Growth Welfare Innovation Productivity

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Macroeconomic policy for a rapid and orderly transition

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1 Introduction

Large reductions of global greenhouse gas emissions are increasingly urged to mitigate climate physical risks. Indeed, the most recent IPCC report indicates that the impacts of a 2°C increase would be considerably more severe than previously estimated (IPCC, 2021). To cut emissions, economies must reduce their carbon intensity and, given currently prevailing technologies, this implies a decisive shift away from fossil-fuel energy and related physical capital. In an adverse scenario, the transition to a low-carbon economy occurs either late or abruptly, with the costs of such transformation being potentially high and systemic (van der Ploeg, 2020; Mercure et al., 2018; Battiston et al., 2017; Semieniuk et al., 2021). Indeed, policymakers increasingly emphasize the need of balance between a rapid transition and its macroeconomic outcomes (Carney, 2015; NGFS, 2019). However, while there is widespread agreement about the urgency of climate action to mitigate risks from uncontrolled climate change, the evidence on the suitable policy package to induce an effective and orderly transition is scarce (Stern and Stiglitz, 2021; NGFS, 2019), and the excessive reliance on policy instruments characterized by low political acceptability, such as carbon pricing, brings about concerns for the transition outlook (Patt and Lilliestam, 2018; Pezzey, 2019; Rosenbloom et al., 2020).

In this paper, we employ a macro-financial integrated-assessment agent-based model (labelled as DSK; Lamperti et al., 2018) to assess the economy-wide impacts of a warming climate and to test an ample set of demand side and supply side decarbonization policies. Results robustly show that, overall, decarbonizing an advanced fossil-fuel based economy is best supported by a set of regulatory interventions (command and control with grace periods) coupled with active and targeted innovation policy and very mild carbon pricing. Our evidence supports the inexistence of a trade-off between a rapid transition and growth outlooks; contrarily, our results show that transition costs are minimal under the most effective policy mix and also vanish in the long run, with the transition being accompanied by relatively higher employment levels than in the baseline due to large and publicly-sustained investments. Relevantly, our findings support a marginal role for carbon taxes, which - in the most effective policy mix - must be remarkably low and instrumental to the government's support of low-carbon technology development and adoption.

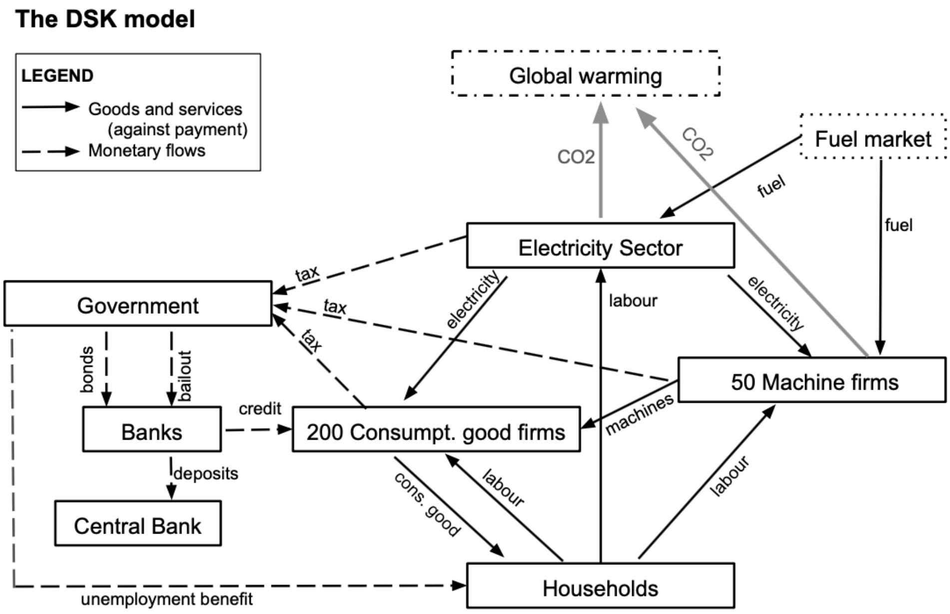
This paper provides two major contributions. First, we show that carbon taxation is often self-defeating. Numerical simulations consistently show that extremely high carbon taxes (about 6 times the current fossil fuel price) are requested to trigger a fast-enough decarbonization process to comply with the Paris agreement. However, such carbon taxes drastically increase the risk of a large unemployment crisis caused by a surge in energy prices, large drops in investments and a rise in bankruptcy rates Kanzig, 2021; Semieniuk et al., 2021. Contrarily, gradually increasing tax schemes are almost ineffective until they reach a threshold, which substantially delays the transition without insulating the economy from high transition costs when the threshold itself is reached. In a nutshell, the standard role of carbon taxes internalizing environmental costs and triggering a green transition finds no support in our analysis.

Second, we find that an ensemble of industrial regulations and innovation policies is found as the most promising policy toolkit to support a rapid and orderly transition. Command-and-control policies forbidding fossil-fuel plant construction and use of fossil fuel in the industrial sectors (both implemented with a 20 years grace period) are effective in stimulating reconversion and low carbon investments both in the energy and manufacturing sectors. Public subsidies for green plant construction and green R&D further (i) accelerate the transition in the power sector, which is crucial to sustain the adoption of electrification-based solutions within industry, and (i) sustain labour demand. Overall budget costs induced by non-tax based policies is low (estimated around between 1.5% [0.5%-3%] of GDP per year in a prototypical European country) and a small carbon tax can be added to the policy mix to speed up the transition and neutralize its impact on the public budget. Numerical simulations suggest that a constant carbon tax until 2100 can provide revenues to finance the innovation and green plant construction policies that are crucial in the early phase of the transition while being sufficiently low not to induce significant transition costs at the macroeconomic level.

2 The model

The *Dystopian Schumpeter meeting Keynes* (DSK) model is an agent-based model featuring an economy with heterogeneous agents and a simple climate module (Lamperti et al., 2018, 2019, 2020, 2021). It belongs to the so-called "Schumpeter meeting Keynes" (K+S) family of models, which provides flexible simulation environments for policy analysis across various fields (from fiscal to monetary and labor market policies) and couples features of Keynesian demand management, Schumpeterian theories of firms' interaction and competition and Minskian credit dynamics (see the survey in Dosi et al., 2017).

Figure 1: Stylized representation of the DSK model.



The model is composed of four sectors, a government body - which implements fiscal, innovation and energy policy - and a central bank running monetary and macroprudential policy. In the upstream sector, capital-good firms produce heterogeneous machines employing labor, electricity and fossil fuel, and they also carry out R&D activities aimed at improving the efficiency of productive processes. In the downstream sector, consumption-good firms employ machines, electricity and labor to manufacture a homogeneous final good, which is consumed by the household sector. The financial system is represented by heterogeneous banks gathering deposits and providing credit to consumption-good firms in need of external funds to finance investment and production. Finally, in the power sector, a variety of energy plants rely either on either low-carbon (green) or fossil-fuel (brown) resources to supply electricity inputs to the rest of the economy.

2.1 Capital and consumption good firms

The unit cost of production of both capital- and consumption-good firms depends on the price of inputs and their productivities. While machine construction requires labour, electricity and fossil-fuel, consumption-good firms need labor and electricity only. Such a difference captures the diverse use of fossil-fuels across sectors of economic activty, with up-stream processes such as cement, steel or chemicals production disporpotionately employing fossil-fuels with respect to down-stream industries.

Hence, given the prevailing wage (w), electricity (p^e) and fossil-fuel (p^f) prices, unit production costs for capital and consumption-good firms read

$$c_i^{cap}(t) = \frac{w(t)}{B_{i,\tau}^{LP}} + \frac{p^e(t)}{B_{i,\tau}^{EE}} + \frac{p^f(t)}{B_{i,\tau}^{FE}}, \tag{1}$$

$$c_j^{con}(t) = \frac{w(t)}{A_{i,\tau}^{LP}} + \frac{p^e(t)}{A_{i,\tau}^{EE}}, \tag{2}$$

where B indicates the productivity of the technology employed by capital-good firm i, A the productivity of machines used by consumption-good firm j, τ refers to the technology vintage while LP, EE and FE stands for labor productivity, efficiency in electricity use and efficiency in fossil fuel use, respectively.

The market for machines is characterised by imperfect information: capital-good firms advertise their machines to a set of consumption good firms by sending a "brochure"; consumption-good firms then select their supplier by comparing the efficiency of machines they are aware of through a payback rule (Dosi et al., 2010, 2013). The price of machines is set applying a constant mark-up on the unit cost of production. In addition, due to time-to-build constraints, consumption-good firms receive their new machines only at the end of the period.

Consumption-good firms produce a homogenous good using their stock of machines, energy and labor under constant returns to scale. Firms plan their production according to adaptive demand expectations. Specifically, the desired level of production Q_j^d of consumption-good firms depends upon adaptive expectations $D_j^e = f[D_j(t-1), D_j(t-2), ..., D_j(t-h)]$, desired inventories ($N_j^d$), and the actual stock of inventories (N_j):

$$Q_j(t)^d = D_j^e(t) + N_j^d(t) - N_j(t), \tag{3}$$

where $N_j(t) = \iota D_j^e(t), \ \iota \in [0,1]$. If the current capital, $K_j(t)$, is not sufficient to satisfy the desired level of production, consumption good-firms can invest and purchase new machines. As machines embed state-of-the-art technologies, innovations diffuse from the capital- to the consumption good sector.

2.2 Innovation, imitation and the substitution of electricity and fossil fuel

Firms in the capital-good industry adaptively attempt to increase market shares and profits. They try to improve their machines and production techniques by means of innovation and imitation, which are costly processes. In particular, firms invest a fraction of their past sales in R&D, in the attempt to discover a new technology or to imitate their more advanced competitors. As explained in Dosi et al. (2010), both innovation and imitation are modeled as two step processes. The first step captures the stochastic nature of technical change and determines whether a firm successfully innovates or imitates. This is formalized in the model through a draw from a Bernoulli distribution, where the (real) amount invested in R&D, that is, ultimately, number of people devoted to search, affects the likelihood of success. The second step determines the size of the technological advance.

In particular, we model innovation as the process of search for novel machines and production techniques. Each technology is defined by a set of technical coefficients representing labour productivities and the efficiency in the use of energy inputs. If the first step is successful, firms stochastically discover a novel technology featuring

$$A^k_{i,\tau+1} = A^k_{i,\tau}(1 + \chi^k_{A,i}) \tag{4}$$

$$B^{LP}_{i,\tau+1} = B^{LP}_{i,\tau}(1 + \chi^{LP}_{B,i}) \tag{5}$$

where $\chi_{A,i}k$ and $\chi^{LP}_{B,i}$ are independent draws from a $Beta(\alpha, \beta)$ distribution over the support $[\underline{x}, \overline{x}]$ and $k = \{LP, EE\}$.

Further, the novel technology will be characterized by a different use of electricity and fossil-fuel, which we determine by following an approach analogous to (Nelson and Winter, 1982, chapter 7). In particular, we assume that capital-good firms cannot decide - a priori - to increase or decrease their needs of electricity and fossil fuel for the production of a machines, but such requirements emerge themselves from a deeply uncertain search process. Let q, E and F be the level of output (in terms of capital goods) and the stock of the two energy inputs required for production of q. We define input coefficients as

$$b^F_{i,\tau} = \frac{1}{B^{FE}_{i,\tau}} = \frac{F_{i,\tau}}{q} \tag{6}$$

$$b^E_{i,\tau} = \frac{1}{B^{EE}_{i,\tau}} = \frac{E_{i,\tau}}{q}. \tag{7}$$

As usual, we assume that proportional changes in input coefficients are distributed independently of the current coefficients (Nelson and Winter, 1982; Dosi et al., 2010; Lamperti et al., 2018). Further, we model the search of novel of techniques as a process of discrete changes of a^E and a^F. To better visualize such process, we use a 2-dimensional (a^F, a^E) plane where

- the **ratio** of input coefficients: $U_{i,\tau} = \frac{b^E_{i,\tau}}{b^F_{i,\tau}}$ and,

- the **sum** of input coefficients: $V_{i,\tau} = b^F_{i,\tau} + b^{E_{i,\tau}}$,

determine the set of available techniques.

Hence, $U_{i,\tau}$ indicates the relative proportions of electricity and fuel that are needed to build a machine of vintage τ, while $V_{i,\tau}$ indicates the total amount of energy inputs. In such a representation we slightly depart from Nelson and Winter (1982), wherein techniques are represented by the product-ratio pairs rather than sum-ratio pairs. Our choice is motivated by the willingness to allow single-input techniques, i.e. production modes involving just electricity or fuel.

At each time t, we consider capital-good firm as being endowed with a given technique, whose energy requirements are uniquely identified by a $(U_{i,\tau}, V_{i,\tau}$ pair. Obviously, for a given U coordinate, a technique with a smaller V coordinate is better than one with a large V coordinate. Contrarily, the desirability of a smaller or larger U depends on relative input prices and the feasible techniques that are known by the firm. Electrification takes place as embedded in the process of innovation and adoption of a novel technology.

Two-independent random draws from two Beta distributions are obtained to characterize a novel technique that might be potentially adopted:

$$U_{i,\tau+1} = U_{i,\tau}(1 + \chi_u) \qquad \chi_u \sim Beta_1[-o_1, +o_1] \tag{8}$$

$$V_{i,\tau+1} = V_{i,\tau}(1 + \chi_v) \qquad \chi_v \sim Beta_1[-o_2, +o_2] \tag{9}$$

where η_v represents a pure efficiency gain (or loss), while η_u provides a new feasible input mix.

Finally, imitation follows a two step stochatic process akin to innovation. The possibilities of accessing imitation come from sampling a Bernoulli and firms successfully entering the second stage are allowed to copy the technology of a competitor, under the assumption that technologically similar firms are easier to imitate than distant ones (Dosi et al., 2010, 2013).

All firms which draw a potential innovation or imitation have to either put it on production or keep producing the incumbent generation of machines. Comparing the technology competing for adoption, firms choose to manufacture the machine characterized by the best trade-off between price and efficiency. More specifically, knowing that consumption good-firm invest following a payback period routine (Dosi et al., 2010; Lamperti et al., 2018), capital-good firms decide the machine to produce by computing the quantity:

$$payback_i = \{p_i(t) + bc_i^{con}(t)\} \tag{10}$$

for the incumbent, imitated and newly discovered technologies, with $b > 0$, and selecting the one displaying the lowest value.

2.3 The banking sector

The structure of the banking sector is akin to Dosi et al. (2015) and Lamperti et al. (2019). It is composed of B heterogeneous commercial banks gathering deposits and providing credit to firms and a central bank running monetary and macro-prudential policies. The number of commercial banks is constant (no entry) and is proportional to the number of firms in the consumption-good sector (F_2): $B = \frac{F_2}{\alpha_b}$.[1] Heterogeneity is crucial to study the emergence of banking crises and their effects on the real side through the credit channel. For example, insolvencies of some banks might have an impact on specific production activities and the public budget, thereby altering the dynamics of competition among firms. If the banking sector was aggregate, the effects of instability would - to the contrary - cut equally across firms. On the opposite side, a change in the risk profile of firms can have a different effect on some banks with respect to others (e.g. small vs. large; more or less leveraged) with aggregate implications that are difficult to derive ex-ante. At the beginning of the simulation, firms are randomly assigned to a bank, so that the distribution of clients per bank follows a Pareto distribution.[2] The relative sizes of banks' balance-sheet, and as a consequence, credit supply, then evolves endogenously depending on micro positive (profits) and negative (bad loans) shocks. Indeed, credit supply is limited by the bank's equity NW_b through a simplified Basel-II capital adequacy rule:

$$TC_h(t) = \frac{NW_h(t-1)}{\tau^b(1 + \beta BadDebt_h(t-1))} \tag{11}$$

where $NW_h(t-1)$ represents previous period bank equity; $\tau^B \in [0, 1]$ is a parameter fixed by the regulatory authority; $BadDebt_h(t-1)$ is the amount of non-performing loans in the previous period; and β is a parameter measuring the banks' sensitivity to her financial fragility, as measured by the stock of bad debts.

Then, banks evaluate applicants in terms of their perceived creditworthness as expressed by the ratio between past net worth, $NW_j(t-1)$, and past sales, $S_j(t-1)$. Let $A_b(t)$ be the set of applicants at bank b in period t

$$Creditworthiness_j(t) = \frac{NW_j(t-1)}{S_j(t-1)} \quad \forall j \in A_b(t). \tag{12}$$

[1] α_b is a parameter controlling for the competitiveness of the banking industry.

[2] In particular, we account for the presence of a "fat" right tail of the distribution. This is obtained setting the shape parameter to 0.8, and is tested for robustness in the range from 0.6 to 1. While we acknowledge that small samples might not adequately reflect the tail of the distribution and vary considerably from run to run, the relatively low standard errors in our Monte Carlo exercises suggest robustness of our results.

Firms applying for a loan are then ranked as follows

$$Rank_j(t) < Rank_k(t) \iff Creditworthiness_j(t) > Creditworthiness_k(t) \quad \forall j,k \in A_b(t) \tag{13}$$

where $Rank_{j,k} \in \mathbb{N}$. Banks provide loans following the ranking and until maximum credit supply is reached.

Banks earn profits from the loans they allocate as well as the government bonds they buy. All banks apply a homogenous mark-up black μ_b on the central bank interest rate (r, see eq. 27): $r_{deb}(t) = (1 + \mu_b)r(t)$. Then, they fix a risk premium on the basis of clients' position in the credit ranking. In every period, four credit classes are created by the banks, corresponding to the quartiles in their ranking of clients. Given the base loan rate r_{deb}, each firm pays:

$$r_{deb,j}(t) = (1 + (q_j - 1)k_{scale})r_{deb}(t), \tag{14}$$

where q_j is the quartile of firm j' ranking and k_{scale} is a scaling parameter. Firms' deposits are provided an interest rate r_D, banks' reserves at the central bank yield the reserve rate r_{res} and government bonds pay a constant return such that $r_D \leq r_{res} \leq r_{bonds} \leq r \leq r_{deb}$.

Hence, the profits of a bank can be expressed as follows:

$$\Pi_b(t) = \sum_{\text{clients}} r_{deb,j}(t)Deb_j(t) + r_{res}(t)Cash_b(t) + r_{bonds}(t)Bonds_b(t) - r_D Dep_b(t) - BD_b(t), \tag{15}$$

where, for each bank b, Deb_j represents clients' debt, $Cash_b$ are the liquidities, $Bond_b$ is the stock of government bonds, and BD_b indicates non-performing loans. Loan losses occur whenever a borrower goes bankrupt and exits the market with a positive debt, which may lead to negative profits. Profits are taxed and added to the net worth of the bank:

$$NW_b(t) = Loans_b(t) + Cash_b(t) + Bonds_b(t) - Dep_b(t) + \Pi_b^*(t), \tag{16}$$

where $Loans_b$ represents the sum of existing loans provided by the bank b to its clients and Π_b^* the after-tax value of bank profits.

A bank goes bankrupt when its net worth becomes negative (due to the accumulation of loan losses), and it is then bailed-out by the government. Since this is the only mechanism of financial instability that we consider, which has been proven large under rapid climate change in Lamperti et al. (2019), we can single out how altering credit allocation to firms may alleviate or exacerbate risks for the banking system.

The cost of the public bail out (GB) is the difference between the failing bank's net worth before and after the public intervention. Specifically, we assume that the bank's equity after the bailout is a fraction of the equity value of the smallest incumbent, provided it satisfies the capital adequacy ratio. Mirroring the entry rule of firms in the real sector, this fraction is a random draw from a Uniform distribution between ϕ_1 and ϕ_2. The bail-outs thus represent part of the public costs of climate-induced financial losses. Such assumption finds in line with the historical evidence of large government spending in rescuing banking institutions during financial crises.

2.4 The power sector

The power sector produces electricity on demand for all firms, using its green and dirty plants. We assume that an electricity firm regulate the power market and make investments in novel power generation capacity, while heterogenous plants compete on costs to produce electricity for firms. All plants produce 1 unit of electricity, if activated.

"Dirty" plants burn fossil fuels (e.g. coal, oil) with heterogeneous, vintage-specific thermal efficiencies A^{τ}_{de}, which expresses the amount of energy produced for each unit of employed non-renewable resource (fossil fuel) and emission intensities em^{τ}_{de}, which indicates the amount of emissions per unit of energy produced.[3] For simplicity, we assume that power plants have a unitary capacity and, in the case of brown energy, they consume one unit of fuel. Hence, the average production cost for a brown plant of vintage τ is:

$$c_{de}(\tau, t) = \frac{p_f(t)}{A^{\tau}_{de}(t)}, \tag{17}$$

where p_f is the price of fossil fuels, exogenously determined on an international market.[4] "Green" plants produce (such as wind and sunlight) energy at a null production cost, i.e. $c_{ge}(t) = 0$.

We assume that plants with the lowest unitary generation costs are the first to be activated, in line with the existence of a merit order effect. The total (potential) production of green plants is K_{ge}, and IM is the set of plants which should be activated to fulfill the energy demand. Then if total demand is lower than total green capacity ($D_e(t) \leq K_{ge}(t)$), the set of infra-marginal power plants IM includes only green plants and the total production cost is zero. Instead if $D_e(t) > K_{ge}(t)$, some dirty plants need to be activated too. The total production cost then corresponds to the sum of the production costs of

[3] τ denotes the technology vintage.

[4] Notice that electricity production is a highly capital-intensive process, which mainly requires power generation assets and resources (either fossil fuels or renewable sources), while the labor input is minimal. We thus assume away labor from electricity production.

the various types of brown plants activated at energy demand level $D_e(t)$. Assuming that the absolute frequency of vintage τ plants is $g_{de}(\tau, t)$, if dirty plants are operative the total production cost is:

$$PC_e(t) = \sum_{\tau \in IM} g_{de}(\tau, t) c_{de}(\tau, t) A_{de}^{\tau}(t) \tag{18}$$

The energy price is computed by adding a fixed markup $\mu_e \geq 0$ to the average cost of the most expensive infra-marginal plant:

$$p_e(t) = \mu_e, \tag{19}$$

if $D_e(t) \leq K_{ge}(t)$, and

$$p_e(t) = \overline{c}_{de}(\tau, t) + \mu_e \tag{20}$$

if $D_e(t) > K_{ge}(t)$, where $\overline{c}_{de}(\tau, t) = \max_{\tau \in IM} c_{de}(\tau, t)$. By setting a markup on this unit cost level, there is a positive net revenue on all infra-marginal plants.

Investments

Investment in the energy sector can be associated to i) the replacement of old and obsolete plants or ii) capacity expansion. Replacement is due to the fact that all (brown and green) plants have a constant life-time corresponding to η_e periods. In turn, in order to fulfill energy demand, new power plants might be necessary, thus requiring capacity investment in the energy sector. An expansion investment is undertaken whenever the maximum electricity production level $\overline{Q}_e(t)$ is lower than electricity demand $D_e(t)$. The amount of new expansion investments EI_e thus equals:

$$EI_e(t) = K_e^d(t) - K_e(t), \tag{21}$$

if $\overline{Q}_e(t) < D_e(t)$, whereas $EI_e(t) = 0$ if $\overline{Q}_e(t) \geq D_e(t)$. Then the question is whether capacity expansion will be done with green or brown new plants. All new plants are built in-house (i.e. within the energy sector), but their production cost is technology-specific. Specifically, the construction costs for new dirty plants are normalized to zero, whereas in order to install a new green plant of vintage τ, a fixed cost IC_{ge}^{τ} needs to be sustained. We assume that new green capacity is constructed if green plants are cheaper than brown counterparts in terms of accounting lifetime costs. This means that green energy technologies are chosen whenever the fixed cost of building the cheapest green vintage is below the discounted (variable) production cost of the most efficient dirty plant. Hence, the following payback rule should be satisfied:

$$\underline{IC}_{ge} \leq b \cdot \underline{c}_{de}, \tag{22}$$

where b is a payback period parameter (as in Dosi et al., 2010, 2013), $\underline{IC}_{ge} = \min_\tau IC_{ge}^\tau$, and $\underline{c}_{de} = \min_\tau c_{de}^\tau$.[5] Accordingly, in case of new green capacity, the expansion investment cost amounts to

$$EC_e(t) = \underline{IC}_{ge} EI_e(t); \tag{23}$$

whereas it is zero if the payback rule is not met and the firm builds new dirty plants.

Plants' costs and characteristics evolve over time due to technical change. Mirroring the process in the capital-good industry, the energy plants invest a fraction $v_e \in (0,1)$ of total past sales in R&D and stochastically improve their cost structure and emission intensity through a two-step procedure. At the end of the period, the central authority computes profits in the energy sector (see eq. 26 below) and levies taxes at the rate tax_p.

Technical change

R&D expenses in the energy sector aim at improving the technology of green and dirty plants. For green plants, this means reducing the fixed cost, while for dirty plants, this means an increase in energy efficiency (A) and a reduction in carbon emissions (em). Part of the budget is allocated to green innovations ($IN_{ge}(t) = \xi_e RD_e(t)$), and the rest to dirty ones. Such expenses in turn increase the probability to pass the first step of the innovation step successfully, for instance in the case of green innovations:

$$\theta_{ge}(t) = 1 - e^{-\eta_{ge} IN_{ge}(t)} \tag{24}$$

with $\eta_{ge} \in (0,1)$. A similar process is at stake for dirty innovations.

In the second step, energy firms draw a random value from a Beta distribution, $x_{ge} \in (0,1)$, which lowers the fixed cost of setting up a new green plant, with respect to the previous vintage. For dirty plants, two independent random draws x_{de}^A and x_{de}^{em} (again, from a Beta distribution) modify the existing characteristics of dirty plants as follows:

$$A_{de}^\tau = A_{de}^{\tau-1}(1 + x_{de}^A) \qquad em_{de}^\tau = em_{de}^{\tau-1}(1 - x_{de}^{em}). \tag{25}$$

Profits and taxes

The revenues of the electicity firm depend on the energy price $p_e(t)$ and quantity produced $D_e(t)$. Its expenses include both production (total costs $PC_e(t)$) and costs of investing $IC_e(t)$ and innovating

[5] Under the assumption that plants are utilized for energy production the same number of periods, equation 22 boils down to a comparison of levelized costs of energy.

$RD_e(t)$.

$$\Pi_e(t) = p_e(t)D_e(t) - PC_e(t) - IC_e(t) - RD_e(t), \tag{26}$$

The energy firm then pays taxes on positive profits at the rate tax_p. Analogously to what happens for banks (Section 2.3), if the net worth of the electricity firm becomes negative, the government bail out and refinances it.

2.5 The central bank and the government

The central bank runs monetary and macroprudential policies. In that, it fixes the policy rate according to a Taylor rule of the following type:

$$r(t) = r^T(t) + \gamma_\pi(\pi(t) - \pi^T) + \gamma_U(U^T - U(t)), \tag{27}$$

where $\gamma_\pi, \gamma_U > 1$, π^T indicates the target level of inflation, U^T the target level of unemployment and r^T the target interest rate. Further, the central bank implements a stylized Basel-II type capital requirements scheme that determines the capital adequacy ratio κ.

Taxes and subsidies are the fiscal instruments that contribute to the aggregate demand management. Our setup includes automatic stabilizers which help the economic system to recover from recessions. Taxes paid by firms and banks on their profits are gathered by the government at the fixed tax rate tax_p. Workers' income is taxed at the rate tax_i,[6] which is also fixed. Total government revenues are indicated as $Taxes$. Direct government expenses G are composed of subsidies to unemployed workers, who receive a fraction (w^U) of the current market wage; In addition to these primary expenses, the government pays interests on its stock of sovereign bonds (SB) owned by banks and the central bank. The cost of public debt on government's deficit is then equal to $CD(t) = r_{bonds}(t)SB(t-1)$. In addition, the goverment bails out and refinance banks and the electricity firm when their net worth becomes negative, incurring in an addition expense amouting to $G^{bailout}(t)$. Finally, $G^{clim}(t)$ represents the fiscal cost of climate policies described in Section 3.

Then, the public deficit corresponds to:

$$Def(t) = G(t) + G^{bailout}(t) + G(t) + G^{clim}(t) - Taxes(t) + CD(t), \tag{28}$$

If the deficit is positive the government issues new sovereign bonds, which are bought by banks according to their share in the total supply of credit (and by the central bank as an eventual lender of last resort);

[6] This excludes unemployed workers.

when the deficit is negative, the government uses its surplus to repay its stock of debt.

2.6 Climate change

The climate module is based on the C-ROADS model described in Sterman et al. (2012, 2013), a simple, but physically consistent climate model tuned against the results of full-grown General Circulation Models. The climate module is initialised at 2010 conditions, which are obtained by performing a simulation with the stand-alone C-ROADS model starting from initial conditions and providing historical carbon emissions $E(t)$ from 1751 to 2010.

Carbon model: Atmosphere-biosphere interaction

In C-ROADS, carbon can be exchanged between several reservoirs: the atmosphere, the ocean, the biosphere (plants) and the humus. In pre-industrial conditions, the model is in equilibrium, i.e. the carbon flux into and out of each reservoir cancel. Anthropogenic emissions E disturb the equilibrium; if emissions cease, a new equilibrium is reached after a few centuries.[7]

Plants remove carbon form the atmosphere by Net Primary Production (NPP; the net carbon uptake per year). Under pre-industrial conditions, NPP equals NPP_0. However, NPP increases (logarithmically) if the atmospheric carbon reservoir C_{at} exceeds its pre-industrial value $C_{at,PI}$; this carbon fertilisation effect is a negative feedback on global warming, but with decreasing strength. On the other hand, NPP decreases with T, the increase of global mean surface temperature w.r.t. pre-industrial, due to the heat stress effect (positive feedback). Thus NPP obeys:

$$NPP = NPP_0(1 + p_{fert} \ln(C_{at}/C_{at,PI})) \times (1 + p_{heat}T) \tag{29}$$

where p_{fert} and p_{heat} are constants governing the strength of the fertilisation and the heat stress effect.

The biospheric carbon reservoir C_{bio} evolves as

$$\Delta_t^{t+1} C_{bio} = NPP - C_{bio}/\tau_{bio} \tag{30}$$

where the second term describes carbon loss due to the decay of dying plants (with decay time τ_{bio}). A fraction p_{hum} of the plants' carbon is converted to humus, the rest enters the atmosphere. The humus

[7]On very long time scales, millennia and longer, geological processes like mineral weathering become relevant. Such very slow processes are disregarded here.

gains carbon from dying plants, but also releases carbon with a decay time τ_{hum}, hence the humus carbon reservoir C_{hum} obeys:

$$\Delta_t^{t+1} C_{hum} = p_{hum} C_{bio}/\tau_{bio} - C_{hum}/\tau_{hum}. \tag{31}$$

Anthropogenic carbon emissions E all enter the atmosphere. The atmospheric carbon reservoir C_{at} thus evolves as

$$\Delta_t^{t+1} C_{at} = -NPP + (1 - p_{hum}) C_{bio}/\tau_{bio} + C_{hum}/\tau_{hum} + E + OP \tag{32}$$

where OP denotes exchange processes with the ocean, which are described below.

Carbon model: Atmosphere-ocean interaction

The ocean is consists of $n_{lay} = 5$ layers, a well-mixed upper layer and $n_{lay} - 1$ deeper ones; the depth of layer k is $d_{lay}(k)$. Each layer contains a carbon reservoir $C_{on}(k)$; the corresponding carbon concentration (per m depth) is $C_{on}(k)/d_{lay}(k)$. The ocean is assumed to be homogenous in the horizontal direction. Carbon is exchanged between the layers through mixing (eddy diffusion). In addition, the atmosphere and the upper ocean layer (which is mixed by winds, waves etc and thus in good contact with the atmosphere) exchange carbon in such a way as to reach equilibrium.

The mixing-related carbon flux $M_{k,k+1}$ between to layers k and $k+1$ (where $k = 1$ is the upper layer) is proportional to the vertical derivative of the carbon concentration:

$$M_{k,k+1} = \chi_{eddy} \frac{C_{on}(k)/d_{lay}(k) - C_{on}(k+1)/d_{lay}(k+1)}{(d_{lay}(k+1) - d_{lay}(k))/2} \tag{33}$$

where χ_{eddy} is the mixing strength, and $M_{k,k+1}$ is positive if carbon is transported from layer k to $k+1$, i.e. downward. The carbon reservoir of the bottom layer changes as $dC_{on}(n_{lay})/dt = M_{n_{lay}-1,n_{lay}}$, while in the intermediate layers $1 < k < n_{lay}$, it evolves as $dC_{on}(k)/dt = M_{k-1,k} - M_{k,k+1}$. In the upper layer, carbon is removed by $M_{1,2}$, but in addition, carbon is exchanged with the atmosphere such that $C_{on}(1)$ and C_{at} are in chemical equilibrium, i.e. they fulfill the relation

$$C_{on}(1) = C_{mix,ref}(1 - R_T T)(C_{at}/C_{at,PI})^{\gamma(C_{at})} \tag{34}$$

where $C_{mix,ref}$ is a reference carbon stock set to the pre-industrial value of $C_{on}(1)$, and R_T governs the decrease of carbon solubility in sea water with global warming T. The exponent obeys $\gamma(C_{at}) =$

$(R_0 + R_C \ln(C_{at}/C_{at,PI}))^{-1}$, where R_0 is the reference Revelle factor, and R_C determines how the Revelle factor depends on the carbon reservoir. Even for fixed T, $C_{on}(1)$ increases only sublinearly with C_{at}, i.e. the ability of the ocean to take up *additional* carbon decreases with increasing carbon concentrations. Numerically, the equilibrium condition is achieved by first computing the total carbon reservoir C_{oa} of the atmosphere and the upper layer (which is determined by atmosphere-biosphere interaction and ocean mixing), and then iteratively solving for C_{at} and $C_{on}(1)$ such that eq.34 and $C_{at} + C_{on}(1) = C_{oa}$ are fulfilled.

Radiative forcing and warming

Under pre-industrial conditions, the Earth looses as much energy from (infrared) black-body radiation as it receives from incoming sunlight. Greenhouse gases "trap" outgoing longwave radiation without impeding incoming solar radiation, leading to an imbalance or "radiative forcing" F (in W/m^2). The contribution from CO2 behaves as

$$F_{CO2} = f_{CO2} \ln(C_{at}/C_{at,PI}) \tag{35}$$

where f_{CO2} is a constant. The full C-ROADS model also explicitly includes other greenhouse gases. For simplicity, we only include them implicitly by assuming $F = F_{CO2} \times 1.12$, based on the rationale that an economy that does (not) curb CO2 emissions will also (not) reduce other pollutants. The factor 1.12 is in a rough agreement with Representative Concentration Pathway (RCP) scenarios.

The Earth reacts to the radiative forcing by warming, which increases the Earth's outgoing longwave radiation. The additional outgoing radiation F_{out} can be approximated by a linear equation: $F_{out} = \kappa_{out} T$. If F is fixed, the Earth will warm until an equilibrium is reached, i.e. $F_{out} = F$ and $T = F/\kappa_{out}$. If the only radiative forcing stems from doubling CO2 w.r.t pre-industrial, then the equilibrium temperature will equal $f_{CO2} \ln(2)/\kappa_{out}$. This value is called the equilibrium climate sensitivity λ. Due to complex feedbacks, there is uncertainty κ_{out} and hence λ, with 1.5-4.5 degree per doubling CO2 being a likely range for λ (Knutti et al., 2017).

Equilibrating temperature takes some time, because the Earth has a certain heat capacity. Air has a low heat capacity due to its small density. Land has effectively a small heat capacity, because heat can only move by conduction, as land is solid. However, the ocean has a large heat capacity, because heat is efficiently transported into its interior. Hence all surplus energy from radiative forcing is assumed to end up in the ocean. Like carbon, heat is exchanged among layers through mixing. Defining $H_{on}(k)$ as the increase (w.r.t. pre-industrial) in heat content per m^2 ocean surface in layer k, the heat flux from layer

k to layer $k+1$ is

$$H_{k,k+1} = \chi_{eddy} \frac{H_{on}(k)/d_{lay}(k) - H_{on}(k+1)/d_{lay}(k+1)}{(d_{lay}(k+1) - d_{lay}(k))/2} \tag{36}$$

and the heat content for the lowest layer evolves as $dH_{on}(n_{lay})/dt = H_{n_{lay}-1,n_{lay}}$, whereas for the intermediate layers with $1 < k < n_{lay}$ it obeys $dH_{on}(k)/dt = H_{k-1,k} - H_{k,k+1}$. In the upper layer, we not only have mixing but also absorption of heat due to the radiative forcing:

$$dH_{on}(1)/dt = -H_{1,2} + (F - F_{out})\alpha_{yr-s}/A_{sea} \tag{37}$$

where the conversion factor α_{yr-s} (nr. of seconds per year) is needed because dH_{on}/dt is measured as change per year, whereas forcing is given in energy/area/second. The factor $1/A_{sea}$, where A_{sea} is the fraction of the Earth's surface covered by oceans, is included because F comes in over the whole Earth whereas the energy is assumed to end up in the ocean only.[8]

Heat content can be converted to temperature by

$$T_{on}(k) = H_{on}(k)/c_{H2O}/d_{lay}(k) \tag{38}$$

where c_{H2} is the heat capacity per water volume, and d_{lay} the layer depth (as H is the heat per ocean surface, H/d_{lay} is heat per volume). The global mean surface temperature (w.r.t. pre-industrial) is taken as $T = T_{on}(1)$.

3 Climate policies for the 2°C target

Though carbon pricing is by far the most popular instrument of climate policy and it is extensively discussed in the scientific and policy arenas, its real-world use is - in fact - limited, and the very determination of the adequate trajectory for the price of emissions is subject to large and fierce debates. In addition, carbon pricing - either implemented through a tax or a cap-and-trade system - has been increasingly recognized to produce non-triavial effects on the macroeconomic and financial dynamics. The high-level commission on carbon pricing has recently acknowleged the need to complement carbon pricing with larger policy packages, aimed at guaranteeing an orderly and rapid transition.

We use the macro-financial agent-based integrated assessment model described in Section 3 to test a variety of climate policy instruments aimed at containing warming within the 2°C threshold by 2100. Beyond carbon taxation - which we analyse across a number of alternative schemes - we include

[8]This does not mean that land surface and atmosphere do not warm; but compared to the ocean, only a very small amount of energy is needed to bring about this warming.

command-and-control (i.e. regulation) policies for the energy and industrial sectors, green subsidies and a long array of combinations (Table 3). Relevantly, we adopt a double perspective: on one side we study the effectiveness of policy packages at decarbonizing the economic system consistently with the climate target; on the other, we carefully analyse the economy-wide effects of the decarbonization process, emphasizing the emergence of risks and opportunities. Such double focus represents a major innovation with respect to the mainstream integrated assessment of climate policy (Nordhaus, 2017, 2018; Weyant, 2017), which is ill-suited to investigate the macroeconomic and financial consequences of mitigation (Lamperti et al., 2019).

Table 1: Summary of climate mitigation policies

Label	Policy instrument	Description
	Carbon Taxation	
Taxcrit	Constant carbon tax	Sufficiently high tax to induce full energy transition by 2100
Tax2d	Constant carbon tax	Sufficiently high tax to keep warming below 2°C
Tax2dh	Constant carbon tax	As Tax2d, with full rebate of revenues on households
Tax2df	Constant carbon tax	As Tax2d, with full rebate of revenues on firms
TaxDICE2d	Increasing carbon tax	Exponentially increasing tax; same rate as the optimal policy of the DICE model constrained to below 2°C warming
TaxDICEopt	Increasing carbon tax	Exponentially increasing tax; same rate as the optimal policy of the (unconstrained) DICE model
TaxDICEhigh	Increasing carbon tax	As TaxDICE2d, but with initial value corresponding to Taxcrit
	Green Subsidies	
Csub	Lump-sum transfer	Subsidy for the construction of green plants in the power sector
RnD	Lump-sum transfer	Subsidy for green R&D in the power sector
	Command and Control	
Elreg	Mandatory regulation with fine	Ban on fossil-fuel use in the capital good sector, with T_{Elreg} years grace period
Ban	Mandatory regulation with fine	Ban on the construction of brown electricity plants, with T_{Ban} years grace period

3.1 Carbon taxation

In our model carbon pricing is implemented through carbon taxes that proportionally increase the price of fossil fuel. We consider two major patterns of carbon taxes: a constant tax rate running from 2021 to 2100, and an exponentially increasing tax rate consistent with previous evidence from the literature (Nordhaus, 2017).

Constant tax schemes mirror policy proposals calling for a sudden implementation of ambitious carbon taxation to kickstart a rapid decarbonization process. We design series of experiments encompassing increasing stringency of carbon taxation to identify the minimum tax level (expressed as a percentage of the prevailing fossil fuel price) granting (i) complete decarbonization of the power sector by 2100 (we label this policy experiment as Taxcrit) and (ii) containment of global warming below 2°C in 2100 (labeled as Tax2d). Revenues from carbon pricing are collected by the public government (see Section 2.5). While the majority of integrated assessment models overlook public finance considerations, we exploit the specificities of our model to account for active fiscal management of proceedings and costs of climate policy. Indeed, we design two full rebate schemes: on households (Tax2dh), wherein revenues from carbon taxation are used to increase unemployment subsidies, and on firms (Tax2df), through subsidies proportional to the employment size.

Increasing carbon taxation has been often suggested as both a cost-effective and optimal solution to the mitigation problem. However, the impact of the policy on economic agents was largely overlooked, thereby leaving unanswered the question of whether - and how - increasingly stringent carbon taxation affect the business cycle and the growth outlook of economies introducing it. Indeed, the debate is vivid both from a theoretical and empirical perspectives (Metcalf and Stock, 2020; Kanzig, 2021). We consider three schemes of exponentially increasing carbon taxes proxying the policy suggestions that emerge from the DICE model (Nordhaus, 2017), arguably the most influential integrated assessment model of climate policy (Nordhaus, 2019). We run DICE in two ways. First, we let it optimize freely, which yields an optimal policy that results in a peak warming of 2.7 degrees . Next, we run it under the constraint that the warming must be limited to 2 degrees (TaxDICE2d). We fit the resulting carbon tax schedules to the following function:

$$X(t) = X_0 \exp[\alpha(t - t_0)]$$

where X_0 is chosen such that in time $t_0 = 2021$ the tax raises the fuel price by the same factor in DICE and in DSK. In this way we obtain the exponential tax of experiments TaxDICEopt and TaxDICE2d, respectively. In addition to the two cases directly based on the two DICE policies, we add an experiment where X_0 equals the critical constant tax rate determined in Taxcrit.

Independently of their implementation and trajectory, carbon taxes negatively affect the fiscal cost of climate policy (see Section 2.5).

3.2 Green subsidies

Public subsidies supporting the development, adoption and diffusion of low carbon technologies and products are potentially effective instruments to induce and speed-up the transition (Acemoglu et al., 2012; Lamperti et al., 2020; Rezai and Van Der Ploeg, 2017; Peñasco et al., 2021). Contrary to taxes, they have a first-order negative impact on public finances, though they might reverse their effect in the long run thanks to growth stimuli they could provide to the economy during the transition. We consider two types of subsidies targeting the power sector, wherein renewable technologies need being developed and diffused to increase they share in the energy mix.

First, we model a subsidy for green Research and Development (experiment RnD). Indeed, R&D expenditures in the power sector are allocated such that $R_g(t)/R_b(t) = N_g(t-1)/N_b(t-1)$ where $\{R_g, R_b\}$ are expenditures on green and brown plants, while $\{N_g, N_b\}$ are the number plants activated for power generation (see Section 2.4); green power technologies are thus under-researched until their relative frequency in the energy mix increases. We let the government provide an R&D subsidy for green plants: $S_{RnD}(t) = \theta_{RnD}[R_g(t-1) + R_b(t-1)]$ with $0 \leq \theta_{RnD} \leq 1$. Hence, the subsidy S_{RnD} increases current green R&D spending by a percentage of total past power R&D expenditure amounting to θ_{RnD}.

Second, we consider a subsidy for the construction of renewable energy plants. Such policy (experiment Csub) starts in 2021 and offers the electricity firm a certain subsidy $S(t)$ for every green plant built: $S(t) = \max\{C_g(t) - \theta_S C_b(t)\, , 0\}$ where C_g and C_b are the lifetime costs of green and brown plants, respectively and encompass, construction, operating and power production costs and $0 \leq \theta_S \leq 1$. Hence, the subsidy reduces the lifetime cost of green plants to at most θ_S of that of brown plants and affect the decision of the electricity firm to invest in renewable or fossil fuel power capacity when it needs to replace energy plants close to lifetime end or to expand its capital stock to serve electricity demand.

Both subsidies contribute to the fiscal cost of climate policy (see Section 2.5).

3.3 Command and control regulation

Command and control policies encompass regulations introduced to discipline economic behaviour. In the context of emission mitigation, they most often refer either to bans on high-emission technologies, products and practices, and to standards setting quantity-based requirements. Often criticized on the ground of efficiency, climate-related regulation is nonetheless widespread across jurisdictions and sectors of economic activity (Peñasco et al., 2021), and has often proved effective at influencing both economic and environmental outcomes (Berman and Bui, 2001; Shapiro and Walker, 2018; Lamperti et al., 2020). However, the economy-wide of effects of command and control policies are poorly understood, as well as their indirect impact on public finances. We consider regulation in two experiments, each aimed at inducing a transition to low-carbon production.

First of all, we study the effects a policy banning the construction of fossil-fuel plants for power generation (Ban). Such experiment is intended to mimic large scale and legally binding international agreements to phase out e.g. coal-fired plants for electricity production. We implement such regulation with a grace period T_{Ban}, which is announced at the time of policy implementation and sets the deadline for fossil-fuel plant abandonment. The regulation is accompanied by a monitoring scheme and a fine for noncompliance F_{Ban}, which is assumed to be sufficiently high to make any fossil-fuel plant economically non-viable since the period wherein the policy is actually implemented (i.e. at the end of the grace period).

Similarly, we analyze a command and control intervention aimed at stimulating the decarbonization of the industrial sector and, more specifically, of capital-good production (see Section 2.1). Such regulation imposes firms in the capital good sector not to use fossil-fuel to manufacture machines starting from year T_{Elreg}. Enforcement is guaranteed, again, by the presence of a prohibitively fine F_{Elref} which would cause insolvency and market exit. Firms subject to regulation are assumed to strive at developing production processes gradually reducing and finally eliminating the use of fossil-fuel through the process of technical change (see Section 2.2). If firm cannot comply to the regulation by T_{Elreg}, they must abstain from production but can still finance R&D activities through internal liquidity.

Finally, we assume that command and control policy announcements are credible.

4 Results

We investigate the effect of climate policy on both emission mitigation and the economy. As in every ABM, the properties of the model are analyzed via extensive computer simulations (Fagiolo and Roventini, 2017; Fagiolo et al., 2019; Dosi and Roventini, 2019). Indeed, since the model is stochastic (see Section 2) and cannot be solved analytically, we rely on numerical simulations by generating a Monte-Carlo ensemble of 50 simulations per experiment.[9] Unless stated otherwise, results are given for the ensemble mean and equipped with confidence bands.

The first 60 years of each simulation are considered as a transient warm-up. After that, the stock of electricity plants is re-initialized such that it contains equally many (brown) plants of all ages $\{1, 2, ...L\}$. The resulting state is defined as mirroring year 2000 conditions and iterated for another 20 years. Unless stated otherwise, all climate policies are assumed to start in 2021.[10] The climate model is initialized to 2020 conditions and is switched on in that model year. As our main interest is deliberately on climate policies for a rapid transition, we do not take into account a possible scarcity of fossil fuel and the ensuing

[9]We run a set of pseudo independent simulations to wash away the cross-simulation variability and to evaluate the statistical significance of our claims. All the results presented below refer to averages across 50 Monte Carlo runs. Since most of the variables under investigation are ergodic (see Guerini and Moneta, 2017; Lamperti et al., 2020), 50 Monte Carlo runs, each composed by 500 time periods lead to 25K observations for each variable and lead to a sufficient number of observations to obtain reliable statistics. Within each scenario and among the 50 Monte Carlo runs, the sole source of variation is given by the pseudo Random Number Generator. Between the 50 batch runs in different scenarios, instead, the Pseudo Random Number Generator is held constant and we only change the climate policy under scrutiny.

[10]Notice that the experiments adopting electricity regulation showed in Section 4.3 assume that such policy is announced in 2031. Preliminary exercises showed that beforehand regulation of the electrification process for capital good firms deliver inferior results.

effect on its price.

4.1 The "no policy" baseline

In the baseline set-up (henceforth called BASE), no climate policy is deployed. The model is is configured to proxy a "business as usual" SSP 5+RCP 8.5 future (van Vuuren et al., 2014), characterized by high output growth (O'Neill et al., 2014), sustained energy demand (Riahi et al., 2011, 2017) and soaring emission concentrations until the end of the century (Riahi et al., 2011). Such scenario closely mirrors the baseline configuration of previous studies (Lamperti et al., 2018, 2019, 2021), with the model exhibiting identical qualitative properties. Figure 2 shows the unfolding of economic and climate trajectories in the baseline configuration (green color).

Indeed, the Schumpeterian engine of the model coupled with its Keynesian demand-side produces sustained GDP growth of about 3% per year (ensemble mean). The model exhibits emergent business cycles of a 3-4 years period. A imperfect labour market leads to involuntary unemployment of around 4-8%, while demand fluctuations and credit rationing shape firm dynamics, leading to upswings and downswings in the bankruptcies likelihood of consumption good firms (which averages 2.5-5% across the Monte Carlo exercise). The financial system in the baseline configuration is healthy, though endogenous cycles can lead to systemic though infrequent insolvencies in the banking sector (Lamperti et al., 2019; Dosi et al., 2015).

From 2000 to 2160, machine and consumption good firms improve their energy efficiency by 13% and 8.5%, respectively. However, as energy costs are relatively lower than labour costs in absence of climate policy, efficiency improvements are not as appealing as labour productivity gains (see equation 10 in Section 2) to consumption and capital good firms deciding which technology to adopt. Further, in our baseline scenario firms do not significantly change their fuel-electricity mix; electricity use stays around 30% of the total energy demand. The electricity firm improves the fuel efficiency of brown plants by 30% over the simulation period, while green plant installment costs drop by a lesser extent; in addition, fuel costs are not so high as to necessitate prioritizing the renewable technologies over fossil fuel-fired plants, consistently with the SSP5 narrative. Indeed, in the absence of climate policy, the lifetime costs remain about twice as high for green plants than for brown ones. Overall, efficiency improvements lower the carbon intensity of the economy (emissions per GDP unit) by 40%, but the atmospheric concentration of carbon rises sharply because of high growth, and the warming in 2100 reaches 4.8 °C (ensemble average; similar to the high-emission SSP5 marker scenario; Riahi et al., 2017).

Although the current version of our model does not include climate damages,[11] we argue in the Appendix that our most pessimistic estimates of GDP reductions due to policies aiming at limiting global warming to 2 degrees, are by far lower than damages from unmitigated climate change of our baseline scenario. In the following, we search for policies which achieve the 2 degree goal while limiting, if not stimulating, economic growth.

4.2 The fallacy of carbon taxation

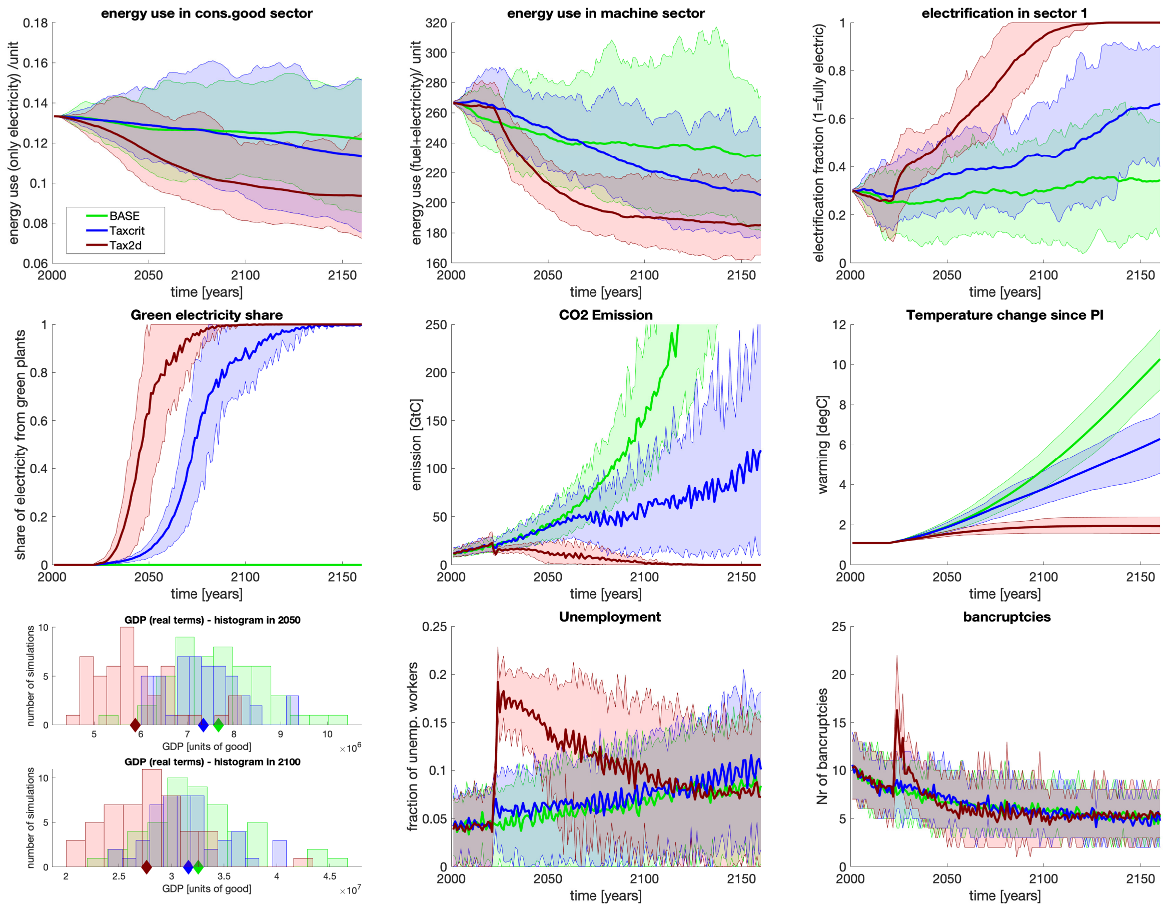
Our results robustly show that excessively low carbon taxation proves completely ineffective at inducing the transition, both in the power and industry sectors. Indeed, we find that the relative likelihood of complying to the 2°C target relying on carbon taxes below 100% of fossil fuel price approaches zero. Indeed, technologies and the knowledge required to master them are indivisible goods, and economic agents (capital good firms and the electricity firms) are more likely to invest in and struggle to adopt those showing economic convince, as measured - in our model - by relatively lower expected lifetime costs. Hence, to have sizable chances to induce and sustain a rapid transition, carbon taxation needs being sufficiently high and bold to make green technology an evolutionary surviving strategy. This result contradicts the narrative suggesting that gradual changes in relative prices incentivize more and more emitters to curb their emissions (e.g. Nordhaus, 1991, 1992).

Our simulations, as well as previous studies (Lamperti et al., 2020), suggest that there is a relatively narrow interval around a critical tax value X_{crit}, such that for taxes above this value we find a positive likelihood of failure at spreading green electricity production. Hence, when the carbon tax is raised above such interval, all ensemble runs show an increasing share of renewables in the energy mix, as the policy suffices to make green plants competitive. Figure 2 shows results for a tax just above $X_{crit} = 2.6p_{ff21}$ (experiment Taxcrit, see table 3), which corresponds to a carbon tax adding 260% to the cost of fossil-fuel ($p_{\text{ff}21}$), starting in 2021.

The value X_{crit} was found by running extensive simulation experiments with tax values gradually increasing in steps of $0.4p_{\text{ff}21}$. Within experiment Tcrit, it takes about 110 years until 80% of the simulations reach 100% green electricity, while all overcome 90%. This long duration of the transition in the power sector is due to several factors. The relatively modest tax, while making green plants just competitive with brown ones, does not suffice to make attractive the early decommissioning of brown plants before the end of their lifetime (at least not until innovations reduce green plant costs). Also, in periods where energy demand upswings require many new plants, the tax does not compensate for the

[11] We refer the reader to Lamperti et al. (2018, 2019, 2020, 2021) for model versions accounting for micro-level climate impacts and a detailed analysis of their emergent macroeconomic costs.

Figure 2: The macroeconomic and climate effects of constant carbon pricing. The thick line depicts the Monte Carlo ensemble mean, the shaded area shows the range between the 10th and 90th percentile.

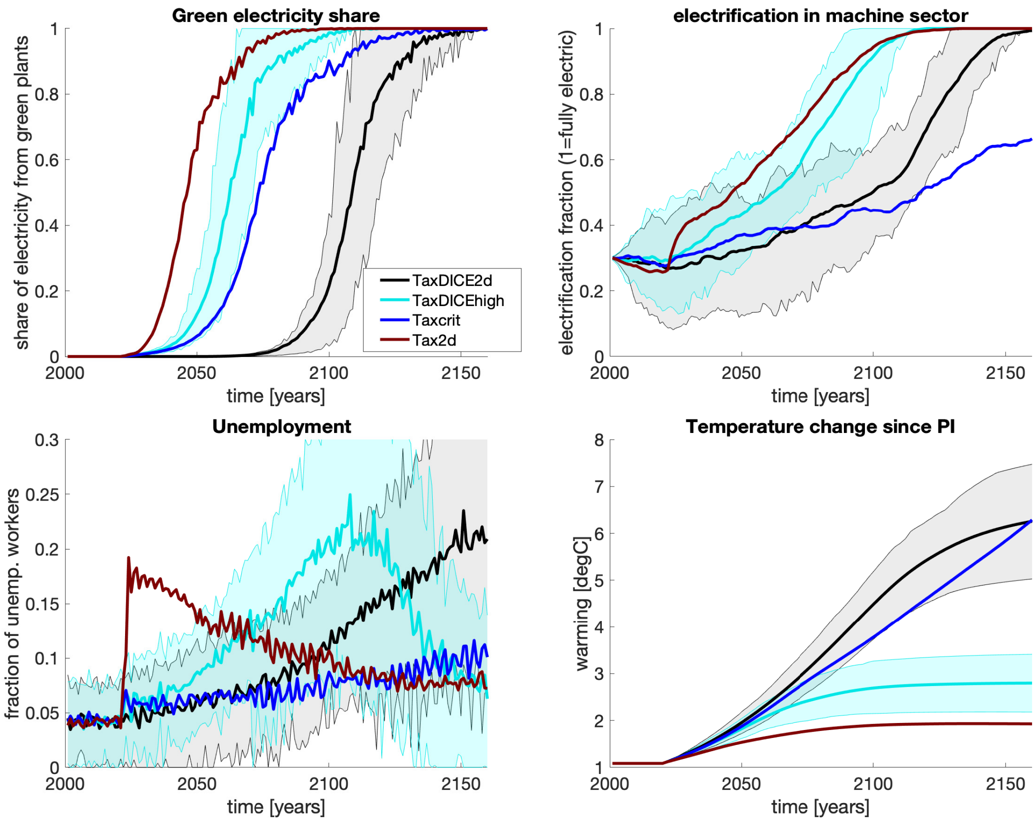


installment costs of a rapid green expansion, which makes new investments in fossil-fuel plants relatively more likely. The slow energy transition contributes to the insufficient emission reduction in the power sector and, further, cuts back the speed of electrification embedded in the process of technical change in the industry sector, wherein the share of fossil-fuel use on total energy requirements keeps above 40% in 2100. As a result, global warming in the Taxcrit scenario averages 3.8 (5.8) degrees in 2100 (2150).

Contrarily, experiment Tax2d (Figure 2, in dark red) shows that it is possible to keep end-of-century temperature anomaly below 2°C by solely employing a carbon tax, though this comes with exceptionally high economic costs. We find that in the DSK model a carbon tax as high as $X_{2deg} = 14.2 p_{\mathrm{ff}21}$ (experiment Tax2d) mitigates emissions rapidly enough to comply with the Paris Agreement target. Indeed, to speed up the green transition by about 30 years relatively to experiment Taxcrit, carbon pricing must be raised to 5.5 times the value X_{crit}, which was needed to bring about a transition in the first place. Our results point to the difficulty to overcome inertia in the process of technology search and adoption simply by raising the carbon tax. In addition, high carbon prices are found to foster economic instability, including a sharp increase of the unemployment rate (17.6% for 2024-2028; baseline: 4.4%) just after policy implementation, a decades-long adjustment process in the labour market, and a shorter rise in firms' bankruptcies, which moves from 7.9 bankruptcies per year in the baseline to 13.4 (average 2023-2027). Indeed, a relatively high carbon tax raises both fuel and electricity price in the energy-intensive machine sector, reducing the attractiveness of investments in consumption-good industry, where firms are constrained to invest in new capital vintages only to replace near to lifetime-end capital stocks. This leads to a drop in machine production, productivity growth and employment. Innovation towards lower overall energy use partially mitigates the high energy costs, but energy efficiency gains are limited, and overall insufficient to prevent slumps in the level of economic activity as well as a sensible reduction of output growth rates in the aftermath of policy implementation. Further, if revenues from carbon taxation were spent on a subsidy for firms hiring workers, (experiment Tax2df), the policy impact on unemployment would have dropped considerably, though remaining sizable large overall (10.2% for 2024-2028). A similar effect is observed when the tax revenues are paid out as unemployment subsidies, which would directly sustain consumption and, thus, aggregate demand (experiment Tax2dh). The fact that economic impacts are not fully mitigated by re-funding the tax revenue is explained by the inertia and hysteresis that modern complex economies show in the aftermath of crises (Dosi et al., 2018; Furlanetto et al., 2020). Overall, these result confirm the low economic and political attractiveness of aggressive carbon pricing (Peñasco et al., 2021; Goulder et al., 2008). Conversely, Figure 2 shows that relatively low carbon taxes (experiment Taxcrit) delaying and smoothing the transition produce statistically indistinguishable economic dynamics than the business as usual "no policy" baseline while fail to contain emissions growth.

Finally, our results show that exponentially increasing carbon pricing is far less effective than DICE and mainstream integrated assessment models suggest. The tax schedule from the TaxDICE2d experiment leads to a warming of 4.4 and 6.1 degree in 2100 and 2150, respectively (Figure 3); for TaxDICEopt, warming is even higher. The reason is that the tax is initially far lower than the price gap between green and brown plants: Even in TaxDICE2d, green plants only become competitive between 2049 and 2076, depending on brown innovation. Once the green plants are competitive, the full transition still takes time, for the reasons outlined above. As shown above, "inertia" can partly be overcome by higher taxes. However, the carbon tax in TaxDICE2d exceeds the level X_{2deg} and rise further, leading to increasing unemployment (20% in 2150; no-policy baseline: 8%). The initially low, but exponentially rising carbon tax suggested by DICE offer thus the worst outcome across both dimensions: initially too low to trigger a green transition, while sufficiently high at a later stage to cause economic instability (until full decarbonisation is achieved). Similarly, starting with a tax $X_0 = X_{crit} = 2.6 p_{ff21}$ (making green plants competitive from the start, experiment TaxDICEhigh) will not cause a green transition quickly enough to

Figure 3: The macroeconomic and climate effects of increasing carbon pricing. The thick line depicts the Monte Carlo ensemble mean, the shaded area shows the range between the 10th and 90th percentile. The ensemble mean for experiments Taxcrit and Tax2d are also shown for comparison.



stay below 2 degrees (peak warming: 2.8 degrees), while causing increasing unemployment until cheap, green electricity becomes available.

4.3 The macroeconomic effects of regulation and green subsidies

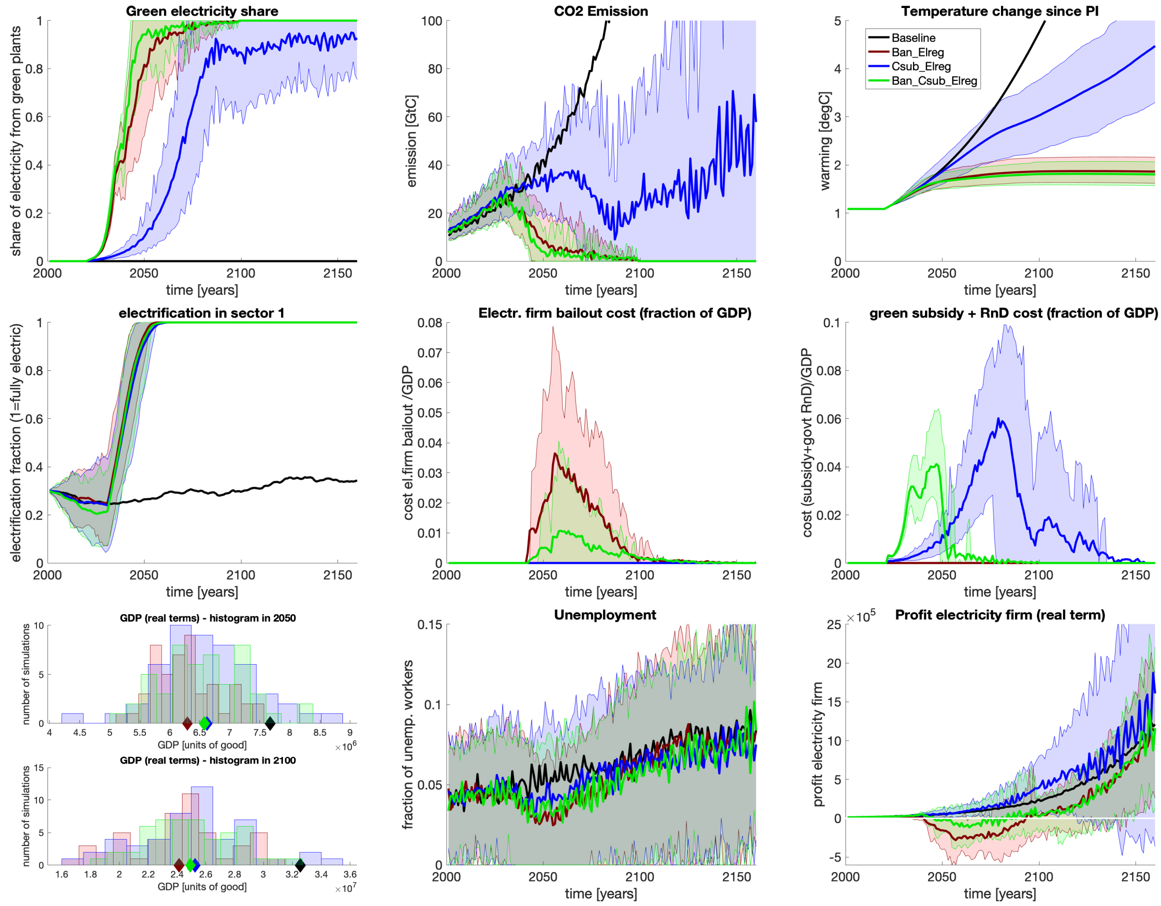
In this section we show that climate policies focusing on regulation and green subsidies are comparatively more effective than carbon pricing at producing a fast decarbonization compliant with the 2°C target, though some trade-offs emerge. Throughout this section, the policy mix we shall discuss will always include an electrification regulation (Elreg) announced in 2031 and enforced from 2051.

We start by considering two alternative policies adding up to electrification regulation and aimed at stimulating green electricity production: a ban on the construction of brown electricity plants (Ban) and a construction subsidy for green plants (Csub). Figure 4 shows the trajectory of the economy for both experiments Ban_Elreg (red) and Csub_Elreg (blue). For the brown plant ban, we assume that the policy announcement is made in 2021 and fossil-fuel fired plants are banned from use in power generation from 2041.[12] After the announcement, the electricity firm reacts by channeling its R&D expenditure to green technologies and progressively building a stock of green plants (even if electricity demand is met) such as to avoid expansionary bottlenecks once investment will be constrainedly green by regulation. Overall, the policy yields a peak temperature anomaly of 1.9°C (ensemble average) and successfully contains warming within the 2°C threshold in the long run (until 2150). Macroeconomic dynamics are relatively smooth, the transition rapidly increase the renewables' share in the energy mix (approaching 100% by 2070), which reinforces the effects of electricity regulation in the industry sector. In addition, we find evidence supporting a green stimulus to employment during the transition, as mirrored by unemployment rates consistently lower than in the "no policy" baseline experiment from about 2030 to 2080. However, the cost of the policy to the government increase (deficit raises by 1.2% of GDP with respect to the baseline, averaged over 2020-2100), due to the rescuing and refinancing the electricity firm during the transition, which might incur in negative profits when forced by the regulation to switch to green plants, which might still not be competitive. Policy experiment Csub_Elreg combines a construction subsidy with electricity regulation. Our results show that it brings about a green transition, but relatively slowly: 50% (95%) of green electricity generation is first reached in 2070 (2087), but during the last 20 years (2141-2160) of simulation period power generation is not fully decarbonized and some use of fossil-fuel fired plants is made in nearly all model runs. This happens because demand peaks within the business cycle still require to the construction of some brown plants, while the subsidy isn't sufficiently large to make full decommissioning of existing brown plants attractive. Global warming reaches 3.0 and 4.4 °C in 2100 and 2160, respectively (ensemble mean). The policy cost to the government averages 2.1% of GDP over 2020-2100, which is slightly less than twice as much the impact on public finances of the experiment Ban_Elreg.

Combining the brown ban and the construction subsidy (experiment Ban_Csub_Elreg; color green in Figure 4) leads to similar warming as the pure ban (1.9 degree; ensemble average). The total policy costs (subsidy and bailout plus refinancing of the electricity firm) is slightly higher than for Ban_Elreg, but significantly lower than in Csub_Elreg. In particular, compared to Ban_Elreg, the instability in the power sector is grossly mitigated: indeed, green construction subsidies reduce the burden of the energy transition from the electricity firm by taking over part of the construction costs enforced by the ban. The sum of the subsidy cost and the electricity firm's losses over 2020-2100 is in fact slightly higher for Ban_Elreg (1.1% GDP) than for Ban_Csub_Elreg (1.0% GDP), making Ban_Csub_Elreg slightly less costly overall. Compared to a no-policy baseline, the Ban_Elreg, Csub_Elreg and Ban_Csub_Elreg simulations still show a reduced GDP growth in ca 2031-2081, caused by the electrification regulation

[12]A number of alternative implementation dates have been tested and found producing inferior economic performance and slower decarbonization rates.

Figure 4: The macroeconomic and climate effect of non-tax policies: a ban on constructing brown plants (red), subsidy for green construction (blue) or both (red), all combined with the regulation on electrification in machine firms. The thick line depicts the ensemble mean, the shaded area shows the range between the 10th and 90th percentile. The black line (without percentile ranges) depicts the no-policy baseline.



making relatively more difficult to adopt a profitable innovation if the latter promotes fossil-fuel use. However, similarly to the Ban_Elreg experiment, we find evidence that the employment level rises considerably during the transition thanks to labor intensive plant-construction. Further, the second part of the century is characterized by sustained growth, which partly offsets the slowdown induced by climate policy. Indeed, when the industry sector approaches full electrification, technical change endogenously shifts across a new, single-input paradigm, the regulation policy does not bind any more and the share of novel yet discarded technologies shrinks, thus fostering green growth.

Finally, in experiment Ban_Csub_Elreg_RnD we let the government provide an R&D subsidy aimed at sustaining research in green power technologies. Including such policy instrument to experiment Ban_Csub_Elreg leads to significantly (up to 25%) lower prices of green plants from 2026 wards; however, the aggregate effects of including research subsidies in the policy package are marginal (see Figure 5), though it is notable that they shrink the fiscal costs of the transition, which are reduced to 1.0% of GDP per year (ensemble average across 2020-2100). This supports the idea that subsidizing green technologies cuts back the installment costs of renewable plants which, in turns, improve the financial conditions of the electricity firm during the central phase of the transition, when relatively expensive green power generation capacity is expanded at highest paces to comply with the command and control regulation. Lower bailout and refinancing costs mitigate the impact of the climate policy package on public finances. In that, the R&D policy acts as a stabilizing factor for transition risks entailed in the decarbonization of the power sector.

4.4 Combining regulation and monetary incentives for a rapid and orderly transition

As we have seen, the non-tax policies produce a fast mitigation of emissions in the power and industry sectors while stimulating employment during the transition. However, they slightly reduce the growth rate of the economy (vis-a-vis the "no policy" baseline) while reaching full electrification of capital-goods production and require some - though modest - fiscal costs to the public government, either directly (subsidies) or indirectly (bailouts and refining in the power sector).

Differently, in section 4.2, we showed that high carbon taxes are detrimental to macroeconomic stability, while sufficiently low carbon pricing does guarantee strong emission mitigation but does not harm the economy and improves public finances (see also Figure 5). Indeed, in our last experiment we find that a constant tax slightly below the critical value X_{crit} (namely, $X_{crit} = 2.2p_{ff21}$) suffices to offset the policy costs of the Ban_Csub_Elreg package. This is not just due to the tax revenues, but also to the fact that combing policy instruments lowers the overall size of construction subsidies for green plants by making fossil-fuel technologies relatively unattractive. Further, the tax lowers the (expected) bail-out costs for the electricity sector; indeed, the tax increases the sector's profit margin as long as some electricity stems from brown plants before the ban is actually enforced (see fig. 5). The policy is also more effective than its tax-free counterpart (experiment Ban_Csub_Elreg) at limiting emissions, with the peak temperature reduced to 1.6 degrees. On the other hand, the carbon tax introduces a (modest) adverse effect on the economy, including a slight initial increase of unemployment in the immediate aftermath of policy announcement, when the economy reacts to higher electricity prices; however, such effect is transitory and compensated by increased labor demand for green plant construction in the central phase of the transition, when unemployment rates drops below the baseline levels (consistently with the evidence collected in the experiments of Section 4.3 . Hence, our results suggest that a policy package composed of a ban to fossil-fuel fired plant construction (with 20 years grace period), electrification regulation in the industry sector, green subsidies reducing the financial burden of green plants installment and a carbon tax roughly doubling the fossil fuel price induces a transition allowing to contain warming well below 2°C, increase employment and absorb transition risk with a neutral impact on public balances.

5 Discussion

In this paper we have employed a global macro-financial agent-based integrated-assessment model to investigate the effects of climate policies for a rapid and orderly decarbonization on macroeconomic dynamics and global warming. Our results suggest that command-and-control regulation policies are most effective at inducing and sustaining the transition, foster employment and enable green growth. Their downside is that they increase public spending by generating financial instability in the power sector, whose costs we assumed are borne by the government (see also Huang et al., 2021). Coupling regulation with subsidies for green energy plants construction and a mild carbon tax mitigates such frictions and neutralizes the adverse effects on the public budget, thereby delivering a win-win policy package.

Our simulation experiments contradict the mainstream narrative on the desirability of gradually increasing carbon pricing, which suggests to start decarbonizing with low-hanging fruits and tackle expensive measures later. This narrative ignores inertia and the evolutionary nature of the process of technical change, which lies at the core of the transformation that a green transition requires. Our results suggests that a carbon tax should be substantial from the outset, mainly intended as sources of financing for other policy measures rather than as a price signal inducing system-wise transformations; further, it should be potentially sector dependent, to avoid all sectors facing very high costs for sake of the most expensive-to-decarbonise ones (Vogt-Schilb et al., 2018). Indeed, our results support the idea that if a sector takes long to decarbonize, it should be tackled without delay, even if (initially) expensive.

Green technologies' development and adoption are at the basis of the decarbonization process, and both need an adequate institutional environment actively sustaining them. Policy packages including regulation and public support to low-carbon energy technology all increase the pace of green innovation and temporarily reduce unemployment w.r.t. the "no policy" baseline. The reason is that, in addition to avoiding the adverse impact of taxation, the rapid expansion of green plants leads to more jobs in electricity plant construction (3.2% of the workforce in 2060 for Ban_Csub_Elreg, compared to 0.5% in the baseline). Once the green transition is mostly completed, employment shifts again towards the industry sector, where technical change occurs relatively faster thanks to less binding regulation. This also enables relatively higher economic growth in the later stage of the transition rather than in its infancy.

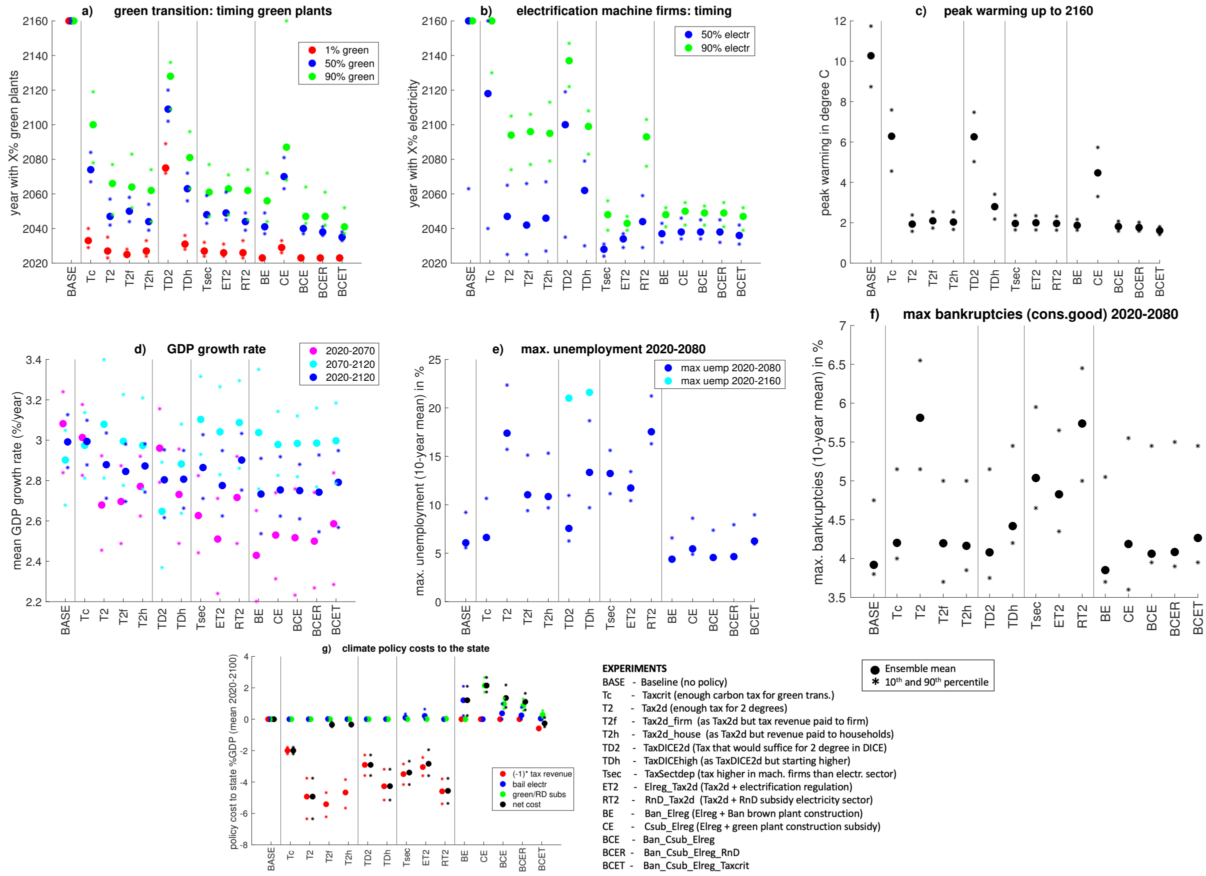
Indeed, our evidence supports the in-existence of a trade-off between a rapid transition and favorable growth outlooks; contrarily, this study shows that transition costs are minimal under the most effective policy mix and also vanish in the long run, with the transition being accompanied by relatively higher employment levels than in the baseline due to large and publicly-sustained investments.

However, we notice that our preferred policy package produces higher employment level accompanied with relatively lower output growth than the "no policy" baseline during the transition. This reflects the fact that an increased need of labor to expand green power generation capacity comes with a constrained process of technological adoption in the industry sector, wherein potentially productive yet high-emission technologies are disregarded by policy prescription. Given our calibration, the adverse effect on the Schumpeterian engine of growth more than compensate the Keynesian aggregate demand effect brought about by employment. However, we observe only a temporary and mild reduction of the growth pace of the economy, which keeps being significantly positive during the whole transition period.

Appendix

Summary of results

Figure 5: Overview over all policies discussed. Tc stands for Taxcrit, T2 for Tax2d, TD for TaxDICE. El for Elreg, B for ban, C for Csub, R for RnD. (a) the year where X% of electricity stems from green plant (if never occurring, the last year (2160) is plotted). (b) the year where X% of energy in machine production is electricity. (c) the highest warming occurring up to 2160. (d) mean GDP growth rate over 50 and 100 year blocks. (e) the highest 10-year-mean unemployment (% of workforce) occurring between 2020 and 2080 (the light blue dots in two simulations denote a sharp peak occurring after 2080). (f) The highest 10-year-mean fraction of consumption good firms going bankrupt. (g) government expenditure on climate policy. In TDf and TDh, the revenue is smaller than the tax because most of the tax is paid back to firms or households. In all plots, thick circles denote the ensemble mean, while stars are the 10th and 90th percentile.



Mitigation impacts and climate damages

Here we provide a off-line evaluation of the climate damages, intended as physical impacts to the economic system, implied by the experiments of the present study. We show that even using a conservative model (i.e. DICE2016) to perform the exercise, the "no policy baseline" and all policy packages which do not comply to the 2°C threshold produce economic losses due to warming that are way larger than what they would cost in terms of transition frictions. We interpret these results as evidence suggesting the desirability and urgency of bold climate action.

We test the following damage functions within DICE2016:

- Zero climate damage (reference case): $D = 1$
- DICE2016 climate damage: $D(t) = 1 - 0.00236T(t)^2$ where T is global warming in degC above pre-industrial
- trebled DICE2016 climate damage: $D(t) = 1 - 3 * 0.00236T(t)^2$
- Weitzman climate damage: $D(t) = [(0.0495T(t))^2 + (0.1645 * T(t))^{6.76})]^{-1}$

Inserting the temperature trajectory of our no-policy baseline (which in 2100 reaches 5 degrees above pre-industrial, in line with the high-emission SSP5 scenario), we find for 2100 a GDP reduction of 7% (DICE2016 damage), 21% (DICE2016*3), and 40% (Weitzman) w.r.t the no-damage reference case. For the Weitzman case, the economy stops growing in 2090. The specification of Burke et al. (Burke et al., 2015) even suggests a GDP reduction of 25-75% in 2100 for a scenario with a final warming of slightly less than 5 degrees. The most drastic policy capable of limiting global warming to 2 degrees which we consider in this paper, a high constant carbon tax, leads to a GDP reduction in 2100 of 15% (Figure 5).

Increasing carbon taxes

Table 2: Details of increasing carbon taxes

Experiment	X_0	α
TaxDICEopt	$0.77p_{ff21}$; fit from DICE optimal	$2.63\%/year$; fit from DICE optimal
TaxDICE2d	$1.02p_{ff21}$; fit from DICE's 2-degree policy	$4.20\%/year$; fit from DICE's 2-degree policy
TaxDICEhigh	$2.6p_{ff}$, i.e. initial critical tax X_{crit}	$4.20\%/year$; fit from DICE's 2-degree policy

Parameter

Table 3: Main model parameters and initial conditions.

Description	**Symbol**	**Value**
parameters not involved in calibration		
Monte Carlo replications	MC	50
Time steps in economic system	T	400
Number of firms in capital-good industry	F_1	50
Number of firms in consumption-good industry	F_2	200
Number of bank's clients	α_b	20
parameters involved in calibration		
Capital-good firms' mark-up	μ_1	0.04
Consumption-good firm initial mark-up	$\bar{\mu}_0$	0.28
Energy monopolist' mark-up	μ_e	0.01
Uniform distribution supports	$[\varphi_1, \varphi_2]$	$[0.10, 0.90]$
Wage setting $\Delta \bar{AB}$ weight	ψ_1	1
Wage setting Δcpi weight	ψ_2	0
Wage setting ΔU weight	ψ_3	0
R&D investment propensity (industrial)	ν	0.02
R&D allocation to innovative search	ξ	0.5
Firm search capabilities parameters	$\zeta_{1,2}$	0.3
R&D investment propensity (energy)	ξ_e	0.01
Share of energy sales spent in R&D	v_e	0.01
Initial share of green energy		0.2
Beta distribution parameters (innovation)	(α_1, β_1)	$(3, 3)$
Beta distribution support (innovation)	$[\chi_1, \bar{\chi}_1]$	$[-0.075, 0.075]$
New customer sample parameter	$\bar{\omega}$	0.5
Desired inventories	l	0.1
Physical scrapping age (industrial)	η	19
Physical scrapping age (energy)	η_e	80
Payback period (industrial)	b	3
Payback period (energy)	b_e	10
Mark-up on base loan interest rate	μ_b	0.30
Scaling parameter for interest rate cost	k_{scale}	0.10
Extremes of support for bailout policy	$[\phi_1, \phi_2]$	$[0.10, 0.90]$
Inflation adjustment parameter	γ_π	1.10
Unemployment adjustment parameter	γ_U	1.10
Income tax rate	tax_i	0.15
Profit tax rate	tax_p	0.15
Unemployment subsidy rate	w^U	0.35
Green R&D subsidy size	θ_{RnD}	0.5
Green construction subsidy size	θ_S	0.67
Grace period for brown plants ban	T_{Ban}	20
Grace period for electrification regulation	T_{Reg}	20

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