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Clean Innovation and Heterogeneous Financing Costs

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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

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JEL Classification

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Address for correspondence:

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

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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, UK*
[d] *Department of Economics, Ca' Foscari University of Venice, Venice, Italy*
[e] *Centre for Applied Macroeconomic Analysis, Australian National University, Canberra, Australia*

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Access to finance is a major barrier to clean innovation. We incorporate a financial sector in a directed technological change model and identify optimal climate policies. The presence of a financing experience effect induces more ambitious policies in the short-term, both to boost clean innovation and production, and to reduce the financing cost differential across technologies. The optimal mix of climate policies (carbon taxes and clean research subsidies) depends on whether experience is gained through production or research. In our benchmark scenario, where clean financing costs decline as cumulative clean output increases, the carbon price premium is 22% in 2025, relative to a case with no financing costs.

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

1 Introduction

Mitigating climate change requires an unprecedented technological transition to carbon-free productive processes (IPCC, 2023). However, despite rapid recent advancement in 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 thus 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, Dietz and Stern, 2015, 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 helps direct a higher share of research efforts towards clean technological development.

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

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 a financial sector into an endogenous growth model where innovation can be directed to high-carbon (dirty) and low-carbon (clean) inputs. In our economy: i) a manufacturing sector produces a homogeneous final good using clean and dirty intermediate inputs; ii) two (clean and dirty) intermediate sectors produce the required inputs using labour and a continuum of machines; iii) two (clean and dirty) research sectors employ scientists to improve the productivity of machines, with technology spillovers across and within sectors; iv) two capital good sectors produce (clean and dirty) machines; and v) a financial sector provides funds to research firms at a cost.

Research firms require external finance to cover the flow mismatch between the payments to input factors and revenue realisation, and thus enter into contracts with financial intermediaries. The optimal contract outlines the advancement of funds from the intermediary to the firm and the payment from the firm back to the intermediary. In the stochastic innovation process à la Acemoglu et al. (2012), research firms have a positive probability of failing, in which case they are unable to repay their loan. The financial sector demands a higher interest rate to clean firms due to greater fundamental risks of such projects succeeding, and to cover direct economic costs that help to mitigate these risks. Indeed, while the probability of success of an individual firm is unobservable, an intermediary can choose to costly asses the project proposed by a research firm, with the aim of increasing the odds of getting repaid. The assessment, whose cost is increasing and convex in these odds, can be interpreted as a combination of screening (King and Levine, 1993), monitoring (Townsend, 1979, Gale and Hellwig, 1985, Williamson, 1986, Cole et al., 2016), and redeployability potential assessment (Shleifer and Vishny, 1992). We add a 'learning-by-lending' effect through a one-factor experience curve, whereby the cost of assessment decreases 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 are 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 research firms by directing 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 and thus production in the relatively novel sector, thus delaying a low-carbon transition unless policy takes account of this differential financing cost.

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 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, the optimal carbon price starts at $201 per

[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).

tonne of CO2 in 2025 and later grows at an annual rate between 4% and 5%, while the optimal clean research subsidy jumps to 0.33% 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 the financial sector and triggering a stronger redirection of funds to clean technologies, further speeding up the transition in a virtuous decarbonisation cycle. A key consequence of this link is that it becomes optimal for the policy-maker to strengthen climate policy ambitions and decrease emissions more rapidly in the near-term. Our benchmark scenario finds a premium in optimal carbon prices of 22% in 2025 (then decreasing over time towards zero), relative to a case without financing costs (where the initial optimal carbon tax is $164).

Finally, we find that the optimal policy mix depends on the nature of the financing experience effect, i.e. on which indicators financial intermediaries build to update their financing conditions. If the financial sector reacts to relative cumulative sector outputs, the endogeneity of this experience effect leads to a higher carbon tax, since this is a more effective instrument at targeting outputs than the clean research subsidy. Conversely, if the experience effect is linked to research, the policy ambition translates into a higher initial clean research subsidy (higher by 26%, or 0.1% of GDP). Therefore, the choice of optimal climate policies will differ across markets, technologies, and geographical areas if the nature of this experience effect differs, possibly due to different lending environments and institutions (see for instance Aghion et al., 2022).

We build on and contribute to three main streams of literature. First, we closely connect to the modelling literature examining clean directed technical change in an endogenous growth setting, originating from Acemoglu et al. (2012). This framework has been extended in many directions: for example, Acemoglu et al. (2016) provide a micro-founded quantitative version of the model; Hémous (2016) adds a second country to examine whether unilateral environmental policies can ensure sustainable growth; Lennox and Witajewski-Baltvilks (2017) adds slowly depreciating capital; Greaker et al. (2018) consider long-lasting patents and decreasing returns to research; Fried (2018) and Hart (2019) introduce technology spillovers across sectors; 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) add expectations about the future path of innovation. Our main novelty is that we add a financial sector.

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

Third, we build on the (mostly) empirical literature on clean innovation and financing constraints. Contributions in this area usually find that environmental innovations face 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 from theirs. Pan et al. (2022) discuss the role of clean innovation in the recovery period after the COVID-19 pandemic, whereas Aghion et al. (2022) analyses differences in the long-run rate of patenting of clean technologies between the EU and selected peers and across EU member states, and how these relates to cross-country differences in venture capital investments. 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 endogenise them.

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] 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 (2023). 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.

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

2.1 Final Good Production

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

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

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

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

2.2 Intermediate Inputs Production

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

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

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

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

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

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 Production of Machines

Machines are produced by two machine producing sectors, each with a continuum of firms of mass one. In line with the endogenous growth literature, each machine producer in a sector acts as a monopolist in the production of its particular machine. In particular, each of these firms has purchased a 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}. As common in this literature (e.g. Acemoglu et al., 2012, Fried, 2018), machines fully depreciate after use.

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

[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 (2023).

acquired a patent,

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

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, i.e. $p_{jit} = \psi/\alpha = \alpha$, thus unique across the economy. Substituting this price into the equilibrium demand function (3b) shows that the demand for a machine i within sector j and the subsequent profits of its producer are, respectively,

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

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

2.4 The Innovation Process

Following the large literature originated from Romer (1990a,b), there is a continuum of firms in each research sector aiming to 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 try innovating, i.e. to increase the quality of its machine. As in Acemoglu et al. (2012), innovation is stochastic: a research firm is successful in the innovation process with probability $\lambda_j \in [0, 1]$, in which case the quality of the machine increases and the research firm can sell the patent to a machine producer in the corresponding sector. Conversely, with the remaining probability $1 - \lambda_j$, the innovation process is unsuccessful and the quality of the machine does not increase; as in Aghion and Howitt (2009), Acemoglu et al. (2012), and Aghion et al. (2022), the patent for this machine with the old quality is then allocated randomly to a research firm drawn from the pool of failed innovators.[4]

The innovation possibility frontier is given by

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

where H_{jit} is the number of scientists hired by firm i in sector j at time t, the parameter $0 \leq \eta < 1$ induces decreasing 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

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

machines in sector j at the end of period t, $A_t \equiv A_{ct} + A_{dt}$ is aggregate technology,[5] and $0 \leq \phi \leq 1$ determines the strength of the cross-sector spillovers. Let H_{jt} represent the total number of scientists employed in sector j: in equilibrium, labour market clearing for scientists requires that $H_{ct} + H_{dt} = H$.

This form of the innovation possibility frontier is quite general and encompasses several characteristics that may be important for the financing conditions of these technologies. First, in line with the baseline model by Acemoglu et al. (2012), it allows for the possibility of failure in the innovation process, thus underlining that innovation is a risky business. We show below that, in our model, this will additionally mean that financial intermediaries 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 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 $(A_{t-1}/A_{jt-1})^{\phi}$.[6] 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, financing conditions may be different across different sectors.

2.5 The Financial Contract

In each period, there are several intermediaries in a competitive financial sector, each owned equally by all agents. Each intermediary has access to international capital markets

[5] 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.

[6] 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.

and enters into financial contracts with research firms to provide funds; without loss of generality, we normalise the cost of raising funds for financial intermediaries to zero. A financial contract lasts one period and specifies the amount of funds that the intermediary will lend to the research firm and the unit repayment $1 + r_{jit}$ that the firm will make to the intermediary. The repayment is contingent on the outcome of the innovation process, which is publicly observable. Research firms are protected by limited liability, which means that the debt of an unsuccessful firm is never repaid.

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

Moreover, we follow King and Levine (1993) and suppose that, in addition to the research firms presented in the previous subsection, there are some other firms seeking to finance innovative projects that are in fact not feasible under any circumstances.[7] In particular, let $1 - \theta_{jt}$ be the probability that a borrower in sector j coming to a financial intermediary has an infeasible project; with the remaining probability θ_{jt}, the borrower is a research firm capable of carrying an innovative project, on which it will succeed with probability λ_j.

The main friction in the financial sector is that the feasibility of a project is unobservable by financial intermediaries. However, this friction weakens as the financial sector accumulates experience with a particular technology. First, the financial sector as a whole 'learns-by-lending' about how to discriminate between feasible and unfeasible projects in a given research sector (similarly to Botsch and Vanasco, 2019, Degryse et al., 2022, Jiang and Li, 2022). To model this, let $\nu_{jt} \in [0, 1]$ indicate *financing experience*, a continuous, differentiable, and weakly increasing function of the cumulative output of the corresponding intermediate input.[8] Then, we assume θ_{jt} to be a continuous, differentiable, and weakly increasing function of financing experience. In other words, the more prominent is a technology in production, the more financing this technology receives, and thus the more information is spread throughout the financial sector on how to discern a feasible project within this technology class.

Second, financial intermediaries can decide to embark on costly activities to better

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

[8]To ensure the stability of the balanced growth path, the limit of the first derivative of this function is zero as cumulative output approaches infinity. Whereas theoretical results are unchanged if experience depends on cumulative sectoral output, research, productivity, labour, or loans, quantitative results may differ: in Section 5.3, we compare simulations where these effects depend on cumulative output versus research.

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

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

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

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

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

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

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

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

where the objective function Π_{jit} represents the research firm's expected profits, which is simply the expected value of the monopoly profits from selling the patent for the production of the new machine $\lambda_j \pi_{jit}$,[9] net of the expected repayment of principal and interest to

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

the intermediary $\lambda_j w^s_{jit} H_{jit}(1 + r_{jit})$. Constraint (9b) reports the profits of the machine producers and the evolution of machine quality. Equation (9c) is the limited liability constraint for the research firm, specifying that the intermediary cannot take more than what the firm obtains in case of success. Finally, equation (9d) is the participation constraint of the intermediary, stipulating that it expects to earn non-negative profits from the financial contract, given the expected repayment, the cost of assessment, and the need to raise funds.

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

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

Proof. See Appendix A.1. □

2.6 Households

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

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

where C_t is household consumption at time t, $\rho > 0$ is the discount rate, and $1/\sigma > 0$ measures the willingness to substitute intertemporally. The budget constraint is

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

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

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

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 $[w_{ct}, w_{dt}, w_{ct}^s, w_{dt}^s]_{t=0}^{\infty}$, prices for inputs $[p_{ct}, p_{dt}]_{t=0}^{\infty}$, prices for each machine $[p_{cit}, p_{dit}]_{t=0}^{\infty}$, prices of patents $[\pi_{cit}, \pi_{dit}]_{t=0}^{\infty}$, financing costs $[r_{ct}, r_{dt}]_{t=0}^{\infty}$, assessment odds $[\mu_{ct}, \mu_{dt}]_{t=0}^{\infty}$, financing experiences $[\nu_{ct}, \nu_{dt}]_{t=0}^{\infty}$, intermediate inputs production $[Y_{ct}, Y_{dt}]_{t=0}^{\infty}$, labour allocations $[L_{ct}, L_{dt}, H_{ct}, H_{dt}]_{t=0}^{\infty}$, quantities of each machines $[x_{ct}, x_{dt}]_{t=0}^{\infty}$, and cumulative carbon emissions $[S_t]_{t=0}^{\infty}$, such that, in each period t, final good producers, intermediate good producers, machine producers, research firms, and financial intermediaries choose, respectively, (Y_{ct}, Y_{dt}), $(L_{ct}, L_{dt}, x_{ct}, x_{dt})$, $(x_{ct}, x_{dt}, p_{cit}, p_{dit})$, $(H_{ct}, H_{dt}, \pi_{cit}, \pi_{dit})$, and $(\mu_{ct}, \mu_{dt}, r_{ct}, r_{dt})$ to maximise profits, the evolution of wages $(w_{ct}, w_{dt}, w_{ct}^s, w_{dt}^s)$ and prices $(p_{ct}, p_{dt}, p_{cit}, p_{dit}, \pi_{cit}, \pi_{dit})$ is consistent with market clearing, and the evolution of S_t is given by (5). In particular, we focus on a balanced growth path, i.e. an equilibrium in which aggregate output and consumption grow at the same constant rate as aggregate technology, $g \equiv (A_{t+1} - A_t)/A_t$ 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 $w_{jt} = (1-\alpha) A_{jt} p_{jt}^{1/(1-\alpha)}$. 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

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

which formalises the natural ideas that the input produced with more productive machines will be relatively cheaper.

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

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

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

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

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 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 $w_{dt}^s = w_{ct}^s \equiv w_t^s$. The following relative equilibrium allocation of scientists ensues

$$\frac{H_{dt}}{H_{ct}} = \left[\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi} \left(\frac{p_{dt}}{p_{ct}}\right)^{\frac{1}{1-\alpha}} \left(\frac{L_{dt}}{L_{ct}}\right) \left(\frac{1+r_{ct}}{1+r_{dt}}\right)\right]^{\frac{1}{1-\eta}}. \tag{16}$$

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, captured by the term $(1+r_{ct})/(1+r_{dt})$, that directs innovation towards the sector with the lower cost of external finance (an effect also stressed in the contemporaneuos paper by Aghion et al., 2022). In our equilibrium, this comprises of two terms. The first, $[1 + c(\mu_{ct}, \nu_{ct})] / [1 + c(\mu_{dt}, \nu_{dt})]$, captures the direction of scientists towards the sector with e.g. lower auditing, monitoring, and screening costs, with more advanced risk assessments and due diligence processes, more standardised contracts and investment structures, or with intangible assets more easily valued. The second term, $(\mu_{dt}\lambda_d) / (\mu_{ct}\lambda_c)$, 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 that 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.[10] 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 Assumptions 1, 2, and 3.

Proposition 2. *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. Along the balanced growth path, the price of a patent, the price of each intermediate input, the price of the final good, the financing costs and experiences, and the labour and scientists allocations across sectors are constant.*

Proof. See Appendix A.1. □

[10]See Acemoglu (2002, 2015), 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).[11]

In our model, there are also financing costs that distort choices by 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 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, as Aghion et al. (2022) also argue, these two instruments clearly fall in the realm of government policies, whereas climate actions by central banks might face obstacles from both a legal and an economic perspective (Campiglio et al., 2018, NGFS, 2021).

[11] 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	$Ycum_{c0}$	$2Y_{c0}$	Normalisation
Number of scientists	H	1	Normalisation
Scientist efficiency	γ	1	Acemoglu et al. (2012)
Scientist long-run chance of success	$\lambda_d = \lambda_c$	2%	Acemoglu et al. (2012)
Returns in research	η	0.7	Greaker et al. (2018)
Cross-sector spillovers	ϕ	0.933	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)
Clean financing experience	ν_{c0}	92.97%	Ameli et al. (2021)
Dirty financing experience	ν_d	100%	Normalisation
Experience parameter	ω	1.32	Ameli et al. (2021)

4 Calibration

In this section, we discuss our calibration strategy. Calibrated parameters are in Table 1. Robustness checks are provided in Appendix A.2. Our initial period is calibrated to 2020, and our simulations run for 40 periods, with each period representing five years. The full span of our simulations thus goes from 2025 to 2220, although we will limit our analysis to the end of the century. The discount rate is 1.5% per annum, consistent with Acemoglu et al. (2012) and Nordhaus (2017).[12] 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 $\epsilon = 3$.[13]

[12]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.

[13]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 A.2, we provide results with a lower elasticity.

Patents last one period, as in many directed technological change models (e.g. Acemoglu et al., 2012, Fried, 2018). Fried (2018) also argues that five years (i.e. the length of our time step) is a reasonable time span for the occurrence of within-sector spillovers in clean and fossil technologies. We set the diminishing returns to research parameter to $\eta = 0.7$, close to the values of 0.7 and 0.79 used in Greaker et al. (2018) and Fried (2018), respectively. The strength of the cross-sector spillovers is set such that the economy starts from the interior balanced growth path in our symmetric scenario (discussed below), i.e. $\phi = -(1-\alpha)(1-\epsilon)\eta$ which equals 0.933 given the parameter values in Table 1.[14] We set a research firm's probability of success in both sectors and in each period to $\lambda_c = \lambda_d = 2\%$ and calibrate the efficiency parameter γ so that the long-run annual growth rate is equal to 2% under a low-carbon transition (as in Acemoglu et al., 2012), i.e. as clean output and research shares approach 100%. Without loss of generality, we normalise the number of workers and scientists each to unity, i.e. $L = H = 1$.[15]

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, 20% in our benchmark scenario, also follows from our assumptions of the initial output ratio and clean financing costs.[16] Total output Y_0 is set to the 2020 global GDP using data from the World Bank (2023).

We normalise the emission intensity parameter to $\kappa = 1$. Global CO_2 emissions were approximately 37GtCO_2 in the latest available year of 2019 (Climate Watch, 2022), which we use to calibrate initial dirty intermediate production Y_{d0} and thus initial cumulative emissions S_0. In our policy experiments below, we apply a constraint on future cumulative CO_2 emissions equal to 1350GtCO_2, which is the estimated remaining carbon budget calculated from the beginning of 2020 to achieve a warming of 2°C with a 50% probability (IPCC, 2021, Table 5.8).[17]

[14]The equation fixing spillovers ϕ follows easily from (A.20). 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 A.2 in which our spillover parameter is reduced to 0.233.

[15]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.

[16]For comparison, Acemoglu et al. (2016) reports a share of innovative firms in the US energy-sector classified as clean of 11%, and a share of energy-sector patents classified as clean energy of 14%; Aghion et al. (2016), who focus on automotive patents taken out in the patent offices in the US, Europe, and Japan, classify 25.6% of them as clean.

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

We parametrize the intermediary's probability of drawing an infeasible project to $\theta_{jt} = 1 - (1 - \nu_{jt})\exp(\nu_{jt})$ and, incorporating this, the cost function for assessment to

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

These functional forms respect Assumption 2, while also delivering equilibrium outcomes which are analytically simple: the resulting optimal assessment odds, assessment costs, and financing costs are $\mu_{jt} = \nu_{jt}$, $c(\mu_{jt}, \nu_{jt}) = (1 - \nu_{jt})/\nu_{jt}$, and $1 + r_{jt} = (\nu_{jt}^2 \lambda_j)^{-1}$, respectively.

As dirty technologies are already mature, we abstract from learning in their financing by keeping $\nu_d = 100\%$.[18] We set $\nu_{c0} = 92.97\%$, which means that the initial gap in the financing costs for clean innovative projects is 15.7% (Ameli et al., 2021).[19] Following Rubin et al. (2015), Egli et al. (2018), and Polzin et al. (2021), we calibrate the evolution of clean financing experience ν_{ct} as to impose a 'one-factor experience curve' where financing costs decrease by a constant percentage for each doubling in the cumulative output of clean technologies, i.e.

$$\frac{1}{\nu_{ct}^2} - 1 = \left(\frac{1}{\nu_{c0}^2} - 1\right) \left(\frac{Ycum_{c0}}{Ycum_{c0} + \sum_{\tau=1}^{t} Y_{c\tau}}\right)^{\omega}, \tag{18}$$

where, for simplicity and ease of comparison, we impose cumulative output at the start of the simulation to equal twice the output value in 2020. We let the experience parameter $\omega = 1.32$ (i.e. the relative financing costs of clean to dirty technology decreases by $1 - 2^{-\omega} \approx 60\%$ for each doubling of clean cumulative output) so that the clean financing

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

[19] The financing of environmental innovation is a pressing concern for businesses and policy makers. 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). To the best of our knowledge, an empirical quantification of the wedge in financing costs for innovators across technologies is missing. 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 large heterogeneity across countries, but that gas plants (cf. wind) tend to have the lower (cf. higher) WACC. Ameli et al. (2021) calculate mean global values for WACCs, weighted by GDP, of 5.9% and 5.1% for low-carbon and high-carbon electricity generation, respectively, i.e. a 15.7% financing cost gap.

Table 2: Scenario overview

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

costs gap basically disappear by 2050 as in Ameli et al. (2021).[20]

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 effect 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 effect is modelled through clean financing costs which fall over time with cumulative clean output according to the experience curve in (18).

In the first subsection, we compare this scenario with a *laissez-faire* economy, i.e. an economy with no climate policy but with the endogenous experience effect, with the aim of drawing out the consequences of policy. The second subsection describes how this experience effect changes 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 an exogenous experience curve. The third subsection shows that the optimal policy mix is substantially different in a *research* scenario where the experience effect depends on cumulative clean research (rather than cumulative clean output). Table 2 summarises the characteristics of the scenarios we look at. Robustness checks are in Appendix A.2.

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

5.1 Benchmark and Laissez-Faire Scenarios

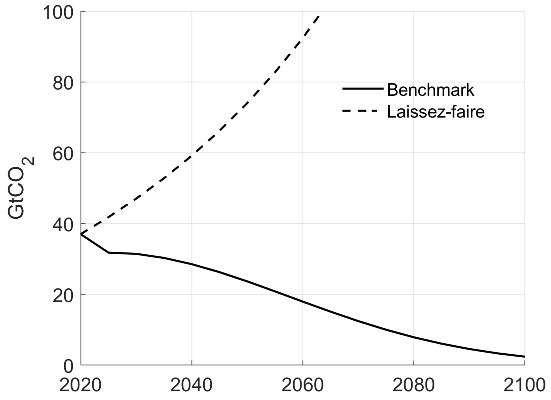
Figure 1 reports the optimal paths for a set of key variables for the benchmark (solid line) and laissez-faire (dashed line) scenarios: 1a) $GtCO_2$ emissions, κY_{dt}; 1b) the carbon tax, τ_t; 1c) the share of scientists working on clean technologies, H_{ct}/H; 1d) positive clean subsidies as a share of GDP, $s_t \int_0^1 \Pi_{cit} di/Y_t$; 1e) clean output share, $Y_{ct}/(Y_{ct}+Y_{dt})$; 1f) the proportional clean financing cost gap, $(r_{ct}-r_d)/(1+r_d)$ or equivalently $1/\nu_{ct}^2 - 1$.

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.[21] 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 $201 in 2025, grows slowly initially, before accelerating to grow at the social discount rate.[22] The clean research subsidy in Panel 1d jumps to 0.33% of GDP in the first period, before dropping progressively to zero by 2050. Under optimal policy, the clean research share (Panel 1c) rises from 23% in 2020 to 71% in 2025 and continues to climb, reaching 89% 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, the clean financing cost gap falls from 15.7% in 2020 to 7.1% in 2025 and 0.6% in 2050, and then continue to fall (Panel 1f). Panel 1a shows that the combination of policies is successful in dropping emissions by 36% below 2020 levels in 2050 and by 94% in 2100.

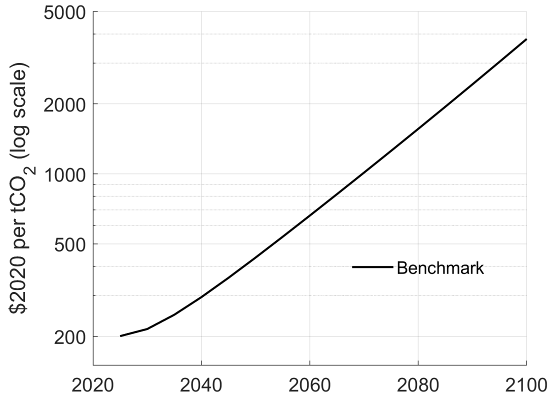
Since the economy is parameterised such that its balanced growth path is an interior equilibrium, clean research and production is pursued even without policy, which means that cumulative output of the clean technologies progressively increases under the laissez-faire scenario, resulting in clean financing costs decreasing over time from 15.7% in 2020 to 8.9% in 2025 and 1.8% 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

[21] Our model is discrete with five-year periods. In the figures, the value of a variable in a given period is in its first year, e.g. in 2025 for the second period (2025-2029), and we linearly interpolate them across periods. Within a period, timing is as follows: i) policies are implemented; ii) research firms innovate; iii) machines are produced; and iv) intermediate and final goods are produced. Whereas the two scenarios are identical in the first period (2020-2024) in Figure 1, the effect of policies implemented in the second period are already evident in that period.

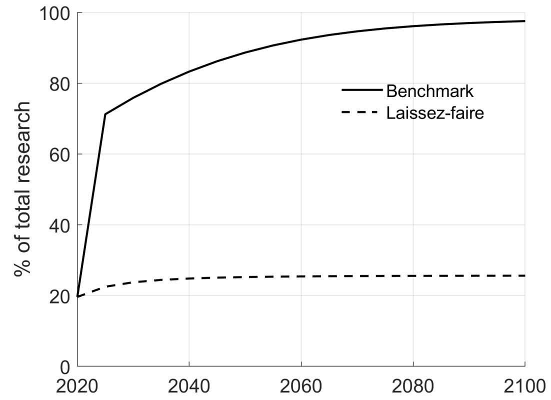
[22] As the timing of emissions does not enter our climate constraint, the optimal tax rises at the interest rate $\rho + g * \sigma$. The subsidy becomes negative after 2050, as the model exhibits higher private clean returns (pre-subsidy) to research than is socially optimal. Without a climate constraint, 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, with high clean share, optimal policy would gradually encourage greater dirty research (a negative clean research subsidy), and the presence of a carbon tax amplifies this effect. We do not consider this effect conveys any economic insight and thus exclude negative subsidy values ex-post in the figures. Doing so numerically (ex-ante) is more challenging computationally and does not change the key insights discussed (results are available upon request).



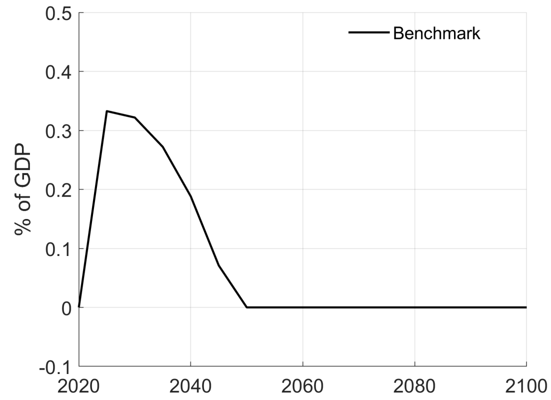
(a) Annual emissions



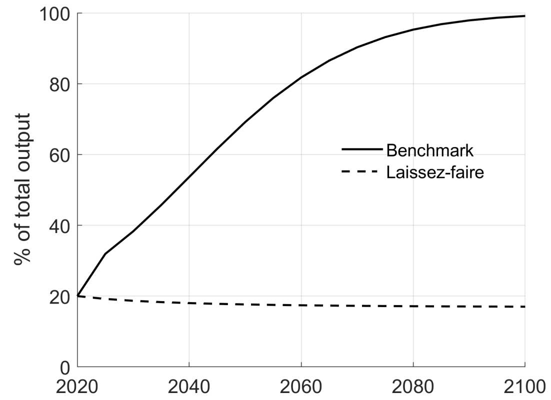
(b) Carbon tax



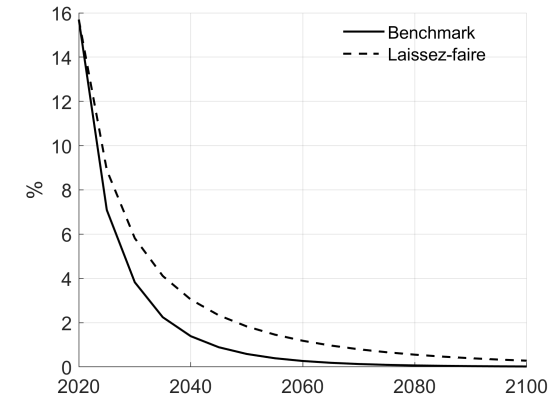
(c) Clean research share



(d) Clean research subsidy



(e) Clean output share



(f) Clean financing cost

Figure 1: Benchmark and laissez-faire scenarios

Notes. The *laissez-faire* scenario comprises financing experience effect but no policy. The *benchmark* scenario includes financing experience effect and optimal policy from 2025 - the deviation between scenarios prior to 2025 is due to linear interpolation (see footnote 21).

with policy: indeed, the share of scientists in the clean research sector stabilises in the long-run on a balanced growth path of 26% (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 17% (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).

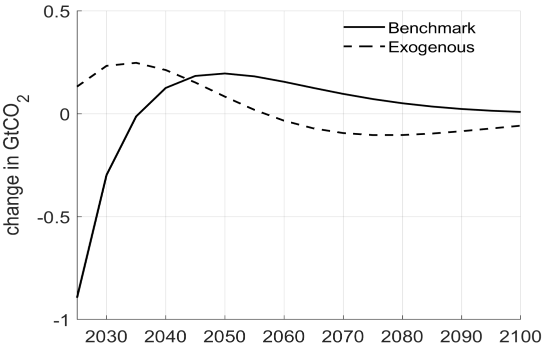
Thus, the simulations in this subsection highlight that the financing experience effect helps the low-carbon transition, but is by no means sufficient in reaching the restricting climate objectives. In line with Acemoglu et al. (2012), we find that an optimal low-carbon transition includes a steeply 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 more 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 innovation 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

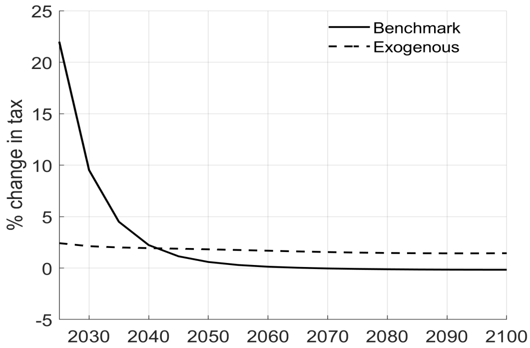
In this subsection, we delve deeper into the effects of an endogenous financing experience curve on optimal policy and the emission transition path. In particular, the solid line in Figure 2 shows results for our benchmark scenario relative to a *symmetric* scenario, i.e. an economy with optimal climate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

As partially explored in the previous simulations, the solid lines in Panel 2b and 2d highlight that an endogenous experience effect increases policy ambition: the carbon tax must be more aggressive initially (it increases by 22% in the first period relative to the symmetric scenario), with the effect diminishing over time. As the higher tax itself induces more clean research, the clean research subsidy is marginally lower in the first period. As a consequence, initial emissions (Panel 2a) are lower, despite a lower initial clean research share (Panel 2c) due to financing costs and a lower clean research subsidy.

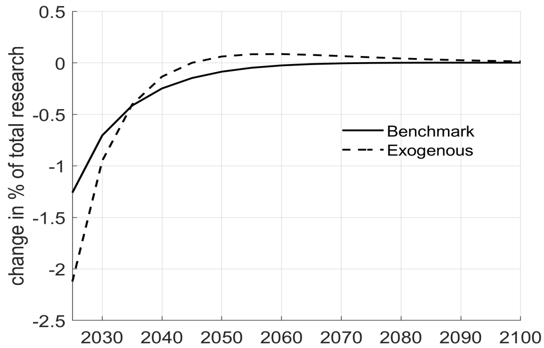
An increase in policy is intuitive: given a fixed emissions constraint, the policy mix needs to be more ambitious as financing clean technology is costlier. A lower clean research share is also intuitive, as in the balanced growth path the relative share of scientists is inversely related to the relative financing cost. 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 the financial sector is



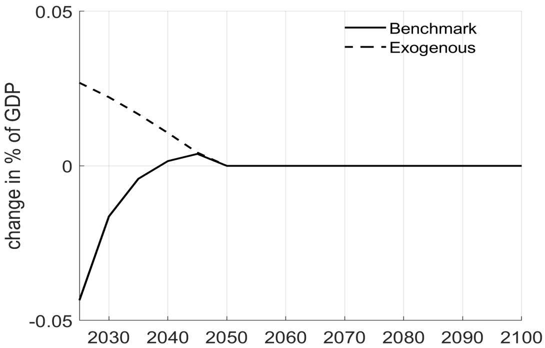
(a) Annual emissions



(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 effect nor heterogeneous financing costs. The *benchmark* scenario includes optimal policy and endogenous financing experience effect. The *exogenous* scenario comprises optimal policy under the same evolution of the experience effect from the benchmark scenario but applied exogenously to this economy.

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 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 (18). 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 the financial sector 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 obtain the symmetric scenario.

5.3 Experience From Cumulative Research

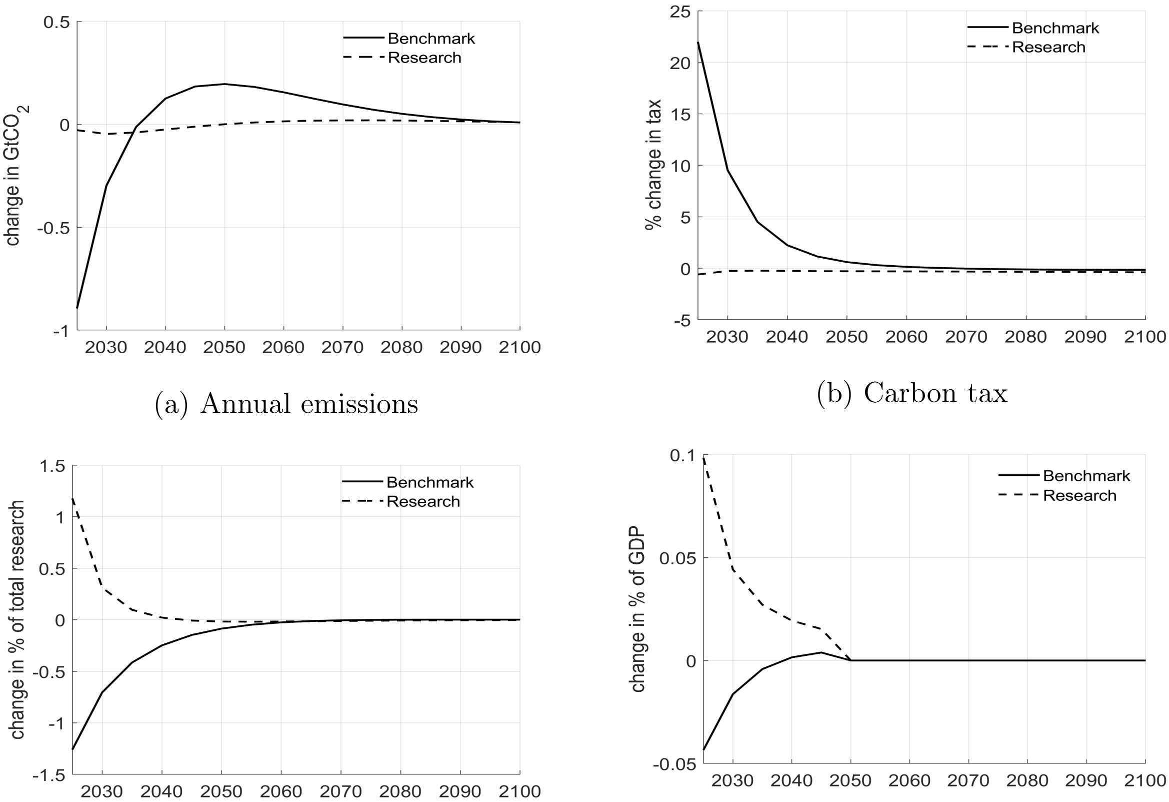
In the previous subsections, we assumed that the financing experience effect is linked to the production side of the economy, and in particular to the cumulative amount of clean intermediate inputs produced to date: as a consequence, we have shown that the endogeneity of this experience effect leads to a much higher carbon tax. In this subsection, we investigate how these results would change if the experience effect were linked to clean research, rather than clean output.[23] 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 (18) as a function of cumulative clean research, i.e.

$$\frac{1}{\nu_{ct}^2} - 1 = \left(\frac{1}{\nu_{c0}^2} - 1\right) \left(\frac{\hat{H}_{c0}}{\hat{H}_{c0} + \sum_{\tau=1}^{t} H_{c\tau}}\right)^{\omega}, \tag{19}$$

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

Figure 3 reports results from the research scenario (dashed lines) and from the benchmark model (solid lines), relative to the symmetric scenario considered in the previous subsection. Panels 3b and 3d show that the optimal combination of policy instruments is sensitive to whether the experience effect is based on output or research: indeed, as the clean research subsidy is a more effective instrument at 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

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



(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 effect nor heterogeneous financing costs. The *benchmark* scenario includes optimal policy and financing experience effect based on cumulative output. The *research* scenario comprises optimal policy and financing experience effect based on cumulative research.

tax begins lower. This 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.

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

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. 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 institutions 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 22% 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 R&D subsidies instead.

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. international financial institutions such as the International Monetary Fund (Stern, 2022), 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 consider lenders always willing to provide funds to both types of firms. At the cost of added complication, one could instead incorporate a variety of different financial actors (Aghion et al., 2022) and the possibility that some firms do not receive credit (Haas and

Kempa, 2023). Finally, our global approach to the modelling and calibration disregard technological and geographical differences (Aghion and Jaravel, 2015, 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.

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A Appendix

A.1 Proofs

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

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

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

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

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

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

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

and thus

$$\frac{w_{dt}}{w_{ct}} = \frac{(1-\alpha)\, p_{dt}^{\frac{1}{1-\alpha}} A_{dt}}{(1-\alpha)\, p_{ct}^{\frac{1}{1-\alpha}} A_{ct}} = \left(\frac{p_{dt}}{p_{ct}}\right)^{\frac{1}{1-\alpha}} \frac{A_{dt}}{A_{ct}}. \tag{A.3}$$

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),

$$Y_{jt} = L_{jt}\, (p_{jt})^{\alpha/(1-\alpha)}\, A_{jt}. \tag{A.4}$$

Therefore,

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

□

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

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

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

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

Therefore,

$$\frac{L_{dt}}{L_{ct}} = \left(\frac{A_{dt}}{A_{ct}}\right)^{(1-\alpha)(\epsilon-1)}. \tag{A.8}$$

□

Derivation of Equation (16). Taking as given the unit cost of the loan r_{jit} and the odds of a successful audit μ_{jit}, the maximisation problem of a research firm is to decide how many scientists to hire, given the probability of innovating, the innovation possibility frontier, and the price of the patent π_{jit}. Formally,

$$\max_{H_{jit}\geq 0} \quad \lambda_j \left[\pi_{jit} - w^s_{jit} H_{jit} \left(1 + r_{jit}\right)\right] \tag{A.9a}$$

$$\text{s.t. } \pi_{jit} = \alpha(1-\alpha) p_{jt}^{1/(1-\alpha)} A_{jit} L_{jt} \tag{A.9b}$$

$$A_{jit} = A_{jt-1} \left(1 + \gamma H_{jit}^{\eta} \left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}\right) \tag{A.9c}$$

This can be simplified to

$$\max_{H_{jit}\geq 0} \quad \lambda_j \alpha(1-\alpha) p_{jt}^{1/(1-\alpha)} A_{jt-1} \left(1 + \gamma H_{jit}^{\eta} \left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}\right) L_{jt} + \\ - \lambda_j w^s_{jit} H_{jit} \left(1 + r_{jit}\right). \tag{A.10}$$

The first order condition then is

$$w^s_{jit} = \frac{1}{1 + r_{jit}} \alpha \left(1-\alpha\right) p_{jt}^{1/(1-\alpha)} A_{jt-1} \gamma \eta H_{jit}^{\eta-1} \left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi} L_{jt}. \tag{A.11}$$

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

$H_{jit} = H_{jt} \forall i$. We then use (A.11) to obtain

$$\begin{aligned}\frac{w^s_{dit}}{w^s_{cit}} &= \frac{(1+r_{ct})\,\alpha\,(1-\alpha)\,p_{dt}^{1/(1-\alpha)} A_{dt-1}\gamma\eta H_{dt}^{\eta-1}\left(\frac{A_{t-1}}{A_{dt-1}}\right)^{\phi} L_{dt}}{(1+r_{dt})\,\alpha\,(1-\alpha)\,p_{ct}^{1/(1-\alpha)} A_{ct-1}\gamma\eta H_{ct}^{\eta-1}\left(\frac{A_{t-1}}{A_{ct-1}}\right)^{\phi} L_{ct}} \\ &= \frac{(1+r_{ct})\,p_{dt}^{1/(1-\alpha)} A_{dt-1}^{1-\phi} H_{dt}^{\eta-1} L_{dt}}{(1+r_{dt})\,p_{ct}^{1/(1-\alpha)} A_{ct-1}^{1-\phi} H_{ct}^{\eta-1} L_{ct}} \\ &= \frac{(1+r_{ct})\,p_{dt}^{1/(1-\alpha)} A_{dt-1}^{1-\phi} L_{dt}}{(1+r_{dt})\,p_{ct}^{1/(1-\alpha)} A_{ct-1}^{1-\phi} L_{ct}}\left(\frac{H_{ct}}{H_{dt}}\right)^{1-\eta}.\end{aligned} \tag{A.12}$$

Since scientists are free to move across sectors and firms, they all must receive the same wage, which means that the left-hand side of (A.12) must be equal to one,

$$\left(\frac{H_{dt}}{H_{ct}}\right)^{1-\eta} = \frac{(1+r_{ct})\,p_{dt}^{1/(1-\alpha)} A_{dt-1}^{1-\phi} L_{dt}}{(1+r_{dt})\,p_{ct}^{1/(1-\alpha)} A_{ct-1}^{1-\phi} L_{ct}}. \tag{A.13}$$

Rearranging, one obtains equation (16) in the text. □

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

$$\begin{aligned}\frac{H_{dt}}{H_{ct}} &= \left[\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\left(\frac{p_{dt}}{p_{ct}}\right)^{\frac{1}{1-\alpha}}\frac{L_{dt}}{L_{ct}}\frac{(1+r_{ct})}{(1+r_{dt})}\right]^{\frac{1}{1-\eta}} \\ &= \left[\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\left(\frac{A_{dt}}{A_{ct}}\right)^{-\varphi-1}\frac{(1+r_{ct})}{(1+r_{dt})}\right]^{\frac{1}{1-\eta}}\end{aligned} \tag{A.14}$$

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

$$\begin{aligned}\frac{H_{dt}}{H_{ct}} = &\left[\left(\frac{\mu_{dt}\lambda_d A_{dt-1}\left(1+\gamma H_{dt}^{\eta}\left(\frac{A_{t-1}}{A_{dt-1}}\right)^{\phi}\right)+(1-\mu_{dt}\lambda_d)A_{dt-1}}{\mu_{ct}\lambda_c A_{ct-1}\left(1+\gamma H_{ct}^{\eta}\left(\frac{A_{t-1}}{A_{ct-1}}\right)^{\phi}\right)+(1-\mu_{ct}\lambda_c)A_{ct-1}}\right)^{-\varphi-1}\right]^{\frac{1}{1-\eta}} \times \\ &\times\left[\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\frac{(1+r_{ct})}{(1+r_{dt})}\right]^{\frac{1}{1-\eta}}.\end{aligned} \tag{A.15}$$

□

Proof of Proposition 2. 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.14) implies

$$\begin{aligned}
\frac{H_{dt}}{H_{ct}} &= \left[\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{1-\phi}\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{-\varphi-1}\frac{(1+r_{ct})}{(1+r_{dt})}\right]^{\frac{1}{1-\eta}} \\
&= \left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{1-\phi-\varphi-1}{1-\eta}}\left(\frac{1+r_{ct}}{1+r_{dt}}\right)^{\frac{1}{1-\eta}} \\
&= \left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{-\phi-\varphi}{1-\eta}}\left(\frac{1+r_{ct}}{1+r_{dt}}\right)^{\frac{1}{1-\eta}}.
\end{aligned} \tag{A.16}$$

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

$$\begin{aligned}
g_{jt} &\equiv \frac{A_{jt}-A_{jt-1}}{A_{jt-1}} \\
&= \frac{\mu_{jt}\lambda_j A_{jt-1}\left\{1+\gamma H_{jt}^{\eta}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}\right\}+(1-\mu_{jt}\lambda_j)A_{jt-1}-A_{jt-1}}{A_{jt-1}} \\
&= \mu_{jt}\lambda_j\left\{1+\gamma H_{jt}^{\eta}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}\right\}+(1-\mu_{jt}\lambda_j)-1 \\
&= \mu_{jt}\lambda_j\gamma H_{jt}^{\eta}\left(\frac{A_{t-1}}{A_{jt-1}}\right)^{\phi}.
\end{aligned} \tag{A.17}$$

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

$$\begin{aligned}
\mu_{dt}\lambda_d\gamma H_{dt}^{\eta}\left(\frac{A_{t-1}}{A_{dt-1}}\right)^{\phi} &= \mu_{ct}\lambda_c\gamma H_{ct}^{\eta}\left(\frac{A_{t-1}}{A_{ct-1}}\right)^{\phi} \\
\text{i.e.}\quad \frac{H_{dt}}{H_{ct}} &= \left(\frac{\mu_{ct}\lambda_c}{\mu_{dt}\lambda_d}\right)^{\frac{1}{\eta}}\left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{\phi}{\eta}}.
\end{aligned} \tag{A.18}$$

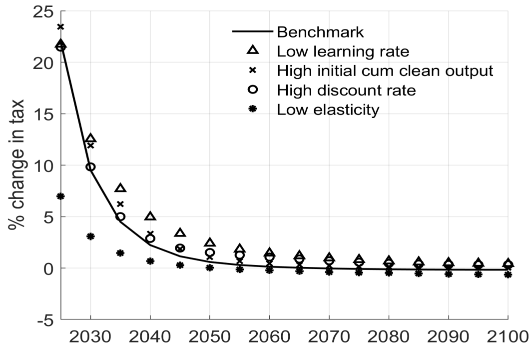
Combining (A.16) and (A.18), one obtains that a condition for an interior steady-state is

$$\left(\frac{1+c(\mu_{ct},\nu_{ct})}{1+c(\mu_{dt},\nu_{dt})}\right)\left(\frac{\mu_{dt}\lambda_d}{\mu_{ct}\lambda_c}\right)^{\frac{1}{\eta}} = \left(\frac{A_{dt-1}}{A_{ct-1}}\right)^{\frac{\phi+\varphi\eta}{\eta}}. \tag{A.19}$$

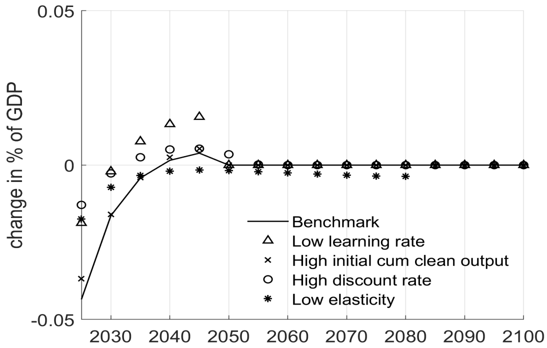
Solving equation (A.19) for ϕ defines the threshold value for the strength of the cross-sector spillovers above which the economy converges to a stable interior balanced growth path,

$$\phi \geq \eta\left[\frac{\ln\left(\frac{1+c(\mu_{ct},\nu_{ct})}{1+c(\mu_{dt},\nu_{dt})}\right)+\frac{1}{\eta}\ln\left(\frac{\mu_{dt}\lambda_d}{\mu_{ct}\lambda_c}\right)}{\ln\left(\frac{A_{d0}}{A_{c0}}\right)}-\varphi\right] \equiv \bar{\phi}. \tag{A.20}$$

□



(a) Carbon tax



(b) Clean research subsidy

Figure A.1: 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).

A.2 Robustness

In this subsection, we discuss the following robustness checks: a decrease in the clean learning rate, $\omega = 0.74$, corresponding to a reduction of 40% (rather than 60%) in clean financing costs for each doubling of clean cumulative output; a higher initial level of cumulative clean output equal to $3Y_{c0}$; 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 A.1 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.

The key results are consistent across sensitivities: the finance experience effect increases the optimal carbon tax and decreases the clean research subsidy in the first period. A lower $\omega = 0.74$ implies a slower experience effect, which leads to clean financing costs decreasing more slowly (10.1% in 2025 and 2.6% in 2050 versus 7.1% and 0.6% in the benchmark), which in turn means that less funding is directed to the clean sector for a given level of climate policy: therefore, a lower ω leads to a higher optimal clean research subsidy and carbon tax compared with the benchmark scenario. A higher initial cumulative clean output equal to $3Y_{c0}$ in 2020, with the same initial financing costs, also implies a slower decrease in clean financing costs (8.8% in 2025 and 1.0% in 2050), and thus a higher carbon tax and lower research subsidy. Changes in the yearly discount rate to $\rho = 3\%$ and elasticity of substitution to $\epsilon = 2$ affect results for the symmetric scenario as well as the 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 A.1a, 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).