Australian National University

Crawford School of Public Policy

CAMA

Centre for Applied Macroeconomic Analysis

Clean Innovation and Heterogeneous Financing Costs

CAMA Working Paper 25/2023
May 2023

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 heterogeneous and endogenous financing costs in a directed technical change model and identify optimal climate mitigation policies. The presence of a financing experience effect induces more ambitious policies in the short-term, both to shift innovation and production towards clean sectors and to reduce the financing cost differential across technologies, which further facilitates the transition. The optimal climate policy mix between carbon taxes and clean research subsidies depends on whether experience is gained through clean production or research. In our benchmark scenario, where clean financing costs decline as cumulative clean output increases, we find an optimal carbon price premium of 47% in 2025, relative to a case with no financing costs.

Keywords

carbon tax, directed technological change, endogenous growth, financing experience effect, innovation policy, low-carbon transition, optimal climate policy, sustainable finance

JEL Classification

H23, O31, O44, Q55, Q58

Address for correspondence:

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

ISSN 2206-0332

Clean innovation and heterogeneous financing costs*

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, United Kingdom*
[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 heterogeneous and endogenous financing costs in a directed technical change model and identify optimal climate mitigation policies. The presence of a *financing experience effect* induces more ambitious policies in the short-term, both to shift innovation and production towards clean sectors and to reduce the financing cost differential across technologies, which further facilitates the transition. The optimal climate policy mix between carbon taxes and clean research subsidies depends on whether experience is gained through clean production or research. In our benchmark scenario, where clean financing costs decline as cumulative clean output increases, we find an optimal carbon price premium of 47% in 2025, relative to a case with no financing costs.

Keywords: carbon tax, directed technological change, endogenous growth, financing experience effect, innovation policy, low-carbon transition, optimal climate policy, sustainable finance

JEL codes: H23, O31, O44, Q55, Q58

---

*Email for correspondence: alessandro.spiganti@unive.it. We thank Louis Daumas, Stephie Fried, Claudia Ghisetti, Christian Haas, Karol Kempa, Francesco Lamperti, 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), and the 2022 Environmental Protection and Sustainability Forum (EPSF) 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, 2021). However, despite rapid recent advancement in certain fields - e.g. electricity generation from renewable sources - technological alternatives are often still not competitive with carbon-intensive incumbents, especially in the so-called 'hard-to-abate' sectors, like steel, cement, chemicals, aviation, and shipping (IEA, 2022b, IPCC, 2022). Similarly, technologies capable of capturing greenhouse gases - either at the source or directly from the atmosphere - are still at the pilot stage (Wang et al., 2021, IEA, 2022a).

A large-scale innovation effort is needed to develop the technologies capable of replacing polluting incumbents. 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 emerging from the environmental externality must be added, as individuals do not fully internalise the net social benefits of using technologies that reduce emissions (Popp, 2010, 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, 2022), identifies two key policy interventions to achieve an optimal low-carbon transition: i) a rising carbon tax to internalise the climate externality; and ii) a generous but temporary clean research subsidy, which help 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 external financing

(Ghisetti et al., 2017).

While financing clean innovation can be harder than other technologies, access conditions to external finance can improve via learning and experience effects. Learning and 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).

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? 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 financing into an endogenous growth model where innovation can be directed to high-carbon (dirty) and low-carbon (clean) inputs. The economy features: i) a manufacturing sector producing a homogeneous final good using clean and dirty intermediate inputs; ii) two intermediate sectors, producing the intermediate inputs using labour and a continuum of machines; iii) two research sectors improving the productivity of the machines by employing scientists, with technology spillovers across and within sectors; and iv) two sectors producing machines.

We assume that both machine producers and research firms require external finance (loans) to cover the flow mismatch between the payments to input factors and revenue realisation. These loans are subject to two types of financing costs (which we assume lenders pass on to borrowers), where clean producers and research firms face a disadvantage relatively to their dirty counterparts. First, clean firms suffer from a higher economic cost (in units of the final good), which is assumed proportional to the volume of credit (Bernanke et al., 1999) and can be interpreted as a combination of screening (King and Levine, 1993), monitoring (Townsend, 1979, Gale and Hellwig, 1985), and assessment costs (Shleifer and Vishny, 1992). Second, there is misdirection of research funding to clean technology due to inexperience (Egli et al., 2018), leading to a lower chance of research success. In the stochastic innovation process à la Acemoglu et al. (2012), research firms have a positive probability of failing: since in this case they are unable to repay their loan, lenders charge borrowers to internalise the risk of default. Thus, research firms in clean technology have a higher chance of default initially. We parsimoniously assume that both types of financing cost gaps faced by clean firms disappear with financing experience through a 'one-factor experience curve', where costs decrease by a constant percentage for each doubling in the cumulative output of the corresponding technology (Polzin et al., 2021).

We first show that our theoretical model is characterised by an interior equilibrium in which research and production is pursued in both technologies. In addition to the effects already outlined by the literature on directed technical change,[1] we highlight a novel *financing experience effect*. In a given period, this distorts the choices of machine producers and research firms by directing production and research towards the sector for which financing costs are lower. Across periods, these choices have an intertemporal externality, as financing costs depend on cumulative output of each technology. Our theoretical results underline that heterogeneous access conditions to external finance will stifle innovation in the relatively novel sector, thus delaying a low-carbon transition unless policy takes account of financing costs.

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 three main sets of findings. First, we show that the endogenous financing experience effect helps the low-carbon transition even without climate policies, since the decrease in financing costs as cumulative clean output increases redirects some investments away from the dirty sector. However, this is by no means sufficient in reaching the restricting climate objectives. In line with the original contribution by Acemoglu et al. (2012), we find that an optimal low-carbon transition requires a steeply rising carbon tax complemented with generous but temporary clean research subsidies, which help induce a higher clean research share in the near term. In our benchmark scenario, optimal carbon price starts approximately at $217 per tonne of CO2 in 2025 and later grows at an annual rate between 4% and 5%, while the optimal clean research subsidy jumps to 2% of GDP in 2025, before being phased out by 2050.

Second, 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 financing costs decline more rapidly as output becomes cleaner, winning reluctance of financial markets 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 ambitions and decrease emissions more rapidly in the near-term. Our benchmark scenario finds a premium in optimal carbon prices of 47% in 2025 (then decreasing over time towards zero), relative to a case without financing costs (where the initial optimal carbon tax is just below $150).

Finally, we find that the optimal policy mix depends on the nature of the financing experience

[1]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).

effects, i.e. on which indicators financial markets use to update their financing conditions. If financial markets react to relative cumulative sector outputs, the endogeneity of these experience effects leads to a much higher carbon tax, since this is a more effective instrument at targeting outputs than the clean research subsidy. Conversely, if the experience effects are linked to research, the policy ambition translates into a much higher clean research subsidy (higher by almost 1.5% of GDP compared to a case without financing costs). Therefore, if the nature of these experience effects differs among markets, technologies, and geographical areas, due perhaps to different lending environments and institutions (see for instance Aghion et al., 2022, as regards venture capital and R&D investments and green patents across countries), then optimal climate policies will also differ across these environments.

We build on and contribute to two main streams of literature. First, as already discussed above, we closely connect to the modelling literature examining clean directed technical change in an endogenous growth setting, originating from Acemoglu et al. (2012). This framework has been extended in many directions: for example, Acemoglu et al. (2016) provide a micro-founded quantitative version of the model; 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; Wiskich (2021) analyses the presence of multiple equilibria; Nowzohour (2021) adds adjustment costs; Lemoine (2022) adds complementarities between innovations and energy resources; and Smulders and Zhou (2022) show that beliefs about future environmental-friendliness of innovation can overturn the lock-in in polluting technology and create self-fulfilling prophecies. Our main novelty is that we add financing costs.

Second, we build on the (mostly) empirical literature on clean innovation and financing constraints. Contributions in this area usually find that environmental innovations face more hindrances than traditional innovations when it comes to the financing process (Ghisetti et al., 2017, Howell, 2017, Jensen et al., 2019, Cecere et al., 2020, Noailly and Smeets, 2021); Olmos et al. (2012) reviews policy instruments to overcome these challenges. 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 articles try to combine these streams of work, as we do: Pan et al. (2022) and Aghion et al. (2022).[2] While these authors also add financing costs to a model of clean directed technical change, our focus differs to 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

[2]Other authors have tried to investigate the topic using alternative modelling approaches. See for instance Hoffmann et al. (2017), D'Orazio and Valente (2019), Benmir and Roman (2021), and Haas and Kempa (2021). 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.

the EU and selected peers and across EU member states, and how these relates to cross-country differences in venture capital investments. On the contrary, we are interested in the dynamic interaction between climate policies and financing conditions for different technologies. As a consequence, there are many differences in terms of modelling, with the main one being that, while they consider time-independent and exogenous financing conditions, we use an endogenous function of the cumulative output of the corresponding technology.

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. The economy features several sectors: i) a manufacturing sector producing a homogeneous 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 a continuum of machines, iii) two research sectors producing patents by employing scientists, and iv) two machine sectors producing machines (some clean and some dirty) using the final good and patents. Workers and scientists are free to move across sectors, with the decision to move only hinging on wage rates.

2.1 The Final Good Sector

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 The Intermediate Sectors

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,

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

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

where p_{jt} is the price of the intermediate good Y_{jt}, 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}. We normalise cumulative emissions at zero at the beginning of the simulation, so that cumulative emissions at time t are given by[3]

$$S_t = \sum_{\tau=0}^{t} \kappa Y_{d\tau}. \tag{5}$$

2.3 The Machine Producing Sectors

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

[3]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 (2022).

as a monopolist in the production of its particular machine. In particular, each of these firms has purchased a patent from a research firm in the corresponding 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}. Machines fully depreciate after use.

To introduce heterogeneous costs of finance 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. Following e.g. Mendoza (2010) and Jermann and Quadrini (2012), we thus assume that machine producers need intra-period loans from international capital markets, and the expected revenues serve as the collateral for the credit. The existing literature on directed technical change and climate corresponds to the special case in which the cost of these loans is zero (with the exception of Aghion et al., 2022, Pan et al., 2022, as explained in Section 1), whereas here we introduce non-negative costs that are assumed to be directly proportional to the volume of credit (as in Bernanke et al., 1999).[4]

Machine producers are infinitesimal, therefore they take the cost of financing as given. As a consequence, the maximisation problem of the producer of machine i in sector j is, once acquired a patent,

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

where ψ/ν_{jt} gives the total amount of credit needed to pay out the cost of producing one machine; equivalently, for a machine producer in sector j at time t, a fraction $1 - \nu_{jt}$ of credit is used to cover up the financing costs, whereas the remaining part ν_{jt} is effectively available to cover production costs. Note that these costs may vary across time and sectors, and we will indeed endogenise them below.

Without loss of generality, we normalise $\psi \equiv \alpha^2$ (as in Acemoglu et al., 2012, Aghion et al., 2022). 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 they actually face, i.e. $p_{jit} = \psi/(\nu_{jt}\alpha) = \alpha/\nu_{jt}$, thus unique within a sector. 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,

$$x_{jit} = (p_{jt}\nu_{jt})^{1/(1-\alpha)} A_{jit} L_{jt} \tag{7a}$$

$$\pi_{jit} = \alpha(1-\alpha) p_{jt}^{1/(1-\alpha)} \nu_{jt}^{\alpha/(1-\alpha)} A_{jit} L_{jt}. \tag{7b}$$

[4]We remain agnostic about the micro-foundations of these financing costs, but there are a number of possible sources. For example, they could represent costly monitoring to induce compliance to credit rules, similarly to Townsend (1979) and Gale and Hellwig (1985). They could also represent screening costs à la King and Levine (1993), where there are additional agents seeking to finance projects that are in fact not feasible under any circumstances. Additionally, these costs could represent the expenses for risk assessment and due diligence processes, or the lack of standardised investment structures, frame contracts, and partner networks (see Egli et al., 2018, for an analysis of the financing conditions for renewable energy).

2.4 The Research Sectors

Following the large literature originated from Romer (1990a,b), a continuum of firms of mass one in each research sector produce knowledge using scientists and existing knowledge. At the beginning of each period, a research firm is matched randomly with one machine in the corresponding sector, and can then hire scientists to innovate, i.e. to increase the quality of its machine. Innovation is assumed stochastic: the research firm is successful in the innovation process with probability $\lambda_{jt} \in [0, 1]$, 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 $1 - \lambda_{jt}$, 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.[5]

The innovation possibility frontier is given by

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

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 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,[6] 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 $H_{ct} + H_{dt} = H$.

The form of the innovation possibility frontier in (8) 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 additionally mean that financiers require a premium internalising the risk of not getting 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 (like Acemoglu et al., 2012, Fried, 2018, in an environmental setting). In our model, this also introduces a positive externality in terms

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

[6]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.

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 productivity advantage equal to the catch-up ratio $(A_{t-1}/A_{jt-1})^{\phi}$.[7] 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 require access to finance at the same time along the balanced growth path; still, conditions may be different across different sectors.

From the point of view of a machine producer, the decision about undertaking 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}. The problem of the individual research firm is then to choose scientists to maximise own profits, given the profits of the matched machine producer in (7b) and the innovation possibility frontier in (8). However, research firms need loans to cover the flow mismatch between the payments to scientists and the sale of the patents and we assume the presence of a non-negative financing cost, as for machine producers. Therefore, the maximisation problem of research firm i in sector j is

$$\Pi_{jit} = \max_{H_{jit} \geq 0} \ \pi_{jit} - \frac{w^s_{jit}}{\lambda_{jt} \nu^s_{jt}} H_{jit}, \qquad \text{s.t. (7b) and (8),} \tag{9}$$

where $w^s_{jit}/(\lambda_{jt}\nu^s_{jt})$ gives the total cost for a research firm to pay out the wage of one scientist. Indeed, for every unit borrowed, lenders require a premium $1/\lambda_{jt}$ to cover the possibility of default; moreover, a fraction $1 - \nu^s_{jt}$ of credit is used to cover up the proportional costs. Once again, these financing costs can evolve differently across sectors, as explained in Section 2.6. In equilibrium, $H_{jit} = H_{jt}$ $\forall i$, since research firms in the same sector are ex-ante homogeneous; similarly, $w^s_{jit} = w^s_{jt}$ $\forall i$, since workers are free to move across firms.

2.5 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

[7] 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.

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

$$C_t = w_{ct}L_{ct} + w_{dt}L_{dt} + w_{ct}^s H_{ct} + w_{dt}^s H_{dt} + \pi_{ct} + \pi_{dt}. \tag{11}$$

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

$$Y_t = C_t + \psi \int_0^1 \left(\frac{x_{cit}}{\nu_{ct}} + \frac{x_{dit}}{\nu_{dt}}\right) di + (1-\nu_{ct}^s)\, w_{ct}^s H_{ct} + (1-\nu_{dt}^s)\, w_{dt}^s H_{dt}. \tag{12}$$

2.6 Learning-By-Doing and Financing Experience

As explained in Section 1, empirical evidence suggests that, while access to finance is more difficult for new and immature technologies than for incumbent and widely-known technologies, financing costs should decrease as lenders became acquainted with these novel technologies. To parsimoniously capture this, we assume that the proportional financing costs faced by each firm negatively depends on the cumulative production of its technology. Similarly, we assume that a technology matures, and thus becomes more reliable, as more projects in the same technology class are incorporated in the production of the final good.[8] In particular, we take the following assumption:

Assumption 2. *The probability of failure in innovation in each research sector and the proportional financing costs in each machine producing and research sector are continuous, differentiable, and weakly decreasing functions of the cumulative output of the corresponding intermediate input. The limit of the first derivatives of these functions is zero as cumulative output approaches infinity.*

This assumption ensures that financing costs decline as the corresponding technology is used in production. The assumption on the behaviour of the first derivatives means that these financing costs stabilise around constant values in the very long-run, as experience and learning effects run out. This ensures the stability of the balanced growth path, as clarified in Section 3. Whereas

[8] On the one hand, this represents learning-by-doing or learning-by-observing, whereby future innovators benefit from the trials and errors of current innovators. For example, Popp (2010) argue that such spillovers, which are particularly pronounced in the case of clean technologies, occur during the deployment and diffusion of new technologies on the relevant market (see also Haas and Kempa, 2021). On the other hand, this also reflects that, as a technology becomes more mature, it also becomes less prone to default, thus causing a decrease in the premium charged by financiers (as documented by Egli et al., 2018, in the renewable energy sector).

theoretical results are unchanged if these effects depend on cumulative sectoral output, research, productivity, or labour, quantitative results may differ. In Section 5.3, we compare simulations where these effects depend on cumulative output versus research. Finally, in Appendix A.2, we investigate quantitative results where we exclude the endogenous evolution of the likelihood of success.

3 The Equilibrium

In this section, we characterise the decentralised equilibrium of the model without any policy intervention (proofs are formally given in Appendix A.1) and then discuss externalities that can be corrected with policy. An equilibrium is defined by time paths of wages $[w_{ct}, w_{dt}, w^s_{ct}, w^s_{dt}]^\infty_{t=0}$, prices for inputs $[p_{ct}, p_{dt}]^\infty_{t=0}$, prices for each machine $[p_{cit}, p_{dit}]^\infty_{t=0}$, prices of patents $[\pi_{ct}, \pi_{dt}]^\infty_{t=0}$, proportional financing costs $[\nu_{ct}, \nu_{dt}, \nu^s_{ct}, \nu^s_{dt}]^\infty_{t=0}$, probabilities of success in innovation $[\lambda_{ct}, \lambda_{dt}]^\infty_{t=0}$, intermediate inputs production $[Y_{ct}, Y_{dt}]^\infty_{t=0}$, labour allocations $[L_{ct}, L_{dt}, H_{ct}, H_{dt}]^\infty_{t=0}$, quantities of each machines $[x_{ct}, x_{dt}]^\infty_{t=0}$, and cumulative carbon emissions $[S_t]^\infty_{t=0}$, such that, in each period t, final good producers, intermediate good producers, machine producers, and research firms choose, respectively, (Y_{ct}, Y_{dt}), $(L_{ct}, L_{dt}, x_{ct}, x_{dt})$, $(x_{ct}, x_{dt}, p_{cit}, p_{dit})$, and $(H_{ct}, H_{dt}, \pi_{ct}, \pi_{dt})$ to maximise profits, the evolution of wages $(w_{ct}, w_{dt}, w^s_{ct}, w^s_{dt})$ and prices $(p_{ct}, p_{dt}, p_{cit}, p_{dit}, \pi_{ct}, \pi_{dt})$ is consistent with market clearing, the evolution of the proportional financing costs $(\nu_{ct}, \nu_{dt}, \nu^s_{ct}, \nu^s_{dt})$ and of the probabilities of success in innovation $(\lambda_{ct}, \lambda_{dt})$ is consistent with Assumption 2, 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, $g \equiv (A_{t+1} - A_t)/A_t$ for all t.

If the labour markets are characterised by a stable allocation of workers and scientists across sectors, then it is 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 one 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. To solve the model for these balanced growth paths, it is therefore necessary to determine if stable equilibrium allocations in the labour markets exist, which is the focus of the next subsections.

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 $w_{jt} = (1-\alpha)\, A_{jt} p_{jt}^{1/(1-\alpha)} \nu_{jt}^{\alpha/(1-\alpha)}$. 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

$$\frac{p_{dt}}{p_{ct}} = \left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{-\alpha} \left(\frac{A_{dt}}{A_{ct}}\right)^{-(1-\alpha)}, \tag{13}$$

which formalises the natural ideas that the input produced with more productive machines will be relatively cheaper, whereas higher financing costs $1-\nu_{jt}$ will lead to a relative higher price for the corresponding input.

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

$$\frac{Y_{dt}}{Y_{ct}} = \frac{L_{dt}}{L_{ct}} \left(\frac{\nu_{dt} p_{dt}}{\nu_{ct} p_{ct}}\right)^{\alpha/(1-\alpha)} \frac{A_{dt}}{A_{ct}}. \tag{14}$$

Combining (4), (13), and (14) leads to the following relationship among the equilibrium ratio of labour demands from the two sectors, the relative productivity, and the relative financing costs,

$$\frac{L_{dt}}{L_{ct}} = \left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{-\varphi\alpha/(1-\alpha)} \left(\frac{A_{dt}}{A_{ct}}\right)^{-\varphi}, \tag{15}$$

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

Together, the equilibrium ratios (13), (14), and (15) suggest that, if the ratios of the productivities of the technologies and their financing costs 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.

3.2 The Equilibrium Allocation of Scientists

Scientists are also free to move across sectors, and thus in equilibrium $w^s_{dt} = w^s_{ct} \equiv w^s_t$. The following relative equilibrium allocation of scientists ensues

$$\frac{H_{dt}}{H_{ct}} = \left(\frac{A_{dt-1}^{1-\phi} p_{dt}^{1/(1-\alpha)} L_{dt} \nu^s_{dt} \nu_{dt}^{\alpha/(1-\alpha)} \lambda^2_{dt}}{A_{ct-1}^{1-\phi} p_{ct}^{1/(1-\alpha)} L_{ct} \nu^s_{ct} \nu_{ct}^{\alpha/(1-\alpha)} \lambda^2_{ct}}\right)^{\frac{1}{1-\eta}}. \tag{16}$$

Equation (16) 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 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.

In our model, there is an additional financing experience effect 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). This comprises two terms. The first, $(\nu^s_{dt}/\nu^s_{ct})(\nu_{dt}/\nu_{ct})^{\alpha/(1-\alpha)}$, captures the direction of scientists towards the sector with e.g. lower monitoring and screening costs, with more advanced risk assessments and due diligence processes, more standardised contracts and investment structures, or with intangible assets more easily valued. The second term, $(\lambda_{dt}/\lambda_{ct})^2$, directly depends on the default 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 clean technology.

If technologies grow at the same rate and the relative financing conditions are stable, these effects 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. *Ceteris paribus*, the relative allocation of scientists depends on the strength of the cross-sector spillovers, ϕ: if these are relatively weak, the economy converges to a corner solution in which all innovation occurs in the initially more advanced sector, whereas the other stagnates; if they are relatively strong, then there exists a stable interior balanced growth path in which scientists are employed in both research sectors.[9] 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 balanced growth path.*

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

3.3 The Balanced Growth Path and Policies

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

Proposition 1. *The economy exhibits a 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 g. 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, the probabilities of success in innovation, and the labour and scientists allocations across sectors are constant.*

Proof. See Appendix A.1. □

[9] See Acemoglu (2002), Hart (2013), and Fried (2018) for a deeper discussion on the role played by the strength of cross-sector technology spillovers for the stability of an interior long-run balanced growth path.

Note that the equilibrium of this laissez-faire economy is not socially optimal. In Section 5, we present simulations where a combination of subsidies to the provision of machines, a carbon tax, and clean research subsidies are implemented to correct the market failures of the laissez-faire equilibrium and thus decentralise the optimal allocation of resources (following e.g. Acemoglu et al., 2012, Greaker et al., 2018).

First, the laissez-faire equilibrium suffers from under-utilisation of machines due to monopoly pricing that is corrected with a subsidy to the use of machines equal to $1-\alpha$ (see e.g. Acemoglu, 2009, Chapter 15), so that intermediate good production is increased by a factor $\alpha^{-\alpha/(1-\alpha)}$. However, the subsidy is symmetric across sectors, and thus it does not change the relative production of intermediate goods in (14); as a consequence, this market failure is not a focus of this paper and we assume it is corrected with this subsidy in all our simulations.

Second, there is an environmental externality to the production of the dirty intermediate input that can be corrected by introducing a carbon tax τ_t on the use of this input in the production of the final good, so that the price of the dirty intermediate input including the tax becomes $p_{dt}+\tau_t$. This changes the relative prices according to (13) and disincentives research in and production of dirty machines as pointed out in (16), similarly to e.g. Acemoglu et al. (2012) and Fried (2018).

Third, the knowledge externality in the technology frontier can be corrected by a research subsidy that rewards innovation in the research sector with the higher social gain. Here, a subsidy s_t would increase profits Π_{cit} in the clean research sector to $(1+s_t)\Pi_{cit}$, while leaving profits in the dirty sector unchanged, thus redirecting innovation towards the clean sector (as in Acemoglu et al., 2012).[10]

In our model, there are also financing costs that distort choices by machine producers and research firms. These costs are potentially asymmetric, and thus may also change the direction of research relative to the socially optimal allocation. Moreover, inefficient choices of production and research have an intertemporal externality through these financing costs, which depend on the evolution of each technology. There are various policies that could target this inefficiency, but below we choose to focus solely on the role of carbon taxes and research subsidies. Indeed, Aghion et al. (2022) argue that these two instruments fall in the realm of government policies, whereas central banks actions face obstacles from both a legal and an economic perspective.

4 Calibration

In this section, we discuss our calibration strategy. Calibrated parameters are in Table 1. Robustness checks are provided in Section 5.4. Our initial period is calibrated to 2020, and our simulations run for 40 periods, with each period representing 5 years. The full span of our

[10] In the absence of a climate constraint, the social planner will always choose a zero carbon tax but 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.

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	US$85 trillion	World Bank
Initial clean energy share	$Y_{c0}/(Y_{d0}+Y_{c0})$	20%	EIA (2021)
Initial cumulative clean energy	$Ycum_{c0}$	Y_{c0}	Normalisation
Number of scientists	H	1	Normalisation
Scientist efficiency	γ	1	Acemoglu et al. (2012)
Scientist long-run chance of success	λ_d	2%	Acemoglu et al. (2012)
Returns in research	η	0.7	Greaker et al. (2018)
Cross-sector spillovers	ϕ	$-(1-\alpha)(1-\epsilon)\eta$	Normalisation
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)
Initial clean financing costs	$1-\nu_{c0}, 1-\nu_{c0}^s$	10%, 10%	Hafner et al. (2021)
Initial dirty financing costs	$1-\nu_{d0}, 1-\nu_{d0}^s$	0%, 0%	Normalisation
Clean scientist initial chance of success	λ_{c0}	$0.9\lambda_d$	Hafner et al. (2021)
Experience parameter	ω	0.60	Normalisation

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 Nordhaus (2017) and Acemoglu et al. (2012).[11] 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 $\epsilon = 3$.[12]

Patents last one period, as in many directed technological change models (e.g. Acemoglu et al., 2012, Fried, 2018). Fried (2018) also argues that 5 years 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

[11] 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

[12] 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 (2022) 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 5.4, we provide results with a lower elasticity.

(discussed below), i.e. $\phi = -(1-\alpha)(1-\epsilon)\eta$ which equals 0.933 given the parameter values in Table 1.[13] The efficiency parameter γ is calibrated to lead to a long-run growth rate of output equal to $g = 2\%$ per annum under a low-carbon transition, 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. $L = H = 1$.[14]

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}. Here, 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); for comparison, Acemoglu et al. (2012) assume clean energy initially makes up 18% of total energy, whereas Hart (2019) assumes an initial clean share of 5%. The initial share of research in clean technology, 11% in our main scenario, also follows from our assumptions of the initial output ratio and clean financing costs, and happens to equal the share of innovative firms classified as clean in Acemoglu et al. (2016). Total output Y_0 is set to the 2020 global GDP using data from the World Bank.

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 Y_{d0} and thus 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).

The main scenario of our simulations operationalises the concept of financing experience by endogenising the proportional financing costs and the probability of success in innovation, in line with Assumption 2. Following Rubin et al. (2015), Egli et al. (2018), and Polzin et al. (2021), we impose a 'one-factor experience curve' where financing costs decrease by a constant percentage ω for each doubling in the cumulative output of clean technologies, i.e.

$$\nu_{ct} = \nu_{ct}^s = \frac{\lambda_{ct}}{\lambda_{dt}} = 1 - (1-\nu_{c0})\left(\frac{Y_{c0}}{Y_{c0} + \sum_{\tau=1}^{t} Y_{c\tau}}\right)^{\omega}, \tag{17}$$

where, for simplicity and ease of comparison, we impose cumulative output at the start of the simulation equals output value in 2020. As dirty technologies are already mature, we abstract from learning in their financing by keeping $\nu_d = \nu_d^s = 100\%$ and $\lambda_d = 2\%$ in each period (as in Acemoglu et al., 2012).[15] We set $\nu_{c0} = \nu_{c0}^s = \lambda_{c0}/\lambda_d = 90\%$, which means that the initial gap in

[13]The equation fixing spillovers ϕ follows easily from (A.19). Our spillover parameter of 0.933 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 5.4 in which our spillover parameter is reduced to 0.233.

[14]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.

[15]This also means that we do not consider the possibility that financing for dirty technologies will increase under a clean transition, reflecting e.g. asset stranding risks.

the financing costs for clean innovative projects is 10%.[16] We let $\omega = 60\%$, so that the relative financing costs and chance of innovation success of clean to dirty technology decreases by 60% for each doubling of clean cumulative output.[17]

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 *benchmark* model, which includes optimal climate policy and endogenous financing experience effects for the clean technology. As explained in Section 3.3, optimal policy is the combination of a carbon tax and a clean research subsidy, maximising households' lifetime utility while keeping cumulative emissions below the exogenous limit. The endogenous experience effects are modelled through clean financing costs which fall over time with cumulative clean output according to the experience curve in (17).

In the first subsection, we compare this scenario with a *laissez-faire* economy, i.e. an economy with no climate policy but with the endogenous experience effects, with the aim of drawing out the consequences of policy. The second subsection describes how these experience effects change policy and the low-carbon transition path: thus, we compare our benchmark model with a *symmetric* scenario, i.e. with optimal policy but without (heterogeneous) financing costs, and an *exogenous* scenario, i.e. with optimal policy but exogenous experience curves. The third subsection shows that the optimal policy mix is substantially different in a *research* scenario where the experience effects depend on cumulative clean research (rather than cumulative clean output). Finally, the fourth subsection discusses the robustness of the key insights to changes in parameters. Table 2 summarises the characteristics of the scenarios we look at.

5.1 Benchmark and Laissez-Faire Scenarios

Figure 1 reports the optimal paths for a set of key variables for the benchmark (solid line) and laissez-faire (dashed line) scenarios: 1a) $GtCO_2$ emissions, κY_{dt}; 1b) the carbon tax, τ_t; 1c)

[16]The financing of environmental innovation is a pressing concern for businesses and policy makers; as a consequence, the economic literature on the topic is growing and generally finds that firms conducting environmental innovations are more likely to be financially constrained (see Section 1). However, as far as we know, an empirical quantification of the wedge in financing costs across technologies is missing: we take 10% as a starting point, as assumed by Hafner et al. (2021) for their similar green financing gap based on expert interviews. There are, however, data for the cost of capital in electricity generation and for the costs of debt of renewable energy and non-renewable energy firms. For example, Polzin et al. (2021) provide weighted average cost of capital (WACC) for all electricity production technologies and all EU countries showing that there is a lot of heterogeneity across countries, but that gas plants (cf. wind) tend to have the lower (cf. higher) WACC.

[17]Egli et al. (2018, Supplementary Table 7) provide estimate for the experience parameter across countries and technologies, with values ranging from 10% to 16% for clean investments. However, their estimates represent absolute changes in the WACC for these technologies, whereas in our setting this parameter captures a relative change in the cost of external finance with respect to dirty investments. Although 60% may seem high, it leads to clean financing costs falling to low levels (around 2%) by 2040 in our main scenario, when clean output overtakes dirty, which seems reasonable in principle.

Table 2: Scenario overview

Scenario	Carbon budget	Heterogeneous costs	Endogenous experience
Benchmark	✓	✓	✓(output)
Laissez-faire	✗	✓	✓(output)
Symmetric	✓	✗	✗
Exogenous	✓	✓	✗
Research	✓	✓	✓(research)

the share of scientists working on clean technologies, H_{ct}/H; 1d) positive clean subsidies as a share of GDP, $s_t \int_0^1 \Pi_{cit} di/Y_t$; 1e) clean output share, $Y_{ct}/(Y_{ct}+Y_{dt})$; 1f) clean financing costs, $1-\nu_{ct}$.

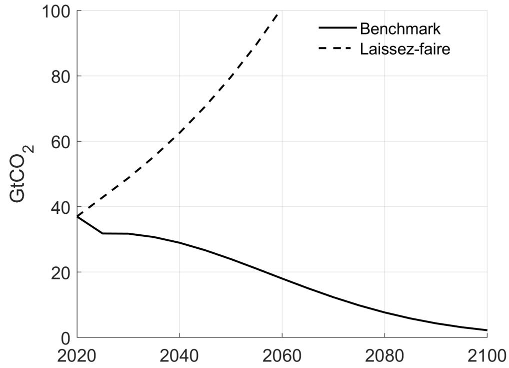
By construction, the two scenarios start from the same point, broadly calibrated to the world economy in 2020. The benchmark is then shocked by policy starting from 2025, whereas the laissez-faire is undisturbed.[18] Optimal policy results are qualitatively in line with the the initial contribution by Acemoglu et al. (2012), with both a carbon tax and clean research subsidy needed. The carbon tax, shown in Panel 1b, starts at \$217 in 2025, grows slowly initially, before accelerating to grow at the social discount rate.[19] The clean research subsidy in Panel 1d jumps to 2% of GDP in the first period, before dropping progressively to zero by 2050. Under optimal policy, the clean research share (Panel 1c) rises from 11% in 2020 to 68% in 2025 and continues to climb, reaching 88% in 2050 and 98% in 2100, while the share of clean output (Panel 1e) rises more slowly, as clean technology takes time to advance. Influenced by the acceleration in clean output share, clean financing costs fall from 10% in 2020 to 5.3% in 2025 and 1.4% in 2050, and then continue to fall (Panel 1f).[20] Panel 1a 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 parameterised such that its balanced growth path is an interior equilib-

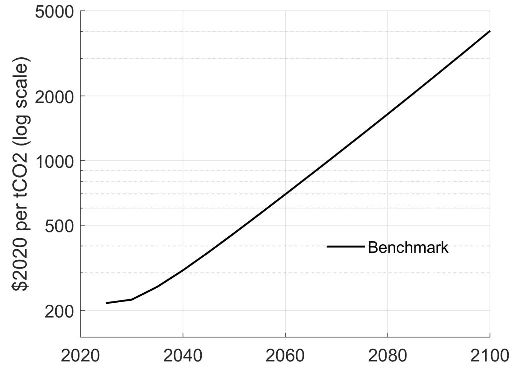
[18]Remember that our model is set in discrete time, with each period lasting 5 years. In the figures, we place the value of a variable in a given period in its first year, e.g. in 2025 for the second period (2025-2029), and linearly interpolate them across periods. Within a period, timing is as follows. First, policies are implemented. Second, research firms innovate. Third, machines are produced. Finally, intermediate inputs and final output are produced. Therefore, whereas the laissez-faire and benchmark scenario are identical in the first period (2020-2024), the effect of policies implemented in the second period (2025-2029) are already evident in that period in Figure 1.

[19]As the timing of emissions does not enter our climate constraint, the optimal tax rises at the interest rate $\rho + g * \sigma$. 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, when the clean share is high, 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 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).

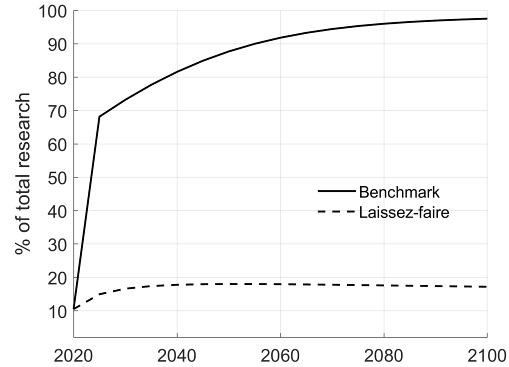
[20]This means that the likelihood of clean innovation success also starts 10% lower than for dirty (1.8% versus 2%) and follows the same path.



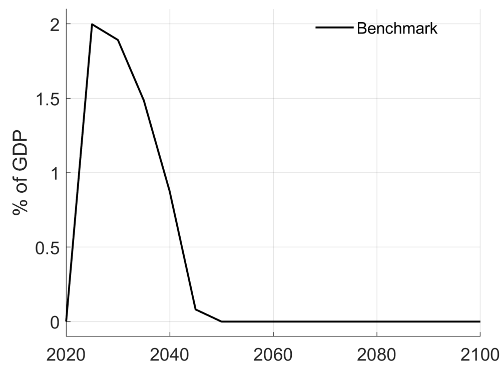
(a) Annual emissions



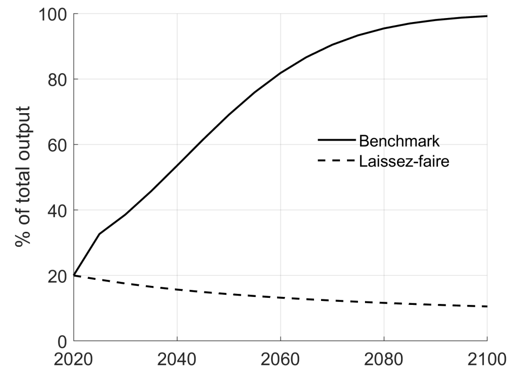
(b) Carbon tax



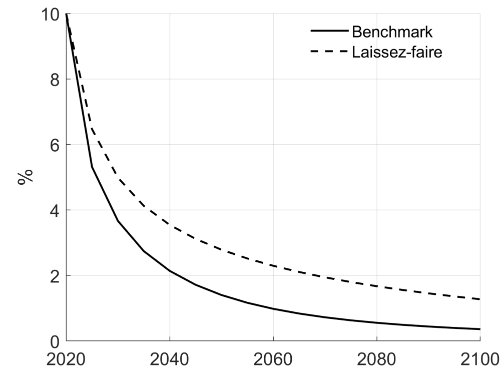
(c) Clean research share



(d) Clean research subsidy



(e) Clean output share



(f) Clean financing costs

Figure 1: Benchmark and laissez-faire scenarios

Notes. The *laissez-faire* scenario comprises financing experience effects but no policy. The *benchmark* scenario includes financing experience effects and optimal policy from 2025 - the deviation between scenarios prior to 2025 is due to linear interpolation (see footnote 18).

rium, clean research and production is pursued even without policy, which means that cumulative output of the clean technologies progressively increases under the laissez-faire scenario, resulting in clean financing costs and the likelihood of failure of clean innovation decreasing over time from 10% in 2020 to 6.5% in 2025 and 2.8% in 2050, as shown by the dashed line in Panel 1f; eventually, they tend to the same level as the dirty technology's. This incentivises scientists to slowly move from dirty to clean research, but at a much lower pace and magnitude than with policy: indeed, the share of scientists in the clean research sector stabilises in the long-run on a balanced growth path value slightly lower than 20% (Panel 1c). Given the limited impact of the experience effect by itself, the proportion of clean output falls from 20% to a balanced growth path value of 10% (Panel 1e). In this scenario, there are no policies constraining carbon emissions (Panel 1a), which thus grow almost exponentially with dirty output (as we assume no change in emissions intensity).

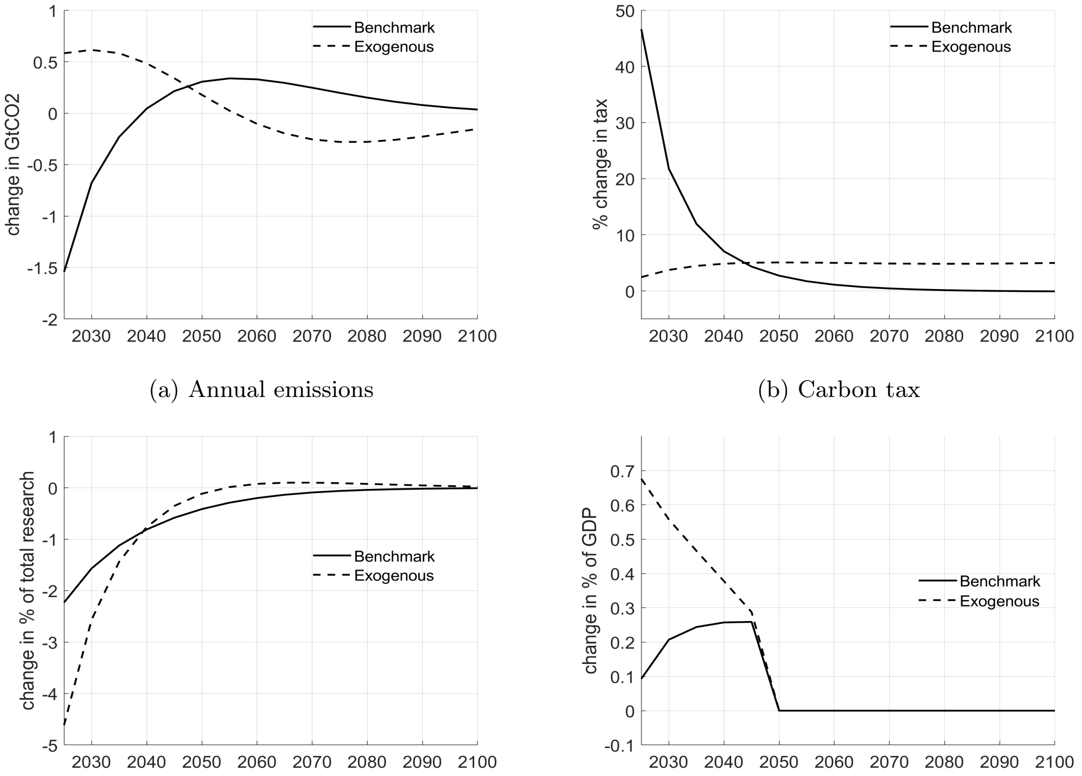
Thus, the simulations in this subsection highlight that the financing experience and learning-by-doing effects help the low-carbon transition, but are by no means sufficient in reaching the restricting climate objectives. In line with Acemoglu et al. (2012), we find that an optimal low-carbon transition includes a steeply rising carbon tax complemented with generous research subsidies, which help induce a higher clean research share in the short-term. When financing institutions endogenously react to technological evolution, the optimal tax and subsidies are powerful, since they not only redirect production and research towards the clean sector, but also help relax credit constraints more rapidly, so that funds are more easily redirected to clean innovations and production, leading to a virtuous decarbonisation cycle. In the next subsection, we investigate the role of this endogeneity in more detail.

5.2 The Clean Financing Experience Effect

In this subsection, we delve deeper on the effects of an endogenous financing experience curve on optimal policy and the emission transition path. In particular, the solid line in Figure 2 shows results for our benchmark scenario relative to a *symmetric* scenario, i.e. an economy with optimal climate policy under the same cumulative emissions constraint but without financing costs (i.e. where proportional financing costs and the likelihood of success of the clean technology are exogenous and constant at the dirty technology levels).

As partially explored in the previous simulations, the solid lines in Panel 2b and 2d highlight that endogenous experience effects increase policy ambition: the carbon tax must be more aggressive initially (it increases by 47% in the first period relative to the symmetric scenario), with the effect diminishing over time; similarly, the clean research subsidy is 0.1% of GDP higher in the first period and increases by about 0.2% of GDP to 2050. As a consequence, initial emissions (Panel 2a) are lower, despite a lower initial clean research share (Panel 2c) due to financing costs.

Increases in policy are intuitive: given a fixed emissions constraint, policies need to be more ambitious as financing clean technology is costlier. A lower clean research share is also intuitive, as in the balanced growth path the relative share of scientists is inversely related to the relative



(a) Annual emissions

(b) Carbon tax

(c) Clean research share

(d) Clean research subsidy

Figure 2: The endogenous financing experience effect

Notes. This figure shows changes relative to a *symmetric* scenario with optimal policy but without financing experience effects nor heterogeneous financing costs. The *benchmark* scenario includes optimal policy and endogenous financing experience effects. The *exogenous* scenario comprises optimal policy under the same evolution of the experience effects from the benchmark scenario but applied exogenously to this economy.

financing costs. But a reduction in initial emissions is somewhat counter-intuitive: one may expect that clean financing costs, which disappear over time, would lead to increased emissions in the near term, when credit to clean firms is more expensive, and lower long-term emissions, once financial markets are willing to finance clean firms at progressively lower costs.

To explore this further, the dashed lines in Figure 2 show results, relative to the symmetric scenario, for an *exogenous* scenario, where the evolution of clean financing costs and the probability of failure in clean innovation is taken from the benchmark scenario but imposed exogenously: therefore, in this scenario the social planner chooses optimal policy without the efficacy boost from the financing experience effect in (17). In this scenario, as compared to the symmetric one, the carbon tax is higher initially and in the long-term (Panel 2b), and the clean research subsidy is also higher to 2050 (Panel 2d). Emissions are higher in the short-term while experience accumulates (Panel 2a), but then drop further due to the higher long-term carbon tax (Panel

2b).

The difference between the two scenarios is therefore due to endogeneity, i.e. the feedback between policy and the evolution of clean financing costs. In our benchmark model, financing experience is not exogenous but is instead driven by increasing cumulative clean output. The presence of this positive spillover from research to output to financial markets induces stricter policy in the near-term and, in terms of the emissions path, dominates over the effect of an exogenous experience process so emissions actually fall in the near-term relative to the symmetric scenario. The preferred instrument for this increased policy is the carbon tax, rather than the research subsidy. Our simulations emphasise that this increase in initial (tax) policy ambition 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 obtain the exogenous scenario; if the feedback approached infinity, so experience was immediate, then we would just obtain the symmetric scenario.

5.3 Experience From Cumulative Research

In the previous subsections, we assumed that the financing experience effect is linked to the production side of the economy, and in particular to the cumulative amount of clean intermediate inputs produced so far: as a consequence, we have shown that the endogeneity of these experience effects leads to a much higher carbon tax. In this subsection, we investigate how these results would change if the experience effects were linked to clean research, rather than clean output.[21] In particular, we present a *research* scenario, which is identical to the benchmark one apart from the fact that we recast the one-factor experience curve in (17) as a function of cumulative clean research, i.e.

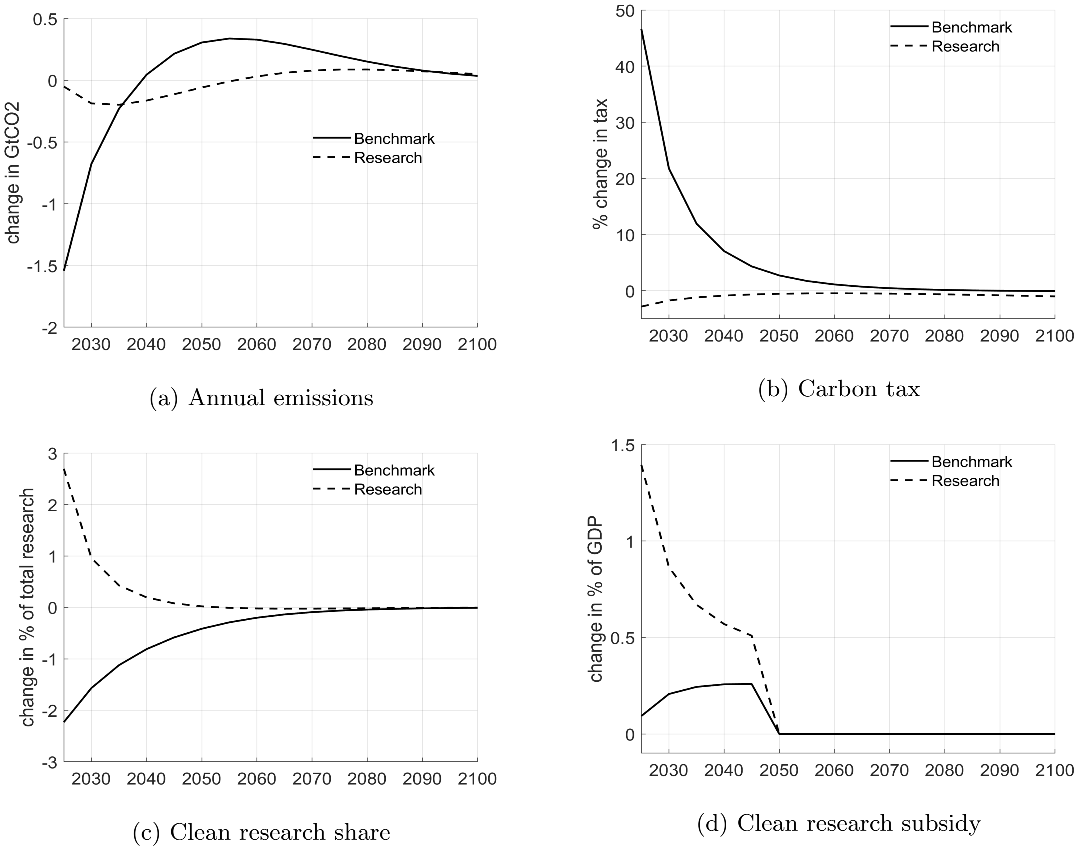
$$\nu_{ct} = \nu_{ct}^{s} = \frac{\lambda_{ct}}{\lambda_{dt}} = 1 - (1 - \nu_{c0}) \left(\frac{\hat{H}_{c0}}{\hat{H}_{c0} + \sum_{\tau=1}^{t} H_{c\tau}} \right)^{\omega}, \tag{18}$$

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

Figure 3 reports results from this research scenario (dashed lines) and from the benchmark model (solid lines), relative to the same symmetric scenario considered in the previous subsection.

[21]Indeed, in our model, the chance of innovation success in the clean sector increases through learning, which arguably would depend more upon the level of clean research, rather than output (similarly to Lucas, 1988). Further, 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.

Panels 3b and 3d show that the optimal combination of policy instruments is sensitive to whether the experience effects are based on output or research: indeed, as the clean research subsidy is a more effective instrument at redirecting research towards the clean sector than a carbon tax, the policy ambition from endogeneity translates into much higher clean research subsidy in 2025 than in the benchmark case, while the carbon tax begins lower. This very high clean research subsidy is able to shift researchers to the clean sector much faster, while the effect on the emissions path is to reduce near-term emissions much less.



(a) Annual emissions

(b) Carbon tax

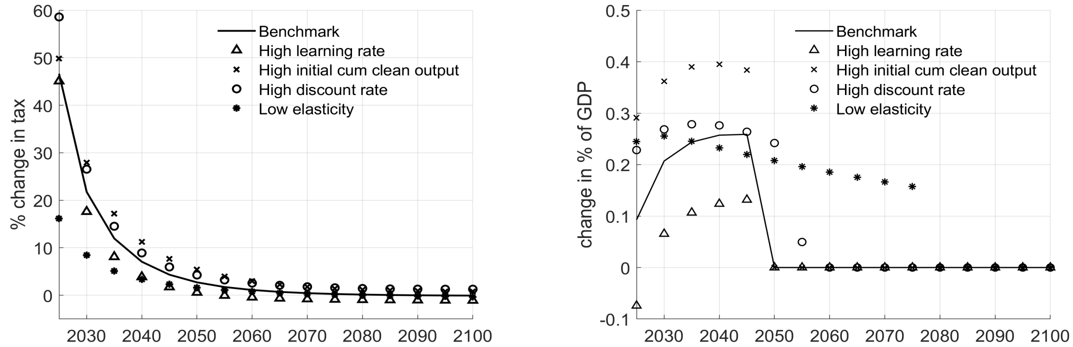
(c) Clean research share

(d) Clean research subsidy

Figure 3: When financing experience is based on cumulative research

Notes. This figure shows changes relative to a *symmetric* scenario with optimal policy but without financing experience effects nor heterogeneous financing costs. The *benchmark* scenario includes optimal policy and financing experience effects based on cumulative output. The *research* scenario comprises optimal policy and financing experience effects based on cumulative research.

Thus, the source of financing experience effects 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: we emphasise that the effectiveness of different climate



(a) Carbon tax

(b) Clean research subsidy

Figure 4: Robustness

Notes. The *benchmark* 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 without experience effects nor heterogeneous financing costs (any parameter change is applied to all scenarios being compared).

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

5.4 Robustness

In this subsection, we discuss the following robustness checks: an increase in the clean learning rate, $\omega = 0.8$; a higher initial level of cumulative clean output equal to $2Y_{c0}$; a higher yearly discount rate, $\rho = 3\%$; and a lower elasticity of substitution between clean and dirty inputs, $\epsilon = 2$. As our focus is on the clean financing experience effect, we show how these parameter changes change the impact of the experience effect on optimal policy. In particular, Figure 4 repeats Panels 3b and 3d with these different parameters and shows that the policy effects in our benchmark scenario are mostly robust to these changes.

A higher $\omega = 0.8$ implies a faster experience effect, which leads to clean financing costs decreasing more rapidly (4.3% in 2025 and 0.7% in 2050 versus 5.3% and 1.4% in the benchmark), which in turn means that more funding can be directed to the clean sector for a given level of climate policy: therefore, a higher ω leads to a lower optimal clean research subsidy and carbon tax compared with the benchmark scenario. A higher initial cumulative clean output equal to $2Y_{c0}$ in 2020, with the same initial financing costs, implies a slower decrease in clean financing costs (6.7% in 2025 and 2.2% in 2050), and thus higher policy levels. 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 benchmark. 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 clean financing experience effect then follows: in Panel 4a, the percentage change in the carbon tax is 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). In both cases, the clean research subsidy persists for longer.

Finally, remember that the financing experience effect impacts two financial cost components: an economic cost proportional to credit (ν_{ct} and ν_{ct}^{s}) and a reduced chance of clean research success due to finance misdirection (λ_{ct}). In Appendix A.2, we show that these two costs have broadly similar effects on optimal policy. For example, omitting the latter cost leads to the same qualitative results, such as increased policy ambition in the short-term and reduced emissions, although the magnitude of the endogenous effect is reduced.

6 Conclusions

Empirical evidence suggests that access to finance is more difficult for novel clean technologies than for incumbent polluting ones, which could slow down the low-carbon transition. In this paper, we introduce financing costs that are heterogeneous across sectors and endogenous in a directed technical change model to study their effects on optimal climate mitigation policies.

We show that heterogeneous financing costs per se are a threat to the decarbonisation transition as they stifle innovation in the clean sector. However, the presence of a *financing experience effect*, whereby financing conditions endogenously improve for clean firms as the cumulative adoption of their technology increases, makes mitigation policies more effective in pushing the low-carbon transition, as two channels are activated: i) policies directly shift innovation and production towards the clean sector, which makes the clean technology more productive, and increases its market share; ii) policies also indirectly reduce the reluctance of financial markets to finance clean innovations, triggering relatively more fund flows and further speeding up the transition.

As a consequence, the social planner has an incentive to strengthen mitigation policies in the short-term. This financing experience effect adds to other endogenous factors that affect optimal policy and depend on the state of clean technology, such as increasing returns to scale (Xepapadeas, 1997), learning-by-doing (Rosendahl, 2004), obsolescence costs (Lennox and Witajewski-Baltvilks, 2017), and adjustment costs (Nowzohour, 2021). However, the optimal climate policy mix depends on how clean financing experience occurs. In our benchmark scenario, where clean financing costs decrease following cumulative clean production, it is optimal to introduce a 2025 carbon tax almost 50% higher compared to the case without this clean financing disadvantage. In our alternative scenario, where the experience effect is instead a function of cumulative research, it would be optimal to raise the R&D subsidies up to 1.5% of GDP in the short-term, while the carbon tax is slightly lower.

Our model could be improved in a number of ways. For example, we do not model a third policy explicitly targeting financing conditions. While this is justified by the decision to focus solely on the role of carbon taxes and research subsidies (as also suggested by Aghion et al., 2022), one could investigate the role played by e.g. green investment banks (Geddes et al., 2018, Mazzucato and Semieniuk, 2018, D'Orazio and Valente, 2019, Waidelich and Steffen, 2023) and monetary tools (Benmir and Roman, 2021). Second, we abstract from an explicit representation of the financial market by considering representative lenders willing to provide funds to both types of firms. At the cost of added complication, one could instead incorporate a more realistic banking sector (as in the environmental dynamic stocastic general equilibrium models, see e.g. Diluiso et al., 2021), a variety of different financial actors (Aghion et al., 2022), and the possibility that some firms do not receive credit (see e.g. Haas and Kempa, 2021). Finally, our global approach to the modelling and calibration disregard technological and geographical differences (Steffen, 2020) that may have an impact on optimal policy.

While we leave these interesting avenues open for future research, we believe that the main take-away messages of our paper are likely 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 stronger mitigation policies, able to close the financing cost gap across technology and make the low-carbon transition happen. In other words, not considering the role of finance in clean innovation likely leads to an under-estimation of the stringency of optimal mitigation policies.

References

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

Acemoglu, D. (2009). *Introduction to Modern Economic Growth*. Princeton University Press, Princeton.

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

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.

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

Benmir, G. and Roman, J. (2021). Endogenous abatement technology. Mimeo.

Bernanke, B. S., Gertler, M., and Gilchrist, S. (1999). The financial accelerator in a quantitative business cycle framework. In Taylor, J. B. and Woodford, M., editors, *Handbook of Macroeconomics*, volume 1 part C, pages 1341–1393. Elsevier.

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.

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.

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

Comerford, D. and Spiganti, A. (2022). The carbon bubble: Climate policy in a fire-sale model of deleveraging. *Scandinavian Journal of Economics*.

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.

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.

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

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

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.

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. (2021). Low-carbon investment and credit rationing. Available at SSRN: https://ssrn.com/abstract=3521332.

Hafner, S., Jones, A., Anger-Kraavi, A., and Monasterolo, I. (2021). Modelling the macroeconomics of a 'closing the green finance gap' scenario for an energy transition. *Environmental Innovation and Societal Transitions*, 40:536–568.

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.

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). Carbon capture, utilisation and storage. Technical report, International Energy Agency.

IEA (2022b). Clean energy technology innovation. 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.

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

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. *The American Economic Review*, 83(2):450–457.

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

Lemoine, D. (2022). Innovation-led transitions in energy supply. *American Economic Journal: Macroeconomics*.

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

Lucas, R. E. (1988). On the mechanics of economic development. *Journal of Monetary Economics*, 22(1):3–42.

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.

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.

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.

Rosendahl, K. E. (2004). Cost-effective environmental policy: Implications of induced technological change. *Journal of Environmental Economics and Management*, 48(3):1099–1121.

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. *The 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.

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.

Waidelich, P. and Steffen, B. (2023). The role of state investment banks for renewable energy technologies in OECD countries. MIT CEEPR Working Paper 2023-07.

Wang, N., Akimoto, K., and Nemet, G. F. (2021). What went wrong? Learning from three decades of carbon capture, utilization and sequestration (CCUS) pilot and demonstration projects. *Energy Policy*, 158:112546.

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.

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

Xepapadeas, A. (1997). Economic development and environmental pollution: Traps and growth. *Structural Change and Economic Dynamics*, 8(3):327–350.

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

A Appendix

A.1 Proofs

Derivation of Equation (13). Substituting (3a) into (3b), the wage rate of a worker in sector j is

$$w_{jt} = (1-\alpha)\, p_{jt}^{\frac{1}{1-\alpha}} \nu_{jt}^{\frac{\alpha}{1-\alpha}} A_{jt}, \tag{A.1}$$

and thus

$$\frac{w_{dt}}{w_{ct}} = \frac{(1-\alpha)\, p_{dt}^{\frac{1}{1-\alpha}} \nu_{dt}^{\frac{\alpha}{1-\alpha}} A_{dt}}{(1-\alpha)\, p_{ct}^{\frac{1}{1-\alpha}} \nu_{ct}^{\frac{\alpha}{1-\alpha}} A_{ct}} = \left(\frac{p_{dt}}{p_{ct}}\right)^{\frac{1}{1-\alpha}} \left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\frac{\alpha}{1-\alpha}} \frac{A_{dt}}{A_{ct}}. \tag{A.2}$$

Since workers are free to choose the sector in which to work, in equilibrium $w_{dt} = w_{ct}$, and one obtains relationship (13) in the main text. □

Derivation of Equation (14). Combining (2) and (7a),

$$Y_{jt} = L_{jt}\,(p_{jt}\nu_{jt})^{\alpha/(1-\alpha)} A_{jt}. \tag{A.3}$$

Therefore,

$$\frac{Y_{dt}}{Y_{ct}} = \frac{L_{dt}\,(p_{dt}\nu_{dt})^{\alpha/(1-\alpha)} A_{dt}}{L_{ct}\,(p_{ct}\nu_{ct})^{\alpha/(1-\alpha)} A_{ct}} = \frac{L_{dt}}{L_{ct}} \left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\alpha/(1-\alpha)} \left(\frac{p_{dt}}{p_{ct}}\right)^{\alpha/(1-\alpha)} \frac{A_{dt}}{A_{ct}}. \tag{A.4}$$

□

Derivation of Equation (15). Use (13) to substitute the ratio of prices on the right-hand side of (14) with a formula involving the ratio of technologies. One obtains

$$\frac{Y_{dt}}{Y_{ct}} = \frac{L_{dt}}{L_{ct}} \left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\alpha} \left(\frac{A_{dt}}{A_{ct}}\right)^{1-\alpha}. \tag{A.5}$$

Using (4) and then (13), the left-hand side can be rewritten as

$$\frac{Y_{dt}}{Y_{ct}} = \left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\alpha\epsilon} \left(\frac{A_{dt}}{A_{ct}}\right)^{\epsilon(1-\alpha)}. \tag{A.6}$$

Therefore,

$$\frac{L_{dt}}{L_{ct}} = \left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\alpha(\epsilon-1)} \left(\frac{A_{dt}}{A_{ct}}\right)^{(1-\alpha)(\epsilon-1)}. \tag{A.7}$$

□

Derivation of Equation (16). 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 P_{jit}. Formally,

$$\max_{H_{jt}\geq 0} P_{jit} - \frac{w^s_{jt}}{\lambda_{jt}\nu^s_{jt}} H_{jt} \tag{A.8a}$$

$$\text{s.t. } P_{jit} = \pi_{jit} = \alpha(1-\alpha) p_{jt}^{1/(1-\alpha)} \nu_{jt}^{\alpha/(1-\alpha)} A_{jit} L_{jt} \tag{A.8b}$$

$$A_{jit} = \begin{cases} A_{jt-1}\left(1+\gamma H^\eta_{jt}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^\phi\right), \text{with probability } \lambda_{jt} \\ A_{jt-1}, \text{with probability } 1-\lambda_{jt}. \end{cases} \tag{A.8c}$$

This can be simplified to

$$\max_{H_{jt}\geq 0} \quad \alpha(1-\alpha) p_{jt}^{1/(1-\alpha)} \nu_{jt}^{\alpha/(1-\alpha)} \lambda_{jt} A_{jt-1}\left(1+\gamma H^\eta_{jt}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^\phi\right) L_{jt} + \\ + \alpha(1-\alpha) p_{jt}^{1/(1-\alpha)} \nu_{jt}^{\alpha/(1-\alpha)} (1-\lambda_{jt}) A_{jt-1} L_{jt} - \frac{w^s_{jt}}{\lambda_{jt}\nu^s_{jt}} H_{jt}. \tag{A.9}$$

The first order condition then is

$$w^s_{jt} = \lambda^2_{jt}\nu^s_{jt}\alpha\left(1-\alpha\right) p_{jt}^{1/(1-\alpha)} \nu_{jt}^{\alpha/(1-\alpha)} A_{jt-1}\gamma\eta H^{\eta-1}_{jt}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^\phi L_{jt}. \tag{A.10}$$

We then use (A.10) to obtain

$$\begin{aligned} \frac{w^s_{dt}}{w^s_{ct}} &= \frac{\lambda^2_{dt}\nu^s_{dt}\alpha\left(1-\alpha\right) p_{dt}^{1/(1-\alpha)} \nu_{dt}^{\alpha/(1-\alpha)} A_{dt-1}\gamma\eta H^{\eta-1}_{dt}\left(\frac{A_{t-1}}{A_{dt-1}}\right)^\phi L_{dt}}{\lambda^2_{ct}\nu^s_{ct}\alpha\left(1-\alpha\right) p_{ct}^{1/(1-\alpha)} \nu_{ct}^{\alpha/(1-\alpha)} A_{ct-1}\gamma\eta H^{\eta-1}_{ct}\left(\frac{A_{t-1}}{A_{ct-1}}\right)^\phi L_{ct}} \\ &= \frac{\lambda^2_{dt}\nu^s_{dt} p_{dt}^{1/(1-\alpha)} \nu_{dt}^{\alpha/(1-\alpha)} A^{1-\phi}_{dt-1} H^{\eta-1}_{dt} L_{dt}}{\lambda^2_{ct}\nu^s_{ct} p_{ct}^{1/(1-\alpha)} \nu_{ct}^{\alpha/(1-\alpha)} A^{1-\phi}_{ct-1} H^{\eta-1}_{ct} L_{ct}} \\ &= \frac{\lambda^2_{dt}\nu^s_{dt} p_{dt}^{1/(1-\alpha)} \nu_{dt}^{\alpha/(1-\alpha)} A^{1-\phi}_{dt-1} L_{dt}}{\lambda^2_{ct}\nu^s_{ct} p_{ct}^{1/(1-\alpha)} \nu_{ct}^{\alpha/(1-\alpha)} A^{1-\phi}_{ct-1} L_{ct}}\left(\frac{H_{ct}}{H_{dt}}\right)^{1-\eta} \end{aligned} \tag{A.11}$$

Since scientists are free to move across sectors, their wages are equalised across sectors, which makes the left-hand side of (A.11) equal to one. Rearranging, one obtains equation (16) in the text.

$$\frac{H_{dt}}{H_{ct}} = \left(\frac{\lambda^2_{dt}\nu^s_{dt} p_{dt}^{1/(1-\alpha)} \nu_{dt}^{\alpha/(1-\alpha)} A^{1-\phi}_{dt-1} L_{dt}}{\lambda^2_{ct}\nu^s_{ct} p_{ct}^{1/(1-\alpha)} \nu_{ct}^{\alpha/(1-\alpha)} A^{1-\phi}_{ct-1} L_{ct}}\right)^{\frac{1}{1-\eta}}. \tag{A.12}$$

□

Analytical Expression for the Relative Share of Scientists. Substituting the expressions for the ratios of prices from (13) and labour demands from (15) in the equilibrium condition (16), one obtains

$$\frac{H_{dt}}{H_{ct}} = \left(\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\frac{\nu^s_{dt}}{\nu^s_{ct}}\left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\alpha/(1-\alpha)}\frac{L_{dt}}{L_{ct}}\left(\frac{p_{dt}}{p_{ct}}\right)^{1/(1-\alpha)}\left(\frac{\lambda_{dt}}{\lambda_{ct}}\right)^2\right)^{\frac{1}{1-\eta}}$$
$$= \left(\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\frac{\nu^s_{dt}}{\nu^s_{ct}}\left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\alpha(\epsilon-1)}\left(\frac{A_{dt}}{A_{ct}}\right)^{-\varphi-1}\left(\frac{\lambda_{dt}}{\lambda_{ct}}\right)^2\right)^{\frac{1}{1-\eta}} \tag{A.13}$$

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

$$\frac{H_{dt}}{H_{ct}} = \left(\left(\frac{\lambda_{dt}A_{dt-1}\left(1+\gamma H^\eta_{dt}\left(\frac{A_{t-1}}{A_{dt-1}}\right)^\phi\right)+(1-\lambda_{dt})A_{dt-1}}{\lambda_{ct}A_{ct-1}\left(1+\gamma H^\eta_{ct}\left(\frac{A_{t-1}}{A_{ct-1}}\right)^\phi\right)+(1-\lambda_{ct})A_{ct-1}}\right)^{-\varphi-1}\right)^{\frac{1}{1-\eta}}\times$$
$$\times\left(\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\frac{\nu^s_{dt}}{\nu^s_{ct}}\left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\alpha(\epsilon-1)}\left(\frac{\lambda_{dt}}{\lambda_{ct}}\right)^2\right)^{\frac{1}{1-\eta}}. \tag{A.14}$$

□

Proof of Proposition 1. In an interior balanced growth path, the ratio of the two technologies is constant over time, i.e. $A_{dt}/A_{ct} = A_{dt-1}/A_{ct-1}$, which from (A.13) implies

$$\frac{H_{dt}}{H_{ct}} = \left(\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\frac{\nu^s_{dt}}{\nu^s_{ct}}\left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\alpha(\epsilon-1)}\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{-\varphi-1}\left(\frac{\lambda_{dt}}{\lambda_{ct}}\right)^2\right)^{\frac{1}{1-\eta}}$$
$$= \left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{-\phi-\varphi}{1-\eta}}\left(\frac{\nu^s_{dt}}{\nu^s_{ct}}\right)^{\frac{1}{1-\eta}}\left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\frac{\alpha(\epsilon-1)}{1-\eta}}\left(\frac{\lambda_{dt}}{\lambda_{ct}}\right)^{\frac{2}{1-\eta}}. \tag{A.15}$$

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

$$g_{jt} \equiv \frac{A_{jt}-A_{jt-1}}{A_jt} = \frac{\lambda_{jt}A_{jt-1}\left\{1+\gamma H^\eta_{jt}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^\phi\right\}+(1-\lambda_{jt})A_{jt-1}-A_{jt-1}}{A_{jt-1}}$$
$$= \lambda_{jt}\left\{1+\gamma H^\eta_{jt}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^\phi\right\}+(1-\lambda_{jt})-1 = \lambda_{jt}\gamma H^\eta_{jt}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^\phi. \tag{A.16}$$

Therefore, we need to impose that, in the interior equilibrium, $g_{dt} = g_{ct}$, i.e.

$$\lambda_{dt}\gamma H^\eta_{dt}\left(\frac{A_{t-1}}{A_{dt-1}}\right)^\phi = \lambda_{ct}\gamma H^\eta_{ct}\left(\frac{A_{t-1}}{A_{ct-1}}\right)^\phi \quad \text{i.e.} \quad \frac{H_{dt}}{H_{ct}} = \left(\frac{\lambda_{ct}}{\lambda_{dt}}\right)^{\frac{1}{\eta}}\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{\phi}{\eta}}. \tag{A.17}$$

Combining (A.15) and (A.17), one obtains that a condition for an interior steady-state is

$$\left(\frac{\nu_{dt}^s}{\nu_{ct}^s}\right)\left(\frac{\nu_{dt}}{\nu_{ct}}\right)^{\alpha(\epsilon-1)}\left(\frac{\lambda_{dt}}{\lambda_{ct}}\right)^{\frac{1+\eta}{\eta}}=\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{\phi+\varphi\eta}{\eta}}. \tag{A.18}$$

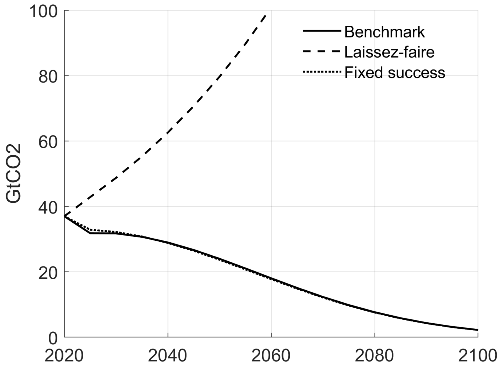
Solving equation (A.18) for ϕ defines the threshold value for the strength of the cross-sector spillovers above which the economy converges to a stable interior balanced growth path,

$$\phi \geq \eta\left[\frac{\ln\left(\frac{\nu_{d0}^s}{\nu_{c0}^s}\right)+\alpha\left(\epsilon-1\right)\ln\left(\frac{\nu_{d0}}{\nu_{c0}}\right)+\frac{1+\eta}{\eta}\ln\left(\frac{\lambda_{d0}}{\lambda_{c0}}\right)}{\ln\left(\frac{A_{d0}}{A_{c0}}\right)}-\varphi\right]\equiv\bar{\phi}. \tag{A.19}$$

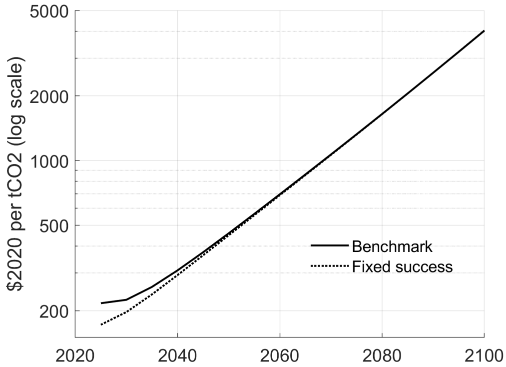
□

A.2 Dynamics without financing misdirection

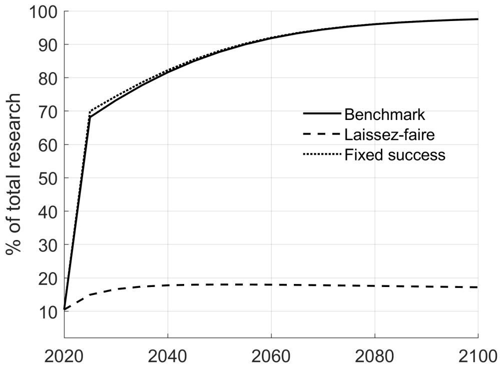
In this subsection, we present all the results from our simulations in Section 5 adding a *fixed success* scenario, i.e. including optimal climate policy and an endogenous clean financing cost, but excluding an experience effect for the likelihood of success in clean innovation due to financing misdirection. In other words, while ν_{ct} and ν_{ct}^s evolve according to the one-factor experience curve in (17), λ_{ct} is constant and equal to λ_d. Figure A.1 presents the comparison of the fixed success scenario with the benchmark and laissez-faire ones, A.2 draws out the effect of endogeneity in this case, and A.3 shows how this scenario is affected by an experience effect depending on cumulative research. These highlight that the main messages of the benchmark model are unchanged, but obviously the magnitude of the effects is reduced.



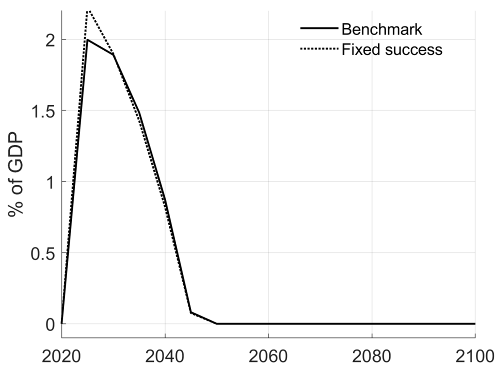
(a) Annual emissions



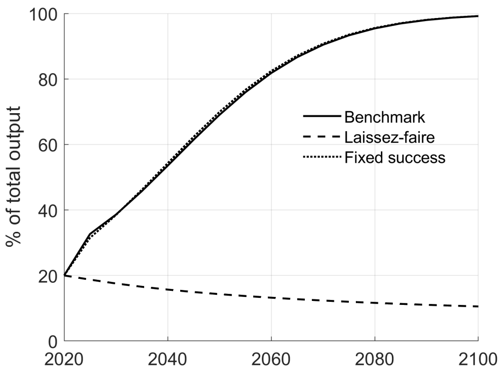
(b) Carbon tax



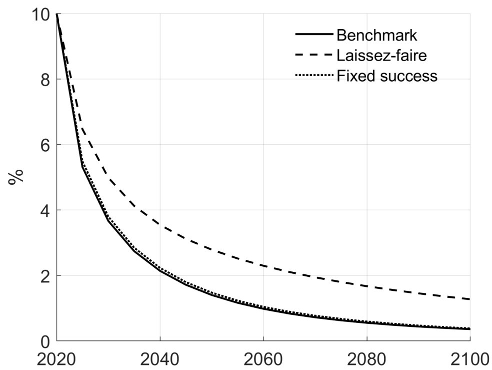
(c) Clean research share



(d) Clean research subsidy



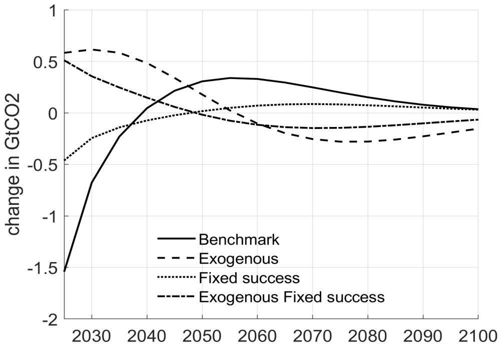
(e) Clean output share



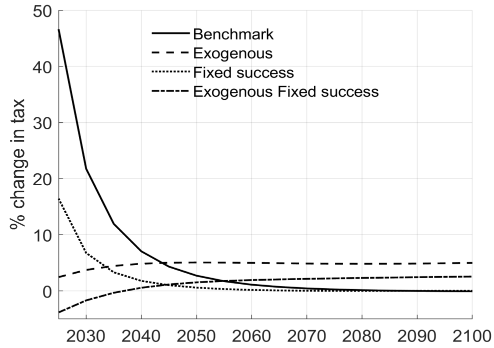
(f) Clean financing costs

Figure A.1: Benchmark and laissez-faire scenarios

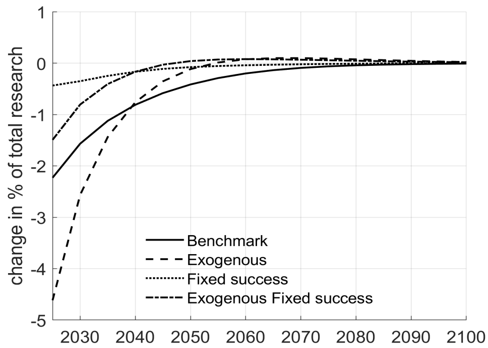
Notes. The *benchmark* scenario includes optimal policy and financing experience effects for clean financing costs and likelihood of success. The *laissez-faire* scenario comprises financing experience effects but no policy. The *fixed success* scenario comprises optimal policy, financing experience effects for clean financing costs, but constant likelihood of success for clean research firms.



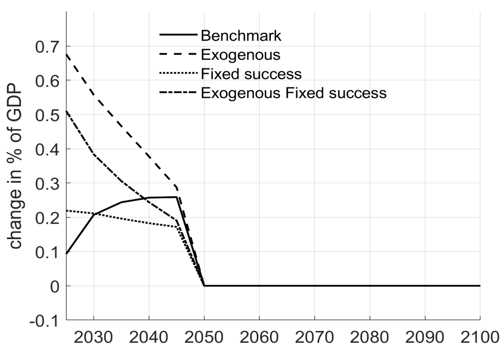
(a) Annual emissions



(b) Carbon tax



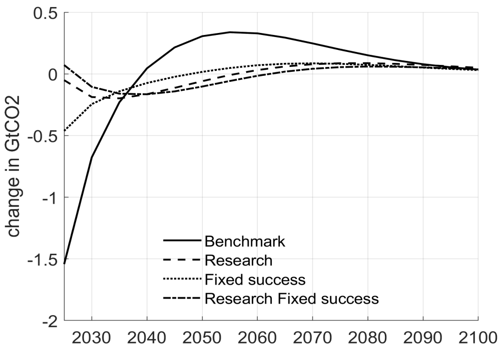
(c) Clean research share



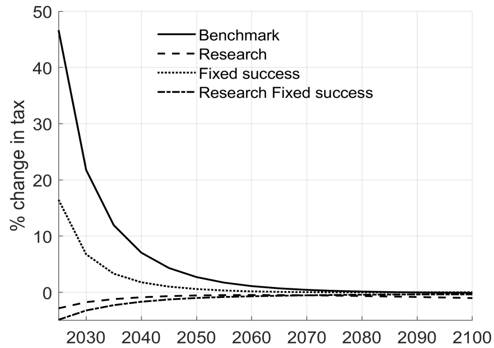
(d) Clean research subsidy

Figure A.2: The endogenous financing experience effect

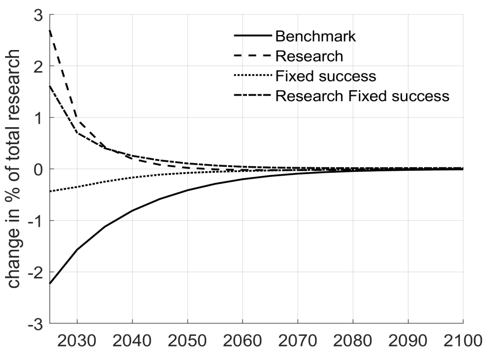
Notes. This figure shows changes relative to a *symmetric* scenario with optimal policy but without financing experience effects nor heterogeneous financing costs. The *benchmark* and *fixed success* scenarios are as above. The *exogenous* and *fixed success exogenous* scenarios comprises optimal policy under the same evolution of the experience effects from the benchmark and fixed success scenarios but applied exogenously to this economy.



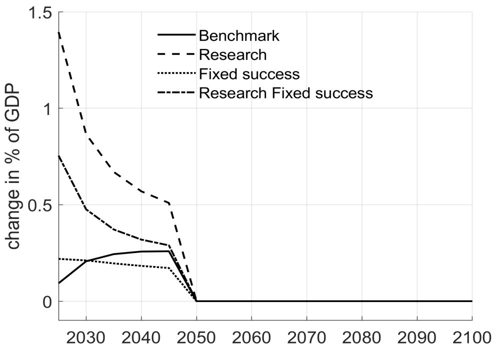
(a) Annual emissions



(b) Carbon tax



(c) Clean research share



(d) Clean research subsidy

Figure A.3: When financing experience is based on cumulative research

Notes. This figure shows changes relative to a *symmetric* scenario with optimal policy but without financing experience effects nor heterogeneous financing costs. The *benchmark* and *fixed success* scenarios are as above. The *research* and *fixed success research* scenarios comprises optimal policy and financing experience effects based on cumulative research.