Directed Technological Change and General Purpose Technologies: Can AI Accelerate the Energy Transition? *

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Abstract

Transitioning away from dirty and towards clean technologies is critical to reduce carbon emissions, but the race between clean and dirty technologies is taking place against the backdrop of improvements in general-purpose technologies (GPT) such as information and communication technologies and artificial intelligence. We show how, in theory, a GPT can affect the direction of technological change, and in particular, the competition between clean and dirty technologies. Second, using patent data, we show that clean technologies absorb more spillovers from AI and ICT than dirty technologies, and that energy patenting firms with higher AI knowledge stocks are more likely to absorb AI spillovers for their energy inventions. We conclude that AI has the potential to accelerate the clean energy transition.

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1 INTRODUCTION

Are low-carbon technologies surfing the Artificial Intelligence (AI) wave better than dirty technologies? Are they benefiting from the broad restructuring of the economy brought about by ICT, AI and the digital transformation? Many corporate actors and technologists seem to think so (see, for example, initiatives such as Microsoft's "AI for the Planet"). According to economic historians and innovation scholars, technologies co-evolve (Perez 2009). Thus, specific technological transitions in the past have often featured strong complementarities between several emerging technologies, together creating a new technological paradigm (Dosi 1982; Rosenberg 1979). These scholars have argued that a new technology can successfully challenge deeply entrenched technologies and infrastructure networks only if it itself connects to new disruptive technology networks and benefits from these interconnections more than the incumbent technology does (Fouquet 2008; Grübler et al. 1999). Thus, if the past is any guide, the question of whether clean technologies can build on digital technologies may be key for the low-carbon transition.

Applied to the low-carbon transition, this argument implies that clean technologies must integrate with and benefit from the digital economy and its technologies in order to displace dirty technologies. The EU's recent industrial policy strategies seem to recognize that making this link is key to a successful transition, yet, to date, there is little to no scholarship to help policy-makers understand these interactions. However, AI and ICT are general purpose technologies (cf. Brynjolfsson et al. 2021; Crafts 2021; Trajtenberg 2018). This means that they have the potential to be applied in many, if not most, areas of the economy, including in high-carbon energy industries. Thus, a priori, there is no reason to believe that they can drive the low-carbon transition, as they may just as well help incumbent technologies continue to gain in productivity.

This paper investigates how a new general purpose technology affects the direction of technological change, and in particular, the competition between clean and dirty technologies. We do so, first, theoretically and then empirically by examining the extent to which energy patents rely on AI and ICT inventions. In line with the literature on directed technological change and the environment, we consider low-carbon electricity and transport to be competing in a race with the incumbent fossil fuel-based technologies, where the latter have an advantage due to their greater maturity (i.e., in the absence of corrective policy, they will attract more talent and RD&D resources). But we recast this race as happening against the backdrop of advances in AI.

Our theory shows that the arrival of a GPT opens new opportunities to shift to a clean technology equilibrium because it disrupts the path dependence mechanisms that otherwise entrench dirty incumbent technologies. In addition, the shift to the clean technology equilibrium is made easier if these technologies have a higher capacity to absorb the GPT than dirty technologies. This absorptive capacity is shaped both by intrinsic technology characteristics and exposure to the GPT, which both encourage inventors to apply the GPT in their technological field.

Empirically, we then measure the absorption of AI and ICT by clean and dirty energy technologies. The analysis of citations between energy patents and AI (or ICT) patents shows that clean energy technologies absorb digital technologies much more than dirty energy technologies do. This is true both across and within individual firms' patent portfolios. We interpret this as an indication that the differences between clean and dirty technologies arise both from firm-level choices and capacities and characteristics intrinsic to the technologies (i.e. technical reasons why there is more potential to apply AI and ICT in clean technologies than in dirty ones). At the firm level, we then find that a firm's stock of knowledge in AI increases the extent to which it applies AI to its energy innovations, and the effect is much stronger for clean technologies. Interestingly, having a lot of prior experience in energy technologies seems to be a barrier to the use of AI, which suggests that new entrants to clean transport and electricity who have strong AI capabilities are critical to accelerating the diffusion of AI into low-carbon technologies.

In summary, this paper argues on theoretical grounds that it is critical for the low-carbon transition that clean technologies be more successful in "riding the AI wave" (i.e. applying the GPT) than dirty ones. Empirically, we find early evidence that this is the case, both because these technologies are intrinsically more able to use AI and because this, in turn, encourages firms with AI knowledge to invest in those technologies. However, compared to other technological fields, the rate at which AI is entering clean transport and electricity technologies remains low compared to other areas, such as medical technologies or telecommunications. Thus, this suggests that there are good reasons for innovation policy to deliberately target applications of AI (and digital technologies more broadly) to clean technologies.

This paper contributes to both the theoretical and empirical literatures on directed technological change and the environment (Acemoglu et al. 2012; Aghion et al. 2016; Dechezleprêtre et al. 2017; Johnstone et al. 2010; Popp et al. 2020). This literature tends to analyze environment-saving innovations in isolation from other technological developments. Here, we enrich it by studying the interaction with a general purpose technology. In doing so, we also contribute to the economic literature on GPTs (Helpman et al. 1994, 1996; Lipsey et al. 2005; Rosenberg et al. 2010). This literature is mainly concerned with understanding the contribution of GPTs to growth and has not investigated how GPTs can modify the direction of technological change (except for the literature on digital technologies and skill-biased technical change). Economic history, however, has provided detailed accounts of how specific GPTs have created new technological eras by reconfiguring technological systems, creating new complementarities between technologies, and between new technologies and new infrastructure, production methods, lifestyles and consumption habits (Fouquet 2008; Perez 2009; Rosenberg 1979). This qualitative strand of literature is complemented by recent empirical work that aims to quantify technological interdependencies, for the most part using patent data (Acemoglu et al. 2016;

Napolitano et al. 2018; Pichler et al. 2020). These papers find that the patterns of technological interdependencies predict future rates of innovation. This underscores the importance of understanding the complementarity between clean innovation and other fast-improving fields of innovation.

The remainder of this paper proceeds as follows. Section 2 provides background on general purpose technologies, in particular their role in economic transformations, and on ICT and AI technologies with a focus on their potential applications to the low-carbon transition. Section 3 analyses a model of green directed technological change in which we add a GPT. Section 4 describes the construction of our global dataset of 2,488,360 electricity and transport patent families and the extent to which they have absorbed AI and ICT knowledge. Section 5 presents our key result about clean technologies' greater ability to absorb the GPT as compared to dirty technologies. Section 6 presents the results of the firm-level analysis, while section 7 discusses the implications of our results for the low-carbon transition.

2 BACKGROUND

Artificial Intelligence as the next General Purpose Technology Artificial Intelligence (AI) – defined by Miriam-Webster as "the capability of a machine to imitate intelligent human behaviour" – is widely thought to be the next game-changing technology about to unleash large productivity gains and a wave of automation by optimists and pessimists alike (Trajtenberg 2018). AI includes several techniques and functional applications in computer science, such as deep learning, symbolic systems and reasoning, speech processing, and computer vision, all of which are key to advancing optimization, prediction and robotics, which can be deployed in many sectors. According to Cockburn et al. (2018), deep learning has the potential to change the research process itself, thus qualifying as the "invention of a method of invention". There is, therefore, significant evidence that AI qualifies as a general purpose technology, and an emergent literature aspires to model its potential effects on growth and knowledge creation. For example, Aghion et al. (2018) model AI as a process of automation of goods and services, as well as the production of ideas. Agrawal et al. (2018) integrate AI breakthroughs into a knowledge production function as enabling faster discoveries in combinatorial knowledge creation.

Applications of AI in Energy Sectors Some ICT and AI technologies may have applications essential for the transition to clean energy. For example, smart grids may facilitate the integration of distributed renewable energy with bulk power generation plants and bulk energy storage systems (Bose 2017), and smart buildings can benefit from effective load demand forecasting (Raza et al. 2015) and better monitoring through smart meters (Fouquet 2017). AI techniques can also be used to plan, optimise, and manage renewable energy technologies, including solar and wind systems and hydro power (Jha et al. 2017). For example, fuzzy logic controllers can adjust turbine speeds to optimise aerodynamic efficiency and extract maximum power, while neural networks can carry out automatic health checks (Bose 2017). Lee (2020) have analysed patent citations and found that AI has had spillovers to improve battery performance and optimise the car's energy management system and charging systems.

Potential applications of AI in the energy sector are not limited to clean technologies. AI can enhance productivity in many application sectors by automating some tasks and freeing up labour to complete other, more complex ones. It is also valuable for planning the maintenance and deployment of physical capital or inventories. More broadly, and not specific to clean or dirty energy, Lyu et al. (2021) analyse online job postings data from 2010-2019, and find that among emerging digital technologies (among which they include Artificial Intelligence, Big data, Internet of Things, Robotics, Blockchain technology, and Cloud Computing), AI is the most widely applied in the energy sector (as measured by the extent to which new hires are asked to provide expertise in AI). AI related knowledge also carries the highest wage premium compared to average wages and contributes most to energy firms' performance/productivity. Crucially, there are also numerous potential applications for AI in dirty energy. In fossil fuel exploration, AI can increase the efficiency of exploration (such as through well logging or geological mapping), field development and engineering, and other parts of the value chain (cf. Koroteev et al. 2021). In combustion technologies, AI can be used to monitor and optimise combustion processes. Thus, AI could accelerate innovation in clean technologies, but given its wide range of applications, it could also help the productivity of dirty technologies and prolong their attractiveness.

The economics of GPTs Our analysis is informed by several key contributions from the economics literature on GPTs and innovation spillovers. First, as emphasised by Helpman et al. (1994) and Helpman et al. (1996), the economic benefits from a new GPT may accrue only after a lag because applying the GPT does not happen spontaneously: it requires R&D efforts and investments. Helpman et al. (1996) model diffusion of a new GPT, allowing for both early and late adopters. Importantly, advances in the GPT do not diffuse spontaneously: adoption requires complementary co-invention in application sectors. In their model, the extent to which application sectors innovate to make use of the GPT depends on four key factors: their capacity to absorb this technology (that is to learn from it to create large productivity gains in their sector; market size), the historical stock of components developed for the old GPT, and the cost of developing new components. Our theoretical analysis will build on those factors. We also follow Cohen et al. (1990) in considering the absorptive capacity to be endogenous, meaning that it is the result of deliberate investments in an area of knowledge to be better able to learn from other inventors and inventions (thus, knowledge spillovers are not "free" or spontaneous).

While prior literature mainly focused on the effects of GPTs on growth, we examine how GPTs shape the race between two competing technologies and may catalyse the creative destruction of a (dirty) incumbent technology by a newer (clean) challenger. Indeed, in modelling the diffusion of the GPT, Helpman et al. (1996), for example, assume that all viable application sectors will eventually adopt the GPT. In the race between clean and dirty, however, enhancing welfare requires that the dirty sector declines and disappears.

3 THEORY

How should we expect a GPT to affect the direction of technological change? Specifically, under what conditions can a GPT accelerate the pace of innovation more in dirty rather than clean technologies? We build on the seminal model of directed technological change and the environment put forth by Acemoglu et al. (2012) by adding a general purpose technology and letting clean and dirty sectors have potentially differing capacities to absorb the GPT.

We first consider the case where absorptive capacity is entirely exogenous, and then we partially endogenise it by allowing firms or scientists to invest in it. In both cases, we solve for the equilibrium level of innovation in the clean and dirty sectors. Furthermore, endogenising absorptive capacity yields comparative statics that we use as hypotheses to explain the observed variation in the extent that different technologies and firms draw on the GPT.

Baseline model

Let there be an aggregate final good competitively produced from the combination of dirty and clean inputs Y_d and Y_c (e.g. energy source, material):

$$Y = (Y_{ct}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{dt}^{\frac{\varepsilon-1}{\varepsilon}})^{\frac{\varepsilon}{1-\varepsilon}} \tag{1}$$

We assume that clean and dirty inputs are highly substitutable, hence $\varepsilon > 1$. Sector $j \in \{c, d\}$ produces input Y_j competitively using a combination of labor and sector-specific machines:

$$Y_{jt} = L_{jt}^{1-\alpha} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha} di \tag{2}$$

For example, if the input is electricity and $j = c$, the machines may be wind turbines and solar panels, and for $j = d$, gas-fired power plants. The machines form a continuum; machine i has productivity A_{jit} and is consumed by the intermediate producer of input Y_j in quantity x_{jit}.

Meanwhile, scientists choose whether to work on clean or dirty technology. Having made this choice, each scientist is randomly allocated to a single machine in the sector of choice. In the standard model, with probability η_j this scientist successfully innovates on machine i, thus boosting its productivity:

$$A_{jit} = (1+\gamma)A_{jit} \tag{3}$$

where γ is the incremental increase in productivity arising from the innovation. The scientist then obtains a one-period patent and becomes the monopolistic producer of that machine for that period (producing each machine at a cost of τ units of the final good).

Adding Spillovers from a GPT

We modify the dynamic equation governing the change in productivity of machines (Equation 3) by introducing a stock of knowledge in a GPT (GPT_t) and an exogenous absorptive capacity β_j for scientists working on technologies of sector j. Here, we consider that spillovers from the GPT increase the *value* of an innovation, i.e. the resulting increase in the machine's performance. This modeling choice is supported by Table 4 in Section 5, which shows that the value of an energy patent (as measured by the citations it receives) is greater for those patents that draw on the GPT.[1] Formally, we write:

$$A_{jit} = (1+\gamma+\beta_j GPT_t)A_{jit} \tag{4}$$

Appendix A provides the step by step derivation of the equilibrium equations. In the main text, we focus on characterising the profitability of research in each sector, to understand how the GPT affects the direction of technological change. The average productivity of sector j is:

$$A_{jt} = \int_0^1 A_{jit} di \tag{5}$$

It evolves over time according to the following equation:

$$A_{jt} = (1+(\gamma+\beta_j GPT_t)\eta_j s_j)A_{j,t-1}, \tag{6}$$

where s_j is the share of scientists who choose to work in sector j (where market clearing of R&D labor requires $s_c + s_d = 1$). The equilibrium profits of a producer of machine with productivity A_{jit} is:

$$\pi_{jit} = (1-\alpha)\alpha p_{jt}^{\frac{1}{1-\alpha}} L_{jt} A_{jit} \tag{7}$$

Ex-ante, the expected profit from choosing to work in sector j is:

$$\Pi_{jt} = \eta_j(1+\gamma+\beta_j GPT_t)(1-\alpha)\alpha p_{jt}^{\frac{1}{1-\alpha}} L_{jt} A_{jt-1} \tag{8}$$

Solving for equilibrium values of p_{jt} and L_{jt}, and substituting, we obtain the following ratio of R&D profits for working in the clean versus dirty sector:

$$\frac{\Pi_{ct}}{\Pi_{dt}} \equiv f(s_c, s_d) = \frac{\eta_c}{\eta_d} \frac{1+\gamma+\beta_c GPT_t}{1+\gamma+\beta_d GPT_t} \left(\frac{1+(\gamma+\beta_c GPT_t)\eta_c s_c}{1+(\gamma+\beta_d GPT_t)\eta_d s_d}\right)^{-\phi-1} \left(\frac{A_{ct-1}}{A_{dt-1}}\right)^{-\phi} \tag{9}$$

Equation 9 allows us to study how the GPT affects the direction of technological change.

1. Alternatively, we could model the idea that spillovers from the GPT increase the rate of innovation (as in the notion that AI may accelerate discovery of solutions), such that $\eta_j \propto \beta_j GPT_t$. This does not change the results of our analysis.

If $f(1,0) > 1$, then $(s_c = 1,\ s_d = 0)$ is an equilibrium, and technological change is directed towards the clean sector. If $f(0,1) < 1$, then $(s_c = 0,\ s_d = 1)$ is an equilibrium, and technological change is directed towards the dirty sector. If $f(1,0) > 1$ and $f(0,1) < 1$ simultaneously, then we obtain multiple equilibria, meaning that either the dirty or the clean equilibrium is possible, and some coordination device is required to select one equilibrium.

Let's denote $\bar{A}_{c,t-1}(A_{d,t-1})$ the value that $A_{c,t-1}$ must at minimum take given $A_{d,t-1}$, so that a clean equilibrium becomes possible (i.e., the value of $A_{c,t-1}$ such that $f(1,0) = 1$). Conversely, denote $\bar{A}_{d,t-1}(A_{c,t-1})$ the value that $A_{d,t-1}$ must at minimum take given $A_{c,t-1}$, so that a dirty equilibrium becomes possible (i.e., the value of $A_{d,t-1}$ at which $f(0,1) = 1$). These two functions delineate the area in the $(A_{c,t-1}, A_{d,t-1})$ space under which we get a clean equilibrium, a dirty equilibrium, or multiple equilibria, as depicted in Figure 1. Result 1 below summarizes the impact of the GPT. The proof is shown in Appendix A.

Result 1.

(a) An increase in GPT_t causes both $\bar{A}_{c,t-1}(A_{d,t-1})$ and $\bar{A}_{d,t-1}(A_{c,t-1})$ to decrease, which means that we obtain multiple equilibria for a wider set of historical states $(A_{c,t-1}, A_{d,t-1})$.

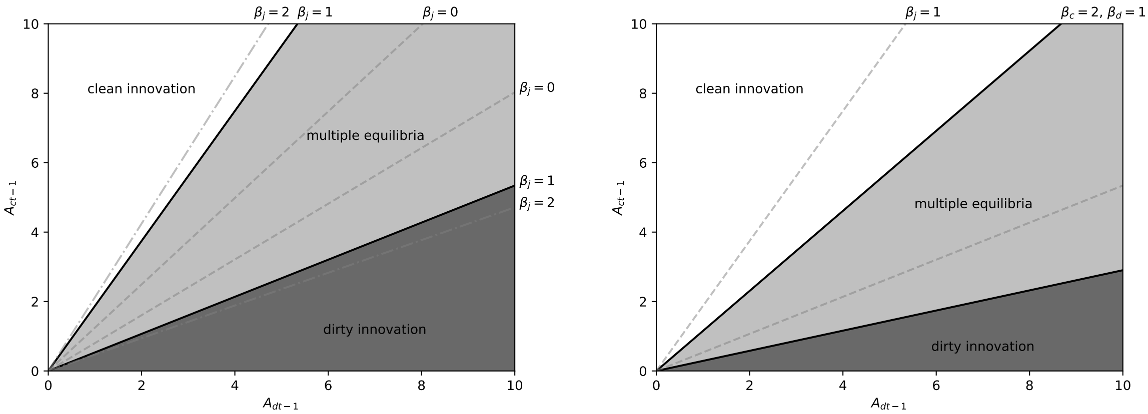
(b) An increase in β_j causes $\bar{A}_{j,t-1}(A_{-j,t-1})$ to decrease and $\bar{A}_{-j,t-1}(A_{j,t-1})$ to increase, thus expanding the range of histories in which all scientists engage in innovation of type j.

Figure 1 illustrates Result 1. As a baseline, consider $\beta_c = \beta_d = 0$ which corresponds to the case where neither sector can absorb the GPT, making it irrelevant and equivalent to the original model by (Acemoglu et al. 2012). In Figure 1a, we see that, in this case, technological change is geared towards the sector that is already the most productive. There is a narrow area, when $A_{c,t-1} is close to A_{d,t-1}$, where multiple equilibria are possible: actors have to coordinate on the clean or the dirty equilibrium. But, for most of the state space, the equilibria are path dependent and reflect what was done in the past. For example, an initial advantage in the dirty sector would lead to a unique equilibrium in which scientists work on dirty innovations.

When the two sectors can both absorb the GPT, as stated in Result 1a), the window of multiple equilibria expands. In other words, thanks to the GPT, the innovation system has more opportunities to break free from the determinism of the past, even when both the incumbent and the challenger technology have the same absorptive capacity. Actors can use the GPT to move either technology sufficiently ahead of the other to make it competitive. The direction of technological change then depends on which technology actors coordinate on.

On Figure 1b, we consider a case when clean and dirty have different absorption capacities to illustrate Result 1b). We see that a higher β_c increases the area where we get multiple equilibria, and, most importantly, shrinks the area where the dirty technology dominates.

Result 1 and Figure 1 highlight what is at stake in studying the GPT's influence on clean and dirty technologies: the GPT can upend the path dependence of technology. In the absence of a GPT, the more mature technology attracts more effort because, being more productive, it



(a) Clean and dirty have equal absorptive capacity (b) Clean has higher absorptive capacity

Note: Direction of technological change in equilibrium, that is the allocation of scientists in the clean or dirty sectors, given each sector's past stock of knowledge ($A_{j,t-1}$) and absorptive capacity (β_j).

FIGURE 1
Direction of Technological Change with a GPT

has a larger market. Thanks to the GPT, however, the less mature technology can catch up. A GPT can therefore fundamentally change the nature of the race between the newer clean technologies and the more mature dirty technologies. It reduces the weight of the past, by providing an opportunity to coordinate on the new clean equilibrium, especially if the clean technology has a higher absorptive capacity than the dirty.

Endogenising the Spillovers from a GPT

We now endogenise absorptive capacity, allowing scientists to invest in their capacity to absorb the GPT. This allows us to derive comparative statics for the level of effort in absorbing the GPT. To do this, let's decompose β_j into an exogenous and an endogenous component, such that:

$$\beta_j = b_j B_j, \tag{10}$$

where b_j is exogenous (coming from the properties of the technology) and B_j is an endogenous investment in absorption which comes at a cost of ψB_j^2. Scientists first choose which sector to work on (i.e. clean or dirty), and then decide how much to invest in their capacity to absorb the GPT.

The expected profit from working on technology j is now:

$$\Pi_{jt} = \eta_j(1+\gamma+b_j B_j GPT_t)\alpha(1-\alpha)p_{jt}^{1/(1-\alpha)} L_{jt} A_{j,t-1} - \psi B_j^2 \tag{11}$$

Hence, a scientist working in sector j would optimally invest in their absorptive capacity as follows:

$$B_j^* = (\eta_j b_j GPT_t)\frac{(1-\alpha)\alpha}{2\psi} p_{jt}^{1/(1-\alpha)} L_{jt} A_{j,t-1} \tag{12}$$

Using Equation 12 in combination with the other equations that characterize the equilibrium, we obtain Result 2.[2]

Result 2. *In equilibrium, investments in absorbing the GPT in a given sector increase with the existing accessible stock of the GPT_t and with the intrinsic absorptive capacity of the application sector:*

(a) $\frac{dB_j^*}{dGPT_t} > 0$

(b) $\frac{dB_j^*}{db_j} > 0$

(c) At the equilibrium for type j: $\frac{d^2B_j^*}{dGPT_t db_j} > 0$

Result 2 tells us that efforts in absorbing the GPT increase with the accessible stock of the GPT and with the intrinsic absorptive capacity of the technology. In other words, the potential for spillovers encourages innovation investments in applying the GPT. We expect the extent of potential spillovers to vary by technology (due to the intrinsic absorptive capacity), but also across firms, region or innovation systems (due to variation in the stock of the GPT across these social units).

Furthermore, as Result 2c) indicates, there is a positive interaction between intrinsic absorptive capacity and the stock of knowledge in the GPT, for the technology chosen in equilibrium. In the empirical section, we will bring these comparative statics to firm-level data.

Technological Lock-In

In this part, we consider the role of technological maturity in absorbing the GPT. Specifically, we allow absorptive capacity to decay with the knowledge stock in the application sector. We now write the absorptive capacity β_j as a function of A_{jt}:

$$\beta_j = b_j B_j A_{jt-1}^{-\delta}, \tag{13}$$

where $\delta \geq 0$ represents an ageing factor. The idea is that more mature technologies are less able to undergo more radical changes, or in other words, ageing causes lock-in.

Result 3.

(a) $\frac{dB_j^*}{dA_{jt-1}} < 0$ *if* $\delta > 1$

(b) $\frac{dB_j^*}{dA_{jt-1}} > 0$ *if* $\delta < 1$

2. The proof for Result 2 is shown in Appendix A.

TABLE 1
Technology Categories

	Electricity	Transport
Clean	Renewable Energy (Wind, Solar, Geothermal, Hydro, Marine), Nuclear Energy, Enabling technologies (e.g., smartgrids)	Electric, Hybrid, or Hydrogen vehicles, Fuel cells, Batteries, Enabling technologies (e.g., energy storage)
Grey	Efficiency, Biomass and waste	Efficiency of internal combustion engines
Dirty	Hydrofracturing, Traditional Fossil Fuels	Internal combustion engines

Result 3 shows that the maturity of the technology in the application sector can impact absorptive capacity.[3] If the ageing factor is large ($\delta > 1$), then an increase in the knowledge stock of technology j leads to a lower absorptive capacity. On the contrary, when the impact of ageing is minimal ($\delta < 1$), an increase in the knowledge stock of technology j leads to a higher absorptive capacity.

4 Data

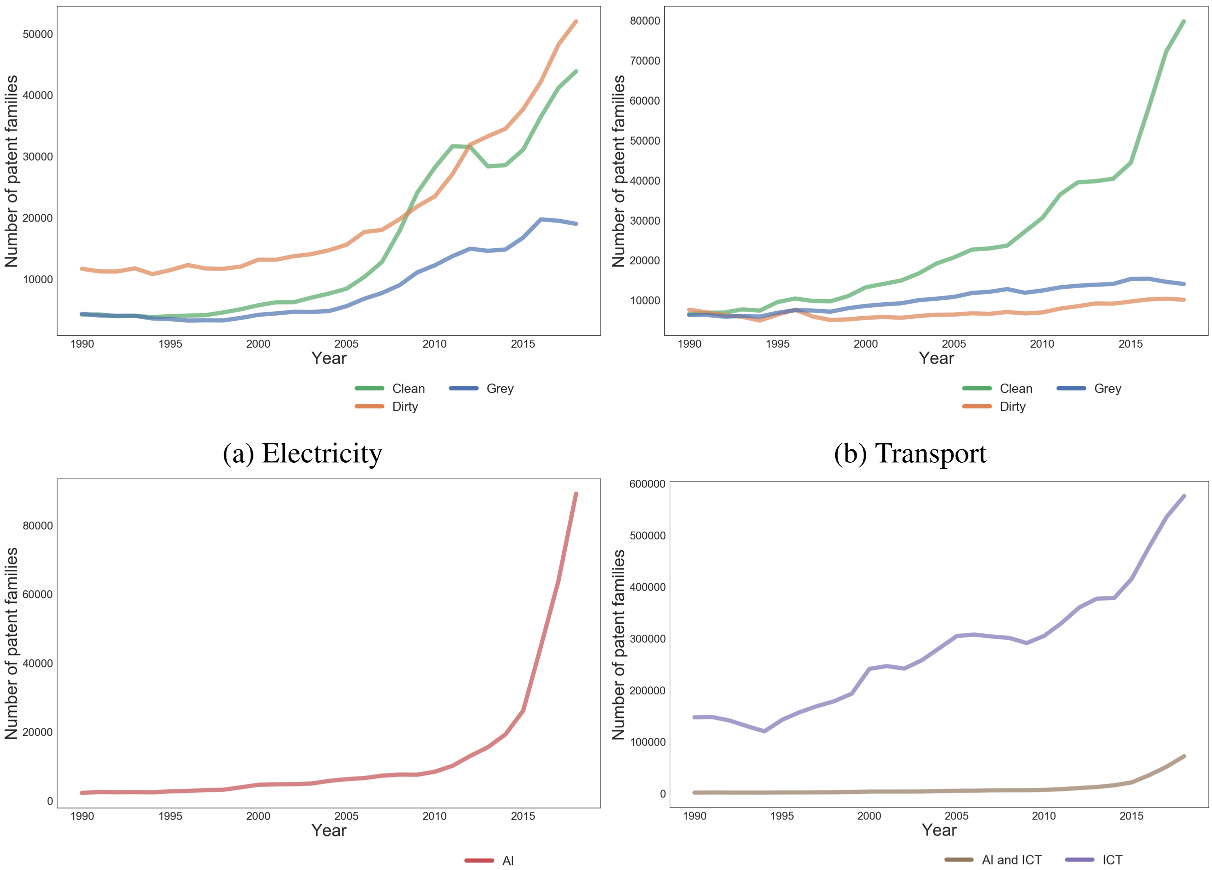
Patent Data. Our next steps focus on measuring the absorption of AI and ICT by clean and dirty energy technologies. To do so, we use data on patent application from PATSTAT and obtain a full coverage of patents filed around the world up until 2018.[4] To avoid double-counting, we aggregate patent applications at the level of DOCDB families, which are groups of patents that have been identified as covering the same invention.[5] To place patent families over time, we use the priority year, that is the year when the earliest application in the family was filed.

Energy Inventions. We use technology codes from the International Patent Classification (IPC) and from the Cooperative Patent Classification (CPC) to identify inventions related to energy technologies for electricity and transportation. The codes are assigned by patent examiners and are often used to classify patents as either clean, grey or dirty (Acemoglu et al. 2012; Aghion et al. 2016; Dechezleprêtre et al. 2017; Johnstone et al. 2010; Lanzi et al. 2011; OECD 2016; Popp et al. 2020). Table 1 summarizes how we classify technologies. "Dirty" refers to conventional, highly polluting technologies, while "clean" includes the least polluting alternatives. The category "grey" captures increased efficiency of dirty technologies. A full list of the codes used is shown in Online Appendix Table SI1.

3. The proof is shown in Appendix A.

4. We use the 2021 Spring edition of PATSTAT. Since there is a delay between when applications are filed and when the data is transferred to the database, the years 2017 onwards are severely truncated.

5. Several patents are typically filed about the same invention because the different applications may cover slightly different claims (about the same invention) or may contain exactly the same claim but are filed in different countries.



(a) Electricity (b) Transport

(c) AI (d) ICT

FIGURE 2
Patenting Trends over Time By Family Type

We keep all energy families with a priority year between 1990 and 2018. For this period, we find a total of 1,314,170 electricity families (449,040 clean, 245,115 grey, 607,934 dirty) and 1,243,416 transport patent families (722,219 clean, 300,363 grey, 206,598 dirty). Figure 2a and 2b show that the number of energy families have been going up both for electricity and transport. The scale of the y-axis highlights that clean patenting in transport is almost twice as high as clean electricity at its peak. Clean electricity patenting temporarily peaked around 2010, and although it has been on a steady increase since 2013, it remains lower than dirty electricity patenting. On the other hand, in transport, clean vastly outpaces dirty and grey throughout most of the period.

AI and ICT Inventions. To identify patents related to AI, we follow the methodology developed by World Intellectual Property Organization (2019) that uses technology codes and keyword searches in abstracts and titles. Keywords include "artificial or computational intelligence", "neural networks" or "learning model or algorithm". For ICT, we use a series of technological codes following Inaba et al. (2017). These codes include inventions classified as related to the "transmission of digital information", "self-organising networks, e.g. Ad hoc

TABLE 2
Examples of Energy Innovations Citing AI Patents

Application title	Sector	Type	Year	Citations to AI #	%
Improved Flow Valve Port for a Gas Regulator	Electricity	Dirty	2007	49	67
Robotic cleaning device	Transport	Clean	2013	297	41
Virtual sensor system and method	Transport	Dirty	2007	37	26
Battery agnostic provisioning of power	Transport, Electricity	Clean	2016	119	13
System and approach for dynamic vehicle speed optimization	Transport	Grey	2015	51	10
Dual fuel heater with selector valve	Electricity	Grey	2011	38	9
Method and apparatus for configuring a communication interface	Electricity	Clean	2014	55	2

networks or sensor networks" or "high speed computing". In the end, this procedure identifies 548,641 AI families and 10,883,849 ICT families (filed in any given year). We note that, to this day, the stock of ICT knowledge is vastly greater than that of AI. Figures 2c and 2d show that the number of AI families remains relatively small and has only begun rising sharply since 2010. On the other hand, more than 150,000 ICT families are filed each year since the early 1990s. We also find that a majority of AI families also qualify as ICT, highlighting that, to some degree, AI can be thought of as a sub-field of ICT (see Online Appendix Figure SI1).

Backward Patent Citations. We use backward citations to quantify the extent to which energy inventions rely on AI and ICT. Specifically, as a measure of absorption, we calculate the percentage of backwards citations that each energy family makes to AI or ICT patent families. In our sample, the average energy family cites about 10 patents with 0.4% going to AI and 6.2% to ICT. This hides considerable variation, however, since some families have 100% of their backward citations going to AI or ICT patents while others cite none. Table 2 provides examples of energy patents with high reliance on AI. The first patent in the table, for instance, corresponds to a dirty electricity family filed in 2017 entitled "Improved Flow Valve Port for a Gas Regulator". The patent makes 49 citations to other patents and 67% of those are citations going to AI families.

Proxies of Patent Quality. We follow prior work and use forward citations (that is, the number of times a family is cited by other families) as a proxy of patent quality (Jaffe et al. 2017; Jaffe et al. 2000). The total number of citations received, however, heavily depends on the number of years since the first filing. Hence, it would be inappropriate to compare families filed many years ago with more recent ones since the later will have mechanically fewer citations. To avoid this problem, our main measure is the number of forward citations received within 3 years. As an additional proxy of patent quality, we also use the number of countries where the patent family was filed as well as the size of the family (i.e., the total number of applications in the family).

Firm-Level Data. We use European Patent Office data obtained from the Bureau Van Dijk Orbis hard-drive to link PATSTAT patent ids to Orbis firm identifiers. We then construct firm-level innovation indicators: for each firm, we count the yearly number of families of different types (e.g., clean electricity or dirty transport). We also construct proxies of firm-level knowledge stocks by calculating cumulative discounted sum of families going back to 1980. We discount stocks by 15% each year following prior work (Hall et al. 2005).[6] Finally, we collect financial and legal data on firms from Orbis. We follow Kalemli-Ozcan et al. (2015) when cleaning the data; in particular, we use multiple vintages to optimise coverage.[7] The end result is a dataset of 10,181,076 observations covering 203,195 firms over 1990 to 2018.

5 To What Extent Are AI and ICT Absorbed into Clean and Dirty Inventions?

This section examines the extent to which energy families have absorbed knowledge spillovers from AI and ICT over the last decades. First, on Figure 3, we plot trends over time in the percentage of backward citations going to AI or ICT for different types of energy families. A key take-away is that, in both the transport and electricity sectors, clean patents build on AI and ICT more than dirty and grey. On Figure 3a, we see that, overall, the average percentage of backwards citations going to AI is low, typically well below 1%, even though it has been increasing since 2010 which coincides with the rise of AI patenting seen on Figure 2c. We also note that AI absorption is higher in clean than in grey or in dirty (especially since 2010) and that it is higher in transport than in electricity.

Figure 3b shows that, like in the case of AI, the percentage of backwards citations going to ICT is higher in clean than in grey or in dirty. The magnitude of ICT absorption in clean electricity is particularly high: the average percentage of citations going to ICT reached 25% in the late 2000s, while other technology groups have remained below 5% throughout. We also note that the share of ICT in backward citations is overall much higher than that of AI, but this should not be surprising since ICT is more mature and constitutes a larger pool of potential patent families to be cited.

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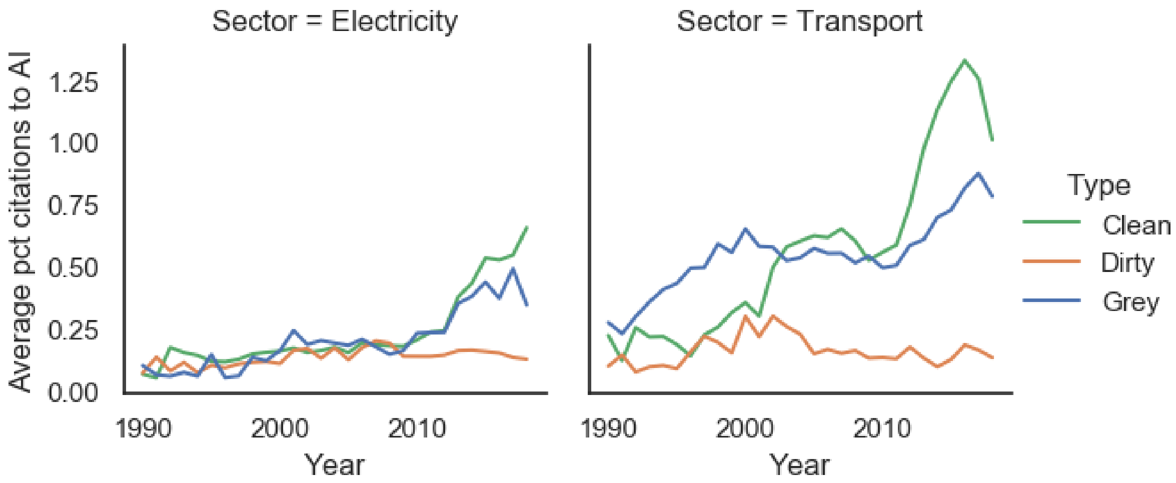
6. We construct both a simple count of new patent families and one in which families are weighted by the number of citations they receive within 3 years of priority. Formally, the family count of firm i in year t for technology j, $FamCount_{ijt}$, is calculated as follows:

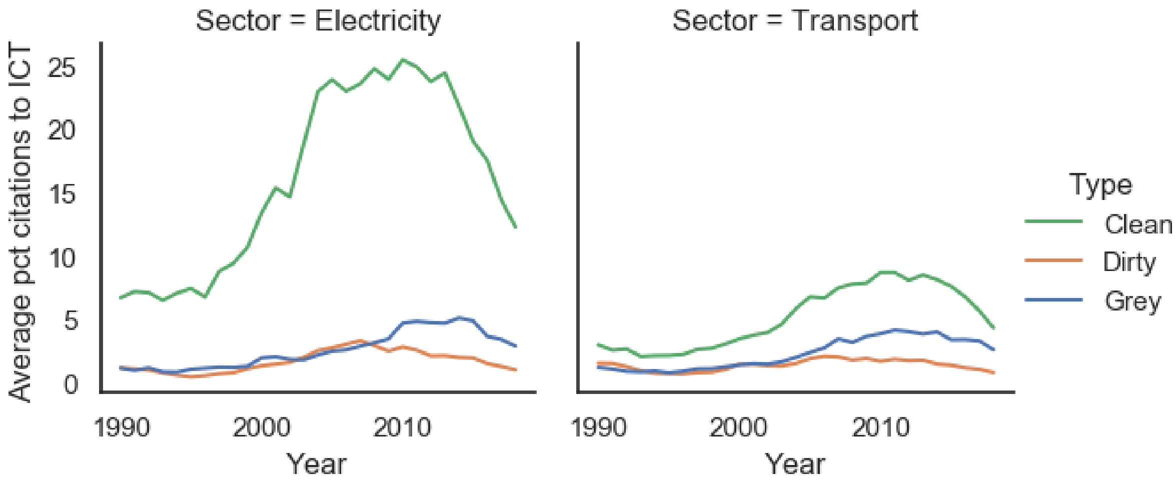
$$FamCount_{ijt} = TotalFamCount_{jt} \times \sum_{k \in P_{ijt}} \frac{1 + cit\_received_k}{\sum_{l \in L_{jt}} (1 + cit\_received_l)} \tag{14}$$

where $TotalFamCount_{jt}$ is the total count of families filed in year t in technology j (by any firm), $cit\_received_k$ is the count of citations received by family k, P_{ijt} is the portfolio of families filed in year t by firm i in technology j, and L_{jt} is the set of families filed in year t in technology j. In our firm-level analysis, stock variables are always citation weighted. The simple count of families is sometimes included as a control variable.

7. We use the following vintages: 201709, 201812, 201912, 202006, and 202012. Please refer to the Online Appendix A.C for more details on our data cleaning process.



(a) Citations to AI



(b) Citations to ICT

FIGURE 3
Percentage of Citations to AI and ICT Over Time

Next, we run a series of regressions to investigate how the absorption of AI and ICT for clean relative to dirty technologies varies when we include firm fixed effects and quality controls. The main specification is as follows:

$$Absorption_{ijt} = \beta_d + \beta_c Clean_i + \beta_g Grey_i + \mathbf{b}\mathbf{X}_i + \delta_t + \delta_j + \varepsilon_{ijt} \tag{15}$$

$Absorption_{ijt}$ is the percentage of backward citations going to AI or ICT for patent family i filed by firm j in year t. $Clean_i$ and $Grey_i$ are binary variables that equal 1 if family i is classified as clean or grey, respectively (either in transport or in electricity). β_d is the intercept which, in this context, corresponds to the reference category: Dirty. $\mathbf{X}_i$ is a series of variable proxying the quality of family i which includes the number of forward citations received by family i in three first years of its filing, the size of family i and the number of countries where family i was filed. δ_t and δ_j are year and firm fixed effects, respectively.

Table 3 presents the regression results. The first 4 columns focus on AI and the last 4 on ICT. Column 1 and 5 show specifications with only year fixed effects. Consistent with Figure 3, the coefficients on "Clean Family" are positive and statistically significant, indicating that clean families rely more on AI and ICT than their dirty counterparts. The line "Ratio Clean/Dirty" displays the values of the relative absorptive capacity of clean vs dirty: following the notations used in Equation 15, this corresponds to the ratio $\frac{\beta_c+\beta_d}{\beta_d}$. Column 1 and 5 indicate that the absorptive capacity of clean is 356% higher than dirty for AI (543% higher for ICT).

The relative absorptive capacity may be high for reasons intrinsic to the technologies (e.g., many clean technologies may simply be technologically closer to ICT or AI) or due to general equilibrium effects (e.g., because R&D is beign redirected towards clean technologies across the economy). Another reason, however, could be that clean inventions are developed by firms that are better able to leverage AI and ICT technologies into their clean inventions. The high relative absorptive capacity may therefore be driven by firm-level characteristics rather than intrinsic technological differences. To investigate whether firm-level characteristics play a significant role, Column 2 and 6 include firm fixed-effects. We find that the ratio decreases, highlighting the role of firm-level characteristics which we further explore in Section 6. The ratio, however, remains high showing that, even within the same firm, clean inventions cite more than twice as much AI than dirty ones.

In Column 3, 4, 7 and 8, we examine whether clean inventions maintain their lead when restricting the analysis to high-quality inventions. To do so, Columns 3 and 7 run the same regressions as Columns 2 and 6 but limiting the sample to triadic patent families that have been granted.[8] Columns 4 and 8 further control for a series of variables proxying for quality (forward citations, family size and number of countries). We find that AI and ICT absorption in clean remain much higher than for dirty (192% and 300% higher respectively) in those specifications

8. A family is said to be triadic if it was filed at the three main patent authorities: the USPTO, the EPO and the JPO.

TABLE 3
AI Absorptive Capacity for Clean, Grey and Clean Technologies

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Clean Family	0.101***	0.161**	0.213**	0.159**	4.041***	5.019***	12.274***	11.117***
	(0.005)	(0.024)	(0.035)	(0.037)	(0.114)	(0.494)	(0.594)	(0.762)
Grey Family	0.185***	0.123*	0.099	0.062	-0.294	-0.411	-0.368	-1.092**
	(0.008)	(0.031)	(0.043)	(0.046)	(0.187)	(0.190)	(0.178)	(0.139)
Nbr Citations Made	14.954**	5.084*	0.210	-0.659	192.851	96.411*	45.991**	1.386
	(3.363)	(1.413)	(0.861)	(0.383)	(94.426)	(25.732)	(8.733)	(23.194)
Constant (Dirty)	0.078**	0.170***	0.561***	0.822***	0.552	1.417***	3.109***	5.150*
	(0.011)	(0.011)	(0.019)	(0.020)	(0.318)	(0.101)	(0.289)	(1.573)
Ratio Clean/Dirty	2.30***	1.94***	1.38***	1.19***	8.32***	4.54***	4.95***	3.16***
	(0.11)	(0.20)	(0.07)	(0.05)	(4.01)	(0.52)	(0.54)	(0.79)
Sample			Gr. Triadic	Gr. Triadic			Gr. Triadic	Gr. Triadic
Year FEs	X	X	X	X	X	X	X	X
Firm FEs		X	X	X		X	X	X
Quality Proxies				X				X
Adjusted R2	0.006	0.028	0.002	0.004	0.058	0.203	0.205	0.227
Observations	5.55e+05	7.73e+05	1.06e+05	1.06e+05	5.55e+05	7.73e+05	1.06e+05	1.06e+05

Linear Regression.
Standard Errors in Parentheses. Clustered at the type and firm level.
Dependent Variable: Percentage of backward citations going to AI or ICT

Note: Ratio Clean/Dirty corresponds to the ratio of the sum of coefficient on Clean plus the constant over the constant. Quality Proxies include the number of citations received within three years, the size of the family and the number of countries where the family was filed.

too.

Next, on Figure 4, we plot the relative absorption of clean vs dirty over the years. We see that, for AI, the relative absorption has increased over the years and, for most years, it is very similar whether or not firm fixed-effects are used in the estimation. Only since 2012, the two lines start departing from each other, indicating that firm characteristics play a more important role in the later part of the sample. Indeed, the dotted lines represent a measure of relative absorption arising from intrinsic characteristics and general equilibrium effects alone, whereas the solid lines should be interpreted as a measure of relative absorption that also includes firm composition effects (e.g., changes in the number of firms with high capacity to use the GPT).

Figure 4 also shows that the relative absorption is higher for ICT than for AI in most years. However, AI has recently caught up, and by the end of our sample, we see that clean inventions have a similar lead in both. The difference between estimating relative absorption with and without firm fixed effects is more striking for ICT than for AI. In particular, we note that the ratio clean/dirty for ICT starts increasing around 2008, indicating that clean inventions filed in those years relied even more on ICT relative to dirty inventions than used to be the case. However, we also note that the ratio estimated with firm fixed effects remains stable throughout the same period. This indicates that the increase in ICT absorption by clean technologies arose mostly from firm composition effects. In other words, new entrants with strong ICT capabilities started innovating in clean technologies.

In Table 4, we explore whether inventions relying on AI generate greater value. For this purpose, we proxy "value" by the number of citations received within 3 years of the priority

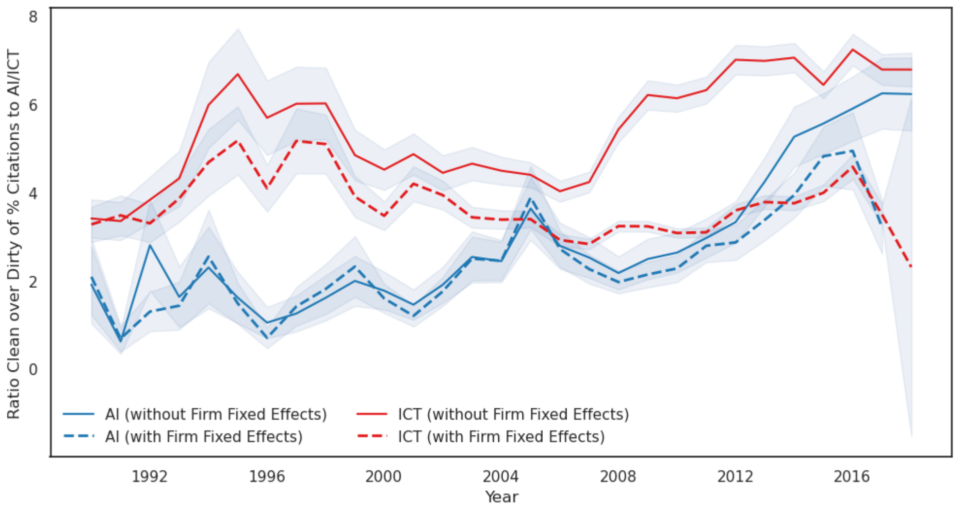


FIGURE 4
Estimates of Absorptive Capacity of Clean Relative to Dirty

Note: Ratio Clean/Dirty corresponds to the ratio $\frac{\beta_c+\beta_d}{\beta_d}$ as in Table 3, estimated for each individual year. The solid line represents the overall difference in absorptive capacity between clean and dirty including that resulting from firm composition effects. The dotted line is based on estimates including firm fixed effects, and proxies absorptive capacity resulting purely from technological complementarity and general equilibrium effects. While the relative absorptive capacity of clean technologies is higher for ICT through most of the period, relative absorptive capacity for AI seems to be catching up in the most recent years.

year. First, in Column 1, we see clean families receive about 64% more citations then dirty.[9] This is consistent with prior work by Dechezleprêtre et al. (2017) and implies that clean inventions are more valuable than dirty. Second, Column 2 shows that families citing AI receive about 26% more citations.[10]. The effect of citing AI declines somewhat when firm fixed effects are included, but the magnitude remains relatively high at around 17%. The interaction between being clean and citing AI is negative and significant implying that the effect of citing AI on forward citations is stronger for dirty than clean inventions.

6 Firm-Level Mechanims

In this section, we examine variation across firms in the capacity to absorb AI and ICT spillovers into energy inventions. The family-level exploration detailed in the previous section highlighted that firm fixed effects absorbed a significant amount of the gap in absorptive capacity of clean and dirty. In addition, recall that, in the theoretical part, we showed that spillovers from the knowledge stock in AI and ICT should be an important factor in explaining variation in the level of absorption (see Result 2). Arguably, some firms may have access to larger GPT stocks, especially as a large number of firms in our sample patent both in energy and AI/ICT (see Online Appendix Figure SI2).

9. The specification is log-linear, hence we convert the coefficients in the following way: $100*(e^{0.486}-1) = 62.6\%$.

10. Similarly: $100*(e^{0.227}-1) = 25.5\%$

TABLE 4
Citations Received Within 3 Years of Priority

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Clean Family	0.486***	0.492***	0.442***	0.441***	0.486***	0.519***	0.442***	0.438***
	(0.029)	(0.030)	(0.040)	(0.040)	(0.029)	(0.049)	(0.040)	(0.048)
Grey Family	0.294***	0.303***	0.289***	0.294***	0.294***	0.368***	0.289***	0.328***
	(0.025)	(0.025)	(0.036)	(0.036)	(0.025)	(0.023)	(0.036)	(0.033)
AI Citing		0.227***		0.160***				
		(0.085)		(0.037)				
Clean X Citing AI		-0.164***		-0.054**				
		(0.008)		(0.027)				
Grey X Citing AI		-0.209***		-0.108***				
		(0.027)		(0.030)				
ICT Citing						0.412***		0.252***
						(0.096)		(0.046)
Clean X Citing ICT						-0.273***		-0.096***
						(0.007)		(0.012)
Grey X Citing ICT						-0.340***		-0.149***
						(0.024)		(0.021)
Constant (Dirty)	-1.973***	-1.978***	-1.752***	-1.752***	-1.973***	-2.018***	-1.752***	-1.767***
	(0.194)	(0.195)	(0.184)	(0.186)	(0.194)	(0.205)	(0.184)	(0.192)
Sample								
Year FEs	X	X	X	X	X	X	X	X
Firm FEs			X	X			X	X
Quality Proxies	X	X	X	X	X	X	X	X
Pseudo R2	0.367	0.367	0.446	0.446	0.367	0.369	0.446	0.447
Observations	5.55e+05	5.55e+05	7.40e+05	7.40e+05	5.55e+05	5.55e+05	7.40e+05	7.40e+05

Poisson Pseudo-Likelihood Regression.
Standard Errors in Parentheses. Clustered at the type and firm level.
Dependent Variable: Citations Received Within 3 Years of Priority.

Note: Quality Proxies include the size of the family, the number of countries where the family was filed, the logged number of citations made by the family, whether it is granted, and whether it is triadic.

TABLE 5
Examples of Top Energy Patenting Firms

Firm Type	Name	Count Energy	% Clean	% Dirty	% Clean Families Citing AI	% Dirty Families Citing AI
Electricity	GE	232	13	47	5	4
Electricity	JFE Steel	135	22	59	4	1
Electricity	Vestas	133	87	3	11	1
Transport	Toyota	3071	50	13	4	1
Transport	Bosch	1491	31	14	13	4
Transport	Denso	1318	28	29	10	1
Both	Panasonic	1154	76	15	3	1
Both	Toshiba	734	73	13	3	1
Both	Mitsubishi	628	47	26	6	2

Note: The values correspond averages over the period 1990-2018.

To estimate the role of GPT spillovers at the firm-level, we construct a dataset at the firm-year-portfolio level where a portfolio is a group of patents of a particular type. Firms' portfolio can be either clean electricity, clean transport, grey electricity, grey transport, dirty electricity or dirty transport. For each firm-year-portfolio observation, we count the number (and percentage) of families in the portfolio that cite at least one AI family. We construct similar measures relative to ICT.

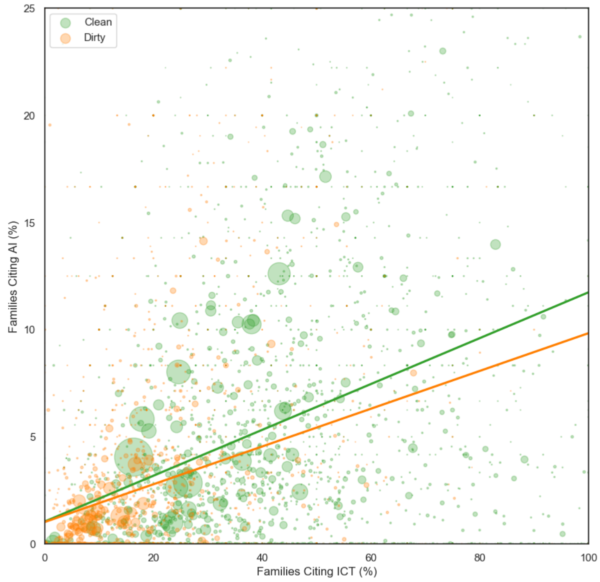
Table 5 provides some examples of top patenting firms, together with the average annual number of clean and dirty families and the percentage citing AI. For clarity, we group firms into three types: those that mostly patent electricity-related inventions, those that patent mostly transport-related inventions and those that do both. We note that, in those examples, the percentage of families citing AI is always higher in clean portfolios than in dirty but the percentage can go from 4% (e.g., Panasonic) to 13% (e.g. Vestas, a leading wind energy firm).

Figure 5 provides more evidence of the variation over time and across firms in our sample. First, on Figure 5a, we see that on average clean portfolios always rely more on AI and ICT than dirty. For AI, we also note that the gap between clean and dirty has somewhat been widening over time, and especially since 2010. Surprisingly, ICT absorption has been going down since 2009, which coincides with a decline in overall clean and dirty patenting.

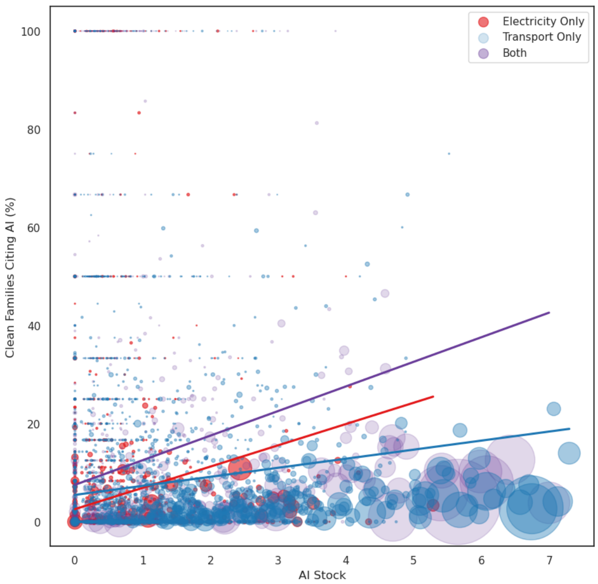
Figure 5b shows the variation across firms in the extent to which their clean and dirty portfolios absorb AI and ICT spillovers. Values for ICT are much higher than those for AI. Cross-sectional correlation confirms that green portfolios tend to absorb more AI and ICT than dirty. Figure 5c illustrates the variation across firms by type of firms and by their level of AI stock. In red, we see that firms that patent mostly in transport (e.g. Denso) tend to have a higher level of absorption. In blue, we see that firms that patent both in electricity and transport (e.g., multitechnology conglomerates such as Panasonic or Mitsubishi) tend to have higher AI stock. Overall, it appears that the higher the AI stock, the higher the percentage of clean families that cite AI families.

Figure 5d goes one step further by showing that firm-level AI absorption varies with the ratio of the firm's AI stock to Energy stock. There is a clear positive relationship between the two. This suggests that firms with a very high energy stock relative to their AI stock are not able to apply AI to energy technologies.

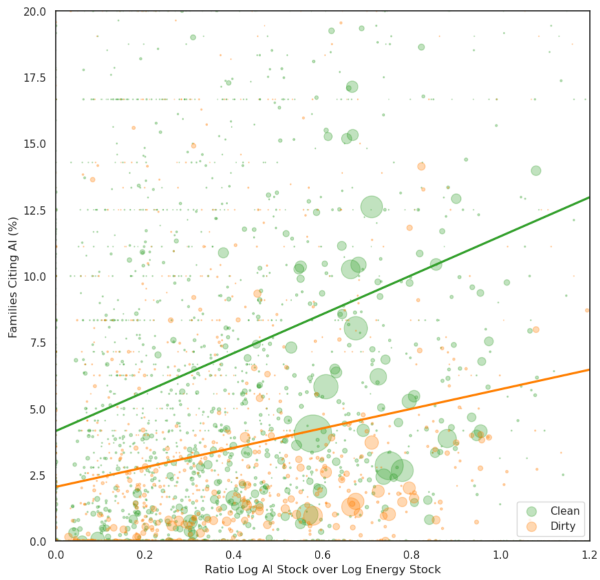
(a) Variation Over Time



(b) Variation Across Firms



(c) Correlation with AI Stock



(d) Correlation with AI to Energy Stock

FIGURE 5

Variation Over Time and Across Firms in the Percentage of Families Citing AI and ICT

Note: Values are firm-level annual averages for period 2005-2015. Each bubble represents a firm and the bubble's size is proportional to the number of families in the portfolio. Figure 5a plots the weighted mean share of families that cite AI/ICT in a given portfolio. The mean is weighted by the size of the portfolio so that firms with larger portfolios weight in more in the calculation.

Next, we estimate more precisely the relationships between firm-level AI absorption and firms' stock of AI and energy patents using linear regressions. The main specification is as follows:

$$FamilyCountCitingGPT_{jtk} = \beta_d + \beta_1 FamilyCount_{jtk} + \beta_2 StockGPT_{jt-1} + \beta_3 StockEnergy_{jt-1} + \beta_c Clean_k + \beta_g Grey_k + \beta_t Transport_k + \mathbf{bX}_{jt} + \delta_t + \delta_j + \varepsilon_{jtk} \quad (16)$$

$FamilyCountCitingGPT_{jtk}$ is the count of families in portfolio k citing some AI/ICT patents. $FamilyCount_{jtk}$ is the count of families in portfolio k. $StockGPT_{jt-1}$ is the count of AI or ICT families firm j had filed up to time $t-1$ (discounted). $StockEnergy_{jt-1}$ is the count of energy families (of any type) firm j had filed up to time $t-1$ (discounted). $Clean_k$, $Grey_k$ and $Transport_k$ are binary variables equal to 1 if the portfolio is clean, grey or transport. As a result, the intercept β_d corresponds to dirty electricity portfolios. $\mathbf{X}_i$ is a series of firm-level controls that include total assets, number of employees and years since incorporation. δ_t and δ_j are year and firm fixed effects. In additional specifications, we examine interactions between $StockGPT_{jt-1}$ and the different types of portfolios: $Clean_k$, $Grey_k$, $Transport_k$.

Table 6 presents the regression results. The first 4 columns focus on AI and the last 4 on ICT. Column 1 and 5 show specifications with only year fixed effects and binary variables for the type of portfolio. We find that firms with a higher GPT stock and a smaller energy stock tend to cite more GPT patents in their inventions. In particular, a 10% increase in the AI stock is associated with a 2.7% increase in the number of energy patents citing AI. This is consistent with Result 2a) which stated that GPT absorption will increase with the existing accessible GPT stock. We also find that a 10% increase in the energy stock is associated with about a 1% decrease in the number of patents citing AI. This is consistent with Result 3 assuming an ageing parameter δ greater than 1; in other words, mature application sectors are less able to absorb the GPT.

We also find that the coefficients on "Clean Portfolio" are positive and statistically significant, which is consistent with Figure 5 and our results from family-level analyses presented in Section 5. This indicates that clean portfolios absorb the GPT on average more than dirty, and this remains true when adding firm fixed effects and firm controls (Columns 3 and 7). The fact that clean technologies maintain their lead also within firms seems indicative that clean technologies have a greater *intrinsic* capacity to use digital technologies.

Finally, we add interactions between the portfolio type and the GPT stock. This is motivated by theory Result 2c), which predicts a positive interaction coefficient between the intrinsic absorption capacity of a technology and the GPT stock (for the technology which is chosen as the direction of technological change). In the cross-section, we do not find a statistically significant positive interaction between "Clean" and the GPT stock (see Columns 2 and 6 in Table 6), which means that having a higher GPT stock does not make a firm more likely to apply the GPT to clean tech relative to firms with a lower GPT stock.[11] Yet, we do find a positive

11. We only show the interaction for "Clean". "Grey" and "Transport" are left out of the tbale but included in the regressions for clarity.

TABLE 6
Firm level - Count

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Family Count (log)	0.917***	0.921***	1.009***	1.000***	0.956***	0.989***	0.994***	1.005***
	(0.031)	(0.032)	(0.029)	(0.032)	(0.024)	(0.021)	(0.019)	(0.017)
Stock AI (log, t-1)	0.277***	0.273***	0.103**	0.073				
	(0.030)	(0.040)	(0.043)	(0.051)				
Stock Energy (log, t-1)	-0.102***	-0.102***	-0.154***	-0.152***	-0.084***	-0.100***	-0.203***	-0.215***
	(0.020)	(0.020)	(0.036)	(0.036)	(0.015)	(0.013)	(0.029)	(0.030)
Clean Portfolio	0.629***	0.493***	0.809***	0.567***	0.763***	0.861***	0.754***	0.711***
	(0.088)	(0.071)	(0.074)	(0.072)	(0.032)	(0.039)	(0.028)	(0.056)
Clean X Stock AI (log, t-1)		0.042		0.066**				
		(0.031)		(0.032)				
Stock ICT (log, t-1)					0.170***	0.209***	0.097**	0.125***
					(0.015)	(0.015)	(0.038)	(0.040)
Clean X Stock ICT (log, t-1)						-0.019**		0.006
						(0.008)		(0.011)
Portfolio FEs	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs			X	X			X	X
Firm level controls			X	X			X	X
Observations	134,891	134,891	54,880	54,880	134,891	134,891	79,963	79,963
R2	0.567	0.567	0.638	0.639	0.702	0.705	0.764	0.765

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing AI or ICT
Firm level controls include total assets (log), number of employees (log), and years since incorporation (log).
The label (log) refers to the natural logarithm of 1 + the variable in question.
Interaction terms for Grey and Transport are included but not shown on the table for brevity.

Note: Stock Energy corresponds to the firm's total stock of energy patents (i.e., the sum of patent stocks for clean, grey and dirty electricity/transportation).

and significant interaction when including firm fixed effects in the case of AI (Column 4). In other words, we observe that, firms increase their AI stock over time, they are more likely to then apply it to clean technologies. This is further evidence of a greater intrinsic component to the absorptive capacity of clean technologies, since firm-level characteristics that could explain a greater focus on clean technologies are controlled for.

7 Discussion and Conclusion

This paper explores theoretically and empirically whether AI has the potential to accelerate the transition to clean energy. We first examine how a GPT can affect the race between clean and dirty in a model of directed technological change. We find that, depending on the relative absorptive capacity of clean and dirty, the GPT can break path dependency and help clean technologies compete with dirty. We then used patent data to develop empirical proxies of absorptive capacity and examine how clean and dirty technologies compared over the last two decades. We find evidence, both at the patent family and firm levels, that clean inventions consistently absorb more AI and ICT spillovers than dirty ones. Moreover, this trend has been particularly clear since 2010 for AI.

These results provide grounds for cautious optimism regarding the potential for AI to accelerate the transition to clean energy. Indeed, our theory highlights that the GPT can make new technologies more attractive for R&D investments, especially if they more effectively absorb the GPT than incumbent technologies. The theory also shows that this can generate a virtuous feedback. If inventors start preferring clean, they will put more effort into applying the GPT to it, which in turn increases the technology's productivity, further encouraging innovators to focus on it.

Our firm-level empirical results provide supporting evidence for this process. First, clean technologies' advantage over dirty ones holds within firms, suggesting that clean tech has a higher intrinsic absorptive capacity and is now the preferred direction of technological change.[12] If this is the case, our theory predicts that a higher stock of the GPT leads innovators to put more effort into applying the GPT, *especially to the clean sector*. We find evidence of this in the data (Column 4 of Table 6). We further find that a firm's prior focus on energy hinders absorption, in line with the idea that the GPT helps break path dependence and open new opportunities.

Our optimism, however, is cautious. Indeed, the rate of AI absorption is still low. On average, only about 2% of backward citations that energy patents make go to AI inventions. Similarly, only about 8% of firms' patents cite any AI invention. These figures are much lower than the trends for ICT between 1990 and 2010. Figure 6 also puts these statistics into a broader context by plotting them along with other technological application sectors. We see that sectors more closely related to AI, such as "Control" or "Digital Communication," absorb AI faster. But more distant technological applications, such as "Medical Technologies", "Telecommunications", or "Transport overall" (i.e. non-road transport and other aspects of transport innovation, such as automated driving), also absorb it faster than our two focal energy sectors.

Our analysis is a first step in understanding the impact of AI on the transition, and further research is needed to address some limitations. First, our analysis focused on comparing broad

12. The within-firm result rules out the alternative explanation that differences in firm capabilities or location are correlated both with working on clean technologies and having more access to knowledge on the GPT.

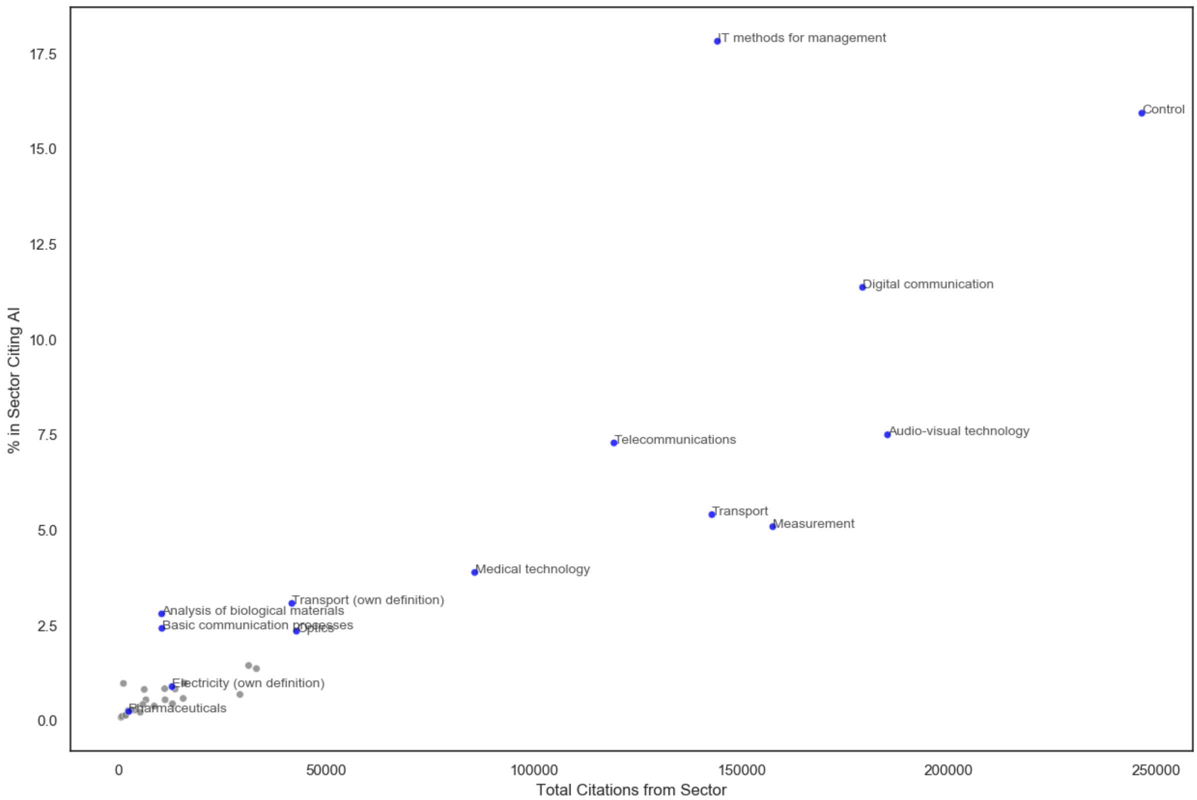


FIGURE 6
Number of Citations to AI and % of Families Citing AI for different technology fields (note that, for readability, we have excluded computer technology, a strong outlier in both dimensions.

categories such as clean and dirty, but further work could develop more granular measures to examine the absorptive capacity of specific energy technologies (e.g., solar or wind). Analyzing the heterogeneous impact on different technologies is important to understand better the extent to which the trends are driven by intrinsic technological factors or endogenous processes that are more amenable to policy intervention. Furthermore, we treat all AI patents similarly. However, some AI patents probably have a greater potential to be applied broadly (to be a GPT), while others are likely more narrow. Furthermore, AI algorithms are often not patented. Additional work could include citations to scientific publications and distinguish between broad and narrow AI patents.

Finally, our analysis only looks at knowledge spillovers through citations and does not examine the extent to which these spillovers impact the rate of progress of clean technologies. Does the integration of AI make them more productive and does it accelerate the rate of subsequent innovation? To answer this question, future research could look at the impact of AI-based energy innovation on firm productivity, sales and subsequent rate of innovation.

Despite its limitations, this paper provides the first empirical analysis of innovation spillovers from AI and ICT to clean and dirty technologies on a global scale. Although policymakers often recognize the potential importance of AI and ICT for clean energy, there has been little research on the topic. Our results, therefore, can help inform energy innovation policy. First, our empirical analysis shows that firms are an essential locus for knowledge spillovers between the GPT and energy applications. This suggests that it is worthwhile to increase the joint development of firm-level capabilities in digital and low-carbon technologies.

Our results also suggest that there is a case to support innovations that specifically draw on AI to advance clean technologies. Indeed, those can help spur a positive feedback loop between more AI absorption in clean and more clean innovations in general. Further research, however, is needed to understand the mechanisms better, particularly the role of different actors in catalyzing spillovers (universities, startups, large firms, regional clusters).

A Model derivations

The equilibrium must satisfy:

- the competitive equilibrium of the two final good inputs: since the final good is produced competitively, the relative prices of the two inputs satisfy:

$$\frac{p_{ct}}{p_{dt}} = \left(\frac{Y_{ct}}{Y_{dt}}\right)^{-1/\varepsilon} \tag{17}$$

  In addition, we normalize the price of the final good to 1 :

$$\left(p_{ct}^{1-\varepsilon} + p_{dt}^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} = 1 \tag{18}$$

- profit maximization of the input j producer, which determines L_{jt} and the inverse demand curve of machine x_{jit}. Specifically, labour demands in each sector satisfy:

$$(1-\alpha)p_{jt}L_{jt}^{-\alpha}\int_0^1 A_{jit}^{1-\alpha}x_{jit}^{\alpha}di = w_t \tag{19}$$

  And the inverse demand for x_{jit} satisfies

$$x_{jit} = \frac{\alpha p_{jt}}{p_{jit}}^{\frac{1}{1-\alpha}} A_{jit}L_{jt} \tag{20}$$

- profit maximization of the machine producer: the machine producer is a monopolist maximizing $\pi_{jit} = (p_{jit} - \psi)x_{jit}$ where x_{jit} is given by Equation 20. This gives $p_{jit} = \psi/\alpha$. We follow the original model in normalizing $\psi = \alpha^2$, which yields $p_{jit} = \alpha$ and

$$x_{jit} = p_{jt}^{\frac{1}{1-\alpha}} L_{jt}A_{jit} \tag{21}$$

  , and

$$\pi_{jit} = \alpha(1-\alpha)p_{jt}^{1/(1-\alpha)}L_{jt}A_{jit} \tag{22}$$

- profit maximization of the research scientist, who decides which sector to work in

Using Equation 21, we get the equilibrium production level of input j:

$$\begin{aligned} Y_{jt} &= L_{jt}^{1-\alpha}\int_0^1 A_{jit}^{1-\alpha}(p_{jt}^{\frac{1}{1-\alpha}}L_{jt}A_{jit})^{\alpha}di \\ &= (p_{jt})^{\frac{\alpha}{1-\alpha}}LjtA_{jt} \end{aligned} \tag{23}$$

Using Equations 21 and 19, we get a second equation for the relative prices of clean and dirty inputs in terms of the relative productivities of the two sectors:

$$\frac{p_{ct}}{p_{dt}} = \left(\frac{A_{ct}}{A_{dt}}\right)^{-(1-\alpha)} \tag{24}$$

Using equations 23 and 17 and 24, we get a new equation for employment in each sector:

$$\frac{L_{ct}}{L_{dt}} = \left(\frac{A_{ct}}{A_{dt}}\right)^{-\phi} \tag{25}$$

where $\phi \equiv (1-\alpha)(1-\varepsilon)$.

The expected profit Π_{jt} for a scientist doing research in sector j is the expected profit from becoming a monopolist producer of a machine with productivity $A_{jit} = (1+\gamma)A_{ji,t-1}$, which is (see Eq 22):

$$\Pi_{jt} = \eta_j(1+\gamma+\beta_j GPT_t)\alpha(1-\alpha)p_{jt}^{1/(1-\alpha)}L_{jt}A_{jt-1} \tag{26}$$

Using Eq 26 with 24 and 25, we get the ratio of expected profit from doing research in teh clean versus dirty sector given by Equation 9. Equations 24, 18, 25 with market clearing $L_{ct}+L_{dt}=1$, and the expressions for the advancement of the technology frontier in each sector gives us the system of equation to solve to obtain the equilibrium.

Proof of Result 1 We defined $\bar{A}_{ct-1}$ as the value of A_{ct-1} for which $f(1,0)=1$. We want to show that $\frac{d\bar{A}_{ct-1}}{dGPT_t} < 0$ and $\frac{d\bar{A}_{dt-1}}{dGPT_t} < 0$.

$$f(1,0) = \frac{\eta_c}{\eta_d}\frac{1+\gamma+\beta_c GPT_t}{1+\gamma+\beta_d GPT_t}\left(1+(\gamma+\beta_c GPT_t)\eta_c\right)^{-\phi-1}\left(\frac{\bar{A}_{ct-1}}{A_{dt-1}}\right)^{-\phi} = 1$$

$$\Rightarrow \bar{A}_{ct-1} = A_{dt-1}\left(\frac{\eta_c}{\eta_d}\frac{1+\gamma+\beta_c GPT_t}{1+\gamma+\beta_d GPT_t}\right)^{1/\phi}\left(1+(\gamma+\beta_c GPT_t)\eta_c\right)^{-\frac{\phi+1}{\phi}}$$

$$\frac{d\bar{A}_{ct-1}}{dGPT_t} = \frac{1}{\phi}\bar{A}_{ct-1}\left(\underbrace{\frac{\eta_c}{\eta_d}\frac{(\beta_c-\beta_d)(1+\gamma)}{(1+\gamma+\beta_c GPT_t)(1+\gamma+\beta_d GPT_t)}}_{\sim 0}\underbrace{-(\phi+1)\frac{\eta_c\beta_c}{1+(\gamma+\beta_c GPT_t)\eta_c}}_{<0}\right)$$

The first term goes as GPT_t^{-2} whereas the second one goes as GPT_t^{-1}. Thus the sign of the derivative is dominated by the second term, which is negative iff $\phi < 1$. The converse derivation works for $\bar{A}_{dt-1}$.

We now want to show that $\frac{d\bar{A}_{ct-1}}{d\beta_c} < 0$ and $\frac{d\bar{A}_{dt-1}}{d\beta_c} > 0$.

$$\frac{d\bar{A}_{ct-1}}{d\beta_c} = -\bar{A}_{ct-1}GPT_t\underbrace{\frac{\eta_c(1+\phi(1+\gamma+\beta_c GPT_t))-1}{\phi(1+\gamma+\beta_c GPT_t)(1+\eta_c(\gamma+\beta_c GPT_T))}}_{>0} < 0$$

The term in bracket is positive because under the assumption that $\phi < 1$, both the numerator and denominator are negative. Finally:

$$f(0,1) = \frac{\eta_c}{\eta_d}\frac{1+\gamma+\beta_c GPT_t}{1+\gamma+\beta_d GPT_t}\left(1+(\gamma+\beta_d GPT_t)\eta_d\right)^{\phi+1}\left(\frac{\bar{A}_{dt-1}}{A_{ct-1}}\right)^{\phi} = 1$$
$$\Rightarrow \bar{A}_{dt-1} = A_{ct-1}\left(\frac{\eta_d}{\eta_c}\frac{1+\gamma+\beta_d GPT_t}{1+\gamma+\beta_c GPT_t}\right)^{1/\phi}\left(1+(\gamma+\beta_d GPT_t)\eta_d\right)^{-\frac{\phi+1}{\phi}}$$
$$\frac{d\bar{A}_{dt-1}}{d\beta_c} = -\frac{\bar{A}_{dt-1}GPT_t}{\phi(1+\gamma+\beta_c GPT_t)} > 0$$

Proof of Result 2 We start with studying the behavior of B_j^* with respect to GPT_t and b_j.

$$B_j^* = \eta_j b_j GPT_t \frac{\alpha(1-\alpha)}{2\psi} p_{jt}^{1/(1-\alpha)} L_{jt} A_{jt-1}$$

GPT_t and b_j occupy symmetric positions in the equation, so the proof is the same for both variables. We thus proceed studying the behaviour with respect to GPT_t.

$$\frac{dB_j^*}{dGPT_t} = (\eta_j b_j \frac{\alpha(1-\alpha)}{2\psi} p_{jt}^{1/(1-\alpha)} L_{jt} A_{jt-1})\left(1+\frac{1}{1-\alpha}\frac{GPT_t}{p_{jt}}\frac{dp_{jt}}{dGPT_t}+\frac{GPT_t}{L_{jt}}\frac{dL_{jt}}{dGPT_t}\right) \quad (27)$$

WLOG, we describe what happens in the clean equilibrium $s_c = 1$ (the dirty equilibrium can then be analyzed symmetrically). Using Equations 24 together with $A_{jt} = (1+(\gamma+b_j B_j^* GPT_t)\eta_j s_j)A_{jt-1}$, we see that

$$\frac{p_{ct}}{p_{dt}} \equiv r_p = \left(\frac{A_{ct}}{A_{dt-1}}\right)^{-(1-\alpha)}$$

This tells us that in the clean equilibrium, $\frac{dp_{jt}}{dGPT_t} = \frac{dp_{jt}}{dA_{ct}}\frac{dA_{ct}}{dGPT_t}$. In the clean equilibrium, $\frac{dA_{ct}}{dGPT_t} \geq 0$. Since A_{dt-1} is fixed and $-(1-\alpha) < 0$, the relative price ratio $r_p \to 0$ as A_{ct} increases. To understand how this affects $\frac{dp_j}{dA_{ct}}$, take Eq. 18, the normalization of the price of the final good, and rewrite it as:

$$(p_d^{1-\varepsilon}(r_p^{1-\varepsilon}+1))^{(\frac{1}{1-\varepsilon})} = 1$$
$$p_d = \frac{1}{(r_p^{1-\varepsilon}+1)^{1/(1-\varepsilon)}}$$
$$\lim_{r\to 0} p_d = \frac{1}{r} \to \infty$$
$$\lim_{r\to 0} p_c = r p_d = 1$$

These limits imply that $\frac{dp_c}{dGPT_t}$ is negative but goes to 0 (since p_c asymptotes to 1), and $\frac{dp_d}{dGPT_t} > 0$.

We follow a similar reasoning to examine the behavior of equilibrium labour allocations. From Equation 25, we have:

$$\frac{L_{ct}}{L_{dt}} \equiv r_L = \left(\frac{A_{ct}}{A_{dt-1}}\right)^{-\phi}$$

This tells us that in the clean equilibrium, $\frac{dL_{jt}}{dGPT_t} = \frac{dL_{jt}}{dA_{ct}} \frac{dA_{ct}}{dGPT_t}$. With A_{dt-1} fixed and $-\phi > 0$, the relative labour ratio r_L increases as A_{ct} increases. Given the market clearing condition $L_{ct} + L_{dt} = 1$, this implies that $L_{ct} \to 1$ and $L_{dt} \to 0$ as GPT_t, and therefore A_{ct}, increase. Hence $\frac{dL_{jt}}{dGPT_t} \to 0$.

Thus, Eq. 27 now gives us:

$$\frac{dB_c^*}{dGPT_t} \to \eta_c b_c \frac{\alpha(1-\alpha)}{2\psi} A_{ct-1}$$

Hence, in the clean equilibrium, investments in absorptive capacity by the clean sector increase with the GPT stock, and this is even more true if b_c (the intrinsic absorptive capacity) and A_{ct-1} (the prior stock) are higher.

For the dirty sector, i.e. the sector which is not favoured by the equilibrium, investments in absorptive capacity also have a positive relationship to the GPT. This is because $\frac{dp_{dt}}{dGPT_t} > 0$ and does not asymptote, unlike $\frac{dL_{dt}}{dGPT_t}$. However, the derivative remains small because $L_{dt} \to 0$.

Proof of Result 3 We now consider the role of the energy stock in investments towards absorptive capacity, allowing for an ageing factor that reduces the intrinsic absorptive capacity of more mature technologies.

$$B_j^* = \eta_j \frac{b_j}{A_{jt-1}^{\delta}} GPT_t \frac{\alpha(1-\alpha)}{2\psi} p_{jt}^{1/(1-\alpha)} L_{jt} A_{jt-1}$$

with $\delta > 0$, the ageing paramter.

$$\frac{dB_j^*}{dA_{jt-1}} = (\eta_j b_j GPT_t (1-\delta) \frac{\alpha(1-\alpha)}{2\psi} p_{jt}^{1/(1-\alpha)} L_{jt} A_{jt-1}^{-\delta}) \left(1 + \frac{1}{1-\alpha} \frac{A_{jt-1}}{p_{jt}} \frac{dp_{jt}}{dA_{jt-1}} + \frac{A_{jt-1}}{L_{jt}} \frac{dL_{jt}}{dA_{jt-1}}\right) \tag{28}$$

The reasoning we developed in proof A regarding the derivatives of prices and labour with respect to GPT_t and their limiting behaviour carry over to the behaviour of these derivatives and limits with respect to A_{jt-1}. Hence, in the clean equilibrium, we have:

$$\frac{dB_c^*}{dA_{ct-1}} \rightarrow (\eta_c b_c GPT_t (1-\delta) \frac{\alpha(1-\alpha)}{2\psi} A_{jt-1}^{-\delta})$$

Clearly, if $\delta = 0$, this derivative is positive. However, if $\delta > 1$, then the ageing effect - impeding absorption of the new GPT - is larger than the "building upon the shoulders of giants" effect (innovation opportunities arising from having a larger stock of past knowledge). In this case, the derivative is negative, indicating that effort in absorbing the GPT will decrease with the maturity of the technology.

SUPPLEMENTARY MATERIAL

The Online Appendix for this article can be found by clicking here.

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