Directed Technical Change and Environmental Economics

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June 3, 2022

1 Introduction

While policymakers and climate scientists have long argued that overcoming the challenges brought about by climate change requires policies that encourage the development of new technologies which reduce the energy- and emissions-intensity of production and consumption, the economics literature had initially focused on models with exogenous technological change (see e.g. Nordhaus, 1994). In these models, the optimal policy response is a Pigovian tax on greenhouse gas emissions, which progressively increases over time. The growing theoretical literature on directed technical change (henceforth DTC) in the environmental context shows that taking into account the endogeneity of innovation can profoundly affect policy recommendations, and the empirical literature has provided ample evidence that innovation indeed responds to economic incentives such as an increase in fuel or energy prices. This chapter presents a short and non-exhaustive review of this literature, which notably builds on Acemoglu, Aghion, Bursztyn and Hémous (2012, henceforth AABH) and Aghion, Dechezleprêtre, Hémous, Martin and van

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Reenen (2016). The review (especially the theoretical part) reproduces in part our recent review in Hémous and Olsen (2021).[1]

DTC has a long tradition in economics. Hicks (1932) already suggested that an increase in relative prices should induce innovation to economize on the more expensive input, so that labor scarcity with respect to capital should induce labor-saving innovation; and Kennedy (1964) linked the direction of innovation to input cost shares. While early endogenous growth theory models, such as Aghion and Howitt (1992) only introduce one type of innovation, a key feature of DTC growth models is the presence of several types of innovation. The earliest example is Aghion and Howitt (1996) who model separately research and development and analyze researchers' incentives to allocate their effort to one or the other stage of innovation.[2] Closer to the original questions of Hicks (1932) and Kennedy (1964), Acemoglu (1998, 2002) developed the canonical DTC model where innovation can augment either low- or high- skill labor.

While growth theorists developed endogenous growth models with DTC in the 1990s, environmental economists did not adopt these until later. Yet, a growing empirical literature investigated the impact of energy prices on innovation (Newell, Jaffe and Stavins, 1999, Popp, 2002), and on the quantitative side, several papers added induced technical change to computable general equilibrium (CGE) models. Still, these authors did not build on modern growth theory and therefore either ignored knowledge externalities or modeled them in an ad-hoc way: for instance, in Nordhaus (2002) and Popp (2004, 2006), technological progress results from the accumulation of an R&D stock similar to capital.[3] Bovenberg and Smulders (1995, 1996) present endogenous growth models in an environmental context but with only one type of innovation.

We focus our review on DTC models in environmental economics which build on modern endogenous growth theory and especially Acemoglu (1998, 2002)'s framework. This literature largely focuses on energy and climate-change economics. The main source of difference between these models is whether they consider directed innovation affecting two inputs which are complement or substitute. The complement case (starting with Smulders and de Nooij, 2003) is used to study energy or fossil fuel resource-saving in-

[1]For other literature reviews see Popp, Newell and Jaffe (2010), Fischer and Heutel (2013), Popp (2019) and Grubb et al. (2021).

[2]In their model, research corresponds to the arrival of a new potential line of products and development to secondary innovations which introduce one of these products.

[3]See also Goulder and Schneider (1999), Massetti, Carraro, and Nicita (2009) or Sue Wing (2003). Gerlagh and Lise (2005) and Grimaud and Rouge (2008) microfound innovation but still impose ad-hoc relationships between its social and private values.

novation as energy and fossil fuel resources are complement to capital or labor. The substitute case (starting with AABH) focuses on the development of clean technologies which can replace dirty ones such as renewables versus fossil fuels in electricity production. The substitute case offers policy recommendations that contrast more sharply with the earlier exogenous technical change literature than the complement case—essentially because the complement case naturally leads to an economy featuring a balanced growth path, while the substitute case does not. Models with DTC have since been used to study the impact of energy price shocks on innovation in green technology, the determinants of historical energy transitions and the optimal design of unilateral carbon taxes with endogenous innovation and international trade. On the empirical side, the literature has provided unambiguous evidence that energy and carbon prices are able to redirect innovation activity toward clean technologies, providing strong empirical validation of the basic DTC framework, although many specific questions remain largely unexplored.

Section 2 presents our review of the theoretical literature and a simple original extension of the AABH framework. Section 3 discusses the empirical evidence. We conclude and discuss future research avenues in Section 4.

2 Theoretical insights from the DTC literature

In this section, we first review the main lessons from AABH. This paper presents a framework where clean technologies (such as renewables) can substitute for dirty ones (such as fossil fuels) and shows that the optimal policy with endogenous innovation is markedly different from that with exogenous innovation. We then adapt this model to contrast the substitute case with that of two complement inputs, which is adapted to study energy-saving innovation for instance. Section 2.3 presents further applications of the DTC framework. Section 2.4 presents an original extension to the AABH's model, where innovations in the dirtier sector can also reduce the emission rate.

2.1 The substitute case: clean and dirty energy

In AABH, a final good Y_t (the numeraire) is produced with a dirty input Y_{dt} and a clean input Y_{ct}, according to a CES production function:

$$Y_t = \left(Y_{ct}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{dt}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} . \tag{1}$$

The elasticity of substitution between the two inputs, ε, is greater than 1 so that the two inputs are gross substitutes.[4] This framework is appropriate to study a situation where the clean input can replace the dirty input over time as the latter is not necessary for production. It applies for instance to the choice between renewable or nuclear energy and fossil fuels, between electric and fossil fuel vehicles or between bioplastics and traditional plastics. Both Papageorgiou, Saam and Schulte (2017) using macro data and Jo (2020) using micro data estimate elasticities of substitution between clean and dirty energy inputs between 2 and 3; while Stöckl and Zerrahn (2020) and Wiskich (2021) find elasticities larger than 3 in electricity production.

Greenhouse gas emissions are proportional to the use of the dirty input: $P_t = \xi Y_{dt}$. This formulation is equivalent to one where emissions are the result of consuming a freely available fossil fuel resource which enters production in a Leontief way with the dirty input. It is also equivalent to the case where the dirty input is an extraction input and Y_{dt} represents the extracted fossil fuel resource. Therefore, AABH focus on innovations which reduce the effective costs of dirty inputs such as fossil fuel power plants, fossil fuel vehicles or fossil fuels themselves but which keep the emission intensity of these inputs constant. This ignores innovations aimed at improving energy efficiency or resource productivity ("thermal efficiency"), which we introduce in section 2.4.

The clean and dirty inputs are each produced using a combination of labor and a sector-specific set of machines indexed by i and of mass one. These machines are distinct for each sector $j \in \{c, d\}$, and their productivity evolves endogenously. The current level of productivity for machine $i \in [0, 1]$ employed in sector $j \in \{c, d\}$ is denoted $A_{ji} > 0$. The production functions for the two sectors are:

$$Y_j = \frac{1}{1-\beta} L_j^\beta \int_0^1 A_{ji}^\beta x_{ji}^{1-\beta} di \ \text{ for } \ j \in \{c, d\}, \tag{2}$$

where L_j is the mass of workers hired in sector j. Machines are produced monopolistically and their production costs $1 - \beta$ units of the final good.

Innovation is modeled in a quality-ladder fashion (Aghion and Howitt, 1992). Time is discrete, and at the beginning of every period, scientists of mass $S = 1$ can work to innovate either in the clean or the dirty sector. Given this choice, each scientist is randomly allocated to one machine in their target sector without congestion (i.e. at most one scientist is allocated to each sector). The probability of a successful innovation

[4] Aghion and Howitt (2009, ch. 16) look at the perfect substitutes case, $\varepsilon = \infty$, and preempt some of AABH results.

in sector j is given by η_j and there are no cross-sectoral spillovers in innovation. An innovation increases the quality of the targeted machine by a factor $1+\gamma$ (without loss of generality we assume $1+\gamma > (1-\beta)^{\frac{\beta-1}{\beta}}$, so that the technological leader charges the unconstrained monopoly price). AABH assume that the innovator obtains a patent for one period only. As we discuss below, this assumption makes the gap between the private and social returns of innovation particularly salient, but the insights of AABH generalize to settings where patents last longer.[5] As the supply of R&D resources is fixed, clean R&D fully crowds out dirty R&D. This is not an innocuous assumption as a policy which aims at increasing clean innovation also depresses dirty innovation and output growth (see Popp, 2004).

The aggregate technology in sector j can be defined as $A_j \equiv \int_0^1 A_{ji} di$. The innovation process then leads to the following law of motion for input $j \in \{c, d\}$ technology:

$$A_{jt} = (1 + \gamma \eta_j s_{jt}) A_{jt-1},$$

where s_{jt} is the mass of scientists in sector j, η_j their productivity and γ the innovation size. This innovation set-up features a "building-on-the-shoulders-of-giants" externality typical of Schumpeterian growth models: a successful innovator at time t will not only improve the current technology from $A_{j,t-1}$ to $(1+\gamma)A_{j,t-1}$, but she will also enable future innovators to build on the technology $(1+\gamma)A_{j,t-1}$ instead of having to build on $A_{j,t-1}$. This stands in contrast with horizontal innovation models where future innovators still need to develop new products "from scratch".

To determine the allocation of scientists, one needs to compute the expected profits realized by innovators in the two sectors. The maximization problems of the clean and dirty input producers give rise to iso-elastic demand functions (with a demand elasticity of $1/\beta$) for the machines. As the monopolists maximize profits given by $\pi_{ji} = p_{ji}x_{ji} - (1-\beta)x_{ji}$, they charge a mark-up $1/(1-\beta)$ leading to machine price of 1. The quantity x_{ji} produced by a monopolist and their profits π_{ji} are given by:

$$x_{ji} = p_j^{1/\beta} L_j A_{ji} \text{ and } \pi_{ji} = \beta p_j^{1/\beta} L_j A_{ji}. \tag{3}$$

[5] For simplicity, in sectors without innovation and therefore with no patent, the monopoly rights are attributed at random to an entrepreneur.

Plugging (3) in (2) gives the equilibrium quantity of intermediate input j:

$$Y_j = \frac{1}{1-\beta} p_j^{(1-\beta)/\beta} A_j L_j. \tag{4}$$

Since scientists are randomly allocated within a sector, the expected technology obtained by an innovator in sector j is given by $(1+\gamma) A_{j(t-1)}$. From (3), the expected profits of a scientist working for sector j are then given by:

$$\Pi_{jt} \ = \ \eta_j (1+\gamma) \beta p_{jt}^{\frac{1}{\beta}} L_{jt} A_{j(t-1)} = \frac{\eta_j \beta p_{jt} Y_{jt}}{1+\gamma \eta_j s_{jt}}, \tag{5}$$

where the second equality uses (4). The ratio of expected profits is then given by:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c (1+\gamma \eta_d s_{dt})}{\eta_d (1+\gamma \eta_c s_{ct})} \frac{p_{ct} Y_{ct}}{p_{dt} Y_{dt}} = \frac{\eta_c}{\eta_d} \underbrace{\left(\frac{p_{ct}}{p_{dt}}\right)^{\frac{1}{\beta}}}_{\text{price effect}} \underbrace{\frac{L_{ct}}{L_{dt}}}_{\text{market size effect}} \underbrace{\frac{A_{ct-1}}{A_{dt-1}}}_{\text{direct productivity effect}}. \tag{6}$$

Scientists will be allocated to the sector with the highest expected profits, namely to the clean one if this ratio is greater than 1, to the dirty one if it is less than 1 or potentially to both if it is equal to 1. The first equality in (6) shows that scientists target the sector with the largest revenue (adjusted with the productivity of the innovation technology) since profits are proportional to revenues. This is in line with Kennedy (1964)'s finding that the relative incentive to innovate combines the innovation possibility frontier (which here is independent of technologies) and the relative factor shares (which here are the revenue shares of the clean and dirty sectors). The second equality decomposes relative revenues between a price effect, a market size effect, and a direct productivity effect.

Labor allocation between the two sectors is endogenous and equating the marginal product of labor in the two sectors implies that the price ratio is given by

$$p_c/p_d = (A_c/A_d)^{-\beta}. \tag{7}$$

Therefore, the price effect pushes innovation toward the less advanced sector. Demand from the final good producer implies that

$$Y_c/Y_d = (p_c/p_d)^{-\varepsilon}. \tag{8}$$

Combining (4), (7) and (8) gives the labor allocation across the two sectors as:

$$L_c/L_d = (A_c/A_d)^{\sigma-1}, \tag{9}$$

where we define $\sigma = 1 + \beta(\varepsilon - 1)$. Since $\varepsilon > 1$, $\sigma > 1$ and the relatively more advanced sector attracts relatively more workers. Intuitively, this occurs because the allocation of labor itself depends on relative technologies and relative prices, and this price effect is dominated when the two inputs are substitute. Therefore, the market size effect in (6) pushes innovation toward the more advanced sector.

Using (6), (7) and (9), we obtain the relative expected profits from innovation as:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c}{\eta_d}\left(\frac{1+\gamma\eta_c s_{ct}}{1+\gamma\eta_d s_{dt}}\right)^{\sigma-2}\left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{\sigma-1}. \tag{10}$$

Since the two inputs are substitute $\sigma > 1$, the direct productivity effect and the market size effect dominate the price effect and innovation tends to be directed toward the most advanced sector. This is the first lesson of the framework: there is *path dependence* in innovation in laissez-faire, as societies with a relatively high level of dirty technologies today should expect even more dirty innovations in the future.[6] For sufficiently large or low values of $A_{c(t-1)}/A_{d(t-1)}$, the equilibrium features a corner solution with innovation in only one sector. In particular, for a sufficiently low initial ratio A_{c0}/A_{d0}, all innovation at time 1 occurs in the dirty sector, A_{ct}/A_{dt} further decreases over time and innovation remains locked in dirty technologies. Intuitively, clean innovations will have a hard time taking-off in *laissez-faire* as an innovation which improves a component in a fossil fuel power plant will have a much larger market than one which improves a component in a solar panel. As a result, while the canonical DTC models of Acemoglu (1998, 2002) focus on a balanced growth path (BGP), AABH focus on unbalanced trajectories.[7]

Therefore, the production of the dirty inputs and CO_2 emissions grow without bound if fossil fuel technologies are initially ahead. A social planner can avoid such an outcome by implementing clean research subsidies and/or a carbon tax. A clean research subsidy directly multiplies the right-hand-side of equation (6), while a carbon tax decreases the producer price p_{dt} for given technologies by imposing a wedge between the producer

[6] For more discussion on path dependence see the review of Aghion, Hepburn, Teytelboym and Zenghelis (2019).

[7] A BGP can be obtained by introducing (strong) cross-sectoral knowledge spillovers in the innovation function. For instance, if scientists' productivity obeys $\eta_j(A_{(-j)t}/A_{jt})^{(1-\delta)/2}$, then a BGP can be obtained when $\sigma < 2 - \delta$, while there is still path dependence if $\sigma > 2 - \delta$.

price of the dirty input and its marginal product in final good production. That is, (6) and (10) become

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{(1+q_t)\,\eta_c p_{ct}^{\frac{1}{\beta}} L_{ct} A_{ct-1}}{\eta_d p_{dt}^{\frac{1}{\beta}} L_{dt} A_{dt-1}} = (1+q_t)\,(1+\tau_t)^{\epsilon}\, \frac{\eta_c}{\eta_d} \left(\frac{1+\gamma\eta_c s_{ct}}{1+\gamma\eta_d s_{dt}}\right)^{\sigma-2} \left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{\sigma-1}, \tag{11}$$

where q_t is a clean research subsidy and τ_t is an (ad-valorem) carbon tax.[8]

Provided that the policy intervention is sufficiently large and maintained for a sufficiently long time, the social planner can redirect innovation away from dirty toward clean technologies, ensuring that clean technologies catch up and eventually overtake dirty ones. Once this has been been achieved, market forces will favor clean innovation. A temporary intervention is enough to ensure that emissions decline in the long-run provided that the two inputs are sufficiently substitute ($\varepsilon > 1/\beta$).[9] Yet, such an intervention is not costless: when clean technologies are catching up with dirty ones, productivity growth is low since innovation targets the less productive input. This makes delaying an intervention costly: while the economy remains in laissez-faire, the gap between clean and dirty technologies grows, requiring a longer and therefore costlier intervention later on. This brings us to the second lesson of the framework: taking endogenous technical change into account calls for an *earlier intervention*.[10]

The third lesson from the framework is that *a carbon tax is not enough to obtain the first best*. Formally, AABH consider a social planner who maximizes the intertemporal welfare of a representative agent who cares about consumption and environmental quality. They show that the first best allocation can be decentralized using a Pigovian carbon tax and research subsidies to clean innovation (plus a subsidy to all machines to remove the monopoly distortion). Why is a carbon tax not enough? Innovation in the first best is allocated to the sector with the highest social value, where the ratio of social

[8]Alsina-Pujols and Hovdahl (2021) show how other instruments such as limited patent enforcement for dirty innovation can also redirect innovation toward the clean sector. Nowzohour (2021) analyzes the role of frictions in the reallocation of scientists.

[9]The laissez-faire production of dirty input is decreasing in the clean technology A_c if $\varepsilon > 1/\beta$. Intuitively, when $\varepsilon < 1/\beta$, the two inputs are sufficiently complement that an increase in the clean technology increases demand in the dirty input so much that dirty input production grows through an increase use of machines even if the dirty technology does not grow.

[10]A similar result is obtained by Gerlagh, Kverndokk and Rosendahl (2009) who find that endogenous innovation in abatement technology calls for a front-loaded policy.

values is given by:

$$\frac{SV_{ct}}{SV_{dt}} = \frac{\eta_c \left(1 + \gamma \eta_d s_{dt}\right) \sum_{\tau \geq t} \lambda_{t,\tau} p_{c\tau}^{\frac{1}{\beta}} L_{c\tau} A_{c\tau}}{\eta_d \left(1 + \gamma \eta_c s_{ct}\right) \sum_{\tau \geq t} \lambda_{t,\tau} p_{d\tau}^{\frac{1}{\beta}} L_{d\tau} A_{d\tau}}, \tag{12}$$

with $\lambda_{t,\tau}$ the discount factor between t and τ. $p_{d\tau}$ is the producer price of the dirty input before any carbon taxation is applied, so a higher social cost of emissions which increases the optimal carbon tax decreases the producer price $p_{d\tau}$ and raises the relative social value of a clean innovation. Therefore, the social planner allocates innovation according to the discounted benefits that a higher technology brings in every period. In contrast, in the absence of a direct research subsidy, the market allocation depends on the ratio of current profits given by equation (6). With a research subsidy, the market allocation is given by (11), so that a properly chosen research subsidy can close the gap between the ratio of private and social values.

This explains why the market and the social planner would generally not allocate innovation in the same way without the appropriate research subsidy, but AABH's claim is stronger: they argue that the social planner needs to systematically implement research subsidies. In other words, one should expect the ratio of clean to dirty private values of innovation to be lower than that of the social values of innovation. How can that be the case? Essentially because the market's "short-termism" affects clean and dirty technologies differently. Assume that dirty technologies are initially more advanced but that the social planner would like to implement an "energy transition" so that clean technologies are expected to dominate in the future (as is arguably the case). Then, in the long-run, dirty technologies will have a small market, $\lambda_{t,\tau} p_{d\tau}^{\frac{1}{\beta}} L_{d\tau} A_{d\tau}$ is relatively small for large τ, and a large share of the social benefits of a dirty innovation (say an improvement in a natural gas power plant) is realized in the short-run. The gap between private and social value for a dirty innovation is not that large. In contrast, the market for clean technologies in the future is large, and a large share of the social benefits of a clean innovation (say an improvement in solar panels) will be realized in the future (here, in the form of even better solar panels), and the gap between the social and private values of a clean innovation is very large.

In AABH, the market is particularly myopic because patents last for only one period but the intuition extends to set-up with longer lived patents (as mentioned in AABH and extensively analyzed in Greaker, Heggedal and Rosendahl, 2018). The reason is that the myopia of the market ultimately stems from the building-on-the-shoulders-of-giants externality, which innovators do not internalize. To show this, consider an extreme case with perpetual patents. That is successful innovators must pay royalties to the previous incumbent to compensate them for their profit loss. Then, the ratio of private values of innovation is given by:

$$\frac{\Pi_{ct}}{\Pi_{dt}} = \frac{\eta_c \left(1 + \gamma \eta_d s_{dt}\right) \sum_{\tau \geq t} \lambda_{t,\tau} p_{c\tau}^{\frac{1}{\beta}} L_{c\tau} A_{ct}}{\eta_d \left(1 + \gamma \eta_c s_{ct}\right) \sum_{\tau \geq t} \lambda_{t,\tau} p_{d\tau}^{\frac{1}{\beta}} L_{d\tau} A_{dt}}. \tag{13}$$

While in (12) the sum involves the technology at time τ, $A_{j\tau}$, the sum in (13) is over the technology at the time of invention, t, A_{jt}. This difference reflects the building-on-the-shoulders-of-giants externality which the social planner internalizes: an innovator improves not only the current technology, but also all future technologies since future innovators will build up on her innovation. It is worth pointing out that the inefficiency in the direction of innovation in AABH is therefore intimately linked to the Schumpeterian nature of innovation in their model: in contrast, the optimal policy in a model with horizontal innovation, permanent patents and DTC need not feature research subsidies on top of Pigovian taxation. In general, finite-lived patents, creative destruction, imitation, and the building-on-the-shoulders-of-giants externality all contribute to make the private value of an innovation short-sighted relative to its social value. In the context of an energy transition, this short-termism of the market leads to too little clean innovation relative to dirty even with Pigovian taxation, which calls for clean research subsidies.[11]

In summary, three lessons can be drawn from the AABH framework. First, there is path dependence in the development of clean versus dirty technologies, which explains why clean technologies have had a hard time taking off without government support. Second, policy action should be more frontloaded than what a model with exogenous technology would predict. Third, climate change policy should not simply involve Pigovian carbon taxation, instead governments should also use clean research subsidies to boost clean innovation. All these features arise because AABH consider the choice between two substitute inputs and their associated technologies.

To derive quantitative predictions, Acemoglu, Akcigit, Hanley and Kerr (2016) embed

[11]Gerlagh, Kverndokk and Rosendahl (2014) make a similar point in a model with clean innovation only. This contrasts the DTC literature covered here with an earlier literature which simply assumed a certain (constant) ratio between private and social values of innovation (Nordhaus, 2002, Popp, 2004, 2006, or Gerlagh and Lise, 2005).

the AABH framework within a firm dynamics model. They assume that the final good is a Cobb-Douglas aggregate of a mass 1 of intermediates. Each intermediate can be produced with a clean or a dirty input which are perfect substitute, and which each have their own technology evolving on their own ladder. In the spirit of Klette and Kortum (2004), a firm is a collection of leading clean or dirty technologies in different lines. There are two types of innovations: incremental innovations build on the clean or dirty technology separately, while radical innovation builds on the leading technology whether it is clean or dirty. This generates cross-sectoral spillovers which mitigate (without eliminating) path dependence in innovation. In addition, the dirty technology input requires the use of an exhaustible resource. This leads to an increase in the resource price over time which ensures that a transition to clean innovation occurs in laissez-faire. They calibrate the model using firm-level data in the energy sector and patent data. They find that the switch to clean innovation occurs too late to avoid large climate damages in laissez-faire. In contrast, the optimal policy implements a rapid switch from dirty to clean innovation thanks to large clean research subsidies and a carbon tax. These conclusions are very much in line with AABH.

2.2 The Complementarity case: Energy-saving Innovation

While AABH focus on the decarbonization of energy production, an alternative way to reduce emissions is to develop energy- or resource-saving innovations. To analyze this case within our framework, assume that the final good is now produced with

$$Y_t = \left(Y_{Pt}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{Et}^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}}, \tag{14}$$

where Y_{Pt} denotes a production input, Y_{Et} an energy-services input and importantly the two inputs are complement: $\varepsilon < 1$. The production input is produced with sector-specific machines and a capital labor aggregate L, while the energy-services input is produced with energy (or a fossil fuel resource) E:

$$Y_P = \frac{L^\beta}{1-\beta} \int_0^1 A_{Pi}^\beta x_{Pi}^{1-\beta} di \text{ and } Y_E = \frac{E^\beta}{1-\beta} \int_0^1 A_{Ei}^\beta x_{Ei}^{1-\beta} di. \tag{15}$$

We define aggregate technologies A_{Pt} and A_{Et}. Since the two inputs are complement, an increase in the energy-augmenting technology A_{Et} is energy-saving (or if E is a resource, resource-saving). Theoretical papers have then made different assumptions about the supply of E: Smulders and de Nooj (2003) assume a constant resource flow, Shanker and Stern (2018) assume a perfectly elastically supplied resource, while Di Maria and Valente (2008), André and Smulders (2014) and Hassler, Krusell and Olovsson (2021) assume that the resource is exhaustible.

This literature derives and analyzes stylized facts on energy consumption and growth. For instance, Hassler et al. (2021) build a quantitative macroeconomic model calibrated to the US economy. As energy demand is very unresponsive to price changes in the short-run, they find an elasticity of substitution between energy and the capital-labor aggregate close to 0. Yet, the energy share is relatively stable in the long-run. They account for this puzzling pattern through a DTC model. In line with this model, they find that energy-saving technical change took off in the 70s with the oil shocks. Their model further predicts that resource scarcity (which could result from climate regulation) will only lead to a small increase in the energy share. Interestingly, they argue that the market allocation of innovation is not systematically inefficient. Such a conclusion contrasts sharply with AABH. What drives this difference? In a word, the complementarity between energy and other inputs, which implies that the economy will feature a BGP.

To see this more clearly, let us assume the same innovation technology and market structure as in section 2.1. Without loss of generality, further assume that L is fixed. The market allocation of innovation then depends on the relative expected profits from labor-augmenting over energy-augmenting innovation, which are given by:

$$\frac{\Pi_{Pt}}{\Pi_{Et}} = \frac{\eta_P\left(1+\gamma\eta_E s_{Et}\right)}{\eta_E\left(1+\gamma\eta_P s_{Pt}\right)}\frac{p_{Pt}Y_{Pt}}{p_{Et}Y_{Et}} = \frac{\eta_P}{\eta_E}\left(\frac{p_{Pt}}{p_{Et}}\right)^{\frac{1}{\beta}}\frac{L}{E}\frac{A_{Pt-1}}{A_{Et-1}} = \frac{\eta_P\left(1+\gamma\eta_E s_{Et}\right)}{\eta_E\left(1+\gamma\eta_P s_{Pt}\right)}\left(\frac{LA_{Pt}}{EA_{Et}}\right)^{\frac{\sigma-1}{\sigma}}. \tag{16}$$

The key difference with the model of section 2.1 is that since the two inputs are complement ($\sigma < 1$), the price effect now dominates. We can consider in turn, the three cases for the path of E. If the resource flow is constant, then following the last equality in (16), innovation favors the least advanced sector so that the economy must converge to a balanced growth path (BGP) where both technologies grow at the same rate and the expected profits are equal ($\Pi_{Pt} = \Pi_{Et}$). Given the first equality, the energy share is constant in the long-run and equal to $\eta_P/(\eta_E + \eta_P)$.

A decrease in the resource flow increases the energy price and the energy share, leading to an increase in energy-saving innovation. As a result, if the resource flow decreases over time (because of resource exhaustion or a growing carbon tax), faster growth in energy-saving innovation compensates for it so that the effective amount of energy $A_{Et}E$ grows at the same rate as effective labor $A_{Pt}L$.[12] The economy still converges toward a BGP with a constant interior energy share. This is the same logic as in Acemoglu (2003) where labor scarcity leads to labor-augmenting technical change. For the same reason, if the resource price is constant, then innovation in the long run is labor-augmenting.

The social planner still allocates scientists according to the ratio of social values which is given by an equation analogous to (12). In general, the social planner allocation and the market allocation still differ, but they converge toward the same balanced growth path provided that a Pigovian tax corrects for the environmental externality. As a result, research subsidies may still be necessary in the transition, but they become much less critical and need not even be in favor of energy-saving innovations. In fact, in the specific example studied by Hassler et al. (2021), the ratio of social values is always equal to that of private values and they are not necessary in the transition either (see also Hart, 2008). As the two inputs are complement, the market now favors the least advanced technology adjusting for resource availability, which ensures that the economy moves toward a balanced growth path, in line with the social planner's solution. While public intervention is crucial to engineer a transition from fossil fuels to clean energy, carbon pricing can do the heavy lifting for the development of energy-saving technologies.

As a result of DTC, a very low short-run elasticity between energy and labor-capital is compatible with a higher long-run elasticity. For instance, in the model sketched here, the long-run energy share is fixed at $\eta_P/(\eta_E + \eta_P)$ when the resource flow is constant (and is still close to this value when it decreases over time). In the long-run, the economy behaves as if the production function were Cobb-Douglas. In fact, climate models with exogenous technological change often assumed such a Cobb-Douglas production function, are they missing a lot by ignoring the dynamics of technical change? Casey (2019) shows that unfortunately this is the case. He considers a similar set-up with a Leontieff production function between energy and the capital-labor aggregate but DTC leading to a unit long-run elasticity and compares it with a Cobb-Douglas economy with exogenous technical change. Both models are calibrated to the US economy. He shows that, following the implementation of a carbon tax, emissions decrease slower in the Leontieff with DTC economy than in the Cobb-Douglas economy, leading to significantly more cumulative emissions and therefore higher damages.

[12] While a tax on energy services Y_E moves innovation toward A_P for any ε, a tax on energy, E, moves innovation toward A_E when $\varepsilon < 1$.

2.3 Applications to Environmental Questions

We now review papers which apply the DTC framework in the context of energy shocks, energy transitions and carbon leakage.

Energy market shocks. Fried (2018) uses the oil shocks of the 1970s to calibrate a more detailed DTC model. As in section 2.2, she considers a final good produced with a production input and energy services. Energy services are themselves a CES aggregate of local fossil fuel energy, oil imports and green energy with an elasticity of substitution greater than 1 (similar to AABH). Innovation can be targeted at the local fossil fuel energy, green energy or the production input, and she introduces cross-sectoral knowledge spillovers. She compares this economy with one without DTC. She finds that a carbon tax has a large effect on the innovation allocation, so that the carbon tax necessary to cut emissions by 30% in 20 years is 19.2% smaller in a world with DTC than in a world without DTC.[13]

Acemoglu, Aghion, Barrage and Hémous (2021) extend AABH to analyze the consequences of the US shale gas revolution on welfare and emissions in the long-run. They model electricity as a CES aggregate of clean, natural-gas based and coal-based electricity (with an elasticity greater than 1). Fossil-fuel electricity is produced with a power plant input and the associated resource. Both coal and natural gas generate emissions but natural gas is much cleaner. Scientists can improve the productivity of fossil-fuel power plants or clean power plants. In the short-run, the shale gas boom reduces the price of natural gas, electricity production relies more heavily on natural gas and less on coal and emissions decrease. At the same time, the market for innovations in fossil-fuel power plants expands, which leads to a reallocation of innovation away from clean and toward fossil fuel technologies. In line with this prediction, they document that the ratio of green to fossil fuel patents in electricity production has decreased substantially since 2011 (2 years after the beginning of the boom). Calibrating their model to the US electricity sector, they predict that because of this innovation response, the shale gas boom will eventually lead to an increase in emissions. They also compute the optimal policy and show that the shale gas boom calls for larger clean research subsidies.[14]

[13]Hart (2019) adds energy-saving innovation, physical limits to productivity and intersectoral knowledge spillovers to an integrated assessment model with AABH features. The optimal policy still features both a carbon tax and clean research subsidies but the presence of knowledge spillovers reduces the relative importance of research subsidies.

[14]Acemoglu and Rafey (2019) similarly find that progress in geoengineering technology can backfire. When the government cannot commit to its environmental policy, an exogenous improvement in geoengineering technology may decrease future environmental taxes, which decreases current clean

Historical energy transitions. A number of papers have used DTC to account for past energy transitions. Stern, Pezzey and Lu (2020) study the transition from wood to coal which occurred during the Industrial Revolution and perhaps in part caused it. The final good is a CES aggregate of a wood-based input and a fossil-fuel based input. The two inputs enter the production function symmetrically but while the supply of wood is fixed exogenously, coal is extracted at a constant cost. Similarly to AABH, the two inputs are substitute, so innovation tends to be allocated toward the more abundant input (everything else given). If wood is initially abundant, the economy first relies on the wood based input and innovates in that sector. Yet, without sufficient increasing returns to scale in innovation, output grows less than exponentially. Over time, however, the relative price of coal drops and the relative supply of coal versus wood increases. This eventually redirects innovation toward the coal-based input, at which point economic growth takes off. Gars and Olovsson (2019) use a similar DTC model, where innovation in fossil fuel technologies can ensure higher growth than innovation in wood powered technologies, to explain the 19^{th} century Great Divergence. They show that when a country starts using fossil fuels, the world fossil fuel price increases, which may discourage other countries from innovating in fossil-fuel technologies.

Lemoine (2020) builds a DTC model which generates endogenous energy transitions. Similar to Acemoglu, Aghion, Barrage and Hémous (2021), he models separetely the resource used in energy production and the complementary input necessary to produce energy. He models and calibrates historical energy transitions but finds that in the climate change context, research subsidies are still necessary to accelerate the transition to renewables.

Carbon leakage. The previous papers ignored international aspects and studied either the whole world or a country in isolation. Yet, given the limited results from international climate negotiations, several countries have been pursuing unilateral climate policies, the effectiveness of which is limited by carbon leakage. Carbon leakage occurs when a reduction in emissions in one country (following the implementation of a carbon policy) is undone by an increase in emissions in the rest of the world. Several papers use DTC models to study whether the innovation response amplifies or mitigate carbon leakage. Di Maria and Smulders (2004) and Di Maria and van der Werf (2008) consider a two-country (North, South), two goods (energy-intensive, non–energy-intensive) trade model. The North introduces a unilateral carbon tax so that part of the production

innovation and can lead to an increase in emissions.

of the energy-intensive good moves to the South. In the first paper, innovation occurs endogenously in the North only and the South imitates exogenously. The unilateral carbon tax then increases innovation in the non-energy intensive good which amplifies carbon leakage when the goods are complement and mitigates it when they are substitute (because energy-augmenting innovation is energy-saving when the two inputs are complement and energy-using otherwise). The second paper instead assumes that innovation occurs globally. Then, global innovation is redirected toward the non-energy-intensive good when the two inputs are substitute and to the energy-intensive good when they are complement, always mitigating carbon leakage. Acemoglu, Aghion and Hémous (2014) and van den Bijgaart (2017) look at the same problem in a two-country version of the AABH model (so with two substitute inputs). Again, a carbon tax in the North leads to a reallocation of part of the production of the dirty input to the South. They take as given the innovation response in the North (contrary to the two previous papers) and respectively find that the imitation and innovation responses in the South amplify carbon leakage.

Hémous (2016) starts from a set-up similar to Di Maria and Smulders (2004) and Di Maria and van der Werf (2008) with trade in an energy-intensive good and a non–energy-intensive good, but he now assumes that the energy-intensive good is itself produced like the final good in AABH as a CES aggregate between a clean input and a dirty input. His model can capture the fact that the emission intensity of the same (energy-intensive) good varies across countries depending on whether the good is produced with clean or dirty energy. Innovators optimally decide to improve the non-energy-intensive technology, the clean one or the dirty one. In addition, he assumes that utility is Cobb-Douglas between the energy-intensive and non-energy-intensive goods. The paper contrasts two policies. As before a unilateral carbon tax in the North leads to carbon leakage, and the innovation response in the South tends to amplify leakage: as the market for the energy-intensive good expands in the South, innovation there is reallocated toward that sector, and within that sector to dirty technologies (provided that dirty technologies are initially more advanced). In contrast, the North government could implement a green industrial policy, which boosts the development of clean technologies within the energy-intensive sector in the North, and as a result, decreases Northern emissions. Importantly, such a policy can also reduce emissions in the South through two channels. First, because innovation in the North is allocated toward clean instead of dirty or non-energy-intensive technologies, the North builds a comparative advantage in that sector.

This leads to negative leakage and less dirty innovation in the South (instead the South innovates more in the non-energy-intensive good). Second, if knowledge spillovers are large enough, the South may start innovating in clean instead of dirty technologies in the energy-intensive sector. Therefore, trade acts a double-edged sword: it diminishes the effectiveness of unilateral carbon taxes but also ensures that the appropriate policy can decrease emissions globally.[15]

2.4 Modeling grey innovation

As mentioned before, the baseline AABH model ignores improvements in dirty technologies that reduce the pollution intensity of the dirty good. In contrast, Gans (2012) models innovation in the fossil fuel sector as fossil fuel augmenting. Here, we present a simple extension of AABH which combines both types of dirty innovations. We make two changes to the framework of section 2.1. First, the dirty input Y_{dt} is now produced competitively using a resource-based input Y_{rt} and a non-resource based input Y_{pt}:

$$Y_{dt} = \left(Y_{rt}^{\frac{\theta-1}{\theta}} + Y_{pt}^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}}, \tag{17}$$

where $\theta < 1$ (i.e the two inputs are complement). The clean, resource-based and non-resource-based inputs are all produced competitively according to (2) for $j \in \{c, r, p\}$ and machines are still produced in the same way.[16] Second, we assume that emissions are now proportional to the use of machines in the resource-based sector x_{rit}, that is $P_t = \xi \int_0^1 x_{rit} di$ (implicitly, the use of these machines is associated with the consumption of a fossil fuel in a Leontief way).

In Appendix 5, we derive that the equilibrium level of pollution is given by:

$$P_t = \xi \left(\frac{A_{dt}}{A_{rt}}\right)^{1-\lambda} \frac{A_{dt}^{\sigma-1}}{A_{ct}^{\sigma-1} + A_{dt}^{\sigma-1}} \left(A_{ct}^{\sigma-1} + A_{dt}^{\sigma-1}\right)^{\frac{1}{\varepsilon-1}} L, \tag{18}$$

with $\lambda \equiv 1 + \beta(\theta - 1)$ defined analogously to σ and the average productivity in sector d

[15] Witajewski-Baltvilks and Fischer (2019) also extend AABH to a two-country model but allow for trade directly in machines (instead of the intermediate inputs), so that innovation incentives depend on market conditions in both countries. When the North is large enough, a unilateral clean research subsidy can redirect innovation toward clean technologies in both countries. In addition, it may induce a climate-skeptic South government to implement its own clean research subsidy for purely economic motives as long-run growth is higher if both countries innovate in the same sector.

[16] Note that here we are ignoring energy saving innovations which augment energy productivity in the production of the final good regardless of the source of energy.

defined as $A_{dt} \equiv \left(A_{rt}^{\lambda-1} + A_{pt}^{\lambda-1}\right)^{\frac{1}{\lambda-1}}$. The first fraction reflects the substitution within the production of the dirty intermediate between the resource-based and the non-resource based input, as $\theta < 1$, $\lambda < 1$ and this term is decreasing in A_{rt} and increasing in A_{pt}. The second fraction reflects the substitution between the clean and the dirty input, it increases in A_{dt} and decreases in A_{ct}. The third term is the overall productivity in the economy; it reflects a scale effect and increases in all technologies. This equation illustrates well the role of each technology: A_{ct} represents clean alternative to existing fossil-fuel based technologies (for instance, renewables in energy generation or electric cars in transport); A_{rt} represents resource and therefore emission saving innovations in the production of fossil-fuel based inputs (for instance higher thermal efficiency in fossil fuel power plants or higher efficiency in petroleum engines) and A_{pt} represents other improvements in fossil-fuel based technologies which lead to an increase in the demand for fossil fuels and therefore in emissions (labor saving innovations in power plants or faster engines in cars).

An increase in clean technologies reduces pollution provided that the clean and dirty inputs are sufficiently substitute: $\varepsilon > 1+1/\beta$–the threshold is now different because machines instead of the input are associated with emissions. An increase in the non-resource based productivity increases emissions. An increase in the resource-saving technology increases or decreases emissions depending on the relative productivity levels. In that sense, they represent "grey innovations".

The innovation technology is the same as in Section 2.1: scientists decide to innovate in clean, resource-based or non resource-based technologies with a probability of success η_j for $j \in \{c, r, p\}$ depending on the expected profits resulting from their research efforts. Expected profits are still given by (5). Within the dirty sector, the allocation of innovation between the two inputs now depends on the ratio:

$$\frac{\Pi_{rt}}{\Pi_{pt}} = \frac{\eta_r}{\eta_p} \left(\frac{1+\gamma\eta_r s_{rt}}{1+\gamma\eta_p s_{pt}}\right)^{\lambda-2} \left(\frac{A_{rt-1}}{A_{pt-1}}\right)^{\lambda-1}. \tag{19}$$

Since the resource-based and non-resource based inputs are complement, $\lambda < 1$, innovation targets the less advanced sector (as in the energy-saving case of Section 2.2) so that should innovation occur in the dirty sector in laissez-faire, it remains balanced between the resource-based and non-resource based inputs. In contrast, innovation between the clean and the dirty sector still features path dependence and asymptotically only occurs in one of the two sectors (except for a knife-edge case). If the clean sector is initially sufficiently backward relative to the dirty sector, then innovation in laissez-faire occurs in the dirty sector and emissions grow without bound.

Research subsidies can then be used to redirect innovation toward clean or grey technologies. In this context, an interesting question is whether a social planner should aim at making the dirty sector less polluting by focusing on grey innovations or fully switch to clean technologies. A full analysis of the social planner problem is beyond the scope of this book chapter, but a first element of response can be found in looking at the growth rates that can be achieved with either strategy. In the long-run, innovating in clean technologies leads to a growth rate of $\gamma\eta_c$ and, if the clean and dirty inputs are sufficiently substitute, $\varepsilon > 1 + 1/\beta$, to a decline in emissions. As in AABH, a switch to clean innovation can be achieved through a temporary research subsidy.

Innovation in dirty technologies is balanced between the two sectors in laissez-faire, so that asymptotically the mass of scientists in resource-saving innovation is $s_{rt} = \eta_p/(\eta_r + \eta_p)$ and the mass of scientists in the resource-using innovation is $s_{pt} = \eta_r/(\eta_r + \eta_p)$ leading to a growth rate of output and emissions given by $\gamma\eta_r\eta_p/(\eta_r + \eta_p)$. Nevertheless, it is possible to ensure a decline in emissions through innovation in the resource-using technology only. From (18), note that P_t would decrease over time if the resource-saving technology A_{rt} grows faster than the average dirty productivity A_{dt} (even if clean productivity A_{ct} is constant). Since $\lambda < 1$, the dirty productivity grows asymptotically at the minimum rate of the resource-saving and the resource-using technology. Therefore, a permanent subsidy to resource-saving innovation can guarantee long-run economic growth with declining emissions but only at the cost of a reduction in long-run economic growth.[17] In Appendix 5, we demonstrate:

Proposition 1. *i) A temporary subsidy to clean innovation can ensure positive long-run growth at rate $\gamma\eta_c$ with declining emissions when $\varepsilon > 1 + 1/\beta$. ii) A permanent subsidy to grey innovation can ensure positive long-run growth at a rate approximately equal to $\gamma\eta_r\eta_p/\left(\eta_r + \left(1 + (1-\lambda)^{-1}\right)\eta_p\right)$ when γ is small while ensuring that emissions decline.*

Therefore, provided that $\varepsilon > 1 + 1/\beta$, a patient social planner would tend to prefer a switch toward green innovation when the clean innovation productivity parameter is relatively high and the resource-based and non-resource based inputs are less complement.

[17]The asymptotic results technically require that there are no physical limits to how high A_{rt} can be, which for some type of innovations may not be realistic (see e.g. Hart, 2019). Nevertheless the analysis is informative as long as we are sufficiently far away from the physical limits. At any rate, the presence of physical limits would reinforce the case for a switch to clean innovation.

Intuitively, when the production function for the dirty input is closer to Cobb-Douglas, the resource saving effect of A_{rt} is smaller, requiring to sacrifice more growth to ensure a decline in emissions. This will be the case in particular when $\eta_c = \eta_r \eta_p / (\eta_r + \eta_p)$, that is, absent environmental concerns, the clean and the dirty technologies would have the same growth potential.

Finally, it is easy to show that a carbon tax (now paid on the use of the machines x_{rit}) redirects innovation within the dirty sector toward the resource-saving technology as in Gans (2012) if innovation occurs in the dirty sector; and/or away from the dirty sector and toward clean technologies. Aghion, Dechezleprêtre, Hémous, Martin and van Reenen (2016), which we discuss in Section 3, precisely look at the effect of gas prices on clean, grey and "purely" dirty innovation in the car industry.

3 Empirical evidence

A large empirical literature has looked for evidence of induced technical change in environmental economics. Popp, Newell and Jaffe (2010), Popp (2019) and Grubb et al. (2021) provide extensive literature reviews; here, we briefly review the earlier literature before focusing on a few recent contributions.

3.1 Energy prices and directed technical change

The closest empirical studies to the theoretical directed technical change literature examine the effect of changing energy prices on innovation. Newell, Jaffe and Stavins (1999) provide the first example by showing that the energy efficiency of home appliances available for sale changed in response to energy prices between 1958 and 1993. Technical change in air conditioners was biased against energy efficiency in the 1960s when energy prices were low, but this bias reversed after the oil shocks of the 70s which led to significant energy price increases.

The early paper by Newell, Jaffe and Stavins (1999) was a pioneer and a remarkable exception in at least one dimension: the vast majority of the subsequent literature has turned to patent data as an indicator of innovation induced by energy price dynamics. Patent data have a number of attractive features: they are available over long time periods, at a highly technologically disaggregated level—allowing researchers to precisely distinguish between clean and dirty innovations in various sectors—and can be linked with their owners (companies). They also suffer from limitations: in particular, only a small proportion of inventions are patented, and their value is highly heterogeneous. To date, however, no superior indicator has emerged. The literature using detailed product characteristics, as Newell et al. (1999), is comparably much more limited. This is a remarkable gap in the literature, and an interesting question would be to investigate the extent to which new patents do translate into more energy efficient products.

In a seminal paper, Popp (2002) uses time-series data on patent applications in the US from 1970 to 1994 across eleven energy demand or supply technologies, such as solar panels, fuel cells, heat pumps or waste heat recovery. He then regresses the percentage of all successful domestic patent applications per year in each technology field on the price of energy in the U.S. in that year. He finds a short-run patents-to-price elasticity of 0.03-0.06 and a larger long-run elasticity of energy efficiency innovation on energy prices of 0.35 (with over half of the effect occurring during the first five years after the price shock). Using a methodology similar to Popp (2002), Crabb & Johnson (2010) find an elasticity for energy efficient innovation in the US car industry over 1980-1999 of about 0.3 for retail gasoline price. Verdolini and Galeotti (2011) extend this analysis to 17 OECD countries for the period 1979-1998 and confirm Popp's finding with a short-run (1-year) elasticity of 0.04-0.06. Kruse & Wetzel (2016) further confirm this finding for 11 'green' technologies in 26 OECD countries over 1978-2009. In the buildings sector, Costantini, Crespi, & Palma (2017) find taxation on residential energy consumption to induce patent applications for energy-efficient technologies in buildings across 23 OECD countries (1990-2010). Importantly, a consistent finding from this literature is that the innovative response to policy happens quickly: much of the innovative response to higher (fossil fuel-based) energy prices occurs within five years or less.

Most of the early literature uses macro (sector- or country-level) data, making it difficult to claim causality. For example, in Popp (2002), there is no variation in energy prices across technology fields (average U.S. industry energy prices are used and thus they only vary through time). This prevents the inclusion of time dummies in the estimated equation, making it impossible to control for macro-economic shocks potentially correlated with both innovation and the energy price. The more recent literature has provided microeconomic evidence by constructing or observing firm-specific energy prices. In a direct empirical application of the AABH framework, Aghion, Dechezleprêtre, Hémous, Martin and van Reenen (2016) focus on the car industry and analyze the effect of gasoline prices on innovation, distinguishing between clean patents (associated with electric, hybrid and hydrogen engines), dirty patents (associated with combustion engines) and 'grey' patents (associated with energy efficiency improvements of combustion engines). To construct firm-specific fuel prices, they take advantage of the fact that innovators in the car industry sell their products across various national markets, and are thus differently exposed to country-specific fuel price variations, depending on their sales distribution (as proxied by the geographical distribution of their patent portfolio). This fuel price is computed as a weighted average of country-level fuel prices where the firm-specific weights are computed using a firm's patent history pre-sample (as a proxy for firm's market shares).[18] In the spirit of a shift-share instrument, the effect of fuel price on firms' innovation is identified by cross-country variations in fuel prices or taxes affecting firms differently according to their exposure to different markets. They estimate a large positive effect of fuel prices on clean innovation with an elasticity close to 1 and a negative effect on dirty innovation with an elasticity close to -0.5.[19] Innovation in fuel efficiency technology ('grey' innovation, a subset of dirty innovations) is also stimulated, but to a lesser degree, with an elasticity of 0.3. Furthermore, Aghion et al. (2016) find evidence for path dependence in the direction of innovation at the firm level – the propensity to patent in clean is greater when firms have accumulated more clean knowledge on which to build. Through simulations, they show that, in line with AABH, path dependence exacerbates the gap between clean and dirty knowledge in business-as-usual but reduces the increase in fuel prices necessary to induce clean technology to catch-up with dirty technology.

Several papers have used the same method as Aghion et al. (2016) to generate energy price variation at the firm level and make further contributions to the empirical DTC literature. Noailly and Smeets (2015) focus on the electricity production sector and study how clean and dirty innovations respond to fuel price (as in Aghion et al., 2016) but also to the market size, where firm-level market size is calculated in an analogous manner (see also Lazkano, Nøstbakken and Pelli, 2017; and Lööf, Perez and Baum, 2018). Overall, their results support the DTC hypothesis: increases in renewable market size or fossil fuel prices lead to more renewable innovation and a larger fossil fuel market leads to more fossil fuel innovation. An increase in fossil fuel price also leads to a large increase

[18]As a patent only protects an invention in the country in which it is applied for, whether a firm decides to apply for a patent in a given country or not is indicative of the importance of that country for the firm. Coelli, Moxnes and Ulltveit-Moe (2022) show empirically that this is a good proxy for market share.

[19]In line with these results, Knittel (2011) finds that there is a trade-off between improving fuel efficiency and other vehicle attributes, and that technical progress has responded to the implementation of regulatory standards.

in fossil fuel energy-efficiency innovations. Their results also support path dependency.

Having established the empirical existence of directed technical change from price and market size effects, the literature is moving to study other factors driving technical change as well as interaction effects. For instance, Aghion, Bénabou, Martin and Roulet (2020) extend the set-up of Aghion et al. (2016) to study both the role of consumer value and competition in driving innovation in the car industry. They find that when consumers value the environment more, clean innovation in the car industry increases, particularly when competition is more intense. They estimate that the simultaneous increase in environmental valuation and competition which happened between 1998-2002 and 2008-2012 had the same effect on innovation as a 40% increase in fuel price. Another example is Fredriksson & Sauquet (2017), who find that the innovation effect found by Aghion et al. (2016) is strongest for firms located in countries with French civil law, rather than those with common law, suggesting that the relative 'rigidity' of civil law may provide greater certainty regarding future legislation and lessen incumbents' lobbying, increasing the incentive to innovate.

Using different identification strategies, other recent papers have established a causal effect of climate policies on innovation based on microdata. Calel and Dechezleprêtre (2016) examine the influence of the European Union Emissions Trading System (EU ETS), which from 2005 created an EU-wide carbon price for electricity generation and heavy industry. To assess the impact of the EU ETS on low-carbon innovation, they take advantage of the existence of regulatory thresholds at the plant level which determine inclusion in the system. In order to control administrative costs, the EU ETS was designed to cover only large installations with production capacity above a certain threshold: for example, in the steel sector, only plants with a production capacity exceeding 2.5 tonnes per hour are regulated; in the glass sector, installations are included only if their melting capacity exceeds 20 tonnes per day. Firms operating smaller installations are not covered by EU ETS regulations, although the firms themselves might be just as large as those affected by the regulation. Because innovation takes place at the firm level, Calel and Dechezleprêtre (2016) can exploit these installation-level inclusion criteria to compare firms located in the same country, operating in the same sector, with similar resources available for research and similar patenting histories, but which have fallen under different regulatory regimes since 2005. This provides an opportunity to apply the sort of quasi-experimental techniques most suited to assessing the causal impacts of environmental policies (List et al., 2003; Greenstone & Gayer, 2009). The authors follow a matched difference-in-difference strategy where they compare regulated firms with a control group representing what would have happened, had the EU ETS not been implemented. They show that the EU ETS increased low-carbon innovation (as measured by patent filings at the European Patent Office) by 30% in the matched sample of regulated firms. This result was confirmed by Calel (2020) in a study focusing on the UK. Similar results have been found by studies examining other carbon pricing instruments. For example, Zhang et al. (2019) examine the role of the seven carbon pricing pilot schemes introduced in China in 2013 on 'green' patent applications by regulated firms, and report a significant positive correlation.

3.2 Other environmental policies and induced innovation

Although less directly aimed at testing the validity of the DTC hypothesis, a broader literature has investigated the impact of environmental policy on innovation and is thus worth mentioning here, as these studies collectively reinforce the finding that innovation responds to economic incentives provided by environmental policies, even if the identification strategy is weaker than in microeconomic studies. For example, several early studies used pollution abatement control expenditures (PACE) as a proxy for environmental regulatory stringency. Examples include Lanjouw and Mody (1996), Jaffe and Palmer (1997), and Brunnermeier and Cohen (2003). Each finds a significant correlation within industries over time between PACE and innovative activity, as measured by research and development expenditures or environment-related patent filings.

Renewable energy policies, which require the adoption of renewable energy technologies to generate electricity, have also been shown to incentivize innovation. In a panel of OECD countries, Johnstone, Haščič and Popp (2010) find that public policies have an effect on innovation in renewable energy, as measured by applications for renewable energy patents submitted to the European Patent Office (EPO). Broad policies (such as renewable energy mandates, which do not target a particular technology) have a larger effect on technologies closer to competing with fossil fuels, in particular wind energy, while technologies farther from the market (solar power) require more targeted subsidies. In one of the largest subsequent studies, covering 19 EU countries over 1980-2007, Nicolli & Vona (2016) show that feed-in tariffs increased patenting in solar photovoltaic technology. Such results which speak to a form of path-dependence within renewables are consistent with the AABH framework. Dechezleprêtre and Glachant (2013) show that innovation in wind power technology responds positively to policies both at home and abroad. The marginal effect of domestic policies is 12 times greater than that of foreign policies, but the aggregate effect of foreign markets on innovation is larger, because the overall foreign market is typically much larger than the domestic market - suggesting a large overall impact of demand-pull policies on innovation through global value chains.

Finally, a few studies evaluate the effect of international environmental agreements on innovation. A recent example is Dugoua (2020). In this paper, the identification relies on a difference-in-differences strategy, where innovation in particular molecules directly affected by the signing of the agreement is compared to innovation in related but unaffected molecules. She focuses on the Montreal protocol, which has regulated the use of CFC since 1989, and finds that it led to an increase of 400% in patents pertaining to CFC-substitutes relative to similar molecules. Interestingly, she shows that, by inducing innovation, the initially modest protocol reduced future abatement costs, leading to a series of increasingly ambitious follow-up agreements. The parallel with climate change, and the AABH framework, is clear: carbon prices and technology development are mutually reinforcing. Carbon prices induce new low-carbon technologies, which in turn can build the case for stronger carbon pricing in the future by lowering the cost of future green technologies.

3.3 Addressing the innovation market failures to direct technical change

From the empirical literature, there is clear and unambiguous evidence that energy and carbon prices induce innovation in clean technologies (at least, as measured by patents). However, the AABH framework highlights that reaching the first best requires a combination of carbon prices with subsidies to clean R&D because the social value of clean innovation is relatively more backloaded than that of dirty innovation. From a policy perspective, this raises the question of whether subsidies to clean R&D actually work. Evidence on this issue is - surprisingly - scarce. Pless, Hepburn and Farrell (2020) report that, of the 1700 papers on the impact of direct funding for innovation reviewed by the What Works Centre for Local Economic Growth, only 42 use rigorous statistical methods. This emerging literature suggests that direct R&D grants and R&D tax credits have positive effects on firms' innovative activity (Bronzini et al., 2014; Bronzini and Piselli, 2016; Agrawal et al., 2020; Dechezleprêtre et al., 2016; Ganguli, 2017), with heterogeneous effects across types of firms. In addition, grants and tax credits can be complementary for small firms but substitutes for larger firms (Pless, 2021).

In the literature which seeks to evaluate R&D support policies, only a couple of studies focus on energy-related innovation. Yet, this sector possesses many features (high capital intensity, long time horizons, little product differentiation, among others) which might make the innovation process specific. Howell (2017) exploits the fact that the US Department of Energy's Small Business Innovation Research program allocates R&D grants to small businesses through a grading scheme. Using a regression discontinuity analysis, she finds that receiving a grant increases patenting, survival rate and the probability of subsequently receiving venture capital among recipients, with stronger effects for firms likely to be more financially constrained. Within energy research, Howell (2017) also shows that such R&D subsidies can increase clean innovation specifically (in hydropower, carbon capture and storage, building and lighting efficiency, and alternative automotive technologies) but have no measurable effect on conventional energy technologies (natural gas and coal), likely because firms developing these technologies are less financially constrained.

A related question is whether there are additional reasons than the one highlighted in the AABH framework to subsidize clean R&D. As a matter of fact, recent research has demonstrated that knowledge spillovers are larger for clean than for dirty technologies. In a comprehensive analysis covering 1.3 million patents filed over 60 years, Dechezleprêtre, Martin and Mohnen (2017) show that knowledge spillovers (measured with patent citations) are 40% larger for low-carbon than for high-carbon technologies. The higher knowledge spillovers from low-carbon technologies come primarily from their radical novelty compared with old polluting technologies. New technology fields offer potentially high marginal private returns to first movers and might thus generate large knowledge spillovers. Comparing the spillovers from low-carbon and high-carbon technologies to a range of other emerging technologies, such as IT and biotechnologies, Dechezleprêtre, Martin and Mohnen (2017) find that the intensity of spillovers from low-carbon technologies is comparable to other emerging technologies, while knowledge spillovers from high-carbon technologies lag behind.

4 Conclusion and Future Avenues

This review highlights that the literature has firmly established that environmental innovations respond strongly to market incentives and that the endogeneity of innovation matters for macroeconomic outcomes. In fact, DTC theory often provides policy answers that differ from models with exogenous technology: an environmental policy should be front-loaded to kick-start the green innovation machine; carbon taxes are an important policy tool but not the only one; unilateral environmental policies should not limit themselves to a simple carbon tax; and the development of a bridge technology (such as switching from coal to gas) may backfire if it is not accompanied by further efforts to develop really clean (carbon-free) technologies. Overall, AABH and the unfolding literature provide a strong case for a green innovation policy: climate policy should be designed with innovation at the forefront.

This calls for further integrating DTC in climate change economics. In particular, microfounded DTC should be more systematically incorporated in Integrated Assessment Models. Dietz and Lanz (2019) is a recent example in a detailed multisectoral model with endogenous population dynamics. Kruse-Andersen (2020) also includes population dynamics into a DTC model. Another important avenue is to expand the 2-country setups discussed above for more realistic models of international environmental agreements building on game-theoretic contributions such as Barrett (2006) and Harstad, Lancia and Russo (2019). Finally, climate change is a problem riddled with uncertainties about climate dynamics, climate damages but also technological prospects. The models reviewed here are all deterministic but the interaction between technology and uncertainty is a promising avenue for future research.

Empirically, a number of promising research avenues emerge from this review. First, because of data availability, the empirical evidence has mostly focused on patent filings as a measure of innovation output, but more direct measures of innovation outcomes (e.g. technology cost reductions) are strikingly missing. New and better measures of clean innovation are needed. Understanding the full impact of green innovation policies, through the supply chain (on technology providers or on downstream consumers via cost pass-through), across borders and via spillovers (knowledge spillovers, product market rivalry) is another promising area, although it faces an inherent trade-off with establishing causality. In this regard, measuring the crowding-out effect of policy-induced clean innovation on other types of innovation is crucial to better understand the welfare effects of climate policy. Third, while the impact of energy and carbon prices on clean innovation is clear, investigation of the impact on incremental versus more radical innovation (which might be needed to reach the recently adopted carbon neutrality targets) appears lacking. More generally, exploration of the heterogeneity of the impact of green innovation policies across technologies, firms, countries and sectors, depending on their characteristics (financial constraints, competition, knowledge stock) would enrich our understanding of DTC. For example, carbon prices may work less well in certain sectors (e.g. buildings) because of the existence of additional market failures. Finally, an important area for research is that of policy instrument choice, in particular beyond pollution pricing, and evaluating policy interactions and policy mixes (including, most importantly, combinations of pollution pricing instruments with innovation support policies). More empirical research on the impact of R&D support policies specifically targeting energy innovation is also needed.

In a word, theoretical and empirical applications of the DTC framework to the environmental context surely have fine research days ahead.

5 Appendix

This Appendix provides mathematical details to the model sketched in Section 2.4.

Deriving equation (18). Equations (3) and (4) now apply to sectors $j \in \{c, r, p\}$. Relative demand for the resource-based and non-resource based inputs in the dirty sector leads to the relative demand:

$$Y_{rt}/Y_{pt} = (p_{rt}/p_{pt})^{-\theta}, \tag{20}$$

and allows to express the price of the dirty input as:

$$p_{dt} = (p_{rt}^{1-\theta} + p_{pt}^{1-\theta})^{\frac{1}{1-\theta}}. \tag{21}$$

Next solving for labor demand in subsectors r and p implies:

$$p_{rt}/p_{pt} = (A_{rt}/A_{pt})^{-\beta}, \tag{22}$$

plugging this expression together with (4) in (20) leads to:

$$L_{rt}/L_{pt} = (A_{rt}/A_{pt})^{\lambda-1}. \tag{23}$$

We define the total labor force working in sector d as $L_{dt} \equiv L_{rt} + L_{pt}$. Using (4) for $j = r, p$, (21), (22) and (23) in (17), we get that Y_{dt} also satisfies (4). As a result, (7), (8) and (9) still apply.

Using (3) and (4) for sector r, we get $P_t/Y_{rt} = \xi(1-\beta)p_{rt}$. Then using (21), (22), (7) and the normalization of the final good price to 1, we get

$$\frac{P_t}{Y_{rt}} = \xi\,(1-\beta)\,\frac{\left(A_{dt}^{\sigma-1}+A_{ct}^{\sigma-1}\right)^{\frac{1}{\sigma-1}}}{A_{rt}^{\beta}}.$$

Using (20) and (22), we further get that:

$$\frac{P_t}{Y_{dt}} = \xi\,(1-\beta)\,\frac{\left(A_{dt}^{\sigma-1}+A_{ct}^{\sigma-1}\right)^{\frac{1}{\varepsilon-1}}}{A_{dt}^{\beta}}\frac{A_{dt}^{1-\lambda}}{A_{rt}^{1-\lambda}}, \tag{24}$$

which is decreasing in A_{rt}. Combining (4), (7), (9) and the labor market clearing condition gives the laissez-faire production of dirty input as

$$Y_d = \frac{A_d^{\varepsilon\beta}L}{(1-\beta)\left(A_c^{\sigma-1}+A_d^{\sigma-1}\right)^{\frac{\beta\varepsilon-1}{\sigma-1}}}. \tag{25}$$

Similar steps give the final good production as

$$Y_t = \left(A_{ct}^{\sigma-1}+A_{dt}^{\sigma-1}\right)^{1/(\sigma-1)}\frac{L}{1-\beta}. \tag{26}$$

The ratio of dirty input over final good is then:

$$\frac{Y_{dt}}{Y_t} = \frac{A_{dt}^{\varepsilon\beta}}{\left(A_{ct}^{\sigma-1}+A_{dt}^{\sigma-1}\right)^{\frac{\varepsilon\beta}{\sigma-1}}}. \tag{27}$$

which decreases in A_{ct} and increases in A_{dt}. Combining these terms together gives (18).

Proof of Proposition 1. Part i) is already established in the text. Consider a situation where innovation occurs asymptotically in the dirty sector. First note that asymptotically, we have $g_{A_d} = \min\left(g_{A_r}, g_{A_p}\right)$. From (18), we get that asymptotically

$$P_t \sim \xi A_{dt}^{2-\lambda}A_{rt}^{\lambda-1}L.$$

Pollution decreases in the long-run if $1+g_{A_d} = 1+g_{A_p} < (1+g_{A_{rt}})^{\frac{1-\lambda}{2-\lambda}}$. From (26), the maximal growth rate of final output achievable through this second strategy is then:

$$g_Y = g_{A_d} = g_{A_p} = \gamma\eta_p s_p^*,$$

where the asymptotic allocation of scientists s_p^* solves

$$\left(1+\gamma\eta_p s_p^*\right)^{2-\lambda} = \left(1+\gamma\eta_r\left(1-s_p^*\right)\right)^{1-\lambda}. \tag{28}$$

For γ small, this implies

$$s_p^* = \frac{(1-\lambda)\,\eta_r}{(2-\lambda)\,\eta_p+(1-\lambda)\,\eta_r},$$

leading to the growth rate given in Proposition **1**.

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