CESifo WORKING PAPERS

10364
2023

April 2023

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CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
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CESifo *Working Paper No. 10364*

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Abstract

We consider technology choices between green and brown technologies by firms. We use insights from complexity theory and also take account of true uncertainty in designing public policy. The green technology offers relatively higher returns to scale from adoption, and there are type-contingent differences among firms in their suitability for the green technology. We show that the long-run outcome is unpredictable despite there being no fundamental uncertainty in the model; small accidents of history can lead to large effects; and the final outcome is an 'emergent property' of the system. We describe the role of taxes and subsidies in facilitating adoption of the green technology. We also consider issues of the conflict between optimal Pigouvian taxes and green technology adoption; optimal temporal profile of subsidies; and the desirability of an international fund to provide technology assistance to poorer countries. Despite the simplicity of the framework, several novel results are demonstrated that typically do not arise in the standard analysis of the problem.

JEL-Codes: D010, D210, D900, H320.

Keywords: technology choice, climate change, complexity, lock-in effects, increasing returns, green subsidies, public policy, Pigouvian taxes, stochastic dynamics.

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April 1, 2023
I am very grateful to Francois Lafond and Doyne Farmer for helpful comments and suggestions. The usual disclaimers apply.

1 Introduction

There is growing awareness of the dangers of climate change and the need for action using 'non-standard' approaches, relative to the traditional approaches used in economics (Nordhaus, 2019; Stern, 2022; Stern and Stiglitz, 2023).[1]

The following three key features provide the basis for a 'non-standard' approach that is highlighted in Stern (2022) and Stern and Stiglitz (2022). First, there are strong scale economies of adoption, and increasing returns, in green technologies. Second, the pervasiveness of *true uncertainty*, or Knightian uncertainty or radical uncertainty (Knight, 1921; King and Kay, 2020). This makes the calculation of optimal choices difficult, if not impossible, with the use of standard social welfare functions.[2] Thus, we need a 'guardrail approach' with broad objectives/aspirations/targets such as limiting the increase of global temperatures at 1.5 degrees, based on the best available science, and not on maximizing a standard social welfare function.[3] Third, the presence of complex adaptive dynamics, with the existence of tipping points that lead to large changes arising from small accidents of history. Stern and Stiglitz (2022) lament that none of these features, individually, or as a group, has been satisfactorily incorporated in the standard economic analysis of the problem of climate change.

In actual practice, an important aspect of the problem is that firms have a variety of technological choices to make. These choices typically trade off a *green technology* that is good for the environment against a *brown technology* that produces some environment bads.[4]

We consider the technology adoption decision of firms (in terms of green vs brown technology) and appropriate public policy, while taking account of the three key non-standard features of interest outlined above.[5] We are not particularly interested in the short-run properties of the

[1]Similar observations are made in successive IPCC reports. The implications of climate change are profound (Stern, 2022, p.1261): "...fires associated with heat and drought; severe flooding; hurricanes and typhoons; storm surges; sea level rises; local temperatures at levels dangerous to human life..... Many parts of the world could become uninhabitable...Hundreds of millions, possibly billions, would have to move, likely resulting in severe and extended conflict."

[2]A separate, but not less serious problem is that the social welfare functions might not even be defined in the presence of catastrophic climate change risks, such as deaths/displacement of several billion people. The utility function in this case is likely to tend to minus infinity in the worst states of the world, precluding any meaningful analysis of risk based on, say, expected utility theory (Weitzman, 2009).

[3]Stern (2022, p. 1277) is explicit about this point: "...the consensus across more than 190 countries embodied in the Paris 2015 UNFCCC agreement did not require full agreement on the utility function to be maximised, the correct damage function, discounting or the probabilities of outcomes. Instead, as it became clear, and broadly accepted, that with temperature rise over 2^0C there was a significant probability of extremely bad outcomes, and that those outcomes could be avoided at moderate costs, there emerged consensus that we should act strongly to try to avoid them. It should be noted that it is this understanding that has led the international community to focus on achieving net zero emissions by around 2050, not the recommendations of economists based on IAMs [integrated assessment models]." Other examples include pledges to phase out incandescent bulbs and internal combustion engines by a cutoff date, despite the, then, non-existence of viable alternatives. Yet, once these announcements were made, the alternatives were quickly developed, exhibited increasing returns, and were adopted relatively quickly.

[4]Not all of these technology choices are in terms of plants and equipment. Some of these technology choices are likely to involve a "green package" comprising several useful technologies. For instance, the installation of solar panels for power; use of cloud computing or green data centers that reduce environmental costs of less efficient in-house servers; remote work technologies to save environmental commuting costs; installation of energy efficient devices to monitor energy use; hybrid or EV company vehicles; and green packaging and shipping material.

[5]For this reason, our paper is not related to the large and important literature on *integrated asset models* (IAMs). This literature was pioneered by Nordhaus (1991, 2019) and was further developed in several directions; see Nordhaus, (2017). For an extensive critique of the non-suitability of IAMs to some of the key issues of climate

dynamic system, so we do not focus on transition paths. Our main interest is in the long-run outcomes only.

1.1 Essentials of our model

In our simple model, inspired by the framework in Arthur (1989), a large number of firms make sequential technology adoption choices between a 'green technology' that produces no emissions and a 'brown technology' that produces harmful emissions. We consider the case of increasing returns to scale in the sense that greater adoption of a technology lowers its costs and/or increases its benefits.[6]

Our assumptions on type-contingent and technology-contingent effects of technology, that we outline below, set our work apart from the competing literature. The green technology has relatively 'stronger' returns to scale from adoption (higher benefits or lower costs as more firms adopt it) as compared to the brown technology.[7] Firms are of two types, G (green) and B (brown). Type G firms are relatively more 'suited' to adopting the green technology because their net benefits from adopting it are higher.[8] Type B firms are relatively more 'suited' to adopting the brown technology because their net benefits from adopting it are higher.

In a nutshell, we have *technology-contingent differences* (green technology offers relatively greater returns to scale from adoption) and *type contingent differences* (type G firms are relatively more suited to adopting the green technology). None of the existing theoretical models simultaneously allow for these two differences, which have strong empirical grounds.

In each time period, nature picks one of the firms randomly to make a technology choice. The probability that firms of type G and B are picked to make a choice depends on their respective proportions in the population of firms. We are interested in the long-run dynamics of this system. We show that our results are robust to including uncertainty, time discounting, allowing multiple firms to make a simultaneous technology choice, and to more than two types of technologies. We also extend our model to *stochastic technology dynamics* in Section 6; see

change and for the relevant references, see Stern (2022) and Stern and Stiglitz (2022). We do not contribute to this debate in our paper.

[6]This is a reduced form way of capturing several possible benefits to the firms from adopting the green technology. For instance, a reduction in technological/organizational costs of production on account of learning by doing; an increase in reputational benefits from adopting the green technology over time; network externality effects (Katz and Shapiro, 1985); establishment of common standards that reduce costs; social interaction effects (Young, 2009); and strategic complementarities that reduce costs with greater adoption. In our paper, we are agnostic as to the exact transmission channel.

[7]Any technology improves with greater usage on account of learning by doing that results in improvements in the technology and/or in the organizational use of that technology. Indeed, the literature on learning by doing, and the associated empirical evidence, was developed in the context of brown technologies. Hence, it would be undesirable to assume that brown technologies necessarily become more expensive as more firms use them. However, the evidence does strongly indicate that the rate at which green technologies become relatively cheaper with greater adoption exceeds that of brown technologies; for a review see Stern (2022). This is the assumption we make. It might, however, be the case that in periods of rapid adoption, there could be scarcity of raw materials that creates bottlenecks for both types of technologies. We abstract from such transitory issues and our interest is in the long-run.

[8]For instance, firms that have a higher share of energy costs might benefit more from green energy-saving innovations; firms that have more funds could be in a better financial position to invest in green technologies; or the existing technological/organizational features within a firm may have greater strategic complementarities with the proposed green technology. These type-contingent differences among firms in the relative benefits and costs of adopting green technologies are well supported by the empirical evidence (Arvanitis et al., 2017; Hottenrott et al., 2016; Stucki, 2019).

Young (1993, 1998, 2006) and Dhami (2020, Vol. 6) for an introduction to this literature and methods.

1.2 Main results

Our framework is simple, yet offers powerful results. We discuss the results below under two main headings.

1. *System dynamics*: We show that the system dynamics have the usual features of complex adaptive systems.[9] (i) Ex-ante, the long-run outcome is unpredictable despite there being no inherent uncertainty in the model. For instance, in the long-run, we could either have all firms eventually choosing the brown technology (state $S = b$), or all firms choosing the green technology (state $S = g$). We may observe lock-in effects into a particular technology after certain tipping points are reached. (ii) The long-run outcome is history dependent and the dynamic system is not ergodic. (iii) Small accidents of history can have large effects, as is typical in models of chaotic dynamics, although we do formalize transitory dynamics.

   When we introduce stochastic technology dynamics in Section 6 we show that there might be 'punctuated equilibria' and we give simple conditions that show which of the two states, $S = b$ or $S = g$, is stochastically stable. We also show why evolutionary dynamics are not appropriate in our framework.

2. *Public policy*: The final outcome is unpredictable, yet at the beginning of time, and prior to any technology adoption decisions, governments need to formulate and implement economic policies towards technology adoption. Consistent with the empirical evidence, we consider taxes on benefits and subsidies to cost for both types of technologies. Since the dynamic paths can meander in all sorts of unpredictable directions, a time-varying policy, made on the hoof, will create considerable temporal uncertainty for the government and would appear to be empirically uninteresting. Hence, we assume that the government credibly announces all taxes and subsidies at the beginning of time, before any technology adoption decisions have been made.[10]

   Although, the 'actual' long-run outcome is unpredictable, the government can form ex-ante expectations of the long-run outcomes and base its fiscal policy on these expectations. Indeed, there is no other way to conduct public policy in such an environment. This is the route that we follow. For the reasons mentioned above, the government does not maximize some well defined social welfare function. It follows a 'guardrail' approach suggested in Stern (2022), Stern and Stiglitz (2022). For instance, the government's stated aspiration/objective could be that in the long-run it wishes all firms to adopt the green technology.[11]

[9] For an introduction to complex adaptive systems, the reader can consult Arthur (2015), Dhami (2020, Vol. 6), Hommes (2021) and follow up the extensive references therein.

[10] In the real world, one might imagine periodic reviews of such policies and occasional revisions of the initially announced taxes and subsidies. Although we do not introduce such considerations in the main, we consider their implications in a separate subsection.

[11] Several examples can be given from the real world. For instance, banning diesel cars/incandescent light

Furthermore, political/legal/constitutional/fairness constraints on the imposition of taxes and subsidies are pervasive in the real world and this sets 'feasible bounds' on these fiscal instruments.

We show the following results. (i) Implementing optimal Pigouvian taxes on emissions from brown technology might be inconsistent with the objective of ensuring the long-run adoption of green technologies. The reason is that Pigouvian taxes that simultaneously ensure long-run green technology adoption might violate the feasible bounds on fiscal instruments. In that case, the government will need to abandon one of the two objectives (optimal Pigouvian taxes or the stated objectives on long-term green technology adoption). (ii) In the presence of increasing returns to scale from adoption, the government can announce a time path of subsides that decreases over time.[12] Once enough firms have adopted the green technology, the subsidies can be completely withdrawn, and yet the dynamic system may lock-into the green technology. (3) The level of subsidies needed to ensure adoption of the green technology might be unaffordable for poor countries and lead to the proliferation of global environmental bads. This will require the formation of an international fund to subsidize green technology adoption in poor countries.

1.3 Related literature

The closest paper is the seminal work of Arthur (1989) but there are important differences. First, he allows only for type-contingent differences in returns to scale, while we allow for both type-contingent and technology-contingent differences in returns to scale. Second, he does not consider the role of fiscal policy, which plays an important role in our analysis. Our paper is fundamentally different from Zeppini (2015) in the following ways. In his model, representative firms are all of the same type, so there are no type-contingent and technology-contingent differences. Firms have stochastic utility and the error term is iid across the various firms. Using the framework in Brock and Durlaf (2001, 2002), it is straightforward to show that if the error term has a double exponential distribution, then the proportion of firms that adopt the green technology is given by a one parameter multinomial logit distribution. The size of this single parameter, relative to the other model parameters, then allows for an exploration of interesting complex dynamics such as bifurcations and chaos.[13]

bulbs/ozone-depleting CFCs by a certain cutoff date in different countries. These objectives are not derived from sophisticated cost-benefit considerations based on an underlying social welfare function (Stern and Stiglitiz, 2022). Indeed, such calculations are not feasible in the presence of true uncertainty. Rather, they are based on some sort of holistic public judgement that draws on the best available science, and perhaps a desire to avoid the worse possible states of the world– a form of robust control. We are agnostic about the exact transmission mechanism.

[12] Examples of subsidies to green technologies abound. In the UK, in 2021, within 6 months of the Prime Minister's 10 Point Plan for a Green Industrial Revolution, a £166.5 million cash injection was announced. In 2016, subsidies towards renewable energy technologies in the US amounted to US$140 billion. In China, over the period 2016–2018, government spending on ecological/environmental protection was CNY 2.451 trillion. Similar examples can be given for many of the richer OECD countries. In some cases, tax rebates on the use of green technology also serve to subsidize its usage.

[13] The empirical relevance of the assumptions of stochastic utility, and iid errors across firms that are distributed with a double exponential distribution is not clear (Alós-Ferrer et al., 2021). We also have no empirical basis to evaluate the magnitude of the single parameter of the multinomial distribution whose size determines the dynamics of the resulting system. The model allows for taxes, but, unusually, the taxes are levied directly on the

The endogenous growth theory literature is well developed in economics (Aghion and Howitt, 1997) as is the literature on the economics of innovation (Bloom et al., 2019). Neither of these literatures deal with issues that are central to our paper (Stern and Valero, 2020), such as type-contingent and technology-contingent net benefits from alternative technologies under increasing returns to scale from adoption, nor does it lead to the set of results obtained in our model (endogenous fluctuations, lock-in effects, history-dependent small accidents that have large effects, and emergent phenomena).

1.4 Plan of the paper

Section 2 outlines the model. Section 3 considers the optimization decision of each type of firm; the equilibrium in the model; and its main features. Section 4 takes an ex-ante perspective and asks what is the long-run expected outcome, and the conditions that give rise to desirable and less desirable expected long-run outcomes. Section 5 considers policy applications for Pigouvian taxes, the dynamic path of subsidies, and arguments for a fiscal fund for poorer countries to afford green technologies. Section 6 gives extensions of the model to stochastic technology choices, and relaxes several assumptions in the model.

2 Model

There are $i = 1, ..., N$ firms within a country. Each firm produces 1 unit of output. There are two types of technologies. A "green technology" that produces no emissions and a "brown technology" that produces a fixed amount of emissions with marginal social costs given by $C_s > 0$.

Time $t = 1, 2, ...$ is discrete. In each time period, t, a randomly chosen firm must make a mandatory technology adoption decision between the green and the brown technologies, while all other firms are passive in that period; we relax this assumption in Section 6. At the beginning of time t, before any time t technology choice decisions have been made, t_g firms in the past have chosen the green technology, and t_b have chosen the brown technology.

There are two types of firms, a 'green type' G and a 'brown type' B. At the beginning of time $t = 1$, before any time $t = 1$ technology adoption decisions have been made, a type G firm is relatively better suited to the green technology, while a a type B firm is relatively better suited to the brown technology (type-contingent differences). The notion of 'better suited' is formalized below. At the beginning of time, a share $0 < \lambda_G < 1$ of the firms are type G and the remaining share $\lambda_B = 1 - \lambda_G$ is type B firms. The proportion of brown firms is relatively greater so that

$$\lambda_G < \lambda_B. \tag{2.1}$$

Reflecting the proportions of each type of firm in the population, in each time period $t = 1, 2, ...$ nature randomly picks a type G firm with probability λ_G and a type B firm with probability λ_B to make the technology choice decision.

state variable (the probability of firms adopting a green technology) rather than on the benefits and costs of the technology adoption.

The government can levy taxes on benefits from any of the technologies and give subsidies on costs; we observe both kinds of instruments in the real world. For reasons discussed in the introduction, the government does not choose its taxes and subsidies in the classical manner to optimize a social welfare function. Instead, it follows a guardrail approach and sets broad targets and aspirations, such as the adoption of the green technology by a certain time period.

We use the following notation. The respective variables pertaining to the benefits/costs of the green technology and the brown technology, respectively, are subscripted with a lowercase 'g' and a lowercase 'b.' Variables pertaining to the 'type' of the firm are superscripted with an uppercase $j = G, B$; the only exception is our usage of subscripts in the case of λ_G and λ_B.

2.1 Net type-contingent benefits of each technology

The net benefits from each of the technologies, for each type of firm, are calculated as follows.

The green technology gives the following utility to a firm of type $j = G, B$ at time t,

$$U_g^j = B_g^j (\tau_g, s_g) + r_g t_g;\ j = G, B,\ r_g > 0,\ s_g, \tau_g \in [0, 1], \tag{2.2}$$

where

$$B_g^j (\tau_g, s_g) = b_g^j (1 - \tau_g) - c_g^j (1 - s_g);\ j = G, B, \tag{2.3}$$

is the *time-invariant* net benefit of the green technology to a type $j = G, B$ firm; b_g^j and c_g^j are, respectively, the gross benefits and costs from adoption of the green technology to a type $j = G, B$ firm.[14] The tax rate on benefits, and the subsidy rate on cost, are respectively given by $\tau_g, s_g \in [0, 1]$. For a given technology, the fiscal parameters cannot be differentiated by the type of the firm due to, say, legal/fairness/informational reasons. We have that

$$B_g^G (0, 0) > B_b^G (0, 0)\,; \tag{2.4}$$

so, in the absence of any government policy, the green technology offers a relatively higher time-invariant benefit to type G firms relative to the brown technology. This is the sense in which firms of type G are relatively 'better suited' to the green technology.[15]

The second component on the RHS of (2.2), captures the *time-dependent* variable returns $r_g t_g$ from the green technology. These returns depend on the number of other firms, t_g, that have already adopted the green technology. The parameter $r_g > 0$ captures the effects of returns to scale from the adoption of the green technology. For every green technology adoption by a firm, the extra marginal benefit to a subsequent adoptor of the green technology is r_g.

The utility from the adoption of the brown technology to a firm of type $j = G, B$ is

$$U_b^j = B_b^j (\tau_b, s_b) + r_b t_b;\ j = G, B,\ r_b > 0,\ s_b, \tau_b \in [0, 1], \tag{2.5}$$

[14] The term b_g^j captures several potential benefits to the firm, including the classical gross revenues to the firm from selling its own unit of output. Our interest does not lie in studying the effects of market structure on the benefits to the firm, so we abstract from these issue. Similar comments apply to the benefits to firms adopting the brown technology.

[15] Recall from the introduction, the discussion on this issue and the empirical evidence (Arvanitis et al., 2017; Hottenrott et al., 2016; Stucki, 2019). Some of the factors conducive to making some types of firms more suited to the green technology include the share of energy costs; complementarity of their existing technology and organizational structure with the new green technology; type of output produced; availability of funds for green investment; and the social responsibility of the firm.

where,

$$B_b^j(\tau_b, s_b) = b_b^j(1-\tau_b) - c_b^j(1-s_b)\; j = G, B, \tag{2.6}$$

is the time-invariant net benefit of the brown technology to a firm of type j and b_b^j, c_b^j are the respective benefits and costs; τ_b, s_b are the corresponding tax and subsidy rates on the benefits and costs of the brown technology. In the absence of any government intervention, the brown technology offers relatively greater net benefits to type B firms, so

$$B_g^B(0,0) < B_b^B(0,0). \tag{2.7}$$

The inequality in (2.7) formalizes the sense in which the type B firms are relatively 'better suited' to the brown technology. The second component on the RHS of (2.5), $r_b t_b$, is time-dependent and depends on the number of firms, t_b, that have already adopted the brown technology. The parameter r_b gives the returns to scale from adoption of the brown technology.

We summarize the relevant information in this subsection in Table 1.

Net Benefits	Green technology	Brown technology
Type G firm	$B_g^G(\tau_g, s_g) + r_g t_g$	$B_b^G(\tau_b, s_b) + r_b t_b$
Type B firm	$B_g^B(\tau_g, s_g) + r_g t_g$	$B_b^B(\tau_b, s_b) + r_b t_b$

Table 1: Type and technology-contingent net benefits from technology adoption.

2.2 The robustness and generality of our framework

Our simply model nests several possible extensions such as uncertainty, non-linear net benefits, and time discounting. We show below that this requires a simple relabeling of our variables.

1. Risk and uncertainty: Suppose that the benefits from investing in the green technology are uncertain and there is a distribution of benefits b_g^j defined over the interval $[\underline{b}, \overline{b}]$ with an underlying distribution function F_g; such a distribution can be an objective distribution (risk) or a subjective distribution (uncertainty). Redefine (2.6) as

$$B_g^j(\tau_g, s_g) = (1-\tau_g)\widehat{b}_g^j - c_g^j(1-s_g),$$

where $\widehat{b}_g^j = \int_{\underline{b}}^{\overline{b}} b_g^j dF_g$, and the entire analysis carries over unchanged.

2. Time-varying net benefits and discounting: Suppose that a firm making a green technology adoption decision at time $t = k$ receives time-varying benefits that are discounted. Redefine (2.6) as follows

$$B_g^j(\tau_g, s_g) = (1-\tau_g)\widetilde{b}_g^j - c_g^j(1-s_g), t \geq k,$$

where $\widetilde{b}_g^j = \sum_k^{\widetilde{T}} \delta^{t-k} b_g^j(t)$; $\widetilde{T}$ is some terminal date after which benefits cease, $b_g^j(t)$ is the time t benefit, and $0 < \delta < 1$ is the discount factor.

3. Non-linear utility: Suppose that the utility from net benefits is non-linear, and $B_g^j \subset X$. We can now introduce a utility function $V : X \to R$ and restate all our results in terms of $V(B_b^j)$, without changing any insights.

We can also combine uncertainty, time discounting, and non-linear net benefits by utilizing, say, expected utility and exponential discounting, without altering any insights. All these extensions can also be made analogously for the brown technology.

We consider the following extensions of the model in Section 6. Our results are robust to extending our model to allow for several firms simultaneously making the technology adoption decision at time $t = 1, 2, ...$ The model can also be easily extended to more than 2 technologies. We also extend our model to stochastic technology dynamics where each firm chooses its optimal technology with some probability $0 < \varepsilon < 1$ and engages in some 'experimentation' by randomizing over both technologies with some small probability $1 - \varepsilon$.

2.3 Returns to scale from technology adoption

As noted in the introduction, the empirical evidence suggests that green technologies, because they are newer and developed within the confines of the current technological environment, confer relatively larger economies of scale from adoption.[16] By contrast, brown technologies are older and additional improvements in returns to scale arising from technological/organizational improvements are more limited. Hence, we assume[17]

$$0 < r_b < r_g. \tag{2.8}$$

2.4 Set of Fiscal instruments

Suppose that there are political/legal/constitutional/fairness constraints on the imposition of taxes and subsidies.[18] The government fiscal policy instruments are the technology-contingent

[16] Consumers would not have failed to notice the massive drops in the prices of solar panels, led bulbs, and electric vehicles. Similar, and rapid, drops in prices have also been observed for technological inputs purchased by firms. Costs of electricity from utility-scale solar photovoltaics (PV) alone fell 85% between 2010 and 2020. The United Nations Climate Change press release dated 14 July 2022 points out that over just a period of about an year, the cost of electricity from onshore wind fell by 15%; and offshore wind and solar PV fell by 13%. The report goes on to say that "almost two-thirds or 163 gigawatts (GW) of newly installed renewable power in 2021 had lower costs than the world's cheapest coal-fired option in the G20... given the current high fossil fuel prices, the renewable power added in 2021 saves around USD 55 billion from global energy generation costs in 2022."

[17] With the notation now set, it might be worth considering the differences from two related papers. The seminal model in Arthur (1989) has important differences from our model. The first, and most important, difference is that $r_b = r_g$ for each type of firm, which allows for a simpler model. Second the role of fiscal policy is omitted, which plays an important role in our analysis (see below). Third, there is no consideration of stochastic technology dynamics. Zeppini (2015) also assumes $r_b = r_g$. The taxes are not levied directly on net benefits B but a term of the form $(1-\tau)t_b$ is subtracted from B. The nature of these taxes and their real world counterparts are not entirely clear. Finally, stochastic dynamics that allow for punctuated equilibria are not considered in their model of a representative firm.

[18] Several examples of such constraints can be given. For instance, an entrenched brown technology lobby might prevent variations in τ_b, s_b, which might force governments to rely more on the use of taxes/subsidies on the green technology. The state of government finances might not allow subsidies beyond a certain level. Electoral concerns might make particular taxes either more or less popular. There are several legal constraints on how high certain taxes can be. Taxing two activities that are broadly similar might invite charges of unfairness, and possibly a legal challenge, or have political consequences.

taxes on benefits, and the subsidies on costs, $(\tau_g, \tau_b) \times (s_g, s_b) \in T$, where the set of all taxes and subsidies that respects the relevant constraints on taxes and subsidies is $T \subset R^4$.

As suggested in Stern and Stiglitz (2022), the fiscal instruments are not chosen by maximizing a social welfare function, but by using a guard-rail approach which has broad objectives based on the best available science. We assume that fiscal policy does not alter the intrinsic type-contingent pre-tax relative advantages of the two technologies to the two types of firms in (2.4), (2.7). Thus, post-tax, the type G firms continue to be relatively more suited to the green technology and type B firms relatively better suited to the brown technology. It follows that the set of feasible fiscal instruments lie in the following set.

$$\Gamma = \left\{ (\tau_g, \tau_b) \times (s_g, s_b) \in T : B_g^B(\tau_g, s_g) > B_b^G(\tau_b, s_b), \, B_g^B(\tau_g, s_g) < B_b^B(\tau_b, s_b) \right\}, \tag{2.9}$$

where $B_g^j(\tau_g, s_g)$ and $B_b^j(\tau_b, s_b)$, $j = G, B$, are defined in (2.3) and (2.6).

The set Γ specifies upper and lower bounds on technology-specific taxes and subsidies that are feasible. Suppose that the relevant bounds on the taxes and subsidies that satisfy Γ are as follows:

$$\tau_i \in [\underline{\tau}_i, \overline{\tau}_i], 0 \le \underline{\tau}_i < \overline{\tau}_i \le 1, \; s_i \in [\underline{s}_i, \overline{s}_i], 0 \le \underline{s}_i < \overline{s}_i \le 1; \; i = g, b. \tag{2.10}$$

3 Optimal technology choice and equilibrium

Consider the technology adoption decision at time $t = 1, 2, ...$ when the fiscal instruments belong to the set Γ defined in (2.9). Given our assumptions, one of the firms is randomly chosen to make a technology decision; with probability λ_G this is a type G firm and with probability λ_B this is a type B firm. In this section, we consider a type $j = G, B$ firm making a technology choice decision, at time t, conditional on t_g (respectively, t_b) other firms having made a decision to choose the green (respectively, brown) technology in the past.

3.1 Type G firm

Using the first row of Table 1, a firm of type G chooses the green technology over the brown technology if

$$\left(B_g^G - B_b^G\right) \ge r_b t_b - r_g t_g. \tag{3.1}$$

Factors conducive in the adoption of the green technology are[19]: (1) Relatively higher net time-invariant benefits from the green technology relative to the brown technology, $B_g^G - B_b^G$. (2) Relatively higher returns to scale from the adoption of the green technology, r_g, and greater previous adoptions of the green technology, t_g. (3) Relatively lower returns to scale from the adoption of the brown technology, r_b, and lower previous adoptions of the brown technology, t_b. Conversely, a firm of type G picks the brown technology if $\left(B_g^G - B_b^G\right) < r_b t_b - r_g t_g$. It is more convenient to rewrite (3.1) as

$$\left(B_b^G - B_g^G\right) \le r_g t_g - r_b t_b. \tag{3.2}$$

[19]For pedagogical convenience we use the tie-breaking rule that when the net benefits from the two technologies are identical, firms choose the green technology.

3.2 Type B firm

Using the second row of Table 1, a type B firm chooses the green technology over the brown technology if

$$r_g t_g - r_b t_b \geq \left(B_b^B - B_g^B \right), \tag{3.3}$$

otherwise the firm chooses the brown technology. The conditions conducive to this choice for a type B firm are identical to those of a type G firm. Note that the RHS of (3.2) and the LHS of (3.3) are identical.

3.3 Equilibrium outcome

Define an upper barrier, U, and a lower barrier, L, as follows

$$U \equiv B_b^B - B_g^B > 0;\ L \equiv B_b^G - B_g^G < 0. \tag{3.4}$$

The signs in (3.4) follow from (2.9) and capture the feature that type G firms find the green technology relatively more attractive and type B firms find the brown technology relatively more attractive. Using (2.3), (2.6), we can write L, U in full

$$L = B_b^G - B_g^G = \left[b_b^G(1-\tau_b) - b_g^G(1-\tau_g) \right] - \left[c_b^G(1-s_b) - c_g^G(1-s_g) \right]. \tag{3.5}$$

$$U = B_b^B - B_g^B = \left[b_b^B(1-\tau_b) - b_g^B(1-\tau_g) \right] - \left[c_b^B(1-s_b) - c_g^B(1-s_g) \right]. \tag{3.6}$$

Figure 1 shows the dynamics of the system in time periods $t = 1, 2, ...$; two squiggly hypothetical dynamic paths are shown in continuous time for pedagogical clarity. We measure $y \equiv r_g t_g - r_b t_b$ along the vertical axis and time along the horizontal axis. A single technology adoption decision is made at each time, which either moves the path up a bit, or down a bit, depending on which technology has been adopted, as we explain below; and this accounts for the sqiggles in the paths. The two barriers, U and L, defined in (3.4), are also shown.

Using the technology adoption decisions of the two types of firms in (3.2), (3.3) it is easy to see the following. On and above the barrier U, both types of firms choose the green technology. On and below the barrier L, both types of firms choose the brown technology. In between the two barriers, U, L, type G firms choose the green technology and type B firms choose the brown technology (these choices are indicated in Figure 1 with vertical arrows for each type).

It follows that the two barriers are *absorbing barriers*, in the sense that once a dynamic path reaches one of the two barriers (if it does), the technology choice of all firms becomes identical, or locked-in, for all times to come– green on and above the upper barrier, U, and brown on or below the lower barrier, L. A government with a stated guardrail aim of going fully green by a cutoff year would be particularly interested in paths approaching the upper barrier.

Consider any dynamic path within the two barriers, U and L, and some time period t. There is a an ex-ante probability λ_G that a type G firm gets an opportunity to make a technology choice and it chooses the green technology (see (3.2)). With the probability $\lambda_B = 1 - \lambda_G$, a type B firm is chosen to make a technology choice and it picks the brown technology (see (3.3)). Recall that the vertical axis in Figure 1 measures $y \equiv r_g t_g - r_b t_b$. Thus, ex-ante, before any

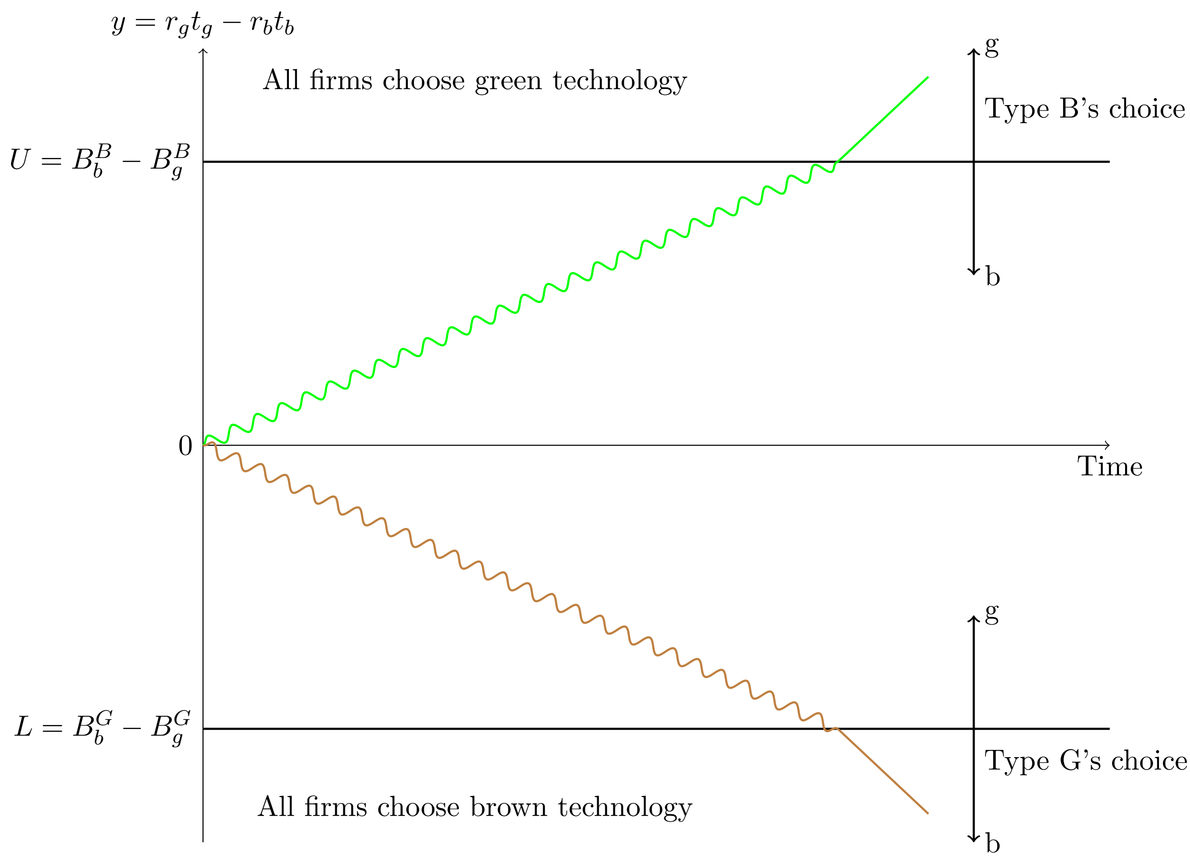

Figure 1: The dynamics of technology adoption.

technology choice is made in any time period, there is a probability that the dynamic path will move down by $\lambda_B r_b > 0$ and up by $\lambda_G r_g > 0$ units.

Ex-ante, it is impossible to predict whether a given dynamic path will reach the upper barrier first or the lower barrier first. Indeed, some dynamic paths might never be expected to converge to one of the two barriers in an ex-ante sense (see Section 4). In Figure 1, for illustrative purposes, we show two hypothetical paths– an upward sloping path that hits the upper barrier, following which the dynamic system is forever locked-into the green technology, and a downward sloping path that hits the lower barrier, following which the dynamic system is forever locked-into the brown technology.[20] There is no inherent fundamental uncertainty in the model. Thus, unlike in business cycle models, or in models in the New Keynesian Synthesis, there are no technology shocks, or benefit/cost shocks, that give rise to fluctuations induced by exogenous factors. Yet, in our model we cannot make a definitive ex-ante prediction as to which of the two technologies will be eventually adopted in the economy and to an outside observer it might appear, looking at the dynamic paths, that there is a source of exogenous fundamental uncertainty. The uncertainty, in terms of the final outcome, is endogenous to the model (and not exogenous) as is typical in complex systems. The final outcome (all-green, all-brown, or a path that does not converge to any of the two barriers) is an *emergent property* of the complex

[20] An infinite number of other shapes for such dynamic paths are possible and some paths could get close to the U barrier, yet turn around and then head for the L barrier and keep irregularly oscillating in this manner. The shape is unpredictable. Our two hypothetical paths are simply shown for illustration purposes.

system.

Different histories, i.e., different starting points for the dynamic path are likely to produce very different outcomes, i.e., the outcome is not ergodic. Small accidents of history may lead a dynamic path to hit the U barrier rather than the L barrier (and vice-versa); i.e., we can have extreme sensitivity to the initial conditions, as is typical in chaotic dynamics, although, like Arthur (1989), we do not study the dynamics formally.[21] These are standard, and well known, properties of complex systems and particularly straightforward to illustrate in our simple model.

Example 1 *: Suppose, and purely for illustrative purposes, that* $\lambda_G = 0.3$, $\lambda_B = 0.7$, $r_g = 1$, $r_b = 0.4$, $U \equiv B_b^B - B_g^B = 2$, $L \equiv B_b^G - B_g^G = -2$, *and* $t = 30$. *Hence, in each period, nature picks a type* G *firm with a* 30% *probability and a type* B *firm with a* 70% *probability. Suppose that at the end of 30 time periods, nature has, purely by chance, picked the type* G *firms* 10 *times and the type* B *firms* 20 *times, so* $t_g = 10$ *and* $t_b = 20$. *Then, ex-post,* $y = r_g t_g - r_b t_b = 10 - 8 = 2$. *Thus, ex-post, the dynamic path hits the upper barrier,* U*, which is an absorbing barrier. All subsequent adoptions of the technology are now green technologies; the system forever locks-into the green technology. Now suppose, due to an accident of history, that nature had picked out the type* G *firms* $t_g = 7$ *times and the type* B *firms* $t_b = 23$ *times. Then,* $y = 7 - 9.2 = -2.2$. *In this case, the dynamic path reaches the lower barrier,* L*, and all firms are forever locked into the brown technology. Thus, the dynamic system exhibits high sensitivity to historical accidents. However, in both cases, the final outcome is unpredictable from the perspective of time period* $t = 1$ *before any technology adoption decisions have been made, yet there is no fundamental uncertainty in the model.*

It is also possible to simulate several possible dynamic paths. In principle, any dynamic path within the barriers U, L, can take infinite number of shapes because the future is truly unpredictable in these models. Furthermore, within the context of our simple model, it is not clear what the empirically relevant benefit, cost, and fiscal policy parameters must be. Hence, there is little to learn from simulating such paths. The important questions to ask in terms of our paper are about the 'expected' long-run properties of the model (the analogue of the steady state under fully deterministic dynamics), such as the following. Ex-ante when economic policy is constructed, do we expect any of the paths to converge to the upper or lower barriers in the long-run where a technology lock-in effect occurs? We might also wish to ask what if governments wish to engage in some sort of course correction if ex-post they observe a dynamic path that seems to approach the lower barrier, L. We deal with some of these questions now.

4 Ex-ante expected convergence and periodic evaluations

4.1 Expected long-run outcomes

Even if we cannot predict the 'actual' outcome, we may try to infer the ex-ante long-run 'expected outcome'. Indeed, this exercise is critical to guide the choice of the fiscal policy quadruple

[21] One can study explicit transitory dynamics in very special cases, as in Zeppini (2015). But this required the assumptions of a representative firm, no type-contingent differences among firms, and assuming stochastic utility on the part of firms with a very specific set of assumptions on the noise term.

$(\tau_g, s_g, \tau_b, s_b)$, announced at time $t = 1$. We now conduct the analysis from the vantage point of time $t = 1$, in terms of expectations about long-run outcomes; these expectations may or may not be realized in the long-run.

In each time period, there is an ex-ante probability λ_G that a type G firm will make a technology choice. Hence, ex-ante, we expect that, within the barriers U and L, the long-run number of expected technology adoptions of the green technology to be $\underset{t\to\infty}{lim}\, t_g = \lambda_G N$, where N is the number of firms. The ex-ante probability that a type B firm is chosen to make a technology choice is $\lambda_B = 1 - \lambda_G$, hence, ex-ante, within the barriers U and L, the long-run expected number of technology choices of the brown technology is $\underset{t\to\infty}{lim}\, t_b = \lambda_G N$. Recalling that $y \equiv r_g t_g - r_b t_b$, and we measure it along the vertical axis in Figure 1, the ex-ante long-run expected value is

$$\underset{t\to\infty}{lim}\, y = \underset{t\to\infty}{lim}\,(r_g t_g - r_b t_b) = r_g \lambda_G N - r_b \lambda_B N. \tag{4.1}$$

It follows that

$$\underset{t\to\infty}{lim}\, y < 0 \Leftrightarrow \frac{r_g}{r_b} < \frac{\lambda_B}{\lambda_G}. \tag{4.2}$$

If (4.2) holds, then, from an ex-ante perspective, the economy is never expected to hit the upper barrier. Hence, ex-ante expectations are that the economy will never completely adopt the green technology at the current levels of taxes and subsidies that are chosen by the government. Furthermore, the condition

$$\underset{t\to\infty}{lim}\, y < L \equiv B_b^G - B_g^G \tag{4.3}$$

is sufficient to ensure, from an ex-ante perspective, in the long-run, all firms in the economy are expected to adopt the brown technology. If (4.3) holds, then the fiscal instruments, currently employed, are 'expected' to be ineffective in persuading firms to adopt the green technology in the long-run, which might be an important guardrail objective. This should perhaps call for a revision of the current long-run public policy.

The conditions that make the perverse outcome in (4.2) 'less likely' are: (1) A higher ratio of green to brown technology returns to scale from adoption, $\frac{r_g}{r_b}$, and (2) a lower ratio of type B to type G firms, $\frac{\lambda_B}{\lambda_G}$. This might be true for some types of technologies, but not others.

Consider now the opposite case to the one shown in (4.2), namely

$$\underset{t\to\infty}{lim}\, y > 0 \Leftrightarrow \frac{r_g}{r_b} > \frac{\lambda_B}{\lambda_G}. \tag{4.4}$$

In this case, from an ex-ante perspective, the long-run expected value of the dynamic path is positive, so all type G firms are expected in the long-run to choose the green technology.

However, even if (4.4) holds, the long-run expected value of y might not be high enough to cross the upper barrier, U, where all firms adopt the green technology. In this case the dynamic path never converges to the barrier U (not shown in Figure 1). This would occur when $\underset{t\to\infty}{lim}\, y < U \equiv B_b^B - B_g^B$, where U is defined in (3.6).

From the perspective of time $t = 1$, a sufficient condition for all firms to adopt the green technology in the long-run is

$$\underset{t\to\infty}{lim}\, y \geq U \Leftrightarrow \underset{t\to\infty}{lim}\,(r_g t_g - r_b t_b) \geq U. \tag{4.5}$$

Using (3.6), (4.1) we get that $\underset{t\to\infty}{lim}\, y \geq U \Leftrightarrow$

$$N\left[r_g\lambda_G - r_b\lambda_B\right] \geq B_b^B(\tau_b, s_b) - B_g^B(\tau_g, s_g), \tag{4.6}$$

where

$$B_b^B(\tau_b, s_b) - B_g^B(\tau_g, s_g) = \left[b_b^B(1-\tau_b) - b_g^B(1-\tau_g)\right] - \left[c_b^B(1-s_b) - c_g^B(1-s_g)\right]. \tag{4.7}$$

If condition (4.6) holds then, from the perspective of time $t = 1$, in the long-run all firms are expected to adopt the green technology.[22] A guardrail approach to policy where the aspiration is to have all firms adopt the green technology in the long-run must then, at a minimum, require, at time $t = 1$, announcing the fiscal policy quadruple $(\tau_g, s_g, \tau_b, s_b)$ to satisfy (4.6). Ex-post, such a policy might not eventually deliver the expected outcomes because of true uncertainty about the shape of the possible dynamic paths. However, at the time of making the policy announcement, it is the best that any government can do.

4.2 Periodic short-run evaluations

In Subsection 4.1 we considered the expected long run, ex-ante, outcome from the perspective of time $t = 1$. This is the only basis on which to base the originally announced policy. However, as noted above, the dynamic path can, ex-post, take any shape and the ex-ante expectations may not turn out to be an accurate guide. In such cases, public policy might have to be periodially evaluated. It is quite clear that public policy cannot be reformulated on a regular basis, on the hoof, as the dynamic path takes unexpected twists and turns. Such a policy would create considerable policy uncertainty for the private sector and would not be viewed favorably by most governments.

Under true uncertainty, one cannot even imagine all the possible shapes of the dynamic paths in Figure 1. Hence, it is not possible to offer general policy insights. However, ocassional path corrections might take the form of public policy revisions if, say, a dynamic path comes within a distance d of the lower barrier, L. Economic theory does not provide firm guidance on the size of d. This must then depend on factors such as the goverment's financial situation, political economy concerns, and the political willpower.

Suppose, for the sake of argument, that there is a agreement within the government which sets a specific size of $d = d^*$. In this case, the obvious intervention, if a dynamic path comes within a distance d^* of the lower barrier L, is to lower it. From (3.5), the barrier L can be lowered using fiscal policy by either increasing τ_b, s_g (taxes on benefits of brown technology and subsidies on costs of green technology) and/or decreasing τ_g, s_b (taxes on benefits from green technology and subsidies on costs of brown technology). From (3.6), such a policy will also simultaneously lower the upper barrier, U.

There is no guarantee that any particular periodic review will ensure that in the future, the dynamic path hits the upper barrier, U. Starting from any history of play t_g, t_b at the start

[22] Several factors are conducive to the satisfaction of this condition. (1) A relatively greater fraction of green firms relative to brown firms, (2) relatively greater returns to scale from the adoption of the green technology relative to the brown technology, (3) lower taxes and higher subsidies on the green technology, and (4) higher taxes and lower subsidies on the brown technology.

of the periodic review, a change in the position of the barriers, arising from the review, simply restarts the entire process once again, with the future remaining truly uncertain. Indeed, for this reason, more than one periodic reviews might have to be carried out.

We have already noted in Section 2.4 that there are likely to be bounds on the maximum and minimum levels of the technology-contingent taxes and the subsidies that can be imposed, due to a variety of constraints. Furthermore, the deadweight loss of a tax increases in the square of the tax rate. Hence, the government might need to use a combination of all available fiscal instruments to efficiently achieve feasible movements in the two barriers, U and L, in order to implement desirable outcomes.

5 Policy implications

Due to the inherent uncertainty in the dynamic system, a continually adjusting policy that responds to every twist and turn in a dynamic path in Figure 1 is undesirable. A pragmatic policy will have to trade-off the policy uncertainty created for the private sector on account of frequent policy changes, versus the flexibility that such a policy offers. For this reason, in this section, we take an ex-ante policy perspective at time $t = 1$, before any technology adoption decisions have been made. Indeed, the government must in actual practice announce the policy parameters before the private sector makes the technology adoption decision, by using its expectations of the future. We assume that the government makes a credible announcement of the choice of the fiscal policy quadruple $(\tau_g, s_g, \tau_b, s_b)$ from the set Γ in (2.9).

5.1 Pigouvian taxes

Recall that the green technology produces no emissions. A firm that adopts the brown technology produces emissions with a constant marginal social costs on society equal to $C_s > 0$. Suppose that at time $t = 1$, the government levies Pigouvian taxes at the socially optimal level, $\tau_P = C_s > 0$, on each firm that chooses the brown technology, in addition to the fiscal policy quadruple $(\tau_g, s_g, \tau_b, s_b) \in \Gamma$, where Γ is defined in (2.9) and the bounds on the taxes and subsidies are given in (2.10).

Since all taxes are determined at time $t = 1$, the government uses it expectations of the dynamic paths in Section 4 in order to choose the tax rates consistent with some stated 'guardrail' objective. Suppose that the stated objective is to get all firms to adopt the green technology in the long-run; this typically takes the form of a cutoff date in actual policy documents. In this subsection, we are only interested in the implications of such Pigouvian taxes and take as given the other policy instruments $(\tau_g, s_g, \tau_b, s_b) \in \Gamma$.

In the presence of Pigouvian taxes, τ_P, on firms adopting the brown technology, we can rewrite (4.6), which ensures that, from the perspective of time $t = 1$, in the long-run all firms are expected to adopt the green technology, as follows

$$N \left[r_g \lambda_G - r_b \lambda_B \right] \geq \left[B_b^B(\tau_b, s_b) - \tau_P \right] - B_g^B(\tau_g, s_g), \tag{5.1}$$

where $B_b^B(\tau_b, s_b) - B_g^B(\tau_g, s_g)$ is defined in (4.7). Rewriting (5.1), we get

$$\tau_P \geq \widehat{\tau} = B_b^B(\tau_b, s_b) - B_g^B(\tau_g, s_g) - N\left[r_g \lambda_G - r_b \lambda_B\right]. \tag{5.2}$$

We assume that the Pigouvian taxes on the brown technology must also obey the bounds for taxes on brown technology specified in (2.10), so $\tau_P \in [\underline{\tau}_b, \overline{\tau}_b]$.

From (5.2) we get the required lower bound on Pigouvian taxes on firms adopting the brown technology such that the guardrail objective of long-run green technology adoption is met, in an ex-ante sense. From (2.9) and (2.10) fiscal constraints that require taxes and subsidies to lie within feasible bounds, may lead to a violation of (5.2) if $\widehat{\tau} > \overline{\tau}_b$, where $\overline{\tau}_b$ is the maximum possible tax that can be levied on the brown technology. A sufficient condition for such a violation is that for the smallest possible value of $\widehat{\tau}$, conditional on the fiscal policy parameters, we still have that $\widehat{\tau} > \overline{\tau}_b$, i.e., if

$$\widehat{\tau} = B_b^B(\overline{\tau}_b, \underline{s}_b) - B_g^B(\underline{\tau}_g, \overline{s}_g) - N\left[r_g \lambda_G - r_b \lambda_B\right] \geq \overline{\tau}_b, \tag{5.3}$$

where the bounds $\underline{\tau}_i, \overline{\tau}_i, \underline{s}_i, \overline{s}_i$, $i = g, b$ are defined in (2.10). We now make two main points.

1. The condition in (5.3) is sufficient to imply the impossibility of simultaneously levying optimal Pigouvian taxes, and ensuring long-run adoption of green technological choices in an expected ex-ante sense. A credible government policy must then forego one of the two objectives (either imposing optimal Pigouvian taxes, or long-run adoption of green technology).

2. Suppose that the sufficient condition in (5.3) does not hold, but at the existing feasible fiscal policy, we nevertheless have $\widehat{\tau} > \overline{\tau}_b$. Then, from (4.7) and (5.2), higher taxes and lower subsidies on the brown technology (higher τ_b, lower s_b), and lower taxes and higher subsidies on the green technology (lower τ_g, higher s_g), if feasible, will reduce $\widehat{\tau}$ and may ensure that Pigouvian taxes become feasible, i.e., $\widehat{\tau} < \overline{\tau}_b$. This is an example of unexpected complementarities between the different fiscal instruments in ensuring the simultaneous feasibility of the long-run adoption of the green technology and optimal Pigouvian taxes; these considerations may not arise in the standard analysis. This also illustrates the importance of considering the full set of policy instruments.

5.2 Dynamic pattern of subsidies

Since $r_g > 0$ (increasing returns to scale from adoption), after every adoption of the green technology, subsequent adoptions of the green technology become less expensive. In the real world, initial adoptions of the green technology often require subsidies to kickstart adoption (e.g., in buying green cars, or installing domestic solar panels, or installing pollution reduction equipment in firms). Yet subsidies are expensive to afford; create distortions elsewhere; and their precise levels may be politically controversial. However, as green technology adoptions increase, its reduced costs, on account of $r_g > 0$, can be used to leverage a fall in subsidies, and ultimately their complete withdrawal.

Suppose that at time $t = 1$, the government credibly announces a time path of subsidies contingent on the subsequent technology adoption decisions of the firms. Suppose that the explicitly declared 'ex-ante' guardrail objectives of the government (Stern and Stiglitz, 2022) are that (i) it aims for all firms to eventually adopt the green technology, and that (ii) the temporal costs of the subsidy will be minimized. For pedagogical simplicity, we assume that the only fiscal instrument used is the subsidy on the adoption of the green technology, $s_g > 0$, but the remaining instruments are set equal to zero, $\tau_b = \tau_g = s_b = 0$. The insights below are easily extended to the case $\tau_b, \tau_g, s_b \geq 0$.

The reader should imagine that the barriers U, L in Figure 1 are now drawn for this special case. Consider dynamic paths that lie in between the two barriers U and L. Within these barriers, type B firms always choose the brown technology and type G firms always choose the green technology. Thus, we can rewrite (3.2), the condition necessary for a type G firm to adopt the green technology as

$$\left[b_b^G - b_g^G\right] - \left[c_b^G - c_g^G(1 - s_g)\right] \leq r_g t_g - r_b t_b. \tag{5.4}$$

Since subsidies are expensive, and the objective is to minimize the subsidy costs, conditional on t_g adoptions of the green technology in the past, s_g solves (5.4) at equality, thus

$$s_g(t_g) = \frac{1}{c_g^G}\left[(r_b t_b - r_g t_g) + \left((b_b^G - b_g^G) - (c_b^G - c_g^G)\right)\right]. \tag{5.5}$$

We have the following results.

1. The dynamic path for subsidies, so long as the system stays within the barriers U, L in Figure 1, is given by (5.5), as the number of adoptions of the green technology $t_g = 0, 1, 2, \ldots$. Every time a type G firm adopts the green technology, from (5.5), the government reduces the subsidy by an amount Δs_g such that

$$\Delta s_g = -\frac{r_g}{c_g^G}, \tag{5.6}$$

and still ensure that subsequent choices by type G firms will be to adopt the green technology. Conditional on t_g adoptions having taken place, the level of subsidies in (5.5) is lower if (i) the relative benefits of the green technology are higher but its relative costs are lower, and (ii) the brown technology has low returns to scale from adoption (low r_b) while the returns to scale from the adoption of the green technology, r_g, are high.

2. A decreasing profile of subsidies, consistent with (5.5), will ensure that whenever a type G firm is offered a technology choice, it will adopt the green technology (because (5.4) holds). This contributes to upward movements of the dynamic path in Figure 1 within the barriers U, L. If the upper barrier, U, is hit then both types of firms will find it in their self interest to adopt the green technology (recall that U is an absorbing barrier that locks-in all firms into the green technology). The subsidy can be gradually entirely removed with increased adoptions, so eventually $s_g = 0$.[23]

[23]Setting $s_g = 0$ in (5.5) and solving out for $t_g = t_g^*$ gives the number of technology adoptions of the green technology after which the subsidy can be entirely removed.

5.3 International fund for the adoption of green technologies

The pattern of subsidies in (5.5) may be difficult to implement for poor countries due to severe resource constraints, such as poor tax collections and low incomes, as well as the presence of political/institutional constraints. Suppose that the maximum subsidies on the green technology that a poor country can offer equal $0 \leq \overline{s}_g < 1$. A planner in such a country who can calculate the required dynamic path for subsidies in (5.5) might find that $s_g(0) > \overline{s}_g$, so that subsidies to support the very first adoption of the green technology might not be feasible. Suppose that, in some time period, t_b adoptions of the brown technology have taken place but no green technology adoptions have occurred yet. Then, the problem can be illustrated by setting $t_g = 0$ in (5.5) to get:

$$s_g(0) = \frac{1}{c_g^G}\left[r_b t_b + \left((b_b^G - b_g^G) - (c_b^G - c_g^G)\right)\right] > \overline{s}_g. \tag{5.7}$$

If (5.7) holds, then green technology adoption never takes off in a resource-poor country, in the absence of external intervention equal to the gap $s_g(0) - \overline{s}_g$. From (5.7), this gap is increasing in the existing number of brown technology adoptions, t_b, because an increase in t_b increases the relative benefits from adopting the brown technology. Hence, the longer is such external intervention delayed, the larger is the deficit $s_g(0) - \overline{s}_g$ that needs to be addressed in order to induce the first green technology adoption in the poor country.

Since several forms of environmental bads are global public bads, there might be no other option but to form an international fund, financed by the richer countries, to subsidize the worldwide adoption of green technologies. Such subsidies may also take the form of direct supplies of the green technology at affordable terms to poorer countries.

6 Extensions of the model

This section covers several different extensions to the basic model. We extend the model to stochastic technology dynamics (Subsection 6.1); to the case of simultaneous technology adoptions and more than two kinds of technologies (Subsection 6.2); and to a brief consideration of other types of dynamics (Subsection 6.3).

6.1 Stochastic technological dynamics

In this subsection we use the insights from the 'stochastic social dynamics' framework surveyed in Young (1998, 2006) and Dhami (2020, Vol. 6), and apply it to our model of technology adoption.

Suppose that any firm that is faced with an opportunity to choose a technology makes its technology choice in the following manner. With a high probability $\varepsilon > 0$, the firm chooses the optimal technology (the one that maximizes net benefits, as in Sections 3.1, 3.2), but with the low complementary probability, $1 - \epsilon$, the firm simply randomizes equally between the two technologies. This is a form of "experimentation" that can be formalized in several alternative ways in the theoretical model and can be justified by using different behavioral features (Dhami, 2020, Vol. 6).

Hence, in effect, firms pick their optimal technology with a probability $\varepsilon + \frac{1-\varepsilon}{2} = \frac{1+\varepsilon}{2}$ and the non-optimal technology with a probability $\frac{1-\varepsilon}{2}$. Defining $\rho = \frac{1+\varepsilon}{2}$, it follows that, in effect, each firm chooses its optimal technology with a high probability ρ and the non-optimal choice with the low complementary probability $1-\rho$. We call $1-\rho$ as the probability of experimentation, and the sense in which it is 'low' is specified in the following condition.

$$\frac{\rho}{(1-\rho)} > \frac{\lambda_B}{\lambda_G}. \tag{6.1}$$

The inequality in (6.1) is always satisfied if $1-\rho$ is low enough.

As shown above in Section 3, in the absence of experimentation ($\rho = 1$), there are two stable states – all firms choose the green technology (state $S = g$) and all firms choose the brown technology (state $S = b$). In the presence of experimentation ($\rho < 1$), the key equilibrium concept is that of a *stochastically stable state*; it is the state whose basin of attraction is most difficult to escape from. We now consider this situation below.

Essentially, we have a Markov process in which a firm only needs knowledge of the history in the previous period to make its technology adoption decision. A history here is simply a pair of numbers (t_g, t_b) that specify the number of firms that have adopted the green and the brown technologies in the past. When the dynamic system is able to move between the basins of attractions of more than one asymptotically stable equilibria ($S = g$ and $S = b$) that exist in the absence of experimentation ($\rho = 1$), then we have an irreducible Markov process. Our model can be recast in these terms but this is standard, well known, and does not add new insights relative to our discussion in this section; for a formal exposition, see Young (1998) and Dhami (2020, Vol. 6). However, our slightly more informal and accessible approach below, uses the same methods to find the stochastically stable state below.

Suppose that the dynamic path lies strictly within the two barriers, U and L, in Figure 1, where a firm of type G finds it optimal to choose the green technology (see (3.1)), and a firm of type B finds it optimal to choose the brown technology (see (3.3)). It follows that, in the presence of experimentation, (i) type G firms choose the green technology with a probability ρ and the brown technology with a probability $1-\rho$, (ii) type B firms choose the brown technology with a probability ρ and the green technology with a probability $1-\rho$.

Recall that the vertical axis in Figure 1 measures $y = r_g t_g - r_b t_b$ and nature chooses a type G firm and a type B firm to make a technology choice with respective probabilities λ_G and λ_B. Thus, before the time t technology choice is made, the expected outcome depends on the type of the firms that makes a technology choice; we consider the two possibilities below.

1. A type G firm is chosen to make the time t technology choice: At the beginning of time t, there is a probability λ_G that a type G firm is chosen and a probability ρ that it makes its optimal choice of a green technology. Thus, there is an ex-ante probability $\rho\lambda_G$ that the dynamic path (whose value is given by the vertical axis $y = r_g t_g - r_b t_b$ in Figure 2) will move up by $r_g t_g$; and a probability $(1-\rho)\lambda_G$ that it will move down by $r_b t_b$ (when the type G firm chooses the non-optimal brown technology).

2. A type B firm is chosen to make the time t technology choice: At the beginning of time

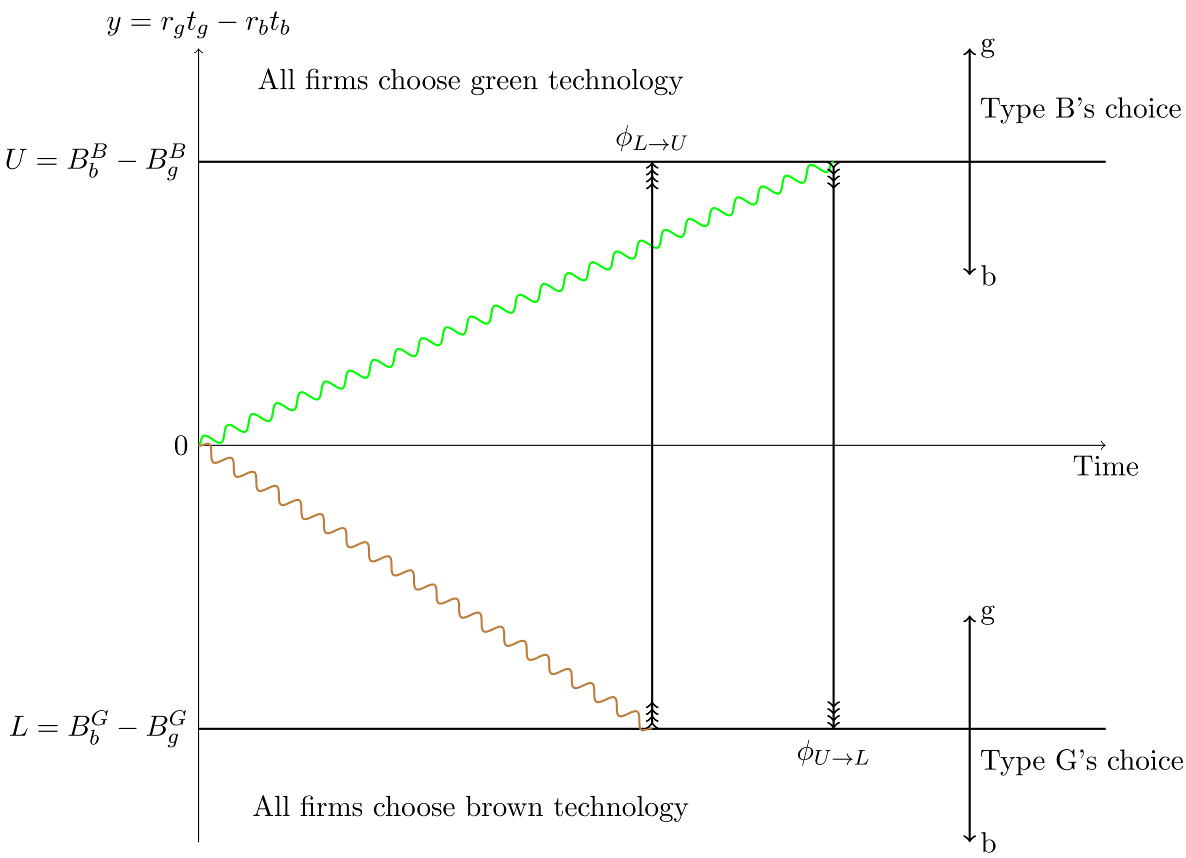

Figure 2: The dynamics of technology adoption.

t, there is a probability λ_B that a type B firm is chosen and a probability ρ that it makes its optimal choice of a brown technology. Thus, there is an ex-ante probability $\rho\lambda_B$ the dynamic path (whose value is given by the vertical axis $y = r_g t_g - r_b t_b$ in Figure 2) will move down by $r_b t_b$; and a probability $(1 - \rho)\lambda_B$ that it will move up by $r_g t_g$ (when the type B firm chooses the non-optimal green technology).

At the beginning of time $t = 1$, one cannot predict which of the two barriers U or L will be eventually reached. In the absence of any experimentation by the players (i.e., $\rho = 1$, as in Section 3), each of the barriers is an absorbing barrier. However, in the presence of experimentation, $0 < \rho < 1$, once a dynamic path reaches any of the barriers, it is not guaranteed to stay there forever. Starting at a point on or within any of the two barriers (above and on U; or below and on L), experimentation by the two types of firms may push the dynamic path back in between the two barriers U and L. Once a dynamic path reaches between the two barriers, there is no guarantee that it will not eventually reach the opposite barrier. Thus, we may get *punctuated equilibria*, in which the dynamic path escapes the basin of attraction of one of the two states ($S = g$ and $S = b$) and moves into the basin of attraction of the other state.

We now formally check for stochastic stability. The relevant situation is outlined in Figure 2.

Consider a dynamic path that has just hit the upper barrier U, which corresponds to the state $S = g$. We now ask, starting at a point on the barrier U, what is the minimum number of successive adoptions of the brown technology that will allow the dynamic path to escape the basin of attraction of the state $S = g$ and arrive at the lower barrier L, which corresponds to the state $S = b$?

The vertical distance between the two barriers is given by $U - L$ where L, U are 'constants' that are defined in (3.5), (3.6). Hence, the shortest distance that any dynamic path starting from U must travel to reach L is the vertical distance, equal to $U - L$. We now calculate the total expected number of technology adoptions that will allow a *path of least resistance* (described below) to travel the distance $U - L$. The relevant path is shown in Figure 2 with arrows pointing downwards.

Recall that the vertical axis of Figure 1 measures $r_g t_g - r_b t_b$. To move downward from a given point on U, conditional on the history of technology adoptions, t_g, t_b, one of the two types of firms must first choose a non-optimal action and pick the brown technology on account of experimentation.[24]

Once the dynamic path enters any point within the barriers, U, L, there are two possibilities. Nature chooses a type G firm to make a technology choice with probability λ_G. A type G firm will choose the non-optimal brown technology with a probability $1 - \rho$. Every time a type G firm chooses the brown technology, the term $r_g t_g - r_b t_b$ moves down by r_b. Thus, ex-ante, the term $r_g t_g - r_b t_b$ moves down by the following expected value

$$\lambda_G(1 - \rho)r_b. \tag{6.2}$$

With probability λ_B, nature chooses a type B firm, who picks its optimal brown technology with probability ρ. In this case, the term $r_g t_g - r_b t_b$ moves down by the following expected value

$$\lambda_B \rho r_b. \tag{6.3}$$

In order to find the *path of least resistance* from a point on the barrier U to the nearest point on the barrier L, we need to determine which of the two expressions in (6.2), (6.3) is bigger. From (2.1), brown firms are relatively more numerous, $\lambda_B > \lambda_G$; the probability of experimentation is relatively small, so $\rho > (1 - \rho)$; and since $r_b > 0$, we have that

$$\lambda_B \rho r_b > \lambda_G(1 - \rho)r_b. \tag{6.4}$$

Thus, the path of least resistance (or the ex-ante fastest route) will require k successive (optimal) technology choices by type B firms of the brown technology to arrive at the barrier L after starting from the barrier U. We can find the value of k by solving out for $k\lambda_B \rho r_b = U - L$, so

$$k = \frac{U - L}{\lambda_B \rho r_b}. \tag{6.5}$$

The number k is known as the 'stochastic potential' of the path of least resistance from U to L and we denote it by $\phi_{U \to L}$. The path of least resistance is shown in Figure 2 as the vertical line

[24] Recall also that on or above the barrier U, both firms find it optimal to choose the green technology. We ignore this single initial move in calculating the 'stochastic potential' (see below) in moving between the two barriers in both directions. So this single move cancels out in both directions.

starting from the barrier U and extending to the barrier L with downward pointing arrows; for ease of reference, we terminate this line with the stochastic potential $\phi_{U\to L}$.

Next, we wish to calculate the analogous stochastic potential, $\phi_{L\to U}$, of the path of least resistance from the all-brown technology state ($S=b$) to the all-green technology state ($S=g$). This path of least resistance is shown in Figure 1 as the vertical line starting from the barrier L and extending to the barrier U with upward pointing arrows; for ease of reference we terminate this line with the corresponding stochastic potential $\phi_{L\to U}$ that we determine below.

Suppose that we begin at the lower barrier L, conditional on some history of the game, t_g, t_b. We now wish to find the least number of technology adoption choices of the green technology that will move a dynamic path vertically upwards to the nearest point on the barrier, U. This follows a single initial non-optimal choice by any of the two types of firms (on account of experimentation) which induces then to choose the green technology.[25]

There are two possible ways in which the green technology may be adopted in between the barriers L and U. A type G firm will choose its optimal green technology within the barriers U, L with a probability ρ whenever it is making a technology adoption decision, an event that occurs with probability λ_G. Hence, every time a type G firm chooses the green technology, the term $r_g t_g - r_b t_b$ moves up by r_g. Thus, ex-ante, before the technology adoption decision, the term $r_g t_g - r_b t_b$ moves up by the following expected value

$$\lambda_G \rho r_g. \tag{6.6}$$

However, with probability λ_B, a type B firms makes a technology adoption decision. It chooses its non-optimal green technology with a probability $(1-\rho)$ on account of experimentation. Thus, within the barriers U, L, in this case, the term $r_g t_g - r_b t_b$ moves up by the following expected value

$$\lambda_B (1-\rho) r_g. \tag{6.7}$$

Using (6.1), we have $\lambda_G \rho r_g > \lambda_B(1-\rho) r_g$. Hence, in order to calculate the path of least resistance from the barrier L to the barrier U, we ask the following question. Starting from the barrier L how many successive technology adoptions, $\widehat{k}$, of the green technology by type G firms do we need in order to reach the nearest point on the barrier, U. Each of these technology adoptions moves the dynamic path upwards by an expected value $\lambda_G \rho r_g$. Thus, in order to determine $\widehat{k}$, we need to solve $\widehat{k} \lambda_G \rho r_g = U - L$, so

$$\widehat{k} = \frac{U-L}{\lambda_G \rho r_g}. \tag{6.8}$$

It follows that the relevant stochastic potential of the path of least resistance is $\phi_{L\to U} = \widehat{k}$. Summarizing our discussion above

$$\phi_{U\to L} = k; \; \phi_{L\to U} = \widehat{k},$$

where k is defined in (6.5) and $\widehat{k}$ is defined in (6.8).

[25] As noted above, we ignore this single initial move in our calculations in both directions.

The state $S = g$ is the stochastically stable state if $\phi_{U\to L} > \phi_{L\to U}$, because (along the path of least resistance) it requires a relatively greater number of successive mutations in order for the dynamic path to escape from its basin of attraction. Conversely, if $\phi_{U\to L} < \phi_{L\to U}$, then the state $S = b$ is the stochastically stable state. We have that

$$\phi_{U\to L} \gtreqless \phi_{L\to U} \Leftrightarrow \frac{r_g}{r_b} \gtreqless \frac{\lambda_B}{\lambda_G}. \tag{6.9}$$

From (6.9), the state $S = g$ is more likely to be the stochastically stable state if $\frac{r_g}{r_b} > \frac{\lambda_B}{\lambda_G}$, i.e., if the returns to scale of the green technology are relatively high and the proportion of type B firms to type G firms is not too high. This might be true for some technologies/countries but not others. Furthermore, any government policy that potentially increases r_g relative to r_b is helpful, for instance, greater information dissemination about the benefits of the green technology through, say, government sponsored technology fairs; nudges; and the provision of requisite public infrastructure and assistance.

In summary, we have shown that in the presence of stochastic technology dynamics, we have *punctuated equilibria*. The equilibrium switches between the green and the brown technologies. We have also derived the conditions for the all-green technology adoption state to be the stochastically stable state so that the dynamic system spends most of its time in the state $S = g$. From (6.9), the stochastically stable state does not depend on the fiscal parameters or on the relative benefits and costs of the technologies to the firm, unless the fiscal system can somehow directly target the returns to scale, r_g, r_b.

6.2 Simultaneous technology choice and several technologies

In our model, outlined in Section 2, in each time period, t, a single randomly chosen firm makes a technology adoption decision between the green and the brown technologies, conditional on the history of technology adoptions t_g and t_b. Our model is readily extended to the case of $n = 2, 3..., m$ firms simultaneously making a technology choice decision at any time t, conditional on the history of technology adoptions t_g and t_b.

Concurrent technology adoptions by several firms do not influence the time-dependent variable returns, $r_g t_g$, $r_b t_b$, from technology adoption. Such returns only depend on the history of past adoptions. Thus, any firm making the technology adoption decision continues to face the same payoff matrix as given in Table 1, irrespective of the number of other firms concurrently making the technology adoption decision. Hence, each firm makes the same decision as in Section 2 (type G firms choose according to (3.1), and type B firms choose according to (3.3)). However, ex-ante, a fraction λ_G of the m firms are expected to be type G and if (3.1) holds, they will all choose the green technology, otherwise they choose the brown technology. Similarly, ex-ante, a fraction λ_B of the m firms are expected to be type B and if (3.3) holds, they will all choose the green technology, otherwise they choose the brown technology.

This extension only makes an "accounting difference" to the way the dynamic path moves up or down in Figure 1. Suppose that we are in between the two barriers U and L in Figure 1. At the end of any time period t we update the history of technology adoptions t_g and t_b appropriately. Suppose that in time period t, k firms have chosen the green technology and

$n-k$ firms have chosen the brown technology. Then, we update t_g to t_g+k and t_b to $t_b+(n-k)$. Otherwise, the model is unchanged.

The model is easily extended to more than 2 technologies. This requires us to check more inequalities of the form (3.1) and (3.3) but the basic analysis and insights are unchanged.[26]

6.3 Other dynamics

Evolutionary dynamics require a well specified strategic game to be played in each time period $t = 1, 2, ...$ One can then apply the relevant equilibrium concepts (e.g., an evolutionary stable equilibrium) and study the properties of the appropriate dynamics of the system (e.g. replicator dynamics). However, we do not have such a strategic game being played. As in Arthur (1989), we have a sequence of technology choices being made in each time period, conditional on the history of technology adoptions so far. Hence, this is more akin to a game against nature, and there are no relevant evolutionary dynamics to consider.

More explicit dynamics can be considered along the lines of Zeppini (2015). However, for the reasons mentioned in the introduction, those specific dynamics are derived in the more restrictive setting of a representative firm and no type-contingent technology differences, hence, they do not apply to our setting. Furthermore, the structure of the noise in those models is arbitrary and it is not clear if those results generalize beyond the assumed noise structure.

7 Conclusions

We present a simple model of technology choice by heterogeneous firms where green technologies have relatively higher returns to scale compared to brown technologies and there are type-contingent differences in the suitability of the technologies. Our approach closely follows the recent suggestions of Stern (2022) and Stern and Stiglitz (2022) in modeling key issues of climate change and the nature of public policy. We show that our simple model nests a large number of important cases and is robust to reasonable extensions of the model. We illustrate the extreme unpredictability of the final outcome, and consider the role of public policy in the form of taxes and subsidies in influencing the long-run expected outcome. Our model is fairly parsimonious, yet it has the ability to provide reasonably powerful insights into the nature of green technology adoption and the design of public policy. It also highlights the challenges and limitations of public policy in such scenarios.

References

[1] Alós-Ferrer, C., Fehr, E., and Netzer, N. (2021). Time Will Tell: Recovering Preferences When Choices Are Noisy. Journal of Political Economy 129(6): 1828–1877.

[2] Aghion, P. and Howitt, P. W. (1997). Endogenous Growth Theory. MIT Press: Massachussetts.

[26] For instance, suppose that we had three technologies. In terms of Figure 1, the relevant change is that we have a three dimensional box, the relevant barriers are the boundaries of the box, and dynamic paths are now in three dimensional space.

[3] Arthur, W.B. (1989). Competing Technologies, Increasing Returns, and Lock-In by Historical Events. The Economic Journal 99(1): 116–131

[4] Arthur, W.B. (2015). Complexity and the economy. Oxford: Oxford University Press.

[5] Arvanitis, S., Ley, M., (2013). Factors determining the adoption of energy-saving technologies in Swiss firms: an analysis based on micro data. Environmental and Resource Economics 54(3): 389–417.

[6] Bloom, N., Reenen, J. V. and Williams, H. (2019). A Toolkit of Policies to Promote Innovation. Journal of Economic Perspectives 33(3): 163-84.

[7] Brock, W., Durlauf, S. (2001). Discrete choice with social interactions. Review of Economic Studies 68: 235–260.

[8] Brock, W., Durlauf, S., (2002). A multinomial choice model with neighborhood effects. American Economic Review 92(2): 298–303.

[9] Hommes, C. (2021). Behavioral and Experimental Macroeconomics and Policy Analysis: A Complex Systems Approach. Journal of Economic Literature, 59(1): 149-219.

[10] Dhami, S. (2020). The foundations of behavioral economic analysis: Models of learning. Volume 6. Oxford University Press: Oxford.

[11] Hottenrott, H., Rexhäuser, S., Veugelers, R. (2016). Organisational change and the productivity effects of green technology adoption. Resource and Energy Economics 43: 172–194.

[12] Katz, M.L., Shapiro, C. (1985). Network externalities, competition and compatibility. American Economic Review 75: 424–440.

[13] King, M., and Kay, J. (2020) Radical Uncertainty: Decision-making for an unknowable future. W.W. Norton: New York.

[14] Knight, F. H. (1921). Risk, uncertainty and profits. Houghton Mifflin Company: New York.

[15] Nordhaus,W. (1991). To slow or not to slow: The economics of the greenhouse effect. The Economic Journal 101(407): 920–37.

[16] Nordhaus, W. (2017). Social cost of carbon in DICE model. Proceedings of the National Academy of Sciences. 114(7): 1518–23.

[17] Nordhaus, W. (2019). Climate Change: The Ultimate Challenge for Economics. American Economic Review 109(6): 1991–2014.

[18] Stern, N. (2022). A time for action on climate change and a tme for a change in economics. The Economic Journal 132(644): 1259–1289.

[19] Stern, N. and Stiglitz, J.E. (2022). The economics of immense risk, urgent action and radical change: Towards new approaches to the economics of climate change. The Journal of Economic Methodology. 29(3): 181–216.

[20] Stern, N. and Valero, A. (2020). Innovation, Growth and the Drive to Net Zero Emissions. Research Policy 50(9): 104293.

[21] Stucki, T. (2019). Which firms benefit from investments in green energy technologies? – The effect of energy costs. Research Policy 48: 546–555.

[22] Young, H. P. (1993).The evolution of conventions. Econometrica 61(1): 57–84.

[23] Young, H. P. (1998). Individual Strategy and Social Structure: An Evolutionary Theory of Institutions. Princeton, NJ: Princeton University Press.

[24] Young, H. P. (2006). Social dynamics: theory and applications. In K. Judd and L. Tesfatsion (eds.), Handbook of Computational Economics, Volume II. Amsterdam: North Holland.

[25] Young, H.P. (2009). Innovation diffusion in heterogeneous populations: contagion, social influence, and social learning. American Economic Review 99: 1899—1924.

[26] Zeppini, P. (2015). A discrete choice model of transitions to sustainable technologies. Journal of Economic Behavior and Organization. 112: 187–203.

[27] Weitzman, M.L. (2009). On modeling and interpreting the economics of catastrophic climate change. Review of Economics and Statistics 91(1): 1–19.