market economy, they are equivalent to the price of the inputs). Additionally, let υ_{jt} be the Lagrangian multiplier related to the financing experience accumulation equation in (A.15j) and ν_{Y_j} the marginal experience deriving from a marginal increase in the relevant intermediate input production. The first-order conditions with respect to Y_{ct} and Y_{dt} then give

$$\hat{p}_{ct} = Y_{ct}^{-1/\epsilon} \left(Y_{ct}^{(\epsilon-1)/\epsilon} + Y_{dt}^{(\epsilon-1)/\epsilon} \right)^{1/(\epsilon-1)} + \frac{\upsilon_{ct}\nu_{Y_c}}{\zeta_t} \tag{A.16a}$$

$$\hat{p}_{dt} = Y_{dt}^{-1/\epsilon} \left(Y_{ct}^{(\epsilon-1)/\epsilon} + Y_{dt}^{(\epsilon-1)/\epsilon} \right)^{1/(\epsilon-1)} + \frac{\upsilon_{dt}\nu_{Y_d}}{\zeta_t} - \frac{\kappa\chi_{t+1}}{\zeta_t}. \tag{A.16b}$$

These conditions imply that, compared to the decentralised equilibrium, the social optimum includes a wedge $\kappa\chi_{t+1}/\zeta_t$ between the marginal product of the dirty intermediate input and its price, which is equal to the cost of an additional unit of the dirty input in terms of cumulative emissions (evaluated in units of the final good at time t). As a consequence, the environmental externality can be corrected by introducing a Pigovian carbon tax $\tau_t = (\kappa\chi_{t+1})/\zeta_t$ on the use of this input in the production of the final good.

Second, from (A.16), it is also evident that the social optimum includes a wedge equal to the value (in units of the final good in t) of an additional unit of the intermediate input in terms of the financing experience that it generates, $\upsilon_{jt}\nu_{Y_j}/\zeta_t$. As a consequence, this positive externality could be corrected by introducing a pair of subsidies $\upsilon_{jt}\nu_{Y_j}/\zeta_t$ on the use of each intermediate input in the production of the final good. However, since in the decentralised equilibrium what matters is the ratio of the prices of the intermediate inputs, $(p_{dt}/p_{ct})[(1+\tau_{ct})/(1+\tau_{dt})]$, the social planner can simultaneously correct the financing experience externality and the environmental externality with a tax on the use of one of the two inputs (here, the dirty one) in the production of the final good; we thus refer to this unique tool as 'carbon tax' in the main text.[31]

Third, the laissez-faire equilibrium suffers from under-utilisation of machines due

[31] When financing experience depends on scientists allocation, as in subsection 5.2, the wedges related to these financing experience externalities show up in the first-order conditions with respect to H_{jt}. Then, the social planner can account for these externalities by setting an appropriate research subsidy.

to monopoly pricing. Indeed, the socially optimal demands for machines is $x_{jit} = (\hat{p}_{jt}/\alpha)^{1/(1-\alpha)} A_{jit} L_{jt}$. Inserting this into the intermediate input production function in (A.15d) leads to $Y_{jt} = L_{jt}(\hat{p}_{jt}/\alpha)^{\alpha/(1-\alpha)} A_{jt}$, i.e. intermediate good production is increased by a factor $\alpha^{-\alpha/(1-\alpha)}$ compared to the laissez-faire equilibrium. Since the marginal cost of producing one machine is $\psi \equiv \alpha^2$ whereas the price set by the monopolistic machine producers is $\alpha(1-s)$ in the decentralised equilibrium with policies, the social planner can correct this inefficiency by paying a subsidy $1-\alpha$ to machine producers: in this way, the net price becomes identical to marginal cost, $[1-(1-\alpha)]\psi/\alpha = \alpha^2$. This subsidy to the supply of all machines is symmetric across sectors, and thus it does not change the relative production of intermediate goods in (12).

Fourth, the social planner must correct for the knowledge externality in the evolution of the technologies, as research firms do not internalise that their innovations enable further productivity gains in the future. Letting o_{jt} denote the Lagrange multiplier associated with the evolution of technology j in (A.15g) and noticing that ζ_t is also the Lagrangian multiplier for (A.15f), the relevant first-order condition is

$$o_{ct}\mu_{ct}\lambda_c\gamma\eta H_{ct}^{\eta-1} A_{ct-1}\left(\frac{A_{t-1}}{A_{ct-1}}\right)^{\phi} - \zeta_t \frac{\partial \hat{c}\left(\mu_{ct}, \nu_{ct}, H_{ct}\right)}{\partial H_{ct}} =$$

$$= o_{dt}\mu_{dt}\lambda_d\gamma\eta\left(H - H_{ct}\right)^{\eta-1} A_{dt-1}\left(\frac{A_{t-1}}{A_{dt-1}}\right)^{\phi} - \zeta_t \frac{\partial \hat{c}\left(\mu_{dt}, \nu_{dt}, H - H_{ct}\right)}{\partial H_{ct}}, \quad \text{(A.17)}$$

where the first term on each side captures the marginal change in average productivities across sectors, whereas the second term on each side represents the marginal change in utility at time t due to the marginal changes in assessment costs. With an appropriate transformation of these second terms, we can express the socially optimal allocation of scientists across sectors as

$$\frac{H_{dt}}{H_{ct}} = \left[\left(\frac{o_{dt}}{o_{ct}}\right)\left(\frac{\mu_{dt}\lambda_d}{\mu_{ct}\lambda_c}\right)\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\left(\frac{1+\hat{r}_{ct}}{1+\hat{r}_{dt}}\right)\right]^{\frac{1}{1-\eta}}. \quad \text{(A.18)}$$

Since the Lagrange multiplier o_{jt} also corresponds to the shadow value of average quality A_{jt}, it equals

$$o_{jt} = o_{jt+1}\left\{1 + \mu_{jt+1}\lambda_j\gamma H_{jt+1}^{\eta}\left(\frac{A_t}{A_{jt}}\right)^{\phi}\left[1-\phi+\phi\left(\frac{A_t}{A_{jt}}\right)^{-1}\right]\right\} +$$

$$+ o_{-jt+1}\phi\mu_{-jt+1}\lambda_{-j}\gamma H_{-jt+1}^{\eta}\left(\frac{A_t}{A_{-jt}}\right)^{\phi-1} + \zeta_{jt}(1-\alpha)\frac{Y_{jt}}{A_{jt}}, \quad \text{(A.19)}$$

where the first term on the right-hand side is the intertemporal knowledge externalities on the technology in the same sector (the standing on shoulders feature), the second one accounts for the knowledge spillovers across sectors, and the third one is the marginal contribution of a unit increase in this average productivity to utility at time t (due to an increase in intermediate input production and thus total output). Combining (A.18) and (A.19), one obtains an expression for the socially optimal allocation of scientists that includes recursively the future shadow values of both average productivities: as a consequence, this allocation depends on the net present values of the future use of intermediate inputs. The social planner must then introduces a subsidy for either clean or dirty innovation in each period in order to achieve the socially optimal allocation of scientists.

Finally, the first-order condition with respect to μ_{jt} is

$$\frac{\partial \hat{c}\left(\mu_{jt}, \nu_{jt}, H_{jt}\right)}{\partial \mu_{jt}} = \frac{o_{jt} A_{jt-1} \lambda_j \gamma H_{jt}^{\eta} \left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}}{\zeta_t}, \tag{A.20}$$

where the left-hand side is the marginal cost of increasing the odds of financing feasible projects, whereas the right-hand side is the social marginal value of having higher productivity (in terms of time-t utility). Differently from the decentralised allocation, the socially optimal one would internalise the positive externality, whose magnitude depends on the shadow value o_{jt} of an increase in average productivity. The social planner can correct this inefficiency by subsidising the marginal costs incurred by financial intermediaries, as to incentivise them to increase the assessment odds.

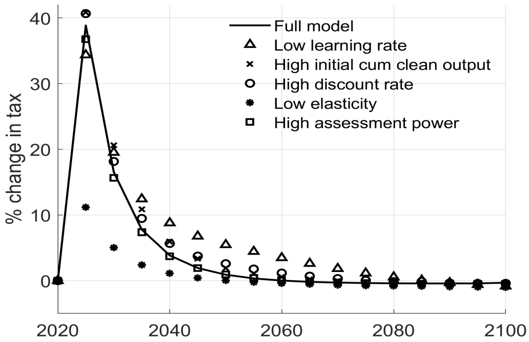
□

A.2 Robustness

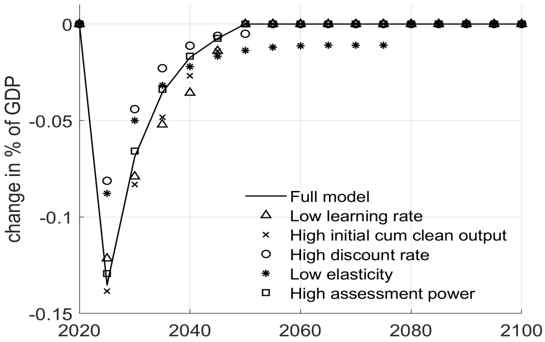
In this subsection, we discuss the following robustness checks: i) a decrease in the clean learning rate, $\omega = 0.74$, corresponding to a reduction of 40% (rather than 60%) in clean financing costs for each doubling of clean cumulative output; ii) a higher initial level of cumulative clean output equal to $3Y_{c0}$; iii) a higher yearly discount rate, $\rho = 3\%$; iv) a lower elasticity of substitution between clean and dirty inputs, $\epsilon = 2$; v) a higher maximum assessment odds of 25% ($\bar{\mu}_t = 0.25 + 0.75\nu_{jt}$); and vi) different initial clean financing cost gaps. As our focus is on the clean financing experience effect, we show how these parameter changes change the impact of the heterogeneous financing costs on optimal policy. In particular, Figure A.1 repeats Panels 4b, 4c, and 4d with different parameter choices i) to v), and Figure A.2 repeats Panels 2a, 2b, and 2c for different initial clean financing cost gaps vi).

Figure A.1 shows that the key qualitative results are consistent across sensitivities: finance costs lead to a higher optimal carbon tax, a lower clean research subsidy, and a clean finance subsidy in the first period. A lower $\omega = 0.74$ implies a slower experience effect, which leads to clean financing costs decreasing more slowly (10.1% in 2025 and 2.6% in 2050 versus 7.1% and 0.6% in the full model), which in turn means a higher clean finance subsidy is required. A higher initial cumulative clean output equal to $3Y_{c0}$ in 2020, with the same initial financing costs, also implies a slower decrease in clean financing costs (8.8% in 2025 and 1.0% in 2050), and thus a higher clean finance subsidy. Changes in the yearly discount rate to $\rho = 3\%$ and elasticity of substitution to $\epsilon = 2$ affect results for the symmetric scenario as well as the full model. A higher discount rate means less ambitious policy in the near term, while a lower elasticity means a much higher tax is required to meet the emissions constraint. The impact of the parameter change on the clean financing cost effect then follows: in Panel A.1a, the percentage change in the carbon tax is slightly higher with a high discount rate (as the symmetric scenario tax is lower), while the percentage change is lower with a low elasticity (as the symmetric scenario tax is higher). A higher power of assessment leads to a higher level of clean finance subsidy, a marginally lower carbon tax (as the finance subsidy is able to close the finance gap more quickly) and a marginally higher clean research subsidy.

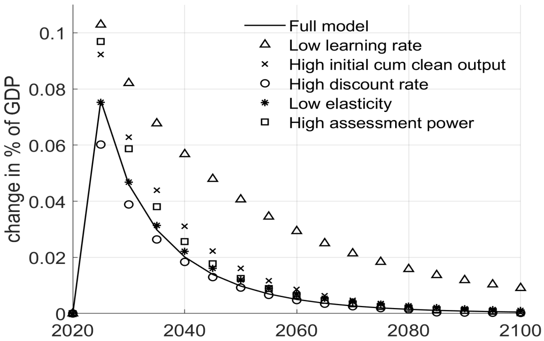
Figure A.2 shows that the boost in optimal carbon tax and the clean finance subsidy



(a) Carbon tax



(b) Clean research subsidy

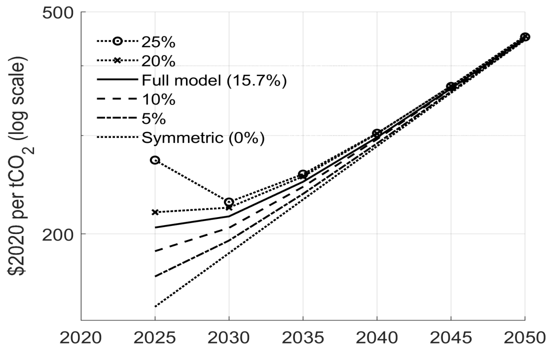


(c) Clean finance subsidy

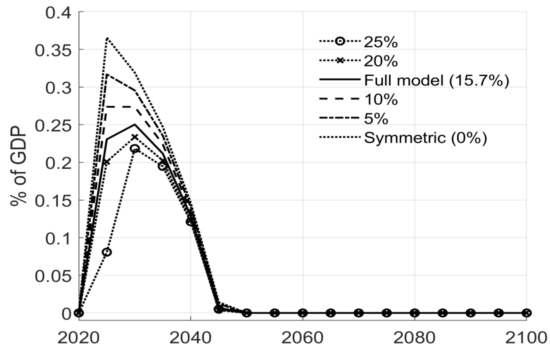
Figure A.1: Robustness

Notes. The *full* scenario includes optimal policy and financing experience effects based on cumulative output; the other scenarios are equal to the benchmark one apart for one parameter. This figure shows changes relative to a *symmetric* scenario with optimal policy but with homogeneous and constant financing costs (any parameter change is applied to all scenarios being compared).

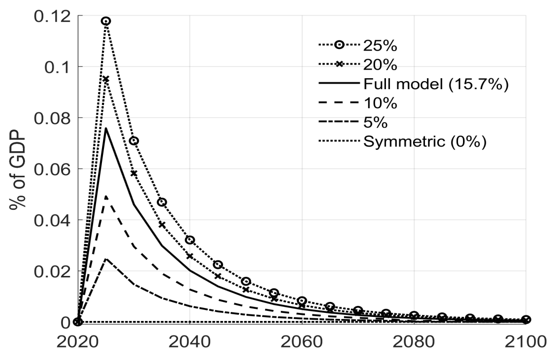
rise as initial clean financing costs increase, while the clean research subsidy falls.



(a) Carbon tax



(b) Clean research subsidy



(c) Clean finance subsidy

Figure A.2: Sensitivity to Initial Clean Financing Cost Gap

Notes. All scenarios includes optimal policy and financing experience effects based on cumulative output, with different initial financing costs gaps.