ENVIRONMENTAL SUBSIDIES TO MITIGATE NET-ZERO TRANSITION COSTS

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ABSTRACT. We explore the role of public subsidies in mitigating the transition costs associated with achieving a climate-neutral objective by 2060. To this end, we develop and estimate a quantitative macro-climate model for the world economy featuring an endogenous market structure for carbon abatement products. Public subsidies, fully financed by a carbon tax, are found to be an efficient instrument to promote firm entry into the abatement good sector by fostering competition and lowering the selling price of such products. We estimate that the subsidy, optimally distributed between startups at 60% and existing companies at 40%, would save nearly $2.9 trillion in world GDP each year by 2060. Finally, delaying the net-zero transition would imply giving an even larger share to startups.

JEL: E32, H23, Q50, Q55, Q58.

Keywords: Climate change, macro-climate model, environmental goods and services sector, endogenous market structure, stochastic growth, Bayesian estimation

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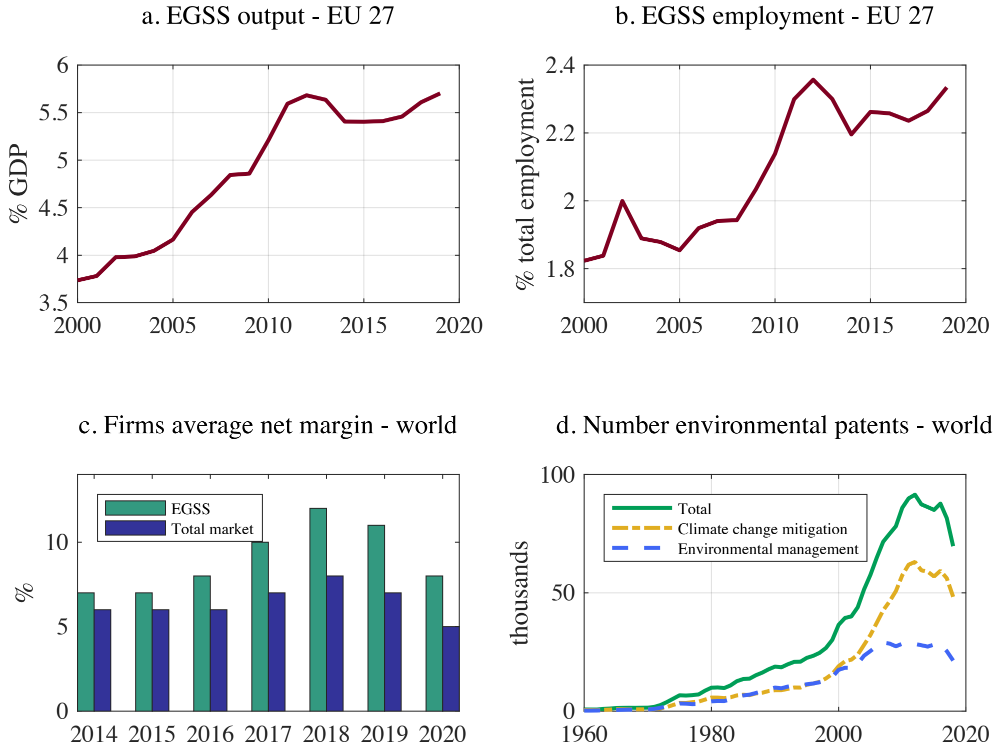
1 INTRODUCTION

The transition to a greener economy is a recognized challenge for today's organizations. It is widely agreed that the corporate sector needs to tackle climate change by adopting models that lead to reduced environmental damage, which requires a profound change in production processes by substituting polluting inputs for low-emissions inputs. However, without any particular expertise, firms cannot create the intermediate inputs (hereinafter "abatement goods") that allow them to lower their carbon footprint by themselves. They must critically rely on a specific sector, namely, the environmental goods and services sector (EGSS), to supply them in sufficient quantity and at low prices. EGSS consists of a heterogeneous set of producers of technologies, goods and services whose main activities are to measure, prevent, limit, minimize or correct environmental damage to water, air and soil, as well as problems related to waste, noise and ecosystems (Eurostat, 2016; OECD, 2017). Unfortunately, this sector is too modest and immature, as illustrated by Figure 1. First, the output value of environmental goods and services and the full-time equivalent employment engaged in their production are too low to achieve the net-zero target. For instance, they account for 5.5% of GDP (Panel A) and 2.3% of total employment (Panel B) in the European Union since 2010 and are even lower in other world regions. Second, this sector is more concentrated than the whole economy, with net margins that are well above the average for all industries (Panel C). In addition, 10% among worldwide companies in EGSS account for almost 80% of the operating revenue (Ecorys, 2009). Such a concentration results from high barriers to entry that prevent potential competitors from challenging incumbent firms. Third, after decades of growth, the number of world environment-related patents has started to decrease since 2012 (Panel D). This means that an EGSS that is too small and insufficiently competitive will certainly increase transition risk through a higher price for environment-related products and thus threaten the achievement of the Paris Agreement.

Motivated by these observations, we assess the role of public subsidies in promoting the development of EGSS. In combination with an existing carbon tax, we introduce subsidies that are expected to compensate for the cost of carbon abatement investments and consequently encourage firms to develop more efficient abatement goods. In practice, using carbon tax revenues to subsidize the abatement good industry could *(i)* increase the size of this market by facilitating entry and exit, and *(ii)* trigger a new wave of green patents, as illustrated by Nesta et al. (2014) and Nicolli and Vona (2016). These developments would accelerate the transition and may make negative emissions an additional levy to decarbonize the economy.

FIGURE 1. Key characteristics of the environmental goods and services sector (EGSS)



Note: Panel A reports the share of EGSS output in total GDP. EGSS output consists of the value of *(i)* products that become available for use outside of the producer unit, *(ii)* any goods and services produced for own final use and *(iii)* goods that remain in the inventories at the end of the period in which they are produced. It is be valued at basic prices (i.e., the prices receivable by the producer from the purchaser minus taxes and plus subsidies on products). Panel B reports the share of EGSS employment in total employment. It is measured in full-time equivalent jobs engaged in the production of output of environmental goods and services. Full-time equivalent is defined as total hours worked divided by the average annual working hours in a full-time job. Panel C reports the average net margin (i.e., the net income on the total revenue) computed from a panel of 600 firms worldwide for EGSS (represented by "Green and Renewable Energy" and "Environmental and Waste Services") and 46,500 firms for the total market. Panel D displays the annual number of environment-related patents by category (Haščič and Migotto, 2015). The data cover all family sizes worldwide. Source: Eurostat, OECD, Bloomberg, Morningstar, Capital IQ, and Compustat.

We make three contributions with this study. First, we develop a quantitative macro-climate model for the world economy featuring an endogenous market structure for the abatement good sector (i.e., EGSS). We build on Bilbiie et al. (2012), who endogenize firm entry and the creation of new products in the economy by introducing a clear distinction between *intensive* margins (i.e., changes in the production of existing goods) and *extensive* margins (i.e., changes in the variety of available goods). This framework is well suited to characterize pricing dynamics as well as the number of abatement goods. Specifically, we merge elements from the standard dynamic integrated climate economic (DICE) and real business cycle models into a unified framework to examine both the level and growth effects of macroeconomic and climate-related variables on the economy.[1] The resulting model has appealing properties that make it amenable to the analysis of alternative economic policies as well as to empirical testing or validation. In particular, it *(i)* formalizes the behavior of economic agents based on explicit microfoundations, *(ii)* manages all interactions between them within general equilibrium, *(iii)* emulates how forward-looking agents form expectations about a future characterized by stochastic events or outcomes, *(iv)* handles complex technological dynamics, and *(v)* incorporates uncertainty into agent decision-making processes, as suggested by Pindyck (2013). Importantly, this framework appropriately controls for the effects of policy measures through expectations, notably those related to climate change, which imply permanent shifts in macroeconomic time series.

Our second contribution is to estimate this nonlinear macro-climate model using full-information methods. First, a nonlinear estimation is deemed necessary to account for unbalanced growth dynamics originating from climate change and by nature makes usual perturbation (around a fixed point) methods unsuitable for climate issues. Second, by revealing the relative strength of environmental and economic forces and accounting for both parametric and stochastic uncertainties, this estimation strategy is essential to properly quantify the effects of climate-oriented policies. To this end, we first use the *extended path solution method* from Fair and Taylor (1983) to numerically solve the model. In summary, the extended path approach uses a perfect foresight solver to obtain endogenous variables that are path consistent with the model equations. Each period, agents are surprised by the realization of shocks but still expect that in the future, shocks are zero on average, consistent with rational expectations. The advantage of this method is that it provides an accurate and fast solution while considering all the nonlinearities of the model. Second, we use an *inversion filter* to calculate the likelihood function. By extracting the sequence of innovations recursively through the inversion of the observation equations for a given set of initial conditions, this filter has recently emerged as a computationally efficient alternative (Guerrieri and Iacoviello, 2017; Atkinson et al., 2020). Finally, using Bayesian techniques, we describe the joint fluctuations of five world's macroeconomic and climate-related time series from 1961 to 2018.

Our third contribution is to propose several projection exercises that are based on two alternative climate scenarios, in line with IPCC (2021). The first scenario assumes that there are no environmental policies, resulting in a continuous increase in carbon emissions (hereafter

[1] The DICE model is part of integrated assessment models (IAM), which aim to provide insights into global environmental change and sustainable development issues by offering a description of key processes in the human and earth systems and their interactions.

called *laissez-faire*). The second scenario assumes that carbon neutrality is reached in 2060 thanks to the introduction of a carbon tax, whose revenues are redistributed to households through lump-sum transfers (hereafter called the *Paris Agreement*). In these simulations, the value of the carbon tax is determined to match the desired control rate of emissions for each scenario, and the model endogenously generates out-of-sample forecasts based on the posterior distribution of both parameters and shocks.[2]

These projections illustrate the contributions of firm entry and creation of new products in the abatement good sector to the response of the economy. In particular, when a government announces the introduction of a carbon tax to reach the *Paris Agreement* target, producing firms seek to rapidly reduce their emissions by purchasing abatement goods. The prospect of future high profits in the abatement good sector boosts firms' market value and, through free-entry conditions, incentivizes prospective entrants to establish a startup. The number of firms increases, and the resulting competition pushes firms to compress their prices to maintain their market share. However, the carbon tax is expected to have a recessive impact on the economy. We thus propose two subsidy experiments designed to mitigate the cost of the transition: *(i)* a subsidy to existing firms in the abatement good sector and *(ii)* an optimal subsidy to both existing firms and startups. In the latter case, the respective shares of carbon tax revenues given to entrants and established firms are chosen to maximize social welfare. In these exercises, carbon tax revenues are fully used to reduce the price of the abatement technology and help its diffusion to the final good sector.

We find that the *Paris Agreement* scenario would lead to a cumulative world GDP loss of $266 trillion from 2019 to 2060 relative to the laissez-faire scenario. Public subsidies, fully financed by the carbon tax, can reduce this loss substantially by fostering competition and lowering the selling price of the abatement good sector. In particular, a subsidy policy targeting startups is more efficient, as it quickly lowers the cost of adopting green production technologies. Allocating 60% of the revenues of the carbon tax to subsidize new firms and 40% to existing firms in the abatement good sector would lead to a cumulated GDP loss of $145 trillion from 2019 to 2060. Hence, the optimal subsidy would reduce the GDP loss by nearly $121 trillion, or equivalently $2.9 trillion each year. In this scenario, the carbon tax would increase to $150 per ton of CO_2 by 2040 and $400 by 2060, the abatement price would

[2] Note that we focus on the positive effects of environmental policies and abstract from any normative aspects. While an optimal level of the carbon tax could be determined from the social cost of carbon (i.e., the cost of the damages created by one extra ton of carbon emissions), our ambition is to conditionally determine carbon taxes from plausible carbon emissions scenarios.

be divided by more than 2.5, and the numbers of firms/varieties in the abatement good sector would substantially increase.

Our paper is related to the scarce literature focusing on climate issues through micro-founded structural models. Fischer and Springborn (2011), Heutel (2012), and Angelopoulos et al. (2013) are among the first contributions to introduce CO_2 emissions in real business cycle models. They assume that emissions stem from production and adversely impact utility or have a negative impact in turn on productivity and production. More recent contributions have extended these models in several directions, including *(i)* multisector aspects (Golosov et al., 2014; Dissou and Karnizova, 2016), *(ii)* labor market frictions (Gibson and Heutel, 2020; Finkelstein Shapiro and Metcalf, 2021), *(iii)* distortionary fiscal policy (Barrage, 2020), *(iv)* endogenous entry (Annicchiarico et al., 2018; Finkelstein Shapiro and Metcalf, 2021), or *(v)* nominal rigidities and monetary policy (Annicchiarico and Di Dio, 2015, 2017; Ferrari and Nispi Landi, 2020; Carattini et al., 2021; Diluiso et al., 2021). These models are mainly used to provide short-run analyses of the effects of pollution policies, such as pollution taxes or cap-and-trade. However, climate issues, especially the trade-off between the costs and benefits of reducing emissions, must be assessed from a long-run perspective. Contrary to these papers, we consider long-run trends in CO_2 emissions and macroeconomic variables, which makes our framework well suited for studying environmental policies aiming to mitigate transition costs.

Finally, our work also complements the literature on directed technical change and the environment (see Fischer and Heutel, 2013, for an overview). The link between environmental quality and economic growth has been formalized by Bovenberg and Smulders (1995) and Acemoglu (2002), building on previous work by Hicks (1932). Using an endogenous growth model with pollution-augmenting technological change, they pointed out that the change in the relative price of factors would stimulate the generation of new technologies. Several papers have subsequently improved this theoretical framework in *(i)* increasing the number of competing (dirty and clean) applications of innovation (Acemoglu et al., 2012), *(ii)* introducing carbon taxes and research subsidies (Acemoglu et al., 2016), *(iii)* incorporating technology spillovers across the different sectors (Fried, 2018) or *(iv)* using firm-level panel data from the auto industry to test for path dependency in innovation (Aghion et al., 2016). Rather than starting from endogenous progress in clean energy technology, we introduce an endogenous determination of the number of producers and varieties in the abatement sector to explore how environmental policies can engender sustainable change.

The remainder of the paper is structured as follows. Section 2 describes the macro-climate model. Section 3 reports our data, the estimation methodology, and the parameter estimates. Section 4 provides details on the contributions of firm entry in the abatement good sector to the response of the economy to changes in the carbon tax and climate scenarios. Section 5 quantifies the macroeconomic and climate-related effects of public subsidies. Section 6 presents additional exercises to check the robustness of our analysis. Section 7 concludes the paper.

2 MODEL

Our model draws on three branches of the economic literature: *(i)* the climate block is derived from DICE models (Nordhaus, 1992, 2018); *(ii)* the macroeconomic block is an RBC version of Smets and Wouters (2007); and *(iii)* the innovation sector block has an endogenous market structure, as in Bilbiie et al. (2012).

FIGURE 2. Overview of the main mechanisms in the model

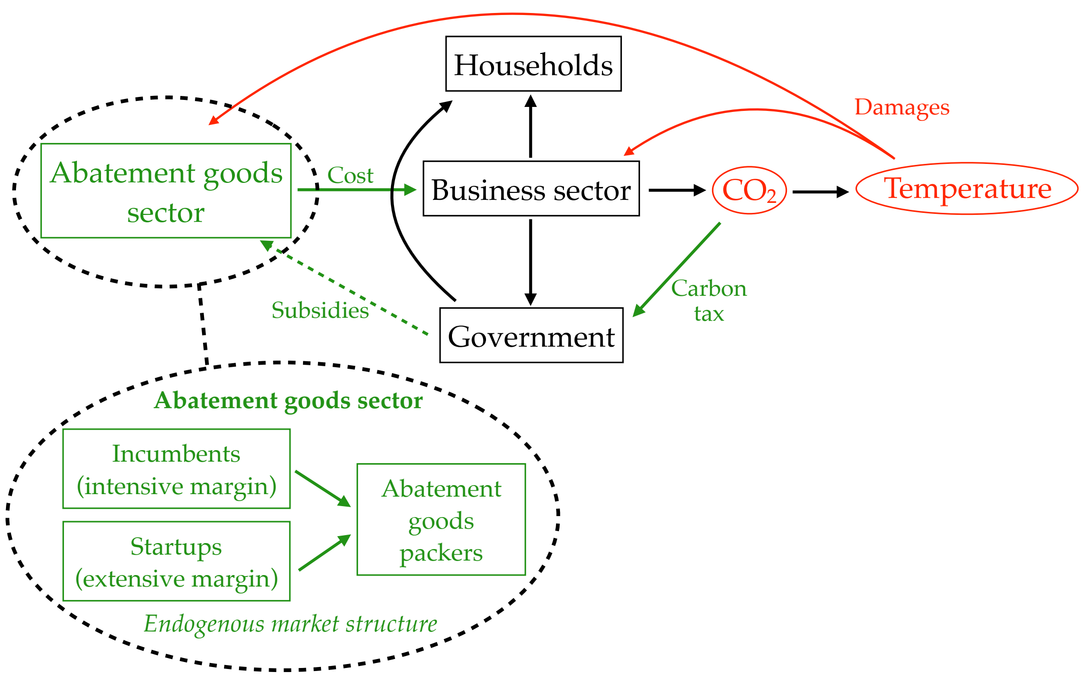


Figure 2 provides an overview of the main mechanisms at stake in the model. In producing goods for households and the government, firms generate CO_2 emissions, which contribute to increasing the surface air temperature. In turn, global warming adversely impacts the total factor productivity of firms through a damage process. However, this damage does not spontaneously push companies to reduce their emissions. Indeed, global warming is the result of the activity of all firms. Therefore, in a decentralized economy, as a "damage taker," each firm would bear the cost of reducing its emissions for a negligible individual impact on global warming. In the absence of any regulation or subsidy, each firm will minimize its mitigation efforts rather than drastically reduce its emissions.

To address this free-rider problem, the government imposes a carbon tax (τ) that corrects the market failure. This tax forces firms in the final good sector to acquire technologies that reduce their individual emissions. Although costly, these *abatement technologies* reduce the amount of carbon tax that firms must pay. Abatement goods are produced by specialized firms in an initially immature abatement good sector. The development of this market is crucial to make the energy transition faster and less costly in terms of output. Indeed, stronger competition may reduce the price of abatement technologies by reducing deadweight losses.[3] From this perspective, policies aimed at fostering competition, such as *public subsidies*, may reduce the abatement price and encourage the use of abatement goods, therefore supporting the reduction of emissions.

2.1 Climate block The climate block relies on a derived version of Nordhaus (1992, 2018) with minor change to make it more consistent with climate dynamics. The law of motion of the atmospheric loading of CO_2 (in gigatons of CO_2) is given by:

$$M_t = M_{1750} + (1 - \delta_M)(M_{t-1} - M_{1750}) + \xi_M E_t, \tag{1}$$

where E_t denotes the anthropogenic carbon emissions in t, $\delta_M \in [0, 1]$ represents the rate of transfer of atmospheric carbon to the deep ocean, and $\xi_M \geq 0$ is the atmospheric retention ratio.[4] The term $M_{t-1} - M_{1750}$ represents the excess carbon in the atmosphere net of its (natural) removal, with M_{1750} representing the stock of carbon in the preindustrial era, i.e., the steady-state level in the absence of anthropogenic emissions (see also Traeger, 2014).

The heat received at the Earth's surface F_t (in watts per square meter, W/m^2) is the sum of the forcing caused by atmospheric CO_2 and the non-CO_2 forcing:

$$F_t = \eta \ \log_2\left(\frac{M_t}{M_{1750}}\right) + F_{EX,t}, \tag{2}$$

[3] As evidence of the impact of competition on prices, the average price of solar photovoltaic modules, measured in 2019 U.S. dollars per watt, was reduced by 45% between 1990 and 2000, by 58% between 2000 and 2010, and by 81% between 2010 and 2019, allowing for a relatively fast spread of solar panels (source: Our World In Data).

[4] More advanced climate blocks were developed to better portray the link between temperature and carbon emissions. While this kind of refinement is important in the context of physical risk assessment (Dietz and Venmans, 2019), in regard to transition risk, this has little added value and would not change the main message from our policy recommendations.

where η denotes the effect on temperature from doubling the stock of atmospheric CO_2. As in the latest version of DICE models, the non-CO_2 forcing $F_{EX,t}$ is an exogenous process:

$$F_{EX,t} = \min(F_{EX,t-1} + F_\Delta, F_{\max}), \tag{3}$$

where the parameter F_Δ denotes the fixed increase in exogenous radiative forcing, while $F_{\max}$ is a cap that is met by 2100.

The global mean temperature anomalies of the surface T_t and deep oceans T_t^* with respect to the preindustrial period are given by:

$$T_t = \phi_{11} T_{t-1} + \phi_{12} T_{t-1}^* + \xi_T F_t + \varepsilon_{T,t}, \tag{4}$$

$$T_t^* = \phi_{21} T_{t-1} + \phi_{22} T_{t-1}^*, \tag{5}$$

where $\xi_T \geq 0$ is the elasticity of surface temperature to Earth surface heat, while parameters ϕ_{11}, ϕ_{12}, ϕ_{21}, and ϕ_{22} capture either persistence or interaction between the temperature of the surface and deep oceans. To disentangle transitory changes in temperature versus permanent drifts, we introduce an exogenous stochastic process, $\varepsilon_{T,t} = \rho_T \varepsilon_{T,t-1} + \eta_{T,t}$ with $\eta_{T,t} \sim \mathcal{N}(0, \sigma_T^2)$, which captures cyclical changes in temperature.[5]

2.2 Household sector The world economy is populated by a mass L_t of atomistic, identical, and infinitely lived households. This mass is time varying and captures the upward trend of the world population observed over the last sixty years. Formally, as in Nordhaus (2014), it is assumed that the world population asymptotically converges to a long-run level $L_T > 0$, such as $L_t = L_{t-1} \left(L_T / L_{t-1} \right)^{\ell_g}$, with $\ell_g \in [0, 1]$ being the geometric rate of convergence to L_T. This formulation for population growth dynamics fits perfectly well with the observed path of the world population from 1960 to the present. Each household indexed by $i \in [0, L_t]$ maximizes its sequence of present and future utility flows that depend positively on consumption $c_{i,t}$ and negatively on hours worked $h_{i,t}$:

$$\mathbb{E}_t \left\{ \sum_{\tau=0}^{\infty} \beta^\tau \left(\frac{c_{i,t+\tau}^{1-\sigma_c}}{1-\sigma_c} - \psi_t \frac{h_{i,t+\tau}^{1+\sigma_h}}{1+\sigma_h} \right) \right\}, \tag{6}$$

subject to the sequence of real budget constraints

$$c_{i,t} + b_{i,t} \leq w_t h_{i,t} + \xi_{i,t} + d_{i,t} + r_{t-1} b_{i,t-1}, \tag{7}$$

[5] We make the conservative assumption that the volatility of the shock to temperature remains stable over time.

where $\mathbb{E}_t$ denotes the expectation conditional upon information available at t, $b_{i,t}$ is the one-period riskless government bond, w_t is the real wage, $\xi_{i,t}$ denotes lump-sum government transfers (or taxes if negative), $d_{i,t}$ is the dividend payments received from holding shares of firms in both the intermediate goods and abatement good sectors, and r_t is the gross real interest rate. $\beta \in (0,1)$ is the subjective discount factor, $\sigma_c > 0$ is the inverse of the intertemporal elasticity of substitution in consumption, $\sigma_h > 0$ is the inverse of the Frisch labor supply elasticity, and $\psi_t > 0$ is a time-varying parameter that cancels out the effects of the productivity trend on labor supply. Such a feature is necessary to obtain a balanced growth path on hours.[6] Anticipating symmetry across households, the maximization problem gives *(i)* the aggregate labor supply equation $w_t c_t^{-\sigma_c} = \psi_t h_t^{\sigma_h}$ and *(ii)* the Euler equation $\mathbb{E}_t \beta_{t,t+1} r_t = 1$, where $\beta_{t,t+\tau} = \beta^\tau (c_{t+\tau}/c_t)^{-\sigma_c}$ is the stochastic discount factor. Note that carbon tax revenues reversed to households through social transfers do not lead to any change in consumption, as this policy does not materialize as a permanent increase in income.

2.3 Business sector The business sector is characterized by final good producers that sell a homogeneous final good to households and the government. To produce, they buy and pack differentiated varieties produced by atomistic and infinitely lived intermediate good firms that operate in a monopolistically competitive market. Intermediate good firms contribute to climate change by emitting CO_2 as an unintended result of their production process.

2.3.1 Final good sector At every point in time t, a perfectly competitive sector produces a final good Y_t by combining a continuum of intermediate goods $y_{i,t}$, $i \in [0, L_t]$, according to the technology $Y_t = \left[L_t^{-1/\zeta} \int_0^{L_t} y_{i,t}^{\frac{\zeta-1}{\zeta}} \mathrm{d}i \right]^{\frac{\zeta}{\zeta-1}}$. The number of intermediate good firms owned by households is equal to the size of the population L_t. $\zeta > 1$ measures substitutability across differentiated intermediate goods. Final good-producing firms take their output price, P_t, and their input prices, $P_{i,t}$, as given and beyond their control. Profit maximization implies the demand curve $y_{i,t} = L_t^{-1} \left(P_{i,t}/P_t \right)^{-\zeta} Y_t$, from which we deduce the relationship between the price of the final good and the prices of intermediate goods $P_t \equiv \left[L_t^{-1} \int_0^{L_t} P_{i,t}{}^{1-\zeta} \mathrm{d}i \right]^{\frac{1}{1-\zeta}}$.

2.3.2 Intermediate goods sector Intermediate good i is produced by a monopolistic firm using the following production function:

$$y_{i,t} = \Gamma_t h_{i,t}^I, \tag{8}$$

[6]Note that ψ_t must grow proportionally to the flow of current consumption. Thus, if Z_t denotes the trend in per capita consumption, then $\psi_t = \psi_h Z_t^{1-\sigma_c}$, with ψ_h as a scaling parameter.

where Γ_t is the total factor productivity (TFP), which affects labor demand $h^I_{i,t}$.[7] The TFP is actually determined by three components:

$$\Gamma_t = \Phi\left(T_t\right) Z_t \varepsilon_{Z,t}, \tag{9}$$

where $\Phi(T_t)$ determines the reduction in TFP due to climate change, Z_t is the deterministic component of productivity, and $\varepsilon_{Z,t}$ is an exogenous productivity shock, which determines the business cycle component of productivity. This shock follows an AR(1) process: $\varepsilon_{Z,t} = (1-\rho_Z) + \rho_Z \varepsilon_{Z,t-1} + \eta_{Z,t}$, with $\eta_{Z,t} \sim N(0, \sigma^2_Z)$. The deterministic component of TFP follows the process $\log Z_t = \log Z_{t-1} + f_Z(Z_{t-1})$, where $f_Z(Z_t) = (1 - \exp(\delta_z))(g_{z,t_0}/\delta_z - \log(Z_t/Z_0))$ is the productivity growth rate, g_{z,t_0} is the initial growth rate of productivity, δ_z is the rate of decline in productivity, and t_0 represents the starting date of our simulations. This formulation follows Nordhaus (2018) and indicates that productivity growth decreases over time by a factor δ_z to match the observed slowdown in economic growth over the last sixty years. The damage function $\Phi(T_t)$ represents the impact of climate change on the production process. Additionally, in line with the DICE literature, the damage depends on the atmospheric temperature T_t as $\Phi(T_t) = 1/(1 + aT_t^2)$, where $a > 0$ is a parameter calibrated to match climate-change damage estimates.

A firm's CO_2 emissions stemming from the production process are denoted by $e_{i,t}$. As they are subject to a carbon tax, which aims at internalizing the social cost of carbon emissions, the firm is incentivized to reduce its impact by investing in an emissions abatement technology (see Section 2.4). The abatement effort by the firm yields a reduction by $\mu_{i,t}$ (in %) in its CO_2 emissions. A firm's emissions take the following form:

$$e_{i,t} = \sigma_t \left(1 - \mu_{i,t}\right) y_{i,t} \varepsilon_{E,t}, \tag{10}$$

where σ_t denotes the aggregate carbon intensity of the production sector. Its law of motion is $\log \sigma_t = \log \sigma_{t-1} + f_\sigma(\sigma_{t-1})$, where $f_\sigma(.)$ has a functional form identical to the trend in productivity, $f_\sigma(\sigma_t) = (1 - \exp(\delta_\sigma))(g_{\sigma,t_0}/\delta_\sigma - \log(\sigma_t/\sigma_{t_0}))$, where g_{σ,t_0} is the initial decrease rate of emissions-to-output, and δ_σ is the rate of decline of the trend. This trend is set to match the decline in the emissions-to-GDP ratio observed over the last sixty years. Last, the firm's carbon intensity can be temporarily affected by an aggregate exogenous emissions shock, $\varepsilon_{E,t} = (1-\rho_E) + \rho_E \varepsilon_{E,t-1} + \eta_{E,t}$, with $\eta_{E,t} \sim N(0, \sigma^2_E)$, which captures the cyclical changes in

[7] Capital can be introduced as an additional factor of production but would further complicate our setup. Given our focus on the abatement good sector and endogenous firm entry, we have not pursued this generalization, but we provide additional results in Section 6.

the emissions-to-output ratio. A rise in $\varepsilon_{E,t}$ induces a cyclical increase in the carbon intensity of the production sector.[8]

Firms have access to a set of abatement actions. These actions, which consist of substituting carbon-intensive technologies with low-carbon technologies, imply costly changes in the existing lines of production. Hence, following Nordhaus (2018), we assume that the cost of abatement technology (in proportion to output) is given by:

$$\Lambda_{i,t} = (\theta_{1,t}\, \mu_{i,t}^{\theta_2}) y_{i,t}. \tag{11}$$

In this equation, $\theta_{1,t} = (p_b/\theta_2)(1-\delta_{pb})^{t-t_0}\sigma_t$ is the time-varying level of the cost of abatement, where $p_b > 0$ is a parameter determining the initial cost of abatement and $0 < \delta_{pb} < 1$ captures technological progress, which lowers the cost of abatement by a factor δ_{pb} per year. Finally, $\theta_2 > 0$ represents the curvature of the abatement cost function. The model assumes the existence of a backstop technology (i.e., producing energy services with zero CO_2 emissions for $\mu = 1$); the corresponding backstop price value is p_b at the start of the simulations but decreases by a factor of δ_{pb} per year. Note also that carbon sequestration technology is available for firms, implying that the share of abatement may exceed one.

The intermediate good firm i chooses $\{h_{i,t}^I, \mu_{i,t}\}$ to maximize its one-period profits:

$$p_{i,t} y_{i,t} - w_t h_{i,t}^I - p_t^A \Lambda_{i,t} - \tau_t e_{i,t}, \tag{12}$$

where $p_{i,t} = P_{i,t}/P_t$ is the relative price of intermediate goods, $p_t^A = P_t^A/P_t$ is the relative abatement price, and τ_t is the carbon tax. Importantly, while the relative abatement price is constant in Nordhaus (2018), we rely on an immature market structure of the abatement good sector that makes the relative abatement price time varying and higher than unity $p_t^A \geq 1$ (see Section 2.4 for details).

Under imperfect competition, the net profit is the distance between the total gains from selling and the cost of producing, $\Pi_{i,t} = (p_{i,t} - mc_{i,t}) y_{i,t}$, with $mc_{i,t}$ denoting the firm's real marginal cost. Maximizing this profit under the demand curve from final good firms and the production function provides the following pricing scheme: $mc_{i,t}/p_{i,t} = (\zeta - 1)/\zeta$.

Anticipating symmetry across firms, we first rewrite the cost of inputs as follows:

$$w_t = \Gamma_t \left[\frac{\zeta - 1}{\zeta} - p_t^A(\theta_{1,t}\, \mu_t^{\theta_2}) - \tau_t \sigma_t \left(1 - \mu_t\right) \varepsilon_{E,t} \right]. \tag{13}$$

[8]Note that emissions from land change are omitted, as this component is fully exogenous to policy decisions and is therefore not useful to investigate mitigation policies. The addition of an exogenous term in the emissions equation would therefore not change the policy results reported in the paper.

A rise in the carbon tax τ_t results in an increase in the real marginal cost and a decrease in the real wage, which in turn reduces the labor supply and aggregate production. In addition, a rise in the abatement effort μ_t triggers lower growth, as it increases the cost of production. Therefore, an environmental policy reduces carbon emissions at the expense of lower output.

Second, the optimal decision of abatement effort is given by:

$$\mu_t = \left(\frac{\tau_t \sigma_t \varepsilon_{E,t}}{\theta_2 \theta_{1,t} p_t^A} \right)^{1/(\theta_2 - 1)}. \tag{14}$$

Firms are atomistic and have no market power to correctly price CO_2 emissions up to their marginal damage on profits. As a result, a standard market failure emerges that can be corrected through the introduction of a policy instrument, i.e., a carbon tax. The first-order condition (14) shows that a carbon tax forces firms to internalize the social cost of their emissions on temperature, output, and their profits. Absent this policy instrument ($\tau_t = 0$), firms would not spontaneously consider their externalities. Furthermore, unlike standard IAMs, we allow for market competition to play a role in the determination of the abatement effort. Specifically, the level of market competition affects the relative abatement price p_t^A. In the case of low competition, firms would benefit from rent opportunities. As a consequence, the abatement price would remain high, which may reduce the abatement effort μ_t, as shown by Equation (14), and ultimately impair the emissions reduction. Different policy measures may be introduced to avoid such a situation and lower p_t^A, as we will see later.

2.4 Abatement good sector Abatement goods are bought by intermediate firms to reduce their emissions. As shareholders of abatement firms, households may decide to create a new abatement good through either *(i)* the introduction of an additional production line in an existing firm (*intensive margin*) or *(ii)* the creation of a startup (*extensive margin*). The adoption of new abatement technologies and the creation of startups are endogenous, following the approach proposed by Bilbiie et al. (2012). In particular, a household will choose to create a startup based on the new firm's expected future profits, which depend on sunk entry costs. Each firm produces one variety of abatement goods, denoted ω, over a continuum of differentiated varieties Ω of abatement goods, the latter reflecting the diversity of abatement solutions available in t. Indeed, in practice, low-carbon production units encompass a large set of goods that are very heterogeneous across industries. Some of these abatement goods are purchased to improve the energy efficiency of production units and buildings, others to improve the internal production process, while the remaining carbon may be captured and stored.[9] Finally, competitive packers buy and transform these varieties into homogeneous abatement goods. Equilibrium conditions in this market determine the abatement price, which is critical in the model, given its influence on the cost of the energy transition. After giving details on packers, we explain each margin of adjustment in turn.

2.4.1 Abatement good packers At every point in time t, perfectly competitive packers produce homogeneous abatement goods $y^A_{i,t}$, $i \in [0, L_t]$ by combining a continuum of varieties of abatement goods $y^A_{i,\omega,t}$, $\omega \in \Omega$, according to the technology $y^A_{i,t} = \left[\int_{\omega\in\Omega}(y^A_{i,\omega,t})^{\frac{\zeta_A-1}{\zeta_A}}\mathrm{d}\omega\right]^{\frac{\zeta_A}{\zeta_A-1}}$, where $\zeta_A > 1$ measures the substitutability across varieties. Packers take their output price, $P^A_{i,t}$, and their input prices, $P^A_{i,\omega,t}$, as given and beyond their control. Profit maximization implies the optimal quantity of goods demanded by packer i to each variety of abatement ω, $y^A_{i,\omega,t} = \left(P^A_{i,\omega,t}/P^A_{i,t}\right)^{-\zeta_A} y^A_{i,t}$ and the relationship between the price of the homogeneous abatement good and the prices of abatement varieties $P^A_{i,t} = \left[\int_{\omega\in\Omega}\left(P^A_{i,\omega,t}\right)^{1-\zeta_A}\mathrm{d}\omega\right]^{\frac{1}{1-\zeta_A}}$.

2.4.2 Intensive margin Each variety ω from already established firms, *incumbents* for short, is produced using labor, which is subject to the TFP as follows:

$$y^A_{i,\omega,t} = \Gamma_t h^A_{i,\omega,t}, \tag{15}$$

where $h^A_{i,\omega,t}$ is the labor demand from firm ω held by household i. Real profits operating in the abatement good market are given by:

$$\Pi^A_{i,\omega,t} = p^A_{i,\omega,t} y^A_{i,\omega,t} - w_t h^A_{i,\omega,t}\left(1 - s^A_t\right), \tag{16}$$

where $p^A_{i,\omega,t} = P^A_{i,\omega,t}/P_t$ is the relative price of abatement good ω and s^A_t is a subsidy rate to incumbents decided by the government, which is expressed as a percentage of the labor input cost. This subsidy rate is not variety/household specific.

Maximizing the profit under the demand curve from abatement good packers and the production function provides the price of variety ω as follows:

$$p^A_{i,\omega,t} = \frac{\zeta_A}{\zeta_A - 1}\left(1 - s^A_t\right)\frac{w_t}{\Gamma_t}. \tag{17}$$

[9] For the energy sector, for instance, switching from fossil fuels to renewable energy production requires the purchase of solar panels and wind turbines as abatement goods. For the cemetery sector, abatement goods are typically energy-efficient ovens. For the transport sector, abatement technologies might be hybrid or electric motorization.

Note that in Equation (17), the optimal pricing depends only on aggregate conditions. As a result, in equilibrium, all the producers choose the same pricing $p^A_{i,\omega,t} = \tilde{p}^A_t$, regardless of the type of packer i and variety ω, where $\tilde{p}^A_t$ denotes the selling price of abatement varieties. Consequently, firms operating in the abatement good sector are symmetric and exhibit the same output, labor demand, and profits.

2.4.3 Extensive margin While each household manages a continuum of abatement varieties Ω, only a subset of goods $\Omega_t \in \Omega$ is available at any given time t. We denote by $N_{i,t}$ the number of firms owned by household i in the abatement good sector (a mass of Ω_t) and by $N^E_{i,t}$ the number of startups created by the household. As in Bilbiie et al. (2012), startups at time t start producing only in $t+1$, which features one period of time-to-build. This assumption is necessary to capture the lag between entry and economic growth that is empirically observed. The number of firms owned by household i in the abatement good sector is given by the following law of motion:

$$N_{i,t} = (1-\delta_A)\left[N_{i,t-1} + \varepsilon_{N,t-1}\left(1 - f_N\left(\frac{N^E_{i,t-1}}{N^E_{i,t-2}}\right)\right)N^E_{i,t-1}\right], \tag{18}$$

where $\delta_A \in [0,1]$ is the probability that any firm incurs an exogenous exit-inducing shock. This exit shock means that a fraction of startups default in every period before actually producing abatement goods (Bilbiie et al., 2012). In addition to the exit shock, startups face another exit probability $f_N\left(N^E_{i,t-1}/N^E_{i,t-2}\right)$, which is proportional to the growth rate of startups, $N^E_{i,t-1}/N^E_{i,t-2}$. This term represents a congestion effect that makes startups less likely to enter the market when many of them arrive at the same time (Lewis and Poilly, 2012). The associated function is quadratic and given by $f_N(\varpi) = 0.5\chi(\varpi - 1)^2$ with $\chi \geq 0$, thus capturing the hump-shaped response of startups to macroeconomic shocks at the business cycle frequency. Finally, firm entry is subject to an exogenous shock $\varepsilon_{N,t}$. This shock stands for possible institutional and financial changes in the conditions driving the creation of firms but may also capture a measurement error between the number of startups in the model and the (highly volatile) change in the number of patents used as an observable variable. This exogenous shock follows an AR(1) process given by $\varepsilon_{N,t} = (1-\rho_N) + \rho_N \varepsilon_{N,t-1} + \eta_{N,t}$, with $\eta_{N,t} \sim N(0, \sigma^2_N)$.

The decision by a household to create a new firm is based on expected future profits, defined by $\mathbb{E}_t\left\{(1-\delta_A)^{t-s}\beta_{t,t+s}\Pi^A_{t+s}\right\}$, with $s > t$. For each period t, startups compute their postentry value v_t, which corresponds to the discounted sum of future profits:

$$v_t = \varepsilon_{N,t} (1 - \delta_A) \mathbb{E}_t \left\{ \beta_{t,t+1} \left(\Pi^A_{t+1} + v_{t+1} \right) \right\}. \tag{19}$$

Prior to entry, firms face two sunk costs, which are composed of labor inputs and the final good, as in Cacciatore and Fiori (2016). First, following Bilbiie et al. (2012), $h^E_{i,t}$ units of labor must be spent to create a startup, such that the labor demand by household i to create $N^E_{i,t}$ firms reads as $h^E_{i,t} = \theta_{1,t} X_w N^E_{i,t} / \Gamma_t$. This equation can be interpreted as a production function of the $N^E_{i,t}$ startups with $X_w \geq 0$ as a productivity parameter that drives the intensity of the sunk cost. Consequently, the household spends $w_t h^E_{i,t} \left(1 - s^E_t\right)$ of labor cost to create $N^E_{i,t}$ new firms, with s^E_t denoting the subsidy rate to the labor cost of startups. This cost is deemed necessary to capture cyclical changes in the number of startups. The second sunk cost is induced by regulatory and administrative barriers to market entry and technological requirements for business creation. To pay this cost, each firm must purchase a quantity $X_q \geq 0$ of a basket of materials in terms of the final good. This cost is fixed and therefore does not affect the number of firms at business cycle frequency. However, as in DICE-type models, a rise in abatement spending resulting from a carbon tax hike triggers a boost in aggregate demand. Therefore, this cost allows us to keep the demand effect when increasing the abatement effort.

Gathering these two costs, the marginal sunk cost per new firm is the same across households and is given by:

$$X_t = \theta_{1,t} \left[X_w \left(1 - s^E_t\right) \frac{w_t}{\Gamma_t} + X_q \right]. \tag{20}$$

To ensure that the effort to enter the market does not asymptotically reach zero, the sunk costs grow proportionally to the level of the cost of abatement $\theta_{1,t}$. As a result, the dynamics of labor in the abatement good sector are such that both final and abatement goods have the same balanced growth.

Given the symmetry in marginal cost X_t and postentry firm value v_t, the free-entry condition in the abatement good sector imposes that the average number of startups is the same across households, $N^E_{i,t} = N^E_t$. Thus, the resulting free-entry condition is:

$$X_t = v_t - v_t \frac{\partial \left(f_N \left(N^E_t / N^E_{t-1} \right) N^E_t \right)}{\partial N^E_t} - \mathbb{E}_t \left\{ \beta_{t,t+1} v_{t+1} \frac{\partial f_N \left(N^E_{t+1} / N^E_t \right)}{\partial N^E_t} N^E_{t+1} \right\}. \tag{21}$$

Household i establishes startups until the marginal cost of their creation (measured by the left-hand-side term of Equation (21)) reaches its marginal return (measured by the right-hand-side term). The free-entry condition is reached when there are no more profits to take from establishing a new firm. Note that upon entry, new entrants exhibit the same pricing as incumbents and therefore are symmetric with existing firms. As a result, there is no ex post heterogeneity across cohorts of producers that entered the market at different points in time. This condition ensures the model tractability.

2.5 Public sector and environmental policy The government issues bonds, collects the carbon tax from firms' emissions, repays the issued bonds with interest payments, makes some unproductive expenditures, pays (or collects) a lump-sum transfer (or tax) to (from) households, and may provide some subsidies to the abatement good sector. The budget constraint is:

$$B_t + \tau_t E_t = r_{t-1} B_{t-1} + G_t + \xi_t + (s_t^A w_t L_t h_t^A + s_t^E w_t N_t^E L_t h_t^E). \tag{22}$$

Public spending is determined exogenously as $G_t = g_y Y_t \varepsilon_{G,t}$, where $g_y \in [0,1]$ is the steady-state share of public spending to output and $\varepsilon_{G,t}$ is a government spending shock. This shock captures exogenous shifts in aggregate demand and follows $\varepsilon_{G,t} = (1-\rho_G) + \rho_G \varepsilon_{G,t-1} + \eta_{G,t}$, with $\eta_{G,t} \sim \mathcal{N}(0, \sigma_G^2)$. The total lump-sum transfer to households and the total issued bonds read as $\xi_t = \int_0^{L_t} \xi_{i,t} \mathrm{d}i$ and $B_t = \int_0^{L_t} b_{i,t} \mathrm{d}i$, respectively.

In the following, we assume that public expenditures are financed by a combination of bond issues (or equivalently debt) and lump-sum taxes. In addition, carbon tax revenues can either (*i*) be returned to households via lump-sum transfers and used for debt repayment or (*ii*) be spent for subsidies to the abatement good sector.

2.6 Market clearing and equilibrium conditions First, the annual flow of emissions is given by the total emissions from firms $E_t = \int_0^{L_t} e_{i,t} \mathrm{d}i$, while output is given by $Y_t = \int_0^{L_t} y_{i,t} \mathrm{d}i$. Note that since firms are symmetric, the abatement rate is the same across firms $\mu_{i,t} = \mu_t$. Therefore, the aggregate flow of emissions reads as follows:

$$E_t = \sigma_t \left(1 - \mu_t\right) Y_t \, \varepsilon_{E,t}. \tag{23}$$

Resource constraints determining the aggregate demand are obtained from the aggregation of household consumption $C_t = L_t c_t = \int_0^{L_t} c_{i,t} \mathrm{d}i$, government spending, and the barrier to entry costs paid in terms of the final good:

$$Y_t = C_t + G_t + N_t^E L_t \theta_{1,t} Z_t X_q. \tag{24}$$

In addition, we define a detrended output as the percentage deviation of output Y_t from productivity and population trends, as follows:

$$\hat{Y}_t = 100 \times \log\left(\frac{Y_t}{Z_t L_t}\right). \tag{25}$$

This metric allows us to compare the dynamics of output more easily than directly focusing on the level of output.[10]

The aggregate demand of abatement goods reads as follows:

$$N_t Y_t^A = \left(\frac{\tilde{P}_t^A}{P_t^A}\right)^{-\zeta_A} L_t \Lambda_t. \tag{26}$$

In this expression, as households are symmetric, the relative price ratio is unchanged at the aggregate level $\tilde{P}_{i,t}^A / P_{i,t}^A = \tilde{P}_t^A / P_t^A$. The aggregate production function reads as follows:

$$N_t Y_t^A = \Gamma_t H_t^A, \tag{27}$$

where $H_t^A = L_t h_t^A = \int_0^{L_t} \int_{\omega \in \Omega} h_{i,\omega,t}^A \mathrm{d}\omega \mathrm{d}i$ corresponds to the total demand in labor inputs from incumbents in this sector and Y_t^A is the intensive margin in the abatement good sector.[11] The aggregate selling price, which takes into account the number of incumbents in the determination of the selling price, is:

$$P_t^A = \tilde{P}_t^A \, N_t^{\frac{1}{1-\zeta_A}}. \tag{28}$$

The labor market is at equilibrium when the total supply of households $H_t = L_t h_t = \int_0^{L_t} h_{i,t} \mathrm{d}i$ is equal to the demand from firms producing intermediate goods $H_t^I = \int_0^{L_t} h_{i,t}^I \mathrm{d}i$, abatement good incumbents H_t^A, and startups $H_t^E = L_t h_t^E = \int_0^{L_t} h_{i,t}^E \mathrm{d}i$:

$$H_t = H_t^I + H_t^A + H_t^E, \tag{29}$$

where the aggregate supply of the final good is given by $Y_t = \Gamma_t \, H_t^I$.

Finally, we compute the share of abatement goods in output as follows:

$$\Psi_t = p_t^A \int_0^{L_t} \left(\frac{\Lambda_{i,t}}{Y_{i,t}}\right) \mathrm{d}i = p_t^A \theta_{1,t} \mu_t^{\theta_2}. \tag{30}$$

3 Bayesian inference and model evaluation

In this section, we estimate the model using Bayesian methods (see An and Schorfheide, 2007, for an overview). The posterior distribution associated with the vector of observable variables is computed numerically using a Markov chain Monte Carlo sampling approach.

[10] We do not remove the trend associated with the increase in temperature because it is endogenous and, thus, would make it impossible to compare different policies.

[11] Aggregate labor demands include the number of firms, as in Bilbiie et al. (2012).

We first describe how the nonlinear model with trends is solved. We then discuss the selected data and our choice of priors, comment on the posterior distribution of the structural parameters, and discuss the dynamic properties of the model.

3.1 Numerical solution method with stochastic growth We consider the *extended path solution method* from Fair and Taylor (1983) and Adjemian and Juillard (2014) to accurately measure the nonlinear effects of the environmental constraint on growth. In summary, the extended path approach uses a perfect foresight solver to obtain endogenous variables that are path consistent with the model equations. Each period, agents are surprised by the realization of shocks but still expect that in the future, shocks will be zero on average (consistent with rational expectations). The advantage of this method is that it provides an accurate and fast solution while considering all the nonlinearities of the model. The drawback of the approach is that Jensen's inequality binds to equality, which means that the nonlinear uncertainty stemming from future shocks is neglected. Note that this drawback also applies to the usual linearized dynamic stochastic general equilibrium models, such as Smets and Wouters (2007).

Taking nonlinear models to the data is a challenge, as nonlinear filters, which are required to form the likelihood function, are computationally expensive. An inversion filter has recently emerged as a computationally cheap alternative (e.g., Guerrieri and Iacoviello, 2017; Atkinson et al., 2020). Initially, pioneered by Fair and Taylor (1983), this filter recursively extracts the sequence of innovations by inverting the observation equation for a given set of initial conditions. Unlike other filters (e.g., Kalman or particle filters), the inversion filter relies on an analytic characterization of the likelihood function.[12]

The inversion takes place using the perfect foresight solution proposed by Juillard et al. (1996). The standard approach is to compute the dynamics of the variables given current and future shocks. In the extended path context, the inversion filter *(i)* substitutes current shocks and some endogenous variables when applying the perfect foresight solution, and *(ii)* computes current shocks and nonobservable variable paths given the set of observable variables. Finally, we use the Metropolis-Hastings algorithm as a sampler to draw from the parameter uncertainty. We obtain a random draw of 320,000 from the posterior distribution of the parameters (8 parallel chains drawing 40,000 iterations, with a common jump scale parameter to match an acceptance rate of approximately 30%).

[12]For a presentation of alternative filters to calculate the likelihood function, see Fernández-Villaverde et al. (2016). See also Cuba-Borda et al. (2019) and Atkinson et al. (2020) for details on the relative gains of the inversion filter.

3.2 Data description The model is estimated using worldwide annual data from 1961 to 2019.[13] Macroeconomic series are from the *World Bank*. Real GDP and private consumption are expressed in current international dollars, converted by the 2017 purchasing power parity (PPP) conversion factor. The PPP conversion factor is a spatial price deflator and currency converter that eliminates the effects of the differences in price levels among countries. We also include some series that are related to the climate block of the model and are intended to pin down the key parameters of this block. Annual CO_2 emissions correspond to the emissions from the burning of fossil fuels for energy and cement production. For temperature, we use the global average land-sea temperature anomaly relative to the 1961-1990 average temperature. CO_2 emissions are from *Our World In Data*, while temperature anomalies are taken from *NASA*. As pointed out by Nordhaus (2018), CO_2 emissions relative to the world GDP exhibit a quasilinear negative trend with a growth rate equal to -1.26% over the full period. While the rate of decarbonization has slightly increased starting in 2000, the temperature has almost continuously increased in the sample. Temperature has increased by 0.8°C over the last 60 years. This evidence is reflected in the model by the dependence of temperature on the stock, not the annual flow, of CO_2 emissions.

Regarding the abatement good sector, we use the number of patents in environment-related technologies (see Panel D. of Figure 1), as collected by the *OECD* (Haščič and Migotto, 2015). In the absence of explicit data since 1960 documenting the number of worldwide firms operating in a green sector, patent data appear to be a reasonable alternative to measure the growth rate of green firms. We map the growth rate of environmental-related patents to the model growth rate of firms, $\Delta \log(N_t^E)$.

Importantly, contrary to most of the business cycle literature that uses a linearized version of the models to infer structural parameters, as exemplified by Smets and Wouters (2007), our solution method explicitly addresses trends and, thus, does not impose that variables must return to a steady state.[14] Consequently, we simply use the growth rate (i.e., the first

[13] Calibrating the model for a particular country or set of countries would raise the issue that climate change is a worldwide phenomenon. For this reason, a large part of the world's carbon would be emitted by regions that are not included in the model. An alternative approach would be to design a multicountry model, as in Kotlikoff et al. (2021). As we focus on environmental policies, this approach is beyond the scope of our paper.

[14] Linearization methods approximate any model decision rules around a fixed point and therefore impose that the model is stationary in the neighborhood of the fixed point. As a result, inference must be assessed based on stationary data; the latter implies a set of transformations (e.g., dividing by the population, business cycle filters).

difference of the logarithm) for quantity variables (GDP, consumption, CO_2 emissions, and number of patents) and the variation for temperature anomaly.[15]

3.3 Calibration and prior distribution of the parameters A first set of parameters is calibrated. They are reported in Table 1, while the initial conditions are described in Table 2.

As our dynamics for carbon cycles are similar to Nordhaus (1992), we borrow from DICE 1992 the value for the annual rate of transfer $\delta_M = 0.00833$ (leading to a carbon lifetime of approximately 120 years). The initial annual growth rate of the world population is set to 2% ($\ell_g = 0.02$) to replicate the observed dynamics of the world population between 1961 and 2018, which is very close to the calibration in DICE 1992 for a similar period of analysis. The initial world population L_{t_0} is 3.307 billion people in 1961 at the start of our sample, while the terminal state for population L_T is set as in DICE 2016 to 11.5 billion.[16]

Most of the other climate parameters and socioeconomic parameters common to the IAM literature are taken from the latest version of DICE in Nordhaus (2018) and Faulwasser et al. (2018). In particular, ϕ_{11}, ϕ_{12}, ϕ_{21}, ϕ_{22}, ξ_M, M_{1750}, σ_c, δ_σ, θ_2, δ_{pb}, and a are taken directly from DICE-2016R2. For initial values of state variables, as our simulations start sooner than DICE (with $t_0 = 1961$), we retropolate the starting values to reach 1961 through backward induction. The corresponding initial values are as follows: the cost of abatement θ_{1,t_0} is 0.1750, the emission-to-output ratio σ_{t_0} is 0.5878 (consistent with world data), atmospheric carbon M_{t_0} is 670 Gt, the surface temperature anomaly T_{t_0} is set to 0.21 (consistent with the mean surface temperature anomaly in 1961 relative to 1750), and the deep ocean temperature anomaly $T^*_{t_0}$ is set to zero. The carbon tax τ_{t_0} is set to \$ 3.8 per ton in order to match an initial abatement effort of $\mu_{t_0} = 3\%$ as in Nordhaus (2018). Revenues from the environmental policy are redistributed to households via lump-sum transfers. The subsidy rates to incumbents and startups are initially set to zero $s_t^A = s_t^E = 0$ in baseline but possibly vary in our policy experiments.

As abatement plays a key role in this paper, we provide a detailed discussion of these parameters. First, the value of $\theta_{1,1961}$ implies that to reach net zero, 17.5% of output should be spent in abatement, but because of exogenous technical change, the cost of abatement decreases by 2.5% every five years. At the end of our sample in 2019, the cost of reaching the net-zero transition — as measured by $\theta_{1,2019}$ — shrinks down to 7% of output as a result of exogenous technological efficiency. This share lies in the confidence intervals provided

[15] In the internet appendix, we provide a figure reporting the evolution of all observable variables used for the inference of structural parameters.

[16] Our predicted population dynamics are fairly in line with 2022 United Nations projections for population: our model predicts that the global population will reach 9.3 billion in 2050 and 10.65 billion in 2100 (versus 9.71 and 10.36 billion for United Nations projections).

by a set of different models provided in Gillingham et al. (2015). Parameter θ_2 is typically calibrated to increase the marginal abatement cost in reducing CO2 emissions. As explained in Nordhaus and Yang (1996), this parameter as well as the functional form of the abatement function are taken to replicate the mitigation cost structure in the US. Regional versions of DICE (referred to as RICE) also rely on a similar calibration. Finally, the discount factor β is set to 0.985 as in Nordhaus (2018), which is consistent with a real interest rate of 5% (i.e., $\beta = g_{z,t_0}^{\sigma_c}/1.05$).[17]

TABLE 1. Calibrated parameter values (annual basis)

PARAMETER	NAME	VALUE	SOURCE
Panel A: Climate parameters			
CO_2 rate of transfer to deep oceans	δ_M	0.0833/10	Nordhaus (1992)
Climate sensitivity to carbon stock doubling	η	3.68	Nordhaus (2018)
Marginal atmospheric retention ratio	ξ_M	3/11	Nordhaus (2018)
Preindustrial carbon stock (Gt)	M_{1750}	588	Nordhaus (2018)
Atmospheric-Atmospheric temperature	ϕ_{11}	0.8718	Nordhaus (2018)
Atmospheric-Oceans temperature	ϕ_{12}	0.0088	Nordhaus (2018)
Oceans-Atmospheric temperature	ϕ_{21}	0.025	Nordhaus (2018)
Oceans-Oceans temperature	ϕ_{22}	0.975	Nordhaus (2018)
Non-CO_2 forcing change	F_Δ	0.00588	Nordhaus (2018)
Non-CO_2 forcing cap	$F_{\max}$	1	Nordhaus (2018)
Panel B: Socio-economic parameters			
Final population (billion)	L_T	11.500	Nordhaus (2018)
Population growth rate	ℓ_g	0.02	Nordhaus (2018)
Discount factor	β	0.985	Nordhaus (2018)
Curvature of utility of consumption	σ_c	1.45	Nordhaus (2018)
Curvature of disutility of labor	σ_h	1	Galí (2007)
Elasticity of substitution between goods	ζ	6	Galí (2007)
Public spending share in output	g_y	0.16	Authors' calculations
Rate of decline of emission-to-GDP trend	δ_σ	0.001	Nordhaus (2018)
Rate of decline of productivity	δ_Z	0.005	Nordhaus (2018)
Damage cost	a	0.00236	Nordhaus (2018)
Panel C: Abatement goods sector parameters			
Elasticity of substitution between abatement goods	ζ_A	6	Galí (2007)
Entry cost to output ratio	$X_q\ \bar{N}_{t_0}^E/(\bar{y}_{t_0}^A \bar{N}_{t_0})$	0.0385	Cacciatore and Fiori (2016)
Abatement cost parameter	p_b	716.7/1000	Nordhaus (2018)
Curvature of abatement cost	θ_2	2.6	Nordhaus (2018)
Persistence in cost of abatement growth	δ_{pb}	0.025/5	Nordhaus (2018)
Sunk cost labor	X_w	1	Bilbiie et al. (2012)

Concerning parameters that are not common with DICE, we mainly build on the macroeconomic textbook of Galí (2007). The elasticity of substitution across varieties in each sector is set to 6, which generates a markup of 20%, and the labor curvature σ_h is set to 1. Regarding the technology, the initial output Y_{t_0} is worth 15.917 trillion in 2017 PPP U.S. dollars, while

[17] We rely on Holston et al. (2017), who provide U.S. estimates of the natural rate of interest, i.e., the real short-term interest rate that would prevail in the absence of transitory disturbances, which is the consistent notion within our framework. Notice, however, that the world real interest rate may be above 5% in the 1960s due to significant sovereign risk premia for many countries, especially emerging countries.

the initial labor supply is normalized to one. We also compute using world data the share of public spending in output g_y and find a value of 16% on the sample period. The resulting calibration pins down the shift parameter in the utility function $\psi_h = 1.07$ and the initial productivity level $Z_{t_0} = 4.81$.

The last parameters to be calibrated concern the magnitude of the sunk costs. Concerning sunk costs paid in terms of the final good, there is no way to measure or infer their values for the environmental goods sectors. We therefore build on previous studies on advanced economies to calibrate these parameters. First, the entry cost-related product market regulation represents 1.98% of output according to Cacciatore and Fiori (2016) in Europe. This value is calculated on the number of business days required to fulfill entry requirements, converted into units of output lost. In addition to these administrative costs, prospective entrants must also pay an additional cost of technology catch-up, which represents 1.87% of GDP in OECD economies. These two costs are gathered into X_q and represent 3.85% of the abatement good sector. In addition to this entry cost, the sunk cost in hours X_w is normalized to one, as in Bilbiie et al. (2012).

The rest of the initial steady-state variables (e.g., number of firms) are pinned down by the model equations.

TABLE 2. Initial conditions for state variables in 1961

NAME	PARAMETER	VALUE	SOURCE
Initial period	t_0	1961	Data availability
Emissions-to-output ratio	σ_{t_0}	0.5878	Data
Abatement effort	μ_{t_0}	0.03	Nordhaus (2018)
Hours demand (normalized)	$H^d_{t_0}$	1	Galí (2007)
Population (billion)	L_{t_0}	3.307	Data
Real output (trillion U.S. dollars)	Y_{t_0}	15.917	Data
Stock of carbon (Gt) in 1961	M_{t_0}	670	Authors' calculations
Atmosphere temperature anomaly	T_{t_0}	0.21	Data
Deep oceans temperature anomaly	$T^*_{t_0}$	0	Data
Non-CO_2 forcing	F_{EX,t_0}	0.235	Authors' calculations
Carbon tax	τ_{t_0}	0.0038	Authors' calculations
TFP level	Z_{t_0}	4.8142	Authors' calculations
Carbon intensity	σ_{t_0}	0.5878	Authors' calculations
Abatement cost (level)	θ_{1,t_0}	0.1750	Authors' calculations
Number of products	N_{t_0}	0.0116	Authors' calculations

Prior distributions of the parameters are reported in Table 3. For exogenous disturbances, the standard deviations impose an inverse gamma "type 2" with a prior mean of 0.001 and a standard error of 0.1. Our prior is inspired by Christiano et al. (2014) but with a less informative prior. The persistence of stochastic disturbances is taken from Smets and Wouters (2007) with a beta distribution with a prior mean of 0.5 and a standard error of 0.2. The deterministic growth rate of the TFP in the initial state, g_{z,t_0}, is indirectly measured by the inference of the deterministic growth rate of output $(Y_{t_1}/Y_{t_0} - 1) \times 100$. Its prior is a gamma distribution with a mean of 4 and a standard error of 1. This prior imposes that the initial growth rate is positive and lies roughly between 2% and 6%. This interval includes the observed annual rate of growth that is approximately 5% in real terms during the 1961-90 period. For the decoupling rate of the emissions-to-output ratio, denoted by $(\sigma_{t_1}/\sigma_{t_0} - 1) \times 100$, a gamma distribution is imposed, with a prior mean of 1 and a standard error of 0.1. This prior imposes that the decoupling rate lies between 0.8% and 1.2%, consistent with the rate observed in the 1960s. The effects of radiative forcing on temperature anomalies are measured by elasticity ξ_T, which is typically 0.1005 in the latest DICE model. Instead of calibrating this parameter, we let the data be informative and impose a prior mean of 0.15 and a standard error of 0.02. The exit rate δ_A is set to 10% in Bilbiie et al. (2012) but is not empirically motivated. In particular, as the exit rate of startups may be higher, we assume a beta distribution to bound the parameter in the support [0,1], with a mean of 0.2 and a standard deviation of 0.1, which is a rather diffuse prior. Finally, the entry congestion cost χ is given a prior consistent with the adjustment cost parameter in Smets and Wouters (2007), i.e., a gamma distribution with a mean of 4 and a standard deviation of 1.5.

TABLE 3. Prior and posterior distributions of structural parameters and shock processes

	PARAMETER	PRIOR DISTRIBUTION			POSTERIOR DISTRIBUTION
		Shape	Mean	Std.	Mean [5%;95%]
Panel A: Structural parameters					
Initial output growth rate	$(Y_{t_1}/Y_{t_0} - 1) \times 100$	$\mathcal{G}$	4	1	4.991 *[4.867;5.129]*
Initial emissions-to-output decoupling rate	$-(\sigma_{t_1}/\sigma_{t_0} - 1) \times 100$	$\mathcal{G}$	1	0.10	1.132 *[1.028;1.232]*
Temp. elast. to radiating forcing	ξ_T	$\mathcal{B}$	0.15	0.02	0.084 *[0.069;0.108]*
Exit rate	δ_A	$\mathcal{B}$	0.20	0.10	0.060 *[0.028;0.095]*
Entry congestion cost	χ	$\mathcal{G}$	4	1.5	5.626 *[3.660;7.794]*
Panel B: Shock processes					
Std dev. productivity	σ_Z	$\mathcal{IG}_2$	0.001	0.1	0.015 *[0.012;0.017]*
Std dev. government spending	σ_G	$\mathcal{IG}_2$	0.001	0.1	0.030 *[0.026;0.036]*
Std dev. CO_2 emissions	σ_E	$\mathcal{IG}_2$	0.001	0.1	0.015 *[0.013;0.017]*
Std dev. firm entry	σ_N	$\mathcal{IG}_2$	0.001	0.1	0.089 *[0.077;0.104]*
Std dev. temperature	σ_T	$\mathcal{IG}_2$	0.001	0.1	0.132 *[0.111;0.160]*
AR(1) productivity	ρ_Z	$\mathcal{B}$	0.50	0.2	0.949 *[0.903;0.982]*
AR(1) government spending	ρ_G	$\mathcal{B}$	0.50	0.2	0.867 *[0.781;0.940]*
AR(1) CO_2 emissions	ρ_E	$\mathcal{B}$	0.50	0.2	0.940 *[0.886;0.979]*
AR(1) firm entry	ρ_N	$\mathcal{B}$	0.50	0.2	0.592 *[0.446;0.728]*
AR(1) temperature	ρ_T	$\mathcal{B}$	0.50	0.2	0.181 *[0.051;0.425]*
Log marginal data density					381.5134

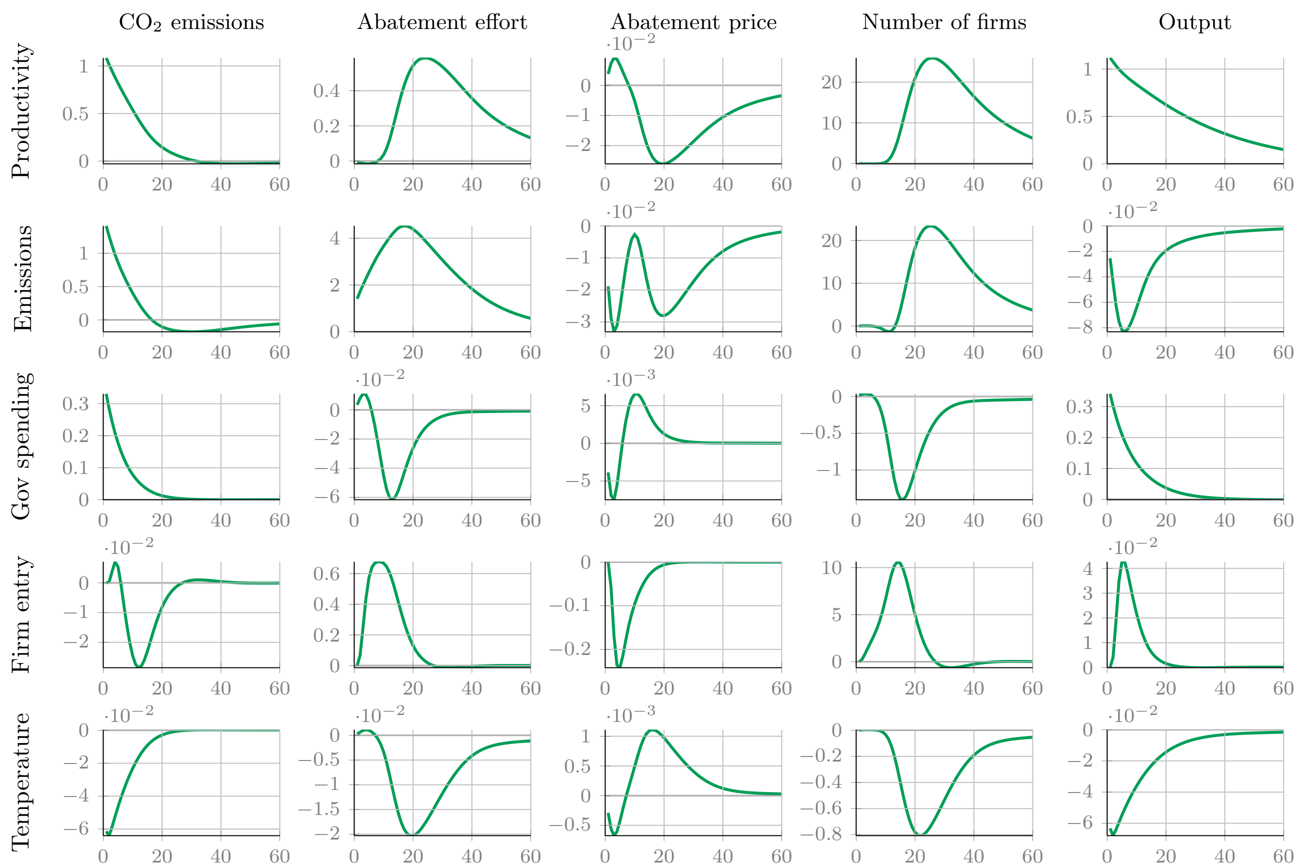
Note: $\mathcal{B}$ denotes the beta, $\mathcal{G}$ the gamma, and $\mathcal{IG}_2$ the inverse gamma (type 2) distributions. The last 160,000 draws are used to compute the posterior mean and 90% confidence interval.

3.4 Posterior estimates of the parameters The last column of Table 3 reports the posterior mean and the 90% confidence interval of the estimated parameters. The first two parameters represent the initial growth rate of the economy and the initial decline rate in the emission-to-output ratio, which are estimated at approximately 4.99% and 1.13% in the initial state, respectively. These values are fairly close to those proposed by Nordhaus (1992) for 1965 (4% and 1.25%, respectively). Regarding the climate block, we estimate the parameter capturing the sensitivity of temperature to radiative forcing (ξ_T in Equation (4)) and obtain a value of 0.084, slightly below the values used in DICE 2013 and DICE 2016. We also estimate two parameters associated with the abatement good sector. The firm's exit rate δ_A is equal to 0.06, and the entry congestion cost χ is equal to 5.63. The exit rate is lower than in Bilbiie et al. (2012) but captures the observed 7% growth rate of environment-related patents in the sample. Our posterior mean of the entry congestion cost is slightly lower than the estimated value of 9.435 obtained by Lewis and Poilly (2012). Finally, we estimate the parameters pertaining to the dynamics of the five shocks introduced in the model ($\varepsilon_{Z,t}$, $\varepsilon_{G,t}$, $\varepsilon_{E,t}$, $\varepsilon_{N,t}$, $\varepsilon_{T,t}$). As usually found in the estimated dynamic stochastic general equilibrium models such as Smets and Wouters (2007), productivity and government spending shocks are highly autocorrelated. This is also the case for the shock on CO_2 emissions, with an autoregressive coefficient of 0.94. The shock on firm entry is less persistent, and the shock on temperature is weakly correlated at an annual frequency, with a coefficient of 0.18.

3.5 Model evaluation This section discusses the dynamic properties of the model through *(i)* the impulse response functions of a number of variables of interest to various shocks and *(ii)* the second moments of the observable variables. Both analyses are useful in assessing how shocks to economic variables reverberate through the system and checking if the model correctly captures the statistical properties of the macroeconomic and climate-related data.

Figure 3 displays the economy's response to a 1% increase in five shocks: productivity, CO_2 emissions, government spending, firm entry, and temperature, in Lines 1 to 5, respectively. They are globally consistent with business cycle theory. For example, a positive productivity shock increases aggregate output, which worsens CO_2 emissions. Hence, the abatement effort increases to meet the emissions target. This effort stimulates the development of the abatement good sector, with a growing number of firms, which makes the abatement price decrease. Then, the variables smoothly return to their initial values (corresponding to 2019) as the highly inertial productivity shock dissipates. As shown in the second line of plots, an exogenous increase in CO_2 emissions immediately raises the abatement effort to meet the

FIGURE 3. Generalized impulse response functions



Note: The figure displays the generalized impulse response functions (GIRFs) of several variables to five shocks: productivity, CO_2 emissions, government spending, firm entry, and temperature, in Lines 1 to 5, respectively. GIRFs are computed using the value of state variables from 2019, and each GIRF is expressed in percentage deviations from its initial value in 2019. GIRFs are averaged based on 500 exogenous draws.

emissions target. This effort again encourages the entry of startups into the abatement good sector and makes the abatement price decrease as the sector develops. Meanwhile, the damaging effect of emissions on TFP, the levy of the carbon tax, and the costly abatement effort adversely affect output, which decreases by almost 5% compared to its initial value in the short run. The third line of plots shows that, as a demand shock, an exogenous increase in government spending stimulates the production of the final good and thus CO_2 emissions at the expense of abatement goods. Hence, the abatement effort and the number of firms fall by -5% and -1.1%, respectively, while the abatement price rises. Then, these variables return to their respective initial levels as the stimulating effect of the initial shock on output fades away. The fourth line of Figure 3 indicates that the number of firms in the abatement good sector rises (by nearly 10% at its peak) because of an exogenous increase in startup entries, which exacerbates competition and thus makes the abatement price drop. Hence, in line with Equation (14), abatement effort is encouraged. Aggregate production benefits from this increase in the number of firms through the increase in revenues paid in the abatement good sector, but without increasing CO_2 emissions. Finally, the responses to an exogenous and temporary increase in temperature, represented at the bottom of Figure 3, are interesting to assess the economic effects of a climate-related shock. By exacerbating damage to firm productivity, this shock strongly depresses output (by more than 6% initially), which reduces CO_2 emissions accordingly. Consequently, abatement efforts decrease, and the number of new firms in the abatement good sector shrinks. Last, reduced competition pushes the abatement price up.

TABLE 4. Empirical and model-implied moments

	DATA	Baseline model [5%;95%]	DICE model [5%;95%]
Standard deviations			
Output growth	1.50	[1.21;1.64]	[1.20;1.66]
Consumption growth	1.18	[1.18;1.60]	[1.21;1.64]
Emission growth	2.24	[1.67;2.39]	[1.70;2.43]
Temperature change	0.12	[0.11;0.16]	[0.11;0.17]
Patent growth	10.01	[7.62;13.15]	–
Autocorrelation			
Output growth	0.43	[-0.05;0.43]	[-0.08;0.45]
Consumption growth	0.51	[-0.05;0.43]	[-0.05;0.45]
Emission growth	0.50	[-0.18;0.34]	[-0.20;0.33]
Temperature change	-0.32	[-0.16;0.34]	[-0.19;0.35]
Patent growth	0.63	[0.26;0.73]	–

Note: Model-implied moments are computed across 1,000 random artificial series, each with the same size as the data sample (57). The baseline model corresponds to our macro-climate model with firm entry and the DICE model is the alternative version without firm entry.

Table 4 provides the empirical second moments of our five observable variables and the 95% confidence interval, as obtained with our model and an alternative model with perfect competition in the abatement good sector. The latter model corresponds to DICE-2016R2. The estimation of the DICE model includes the same observable variables except for patent growth (and no shock $\eta_{N,t}$). Consequently, likelihood or standard information criteria cannot be employed to discriminate across models. We thus rely on the comparison of second moments. We find that both models accurately replicate the empirical moments, although both models yield less persistence than in the data. Importantly, our baseline model can reproduce the standard deviation and the autocorrelation of patent growth fairly well.

4 Inspecting the mechanism

In this section, we explain the contributions of firm entry and creation of new products in the abatement good sector to the response of the economy to changes in the carbon price and climate scenarios. First, we detail the long-term interaction between firm entry and carbon taxation in a static version of the model and explain what this assumption implies compared to a DICE model. Second, we present long-term projections under several CO_2 emissions scenarios, derived from the dynamic version of the model, to understand how an endogenous determination of the number of producers and products affects the path of key variables.

4.1 Long-term interaction between firm entry and carbon taxation We first provide a steady-state analysis in which the carbon tax τ is the only exogenous variable, and we measure how the other variables respond to a permanent change in τ.[18] Figure 4 displays the responses in both the DICE and baseline models.

In typical DICE models, sectors are perfectly homogeneous. A rise in the carbon tax forces firms to purchase some additional intermediate inputs, the latter being produced at the same selling price as the final good. The carbon tax deteriorates the marginal profit of firms and unintendedly reduces the labor income received by households. The real wage falls proportionally to the carbon tax (Panel C), which makes households less willing to supply labor (Panel B). The resulting macroeconomic outcome is a lower level of input (Panel A).

The presence of frictions in establishing a new product in the abatement good sector breaks this sectoral symmetry by lifting the price of abatement above the final good price. With respect to DICE, a fraction of hours is inefficiently spent in entry costs $N^E h^e$ in addition to the standard labor costs wh^A to produce the same quantity of abatement goods as DICE. This friction in entry entails a second-best economy with a lower level of utility (Panel D) and a higher price of reducing carbon emissions.

To dissect the firm entry mechanism, one can first look at the expression of the intensive margin, obtained by equalizing Equations (19) and (20) and replacing H^A, Π^A, and $\tilde{p}^A$ by their expressions in Equations (15), (16), and (17):

$$Y^A = \underbrace{X_w}_{\text{entry cost in labor}} \theta_1 \underbrace{(\zeta_A - 1)}_{\text{pricing decisions}} \underbrace{\left(\frac{r - 1 + \delta_A}{1 - \delta_A}\right)}_{\text{valuation of firms}}. \tag{31}$$

[18]In this exercise, trends are set to their 2019 values, and climate effects on TFP are not considered to isolate only the permanent effects on the abatement good sector of a permanent rise in the carbon tax. In addition, the fixed entry cost X_q is set to zero (without loss of generality) to have simple closed-form expressions.

In addition to the abatement cost θ_1, the intensive margin has three determinants. The first term is the entry cost in labor X_w, which represents a barrier preventing new competitors from entering the market. This means that a high entry cost X_w depresses competition and increases the market share of existing firms. The second term $(\zeta_A - 1)$ originates from the pricing decisions in the wake of CES preferences. When goods are more substitutable (i.e., when ζ_A is high), margins of existing firms are reduced, which discourages new competitors from entering the market. Finally, the last term originates from the valuation of firms: if the opportunity cost of establishing a new firm rises (i.e., when r is high) or if the exit rate δ_A is high, financial markets reduce the financing to startups. As a result, existing firms are favored with respect to prospective entrants, and the intensive margin increases. Importantly, the fact that the intensive margin is inelastic to the carbon tax change constitutes an impediment to entry. To successfully enter a market, a startup must reach the same production level as incumbents to be viable. When a market is immature (measured by a low carbon tax), there is not enough demand for a large number of competitors, and only a few competitors are able to thrive.

Let us now consider the drivers of the number of firms in the abatement good sector determined by the static version of Equations (26), (28), and (14):

$$N = \left(\theta_1 \mu(\tau)^{\theta_2} \frac{Y}{Y^A} \right)^{\frac{(\zeta_A - 1)(\theta_2 - 1)}{(\theta_2 - 1)(2\zeta_A - 1) - \theta_2}}. \tag{32}$$

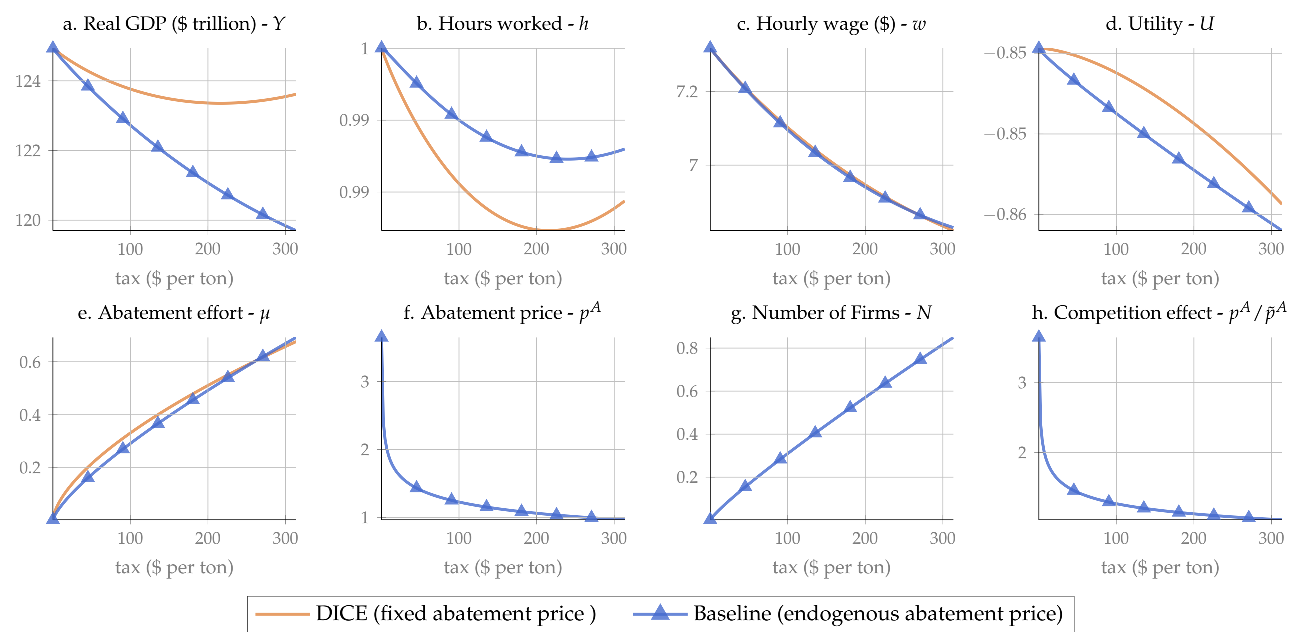
Interestingly, the carbon tax affects the number of competitors in such a way that an increase in market size is fully absorbed by new entrants. As the exponent on the right-hand side of Equation (32) is positive but below unity, the number of firms as a function of the carbon tax is strictly increasing, strictly concave, as reported in Panel G. As a result, the marginal number of entry diminishes as the carbon tax grows. Therefore, the marginal benefits from increased competition are higher when the market structure is immature.

To understand the benefits from increased competition on prices, let us consider the aggregate price index for abatement goods in Equation (28):

$$\frac{p^A}{\tilde{p}^A} = N^{-\frac{1}{\zeta_A - 1}}. \tag{33}$$

This price ratio, referred to as the competition effect in the literature on trade, isolates how the number of competitors affects the price of firms. In the frictionless-entry economy, the number of firms does not play a role; hence, the efficient price of each variety is $\tilde{p}^A$, while the ratio in Equation (33) is one. In the presence of frictions in entry, the aggregate price is higher than its efficient level, and the ratio is above one, as displayed in Panel H. An increased carbon tax tends to boost the number of competitors as the market size grows. The competition effects take place through Equation (33) by reducing the ratio between the effective and the efficient price of green products. These gains from competition, however, exhibit diminishing returns to scale: the more (resp., less) immature the market, the higher (resp., lower) the marginal benefits of having an additional variety of abatement goods.

FIGURE 4. Static effects of an increase in carbon tax on the model's variables



4.2 Model-implied projections under CO_2 emissions scenarios We now present long-term projections derived from the dynamic version of our model, which are based on two alternative scenarios. The first scenario matches the so-called SSP1-1.9 pathway of the IPCC (2021) in terms of carbon emissions (*Paris Agreement*). It assumes that carbon neutrality is reached in 2060 thanks to the introduction of a carbon tax, with net emissions close to -10 Gt by 2100. Although some countries in Europe, for example, have committed to reaching net-zero emissions by 2050, others (in particular, advanced economies) have committed to longer time horizons, which is why we retain the conservative horizon of 2060 for carbon neutrality. The second scenario is equivalent to IPCC (2021)'s SSP3-7.0 pathway, i.e., it assumes that there are no environmental policies, resulting in a continuous increase in carbon emissions (*laissez-faire*). In our simulations, the value of the carbon tax is determined to match the desired control rate of emissions for each scenario, and the model endogenously generates out-of-sample forecasts based on the posterior distribution of both parameters and shocks.[19] In particular, we compute uncertainty intervals from 500 random draws (see Cai and Lontzek, 2019 on the importance of taking into account stochastic features of both the climate and the economy). The future path of the carbon tax rate was announced in 2019, and expectations adjusted in response to this new environment. At this stage of the analysis, the carbon tax revenues are supposed to be redistributed to households through lump-sum transfers. It is important to note that our analysis focuses on climate change mitigation, not on an optimal tax per se.

Figure 5 shows the results of these simulations. The red line corresponds to the laissez-faire trajectory, which would result in a 4°C increase in temperature. The green line is associated with the carbon trajectory that would be consistent with temperatures below 2°C above preindustrial levels. It is worth noting that our scenarios approximately replicate the carbon emissions trajectories of the corresponding scenarios formulated by IPCC (2021), although our temperature projections do not exactly match those reported by the IPCC because of the different parameterization of the model.

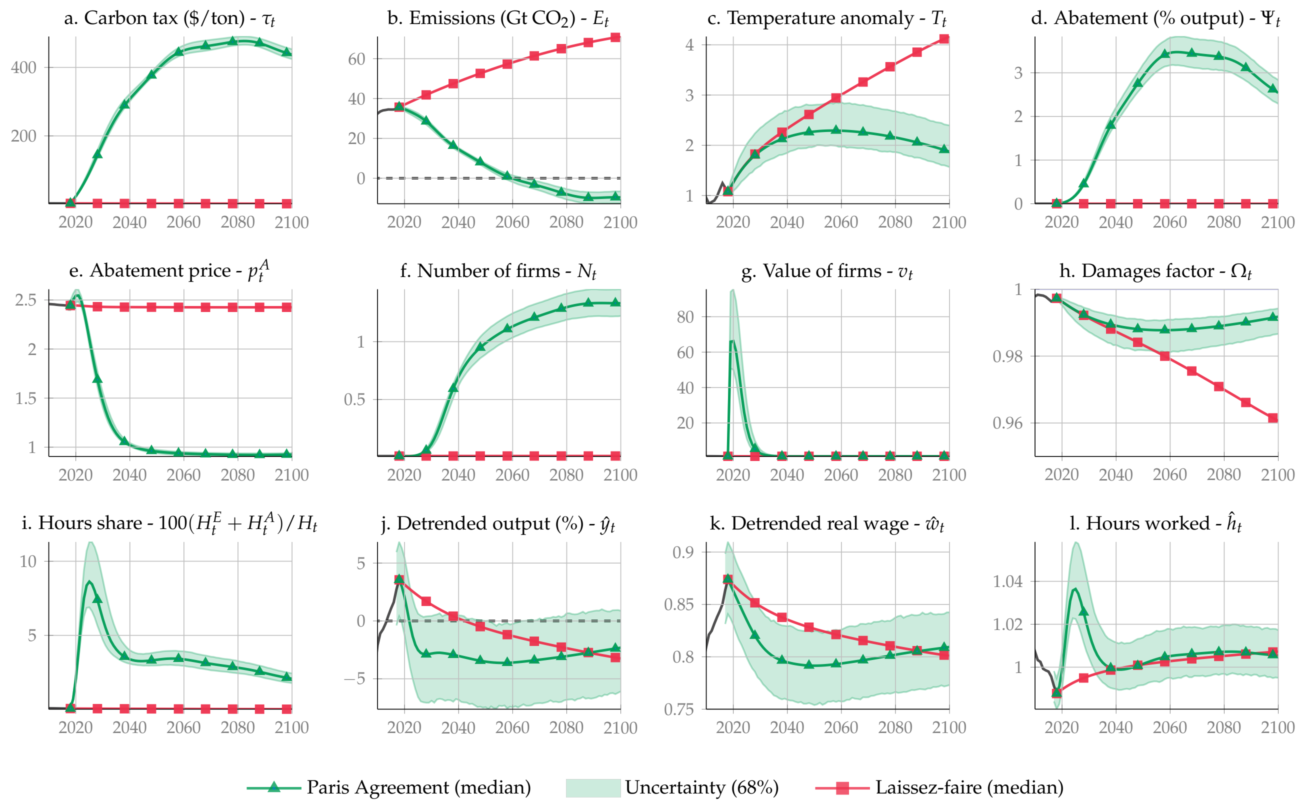
In the laissez-faire scenario, no policy would be implemented to curb CO_2 emissions, which is also reflected by a carbon tax equal to zero and the absence of abatement. Emissions peak up to 57 Gt in 2060 and 70 Gt in 2100, which induces more atmospheric loadings of CO_2, a higher radiative forcing, and finally an increase in temperature by approximately 4°C by 2100. In the medium run of this scenario, there is a recession after 2040 due to the damage induced by climate change. In the long run, damages increase over time and reach a level of 1.5% of GDP per year in 2050 and 4% per year in 2100. The detrended output, currently equal to 3%, decreases slowly to -1% in 2050 and -3% in 2100.

In contrast, the Paris Agreement scenario requires strong control of carbon emissions, which should be negative to reverse the dynamics of the accumulated stock of carbon. To reach this objective, the carbon tax must dramatically increase to a maximum of $480 in 2080 so that emissions turn negative. How are carbon emissions reduced?

Initially, due to the low number of competitors in the abatement good sector, firms behave monopolistically and charge a high selling price. When the government announces the introduction of a carbon tax, producing firms seek to rapidly reduce their emissions by purchasing abatement goods. The prospect of future high profits in the abatement good sector boosts firms' market value and, through free-entry conditions, incentivizes prospective entrants to establish startups. The number of firms increases, and the resulting competition pushes firms

[19] The time horizon of our simulations is $t = 2,500$, as in the DICE-2016R2 model, to ensure that exogenous trends have converged to their asymptotic values.

FIGURE 5. Model-implied projections based on alternative control rates of emissions



Note: This figure displays the projections of the main variables of the macro-climate model under two scenarios, corresponding to temperature increases of +4°C (laissez-faire) and below +2°C (Paris Agreement) relative to preindustrial levels. The light green area denotes both parametric and stochastic uncertainties. Uncertainty intervals are computed from 500 random draws of shocks and parameters.

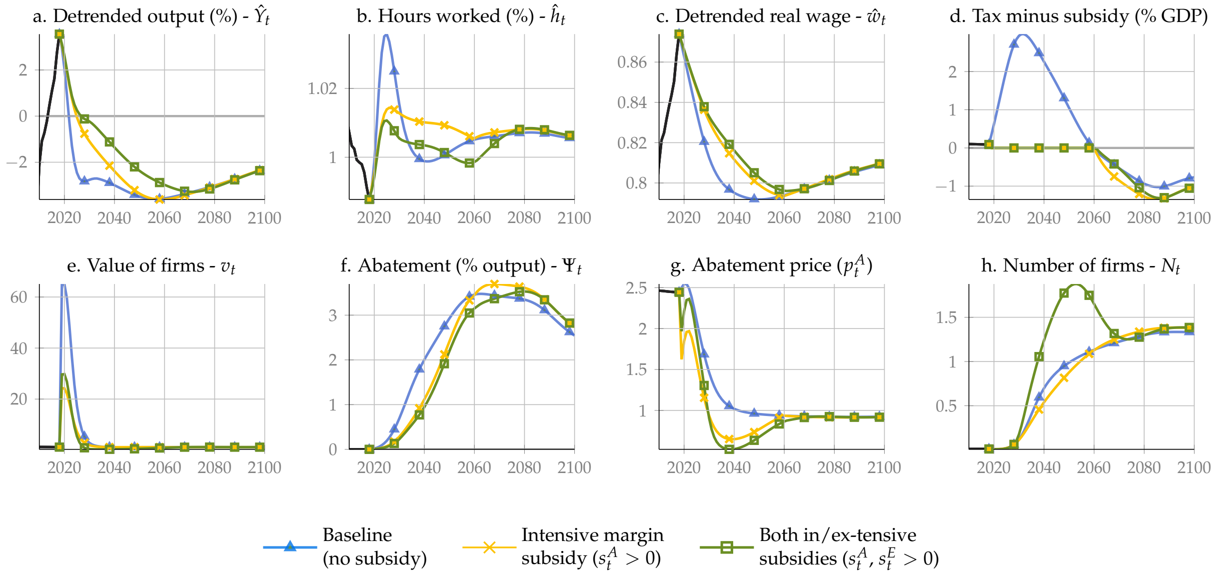
to compress their prices to maintain their market share. The relative cost of entry becomes proportionally smaller as the market size increases. After 2040, due to the increase in the extensive margin, the competition effect stemming from the rise in firm entry is strong, and the abatement price falls below 1.

Resources diversion in hours and inputs to the abatement good sector would have a large negative impact on GDP, with the abatement cost being as large as 3.4% of GDP in 2060. The detrended output would decrease by approximately 4% in the same period. This policy curbs climate change damages in 2100 from 4% in the laissez-faire scenario down to less than 1%.[20]

In the rest of the paper, we present simulations based on the assumption of a temperature increase below 2°C above preindustrial levels, in line with the Paris Agreement.

[20]These results are broadly consistent with the logic of a reduction in the production of consumption goods to curb carbon emissions, as promoted by the Club of Rome (Meadows et al., 1972). Our assessment does not consider the additional gain of curbing the temperature increase for climate events (physical risks).

FIGURE 6. Out-of-sample forecasts under alternative subsidy policies in the abatement good sector



Note: This figure displays the temporal evolution of the main variables of the model under two scenarios, corresponding to a temperature increase of +2°C relative to preindustrial levels. The baseline scenario corresponds to the carbon tax only case, and the subsidy scenarios are associated with a carbon tax and a subsidy to the margin of abatement firms with or without a subsidy to entrant firms.

5 QUANTIFYING THE EFFECTS OF ENVIRONMENTAL SUBSIDIES

We have just seen that the carbon policy can be less stringent under a more competitive abatement good sector. Thus, we assess how subsidizing EGSS could boost competition and mitigate the cost of the transition to a greener economy. Rather than assuming that carbon tax revenues are redistributed to households through lump-sum transfers (a standard practice in environment models), we propose using them in two ways: *(i)* a subsidy to the margin of existing firms in the abatement good sector and *(ii)* an optimal subsidy to both existing firms and startups.[21] Figure 6 presents the projections of the main variables of our model under both alternative policies in the abatement good sector. The period of analysis starts in 2019 at the end of the estimation sample when the carbon tax and subsidy policies are both announced and ends in 2100. The blue line corresponds to the trajectory consistent with a policy that contains temperatures below 2°C with a carbon tax only. The yellow line corresponds to the case where the carbon tax is complemented with a subsidy to the margin of abatement firms ($s_t^A > 0$ in Equation (16)). In this scenario, carbon tax revenues are used to reduce the price of the abatement technology and help the diffusion of the technology to the

[21]The remaining government spending is financed by lump-sum taxes and debt ($G_t = B_t - r_{t-1}B_{t-1} - \xi_t$), and g_y continues to be equal to 0.16, such that the budget constraint suffers only one change.

intermediate goods sector. The green line corresponds to the case where the government uses carbon tax revenues to subsidize both incumbents ($s_t^A \geq 0$) and prospective entrants ($s_t^E \geq 0$ in Equation (20)) in the abatement good sector. In this case, the share of carbon tax revenues attributed to entrants is chosen optimally to maximize social welfare. In the following, we discuss each case in turn.

5.1 Environmental subsidies on the intensive margin We first analyze how the proceeds from the carbon tax revenues can be employed to reduce costs in the abatement good sector and mitigate the recession induced by the carbon tax rise. Formally, the government subsidizes the abatement good sector proportionally to its input costs as follows:

$$s_t^A H_t^A w_t = \tau_t E_t. \tag{34}$$

The introduction of the subsidy massively reduces the selling abatement price (Figure 6, Panel G). The price of the abatement goods, relative to the price of the final good, is instantaneously reduced from 2.5 to 1.5 in approximately 8 years. While parity with the price of the final good is reached after 2040 in the baseline case, such parity is obtained before 2030 in the case with the subsidy. Because the diffusion of the abatement technology is much faster than in the baseline case, the aggregate cost of abatement for society is reduced, from 2% of GDP to 0.8% in 2040 and from 2.7% to 2% in 2050. Consequently, the recessive effect of decarbonization on economic growth is substantially attenuated (Panel A), and fewer hours worked are necessary to produce the same amount of goods. In 2040, the detrended output is increased from -3% in the baseline scenario to -2% in the subsidy scenario (-3.4% and -3.2% in 2050, respectively).[22]

In addition, given the effectiveness of the subsidy, the carbon tax does not increase as much as in the baseline case. While the carbon tax jumps to \$300 per ton in 2040 and \$390 in 2050 when no subsidy mechanism is implemented, the tax increases only to \$160 in 2040 and \$300 in 2050 with subsidies on intensive margins. Finally, the carbon tax revenues become negative when emissions are negative (Panel D). In this case, the initial subsidy policy stops, and the negative carbon tax turns into another type of subsidy, directly financed by households. However, these transfers from households to firms are lump-sum, and they do not affect households' first-order conditions or their behavior.

[22] One should not conclude from Panel G that the economy would be better off without environmental policy. First, in the presence of tipping points, the loss of GDP in the absence of environmental policy would be much larger. Second, in the long run, the absence of policy would imply an almost infinite loss corresponding to a climate cataclysm.

Overall, even if the effect of the energy transition on economic growth is largely reduced, this policy deteriorates competition within the abatement good sector. Incumbents benefit from a subsidy that lowers their cost of production, which increases the equilibrium real wage. As a result, prospective entrants face a higher cost of entry, resulting in a lower number of abatement firms in the transition period.

5.2 An optimal environmental subsidy rate for firm entry In the second experiment, we analyze how the government uses carbon tax revenues to subsidize both incumbents and prospective entrants in the abatement good sector. In a first step, we determine the optimal subsidy, i.e., the share of the proceeds attributed to the incumbents and entrants, to smooth the transition to the low-carbon economy. To explore the policy trade-off faced by policy-makers between subsidizing entrants versus incumbents, we denote by $\varsigma \in [0;1]$ the fraction of the carbon tax that is used to subsidize prospective entrants. The value of ς satisfies the following subsidy-sharing rule across firms:

$$s_t^E H_t^E w_t = \varsigma \tau_t E_t \tag{35}$$

$$s_t^A H_t^A w_t = (1-\varsigma)\tau_t E_t, \tag{36}$$

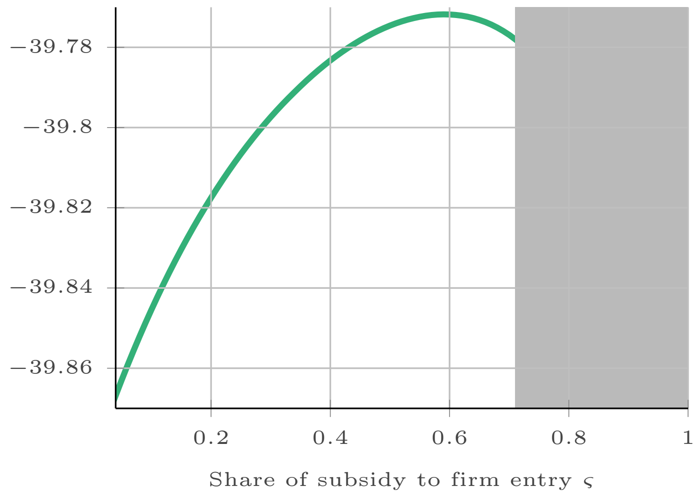
with $s_t^E, s_t^A \geq 0$. Equation (35) defines the subsidy rate to firm entry (s_t^E) such that the fraction ς of the carbon tax revenues is used to reduce the cost of entry in the abatement good sector. Equation (36) defines the subsidy rate to incumbents (s_t^A) such that incumbent firms receive the complementary $(1-\varsigma)$ of the carbon tax revenues.

The optimal share ς is determined by maximizing the social welfare, defined as

$$\mathbb{E}_t \left\{ \sum_{\tau=0}^{\infty} \beta^{\tau} \left(\frac{c_{t+\tau}^{1-\sigma_c}}{1-\sigma_c} - \psi_t \frac{h_{t+\tau}^{1+\sigma_h}}{1+\sigma_h} \right) \right\}. \tag{37}$$

We calculate the welfare value associated with each point of a grid on ς. Figure 7 displays the result and shows that the relationship between the subsidy share and welfare is concave. On the one hand, subsidizing existing firms only reduces the cost of abatement in the short term but could prevent new entries, creating high rents and deteriorating competition in the medium term. On the other hand, subsidizing startups only has a limited effect in the short run, as firm entry follows a gradual process, but definitely boosts competition and reduces the price of abatement in the medium term. Therefore, welfare increases in ς as long as the gradual future gain from competition outperforms the current loss from the short-term higher abatement price. The highest welfare value is obtained with a subsidy rate to startups equal to 60% of the carbon tax revenues.

FIGURE 7. Social welfare for various subsidy rates to startups



Note: The gray area represents the indeterminacy region that is reached when the value of new entrants v_t becomes negative. Social welfare represents the infinite discounted sum of future utilities. It is given in 2019 when the carbon tax policy is announced and reflects the future path of utilities under the net-zero transition.

We then compute the model-implied projections using $\varsigma = 0.6$, which corresponds to the green lines in Figure 6. The total number of firms jumps rapidly because of the sharp increase in the number of entries in the abatement good sector. Until 2050, the number of firms is almost double that in the baseline case. Such a boost of competition eventually results in a drop in the abatement price. After 2030, when the number of startups becomes substantial, the reduction in the abatement price exceeds the reduction obtained in the intensive margin subsidy case. Under this subsidy mechanism, at equilibrium, the deadweight loss is lower, as the cost of abatement is weaker. The abatement cost remains slightly lower than in the intensive margin subsidy case until 2080. The recession induced by the transition is substantially dampened because the recessive attenuation effect starts earlier. In 2040, the detrended output is increased from -2% in the scenario with an intensive margin subsidy to -1% in the efficient subsidy scenario (-3.2% and -2% in 2050, respectively). To reach a similar objective of CO_2 emission reduction in 2040, the carbon tax would increase to \$125 instead of \$300 in the baseline scenario and \$150 in the intensive margin subsidy case.

This analysis demonstrates that competition-friendly policies can become, in the decades to come, a serious source of mitigation at the cost of reaching a low-carbon economy. We also conclude that subsidizing abatement firms on the extensive margin, i.e., by reducing the congestion cost for new entrants, has a higher return on investment than subsidizing firms only on the intensive margin, i.e., by increasing their margin benefits.[23]

[23] Acemoglu et al. (2016) also find that research subsidies encourage production and innovation in clean technologies. Their demonstration relies on a microeconomic model in which a continuum of intermediate

5.3 GDP loss during the transition and subsidy multipliers We now quantify the effects of environmental subsidies in terms of GDP. The cumulative effect of global climate change will depend on how the world economy responds to increasing emissions. We therefore compare the evolution of GDP among three scenarios: *(i) laissez-faire* (no policy at all), *(ii) Paris Agreement* (carbon tax policy only), and *(iii) Paris Agreement* with optimal subsidies. Relative to the *laissez-faire* scenario, the Paris Agreement scenario implies a cumulative GDP loss equal to $266 trillion between 2019 and 2060, when net emissions reach zero. It represents an average annual loss of $6.3 trillion (for illustrative purposes, this amount represents 4.9% of 2019 GDP). This estimation corresponds to the recession implied by the carbon tax burden: firms are incentivized to divert resources from the production of the final good toward the abatement good sector. The distortionary carbon tax directly affects households that suffer a surge in the relative price of the final good. Lump-sum redistribution of the carbon tax revenues to households appears to be a natural solution to address the externality associated with a change in the relative price structure but may not be the most efficient.[24] Indeed, allocating the carbon tax revenues to subsidize the abatement good sector, according to the optimal weight of 60% on startups and 40% on existing firms, leads to a cumulative GDP loss of $145 trillion between 2019 and 2060. According to the green bars in Figure 8, optimal subsidies save $121 trillion of GDP, in other words, the average equivalent of $2.9 trillion each year. Importantly, the largest gains are made during the first 10 to 20 years of the policy, during which the subsidies allow the abatement good price to be drastically reduced and encourage the entry of new firms into the abatement good sector. The subsidy policy, thus, has a double benefit, first by accelerating the development of the abatement good sector and then by reducing the costs associated with the net-zero emissions objective by 2060. Consequently, such a policy substantially mitigates climate transition costs.

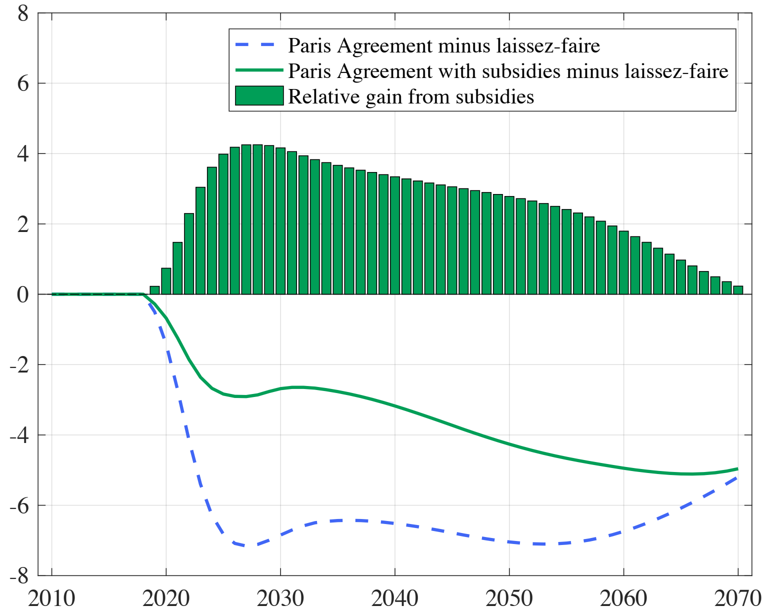
We also compute present value subsidy multipliers, which embody the full dynamics associated with exogenous fiscal actions and properly discount future macroeconomic effects (Fève and Sahuc, 2017; Leeper et al., 2017):

$$\mathcal{M}(t_0, \mathcal{T}) = \frac{\mathbb{E}_t \left\{ \sum_{t=t_0}^{\mathcal{T}} \tilde{\beta}_{t_0,t} \Delta X_t \right\}}{\mathbb{E}_t \left\{ \sum_{t=t_0}^{\mathcal{T}} \tilde{\beta}_{t_0,t} \Delta S_t \right\}}, \tag{38}$$

goods can be produced using either dirty or clean technologies. In our model, the intermediate goods sector reduces its carbon emissions by using abatement goods, such that we focus directly on the dynamics of the EGSS.

[24] Note that the carbon tax captures the transition cost toward a low-carbon economy but does not account for the positive impact of the policy through the reduction in physical risks.

FIGURE 8. Real GDP loss during the transition (in trillion of \$)



where $\tilde{\beta}_{k,t} = \beta^{t-k} g_{z,k}^{\sigma_c} \Pi_{j=k}^{t} g_{z,j}^{-\sigma_c}$, t_0 is the starting date of the fiscal policy experiment, $\mathcal{T}$ is the horizon of interest, and X_t is either Y_t (GDP) or C_t (private consumption). In this formula, ΔX_t is the net GDP (or consumption) gain between the scenario with both carbon tax and subsidy (optimally allocating) policies and the scenario with only the carbon tax policy, and ΔS_t is the related subsidy variation.

TABLE 5. Subsidy multipliers for various policy horizons

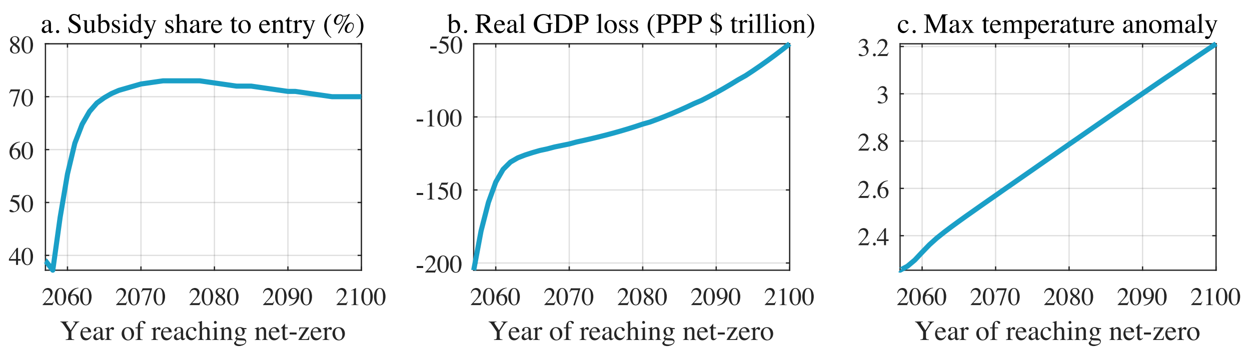
	2025	2030	2035	2040	2045	2050	2055	2060
GDP	2.22	2.01	1.83	1.73	1.67	1.66	1.68	1.73
Consumption	1.87	1.65	1.48	1.39	1.33	1.32	1.34	1.37

Note: Subsidy multipliers are calculated as the present values of additional GDP and consumption over a specific horizon produced by an exogenous change in the present values of public subsidies.

Table 5 displays the subsidy multipliers at various horizons until 2060. We observe that multipliers are large regardless of the horizon, highlighting the interest in implementing a subsidy policy. For GDP, multipliers are above 2 until 2030, when subsidies to startups and existing firms benefit the abatement good sector the most, consistent with Figure 6.

5.4 Subsidy sharing and CO_2 emissions target Reaching net zero by 2060 implies giving 60% of tax carbon revenues to startups. This redistribution policy may conditionally depend on how quickly net zero is reached. Implicitly, reaching net zero earlier is a more stringent policy that targets a lower level of temperature. We run new simulations in which the net zero objective varies between 2055 and 2100, and the subsidy share is thus recalculated optimally at each date. Figure 9 reports the results of this exercise. We find that the subsidy share is conditional on the final horizon of the climate policy objective. Reaching net zero sooner implies giving a larger subsidy share to existing firms (e.g., 80% in 2055) at the cost of a greater GDP loss. The reason is that firm entry is a gradual process that takes time to generate economic effects. Therefore, to transition quickly to net zero, it is more efficient to rely on existing firms rather than seeking to gradually increase the number of startups, which takes time. The drawback is that the price of abatement goods falls less, and therefore, the costs in terms of GDP will be higher. For instance, the cumulative GDP loss would be $190 trillion for a net-zero target in 2055. This cost is reduced when the target is postponed and a larger share is given to startups, as there is enough time to let startups enter the market to fully exploit the gain from competition.

FIGURE 9. Effects of various temperature targets on the share of subsidies to startups



Note: The figure reports on the y-axis (i) the subsidy share to startups (Panel A), (ii) real GDP loss, computed as the cumulative difference between the GDP from the Paris Agreement scenario and the one from the laissez-faire scenario (Panel B), and (iii) maximum temperatures, defined as the peak of temperature generated by the model under alternative emission control policies (Panel C), for various climate policies immediately implemented in 2050, or delayed up to 2100 on the x-axis.

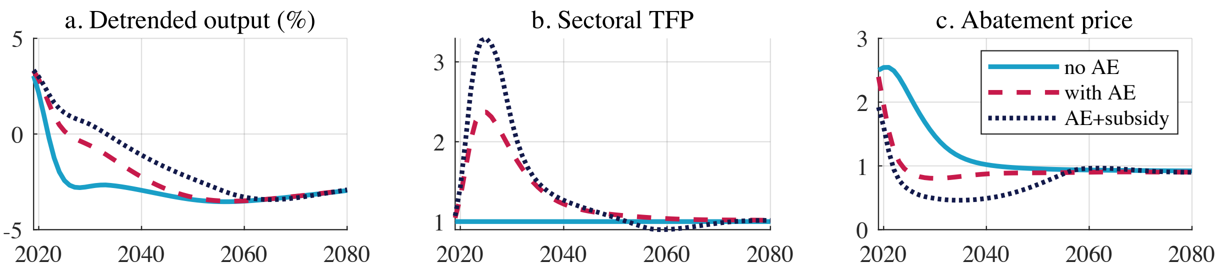
6 Robustness analysis

In this last section, we implement two additional exercises to check the robustness of our main results (details are relegated to the online appendix). First, we incorporate *allocative efficiency* in the abatement good sector. According to the literature on structural reforms, pioneered by Nicoletti and Scarpetta (2003), market competition improves allocative efficiency by forcing least productive firms to exit the market, which in turn allows the remaining resources to be reallocated across the most productive firms. Such a mechanism leads to a higher productivity of the firms concerned by increased competition and generates economic growth. We assume that the production function of abatement good producers is written as

$y_{i,\omega,t} = \Gamma_t \Gamma_t^A h_{i,\omega,t}^A$, where Γ_t^A is a new productivity term whose growth rate depends on the change in the churn rate δ_t as follows $\Delta\Gamma_t^A = \varsigma\Delta\delta_t$, with ς denoting a sensitivity parameter.[25] For any $\varsigma > 0$, less productive firms exit the market, which in turn increases the productivity of this sector. The churn rate is assumed to simply be the sum of the number of entries and exits divided by the end-of-period number of firms: $\delta_t = \left(\delta_A N_{t-1} + (1-\delta_A) N_{t-1}^E\right)/N_t$. Allowing $\varsigma > 0$ generates an endogenous productivity level for the abatement good sector and makes this setup closer to the endogenous growth theory applied to the context of climate models (e.g., Acemoglu et al., 2012; Dietz and Stern, 2015). We simulate this model by starting from a neutral initial sectoral TFP ($\Gamma_t^A = 1$) and with $\varsigma = 3.26$ (Canton et al., 2014).

Figure 10 reports the time path of key endogenous variables of the baseline model (plain blue line) and the model with allocative efficiency (red dashed line). In the presence of allocative efficiency, the TFP of the abatement good sector is twice as high as that in the rest of the economy.[26] As a result, the price of abatement goods falls and thus lowers the cost of the transition in terms of detrended output. In addition, the subsidy policy (dotted black line) is still able to curb the transition cost, while to a lesser extent, as only 33% of the recession is dampened, instead of 50% in the baseline case.

FIGURE 10. Projections with allocative efficiency (AE) and optimal subsidy policy



Note: The figure displays the model-implied projections for three alternative versions of the model: (i) with no allocative efficiency (plain blue), (ii) with allocative efficiency (dashed red), and (iii) with both allocative efficiency and the optimal subsidy policy (dotted black). All parameters are taken at the posterior mean obtained from the estimated labor-only model.

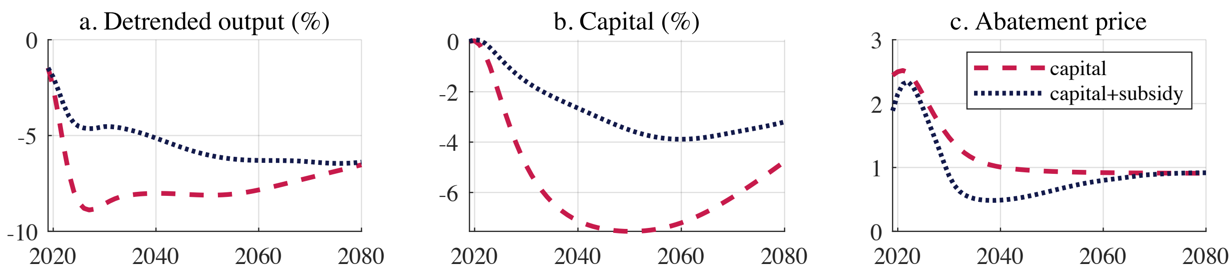
Second, we extend the baseline model by incorporating *physical capital*. The key question is whether the net-zero transition involves cyclical changes in physical capital that are strong enough to alter our findings. To this end, we assume that intermediate goods producers use both labor $(h_{i,t}^I)$ and capital $(k_{i,t}^I)$ to produce their goods according to the Cobb-Douglas

[25] Note that the baseline model is a particular case of this framework, in which $\varsigma = 0$.

[26] In this new scenario, the optimized share of carbon tax revenues going to startups increases up to 71%. The intensive margin is already very effective, and as a result of allocative efficiency, incumbents have less need for subsidies.

production function $y_{i,t} = \Gamma_t \left(h^I_{i,t}\right)^{\alpha} \left(k^I_{i,t}\right)^{1-\alpha}$, with $\alpha \in (0,1)$ denoting the labor share. Investment in physical capital requires the use of the same composite of all available varieties as the consumption basket. Physical capital obeys a standard accumulation process with depreciation rate $\delta_k \in (0,1)$.

FIGURE 11. Projections with capital and optimal subsidy policy



Note: The figure displays the model-implied projections for three alternative versions of the model: *(i)* without capital in the production function (plain blue), *(ii)* with physical capital in the production function (dashed red), and *(iii)* with both capital in the production function and optimal subsidy policy (dotted black). All parameters are taken at the posterior mean obtained from the estimated labor-only model. Note that smoothed shocks are not included in this simulation, which creates a gap with the previous simulations reported in the paper.

As with the baseline model, we simulate the capital model with $\alpha = 0.7$ and $\delta_k = 0.02$ as in the latest snapshot of DICE. Figure 11 reports the time path of key endogenous variables of the model with labor only (plain blue) and its counterpart with both labor and capital (dashed red) in the production function. Inclusion of physical capital amplifies the cost of the net-zero transition. The reason is that an increase in abatement spending by intermediate good firms results in a reduction in investment spending, in a persistent reduction in the capital stock, and eventually in a deeper recession. However, even though the recession is stronger with capital, the subsidy policy (dotted black line) is able to dampen it in a proportion similar to that obtained in the framework without capital.[27] This exercise highlights that our main results would still hold with capital, the only change lying in the magnitude of the recession.

7 CONCLUSION

This study has investigated the role of public subsidies in mitigating net-zero transition costs. The implementation of a pure carbon tax policy to reduce CO_2 emissions would result in substantial GDP losses because firms would divert resources to invest in environmental goods and services that are provided by an immature and low-competition sector. Mitigating the induced recession is possible through a massive subsidization of EGSS. By reducing labor costs for both entrants and incumbents operating in this sector, such a policy would accelerate

[27] In this setup, the optimal fraction of subsidy policy going to startups is lower (40%).

its development and offer a large reduction in the selling price of abatement technologies. This subsidy policy would have two main effects on the economy. First, in the transition phase, it would almost halve the distorting effect of the carbon tax compared to the carbon tax policy only. Second, accelerating the development of EGSS would significantly reduce GDP losses due to the transition to a low carbon economy. Eventually, the GDP loss would be reduced from $266 trillion between 2019 and 2060 to $145 trillion. Importantly, reducing entry costs in EGSS would accelerate the transition and reduce the GDP loss mainly at the beginning of the transition.

To the best of our knowledge, this is the first attempt to estimate a nonlinear macro-climate model including environmental and macroeconomic trends. By combining the extended path solution method to solve the model and the inversion filter to calculate the likelihood function (Fair and Taylor, 1983), we can use Bayesian techniques for the estimation of the model parameters. This confrontation of the model with the data is essential for providing precise scenario assessments and thus credible policy recommendations.

Our new estimated model contributes to the literature by studying the transition to net-zero carbon emissions and by quantitatively characterizing the benefits of subsidy policies to EGSS. Its structure can nevertheless be extended in several dimensions, which represent interesting avenues of research. For example, our model is worldwide and implicitly assumes international coordination and an orderly transition. In practice, each country may or may not implement its own environmental policy and have a different ability to raise funds to finance the transition. This highlights in particular the issue of effort sharing between advanced and emerging countries. From this perspective, it would be interesting to extend our model to a multicountry framework and investigate how using carbon tax and/or carbon border tax revenues can support the efforts of emerging countries. Another extension may concern the introduction of specific capital and skills in EGSS (see Finkelstein Shapiro and Metcalf, 2021), which would slow down the reallocation of resources between sectors, making it economically more costly.

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