Essays on Trade, Competitiveness and Innovation in the Transition to Clean Technology

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Declaration

I certify that the thesis I have presented for examination for the MPhil/PhD degree of the London School of Economics and Political Science is solely my own work other than where I have clearly indicated that it is the work of others (in which case the extent of any work carried out jointly by me and any other person is clearly identified in it).

I warrant that this authorisation does not, to the best of my belief, infringe on the rights of any third party.

I declare that my thesis consists of 36,551 words.

Statement of co-authored work

I confirm that Chapter 4 was jointly co-authored with Penny Mealy, Nils Handler and Sam Fankhauser and I contributed 70% of this work.

I confirm that Chapter 5 was jointly co-authored with Eugenie Dugoua and Marion Dumas and I contributed 35% of this work.

Inclusion in Other Work

Chapter 2 was published as Grantham Research Institute Working Paper 388 in January 2023 and updated in September 2024.

An earlier version of Chapter 3 was published as Grantham Research Institute on Climate Change and the Environment Working Paper 379 in October 2022. A more recent version with the title 'Adapting to competition: Solar PV innovation in Europe and the impact of the "China shock"' has been accepted and is soon to be published in the Springer Nature journal Environmental and Resource Economics (DOI 10.1007/s10640-024-00904-8).

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Abstract

This thesis studies how the global transition to a low carbon economy affects, and is affected by, countries' interactions in global trade, as well as broader technological developments. It contains four self-contained chapters.

Chapter 2 presents a strategic model of trade in a clean technology in the presence of differential country-level production costs and imperfect competition. I show that when production cost disparities surpass a critical threshold, and learning-by-doing facilitates catch-up for the laggard, opting for autarky during Stage 1 can enhance overall welfare for both countries.

Chapter 3 examines the effects of Chinese import competition on firm-level innovation in solar photovoltaic technology by European firms using a sample of 10,137 firms in 15 EU countries over the period 1999-2020. I show that firms which were exposed to higher import competition innovated more if they had a relatively small existing stock of innovation, but less if their historical knowledge stock fell within the top 10th percentile of firms in the sample. As firms with a smaller knowledge stock tended to innovate more overall, trade with China appears to have been beneficial in encouraging innovation among the most innovative firms. However, I also find evidence that import competition increased the probability of exit among firms in the sample.

Chapter 4 highlights which countries are most at risk of seeing their productive capabilities 'stranded'. Using methods from economic geography and complexity, we show that countries exporting a high number of technologically sophisticated brown products should find it relatively easy to transition. Conversely, those relying on few, low-complexity brown products for a large percentage of export volume have few diversification opportunities.

In Chapter 5 we show how, in theory, a General Purpose Technology such as AI might affect the competition between clean and dirty technologies. We then use patent data to 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.

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Chapter 1

Introduction

Meeting the climate challenge requires a rapid and pervasive shift towards cleaner modes of production, particularly in the energy, transport and agricultural sectors. Both research and public discourse have previously focused largely on the economic cost of doing so and how much mitigation is optimal given the implied welfare trade-offs (see e.g. Crost and Traeger 2014; Jensen and Traeger 2014; Nordhaus 1992, 2007; Stern 2006), as well as how costs should be distributed across nations and how to solve collective action problems arising from the global nature of climate change (e.g. Barrett 1994a, 2005; Finus 2008; Harstad 2016).

There have been two important narrative shifts in recent years. First, there is an increasing recognition of the importance of technological change in reducing mitigation costs (Acemoglu et al. 2012; Acemoglu et al. 2016a; Jaffe et al. 2005). Some scholars even argue that transitioning to renewable energy sources will significantly reduce energy costs in the long term (Way et al. 2022). Second, the policy discourse has increasingly focused on ambitions to become a 'green leader' and promote 'green growth' by becoming competitive in emerging green industries and reaping associated benefits in terms of growth and job creation (Bowen and Fankhauser 2011).

The literature on technological change and the green economy focuses on what innovation in clean technologies implies for the optimal policy path, usually arguing in favor of R&D subsidies in addition to a carbon price (Acemoglu et al. 2012; Acemoglu et al. 2016a; Jaffe et al. 2005). However, interactions of this shift with its broader technological and geopolitical context have received considerably less attention. The literature on the 'green race', on the other hand, has focused largely on which countries have the productive capabilities needed to take advantage of demand for new, green technologies (Fankhauser et al. 2013; Mealy and Teytelboym 2020). Less work has been done on the characteristics of countries whose economic viability is at risk, and what a just transition might look like for them.

This thesis therefore considers how the low carbon transition affects, and is affected by, (1) the trade regime, as well as the ability and desire of national governments to be competitive in global trade; and (2) the broader technological shift towards artificial intelligence (AI) and other digital technologies.

Chapter 2 presents a conceptual model highlighting the importance of enabling learning-by-doing in order to realise gains from trade through increased market competition. I show that when a product has positive consumption externalities – as clean technologies do by replacing dirty ones – catching up can be globally beneficial; even at the cost of temporarily remaining in autarky. The model also highlights how the motive of extracting rents from other countries may be at odds with, and even outweigh, a preference for greater climate action and consumer surplus on the part of more advanced countries.

Chapter 3 uses the solar photovoltaics (PV) sector as a case study within the 'China Shock' literature (e.g. Autor et al. 2013; Autor et al. 2016; Bloom et al. 2016; Bloom et al. 2021). I use an instrumental variable strategy to study how import competition from China affected innovation in solar PV in 15 EU countries between 1999 and 2020. I find that firms which were exposed to higher import competition tended to innovate more if they had a low, and less if they had a high, historical stock of innovation. Innovation was driven by newcomers more than incumbents. Finally, import competition significantly increased the probability of firm exit.

While previous work has considered which countries are well placed to 'win' in the green transition (Fankhauser et al. 2013; Mealy and Teytelboym 2020), less work has been done on measuring transition risk based on the path dependency of industrial development. Chapter 4 therefore develops measures of country dependence on declining sectors – such as coal, oil or internal combustion engines – and the ease of transitioning out of those sectors. We find that most countries whose production capabilities are diverse and technologically sophisticated will likely find it easy to transition; even if they export many dirty products. Conversely, countries which heavily depend on exports of unprocessed fossil fuels have few transition opportunities. This highlights the importance of policy to enable path-breaking diversification in those countries.

Finally, prior work has considered the policy implications of path dependency for the competitive race between clean and dirty technologies (Acemoglu et al. 2012; Acemoglu et al. 2016a). However, there is little existing research on how broader technological developments such as the arrival of a new General Purpose Technology (GPT) might affect these dynamics. In light of the recent rise of AI, Chapter 5 therefore studies theoretically how we would expect a GPT to affect this 'race', arguing that a new GPT can weaken path dependence. We then use patent data to proxy the absorptive capacity of clean and dirty innovations and show that clean transport and electricity technologies use AI more than dirty ones.

The overall contribution of this thesis is to place the transition to clean technology in its broader technological and geopolitical context. The results highlight the importance of coordinating and aligning policy with broader objectives and technological developments.

Chapter 2

Industrial Policy and Global Public Goods Provision: Rethinking the Environmental Trade Agreement

2.1 Introduction

Climate change has been an item on the agenda of global diplomacy and politics for decades. Policy action at the level of nation states, however, has to date remained woefully insufficient to achieve stated aims to reduce greenhouse gas emissions and avoid catastrophic warming. The reason for this is, according to much of the economics literature, the cost of reducing emissions – and the fact that due to the global nature of climate change, each country has an incentive to free-ride on others' efforts (Barrett 1994a, 2005; Finus 2008). One might therefore expect that reductions in the cost of technological solutions would be universally welcomed. And yet, policy support for renewable energy, which is a key component of a climate-compatible global production system, has frequently been accompanied by or met with trade barriers, which are associated with increased user costs.[1] Such decisions are taken in the interest of each country's domestic industry producing renewable energy technology.

Are there conditions under which this might prove beneficial to climate action? Fischer (2017) shows how domestic incentives to expand global market share in a green industry can balance out environmental externalities in a framework in which two producer countries use

1. For example, China required 40% of wind turbines and blades to be manufactured locally for projects to be eligible for public tenders as early as 1997. Between 2011 and 2017, India imposed a 60% local content requirement on tenders for solar photovoltaics (PV), and 30% for concentrated solar power. France's feed-in tariff for solar PV between 2002 and 2012 came with a 60% local content requirement (Scheifele et al. 2022). More recent examples include domestic content requirements in the US Inflation Reduction Act, as well as the EU's Net Zero Industry Act which includes the explicit aim that 'by 2030, the manufacturing capacity in the Union of [strategic net-zero technologies] approaches or reaches at least 40% of the Union's annual deployment needs' (European Commission 2023).

upstream subsidies and compete for a third market. Here, I consider instead the intertemporal trade-off between foregoing gains from trade early on in order to realise greater gains later, by allowing an infant industry to mature. The literature on industrial policy and infant industry maturation tends to focus on the effectiveness of industrial policy and the cost-benefit trade-off at the level of the country promoting its infant industry (e.g. Krueger and Tuncer 1982; Melitz 2005; Young 1991). In contrast, I analyse the global as well as the local welfare implications of allowing an infant industry to mature in the context of a product with positive consumption externalities. The analysis suggests that such externalities could make infant industry maturation beneficial for both the initially laggard and the initially frontier country. Conversely, in the absence of positive consumption externalities, the frontier country prefers to extract rents from the laggard country's consumers. However, the laggard country, acting strategically, may still opt to protect its infant industry.

China's entry into the solar photovoltaics (hereafter PV) market, which was enabled by targeted industrial policy, considerably increased competition in this market[2] and is widely credited to have contributed to the dramatic declines in the cost of solar PV energy over the past decade (Carvalho et al. 2017; Dent 2018; Nemet 2019). This raises the following question: if industrial policy – possibly including temporary protectionist measures – is necessary to allow a potential supplier country of clean technology to realise its potential and increase competition in the future, can the long-term global benefits of doing so outweigh the short-term cost of protection? I present a stylised model highlighting conditions under which this may be the case. I then add the use of quantity subsidies, and show how this alters the trade-offs considered. The key insight is that allowing the initially laggard country to more effectively compete with the frontier country can be beneficial for the global economy, and allowing for the use of producer subsidies can accomplish this goal while avoiding the temporary cost of protectionism.

I model the production and consumption of an environmentally beneficial product in a 2-country, 2-stage game with imperfect competition, differences in initial production cost, and learning-by-doing. Each country has a representative firm which can produce a technology capable of generating private as well as public benefits. We can think of this as a renewable energy technology which benefits consumers directly by supplying energy, as well as reducing negative externalities which would result if fossil fuels were used instead. While the chapter is motivated by the global challenge of addressing climate change, the model is potentially relevant to any game in which consuming a technology carries benefits to other consumers at home and abroad. Other examples include the use of vaccines, which also generate both private

2. In 2008, the 10 largest solar PV equipment manufacturers accounted for almost 90% of global market share, operating in just four countries (Germany, the US, Switzerland and Japan). By 2021, the top ten manufacturers' share had dropped by half due to new firm entry. Today, all top ten equipment manufacturers are in China and claim over 45% of the global market share (IEA 2022).

and public benefits (Brito et al. 1991; Fisman and Laupland 2009; Francis 1997).

I start with the assumption that there are no subsidies and governments can choose only whether to trade or not. Firms play a Bertrand game if countries engage in trade, and act as local monopolists otherwise. If the laggard (high cost) firm is active during Stage 1, it 'catches up' with the frontier (low cost) firm by Stage 2. If countries trade, then the laggard firm remains inactive and the frontier country extracts rents from the laggard country's consumers. Under both trade and autarky and in the absence of other policy action, consumption and positive externalities are inefficiently low even without the additional factor of transboundary (global) positive externalities. This is due to imperfect competition.[3]

If the laggard firm catches up, Bertrand competition leads to marginal cost pricing in Stage 2. The model shows how for a sufficiently large difference in initial marginal cost, and in the absence of other policy tools, autarky in Stage 1 can benefit both countries through increased consumer surplus and positive externalities in Stage 2. The frontier country loses the rents it could otherwise extract from the laggard country.

In the presence of market failures, such as those arising from the positive externality and imperfectly competitive market structure considered here, a social planner will usually wish to intervene beyond the decision of whether or not to trade. Indeed, various subsidies, preferential loans and other incentives implemented by policy-makers around the world have been decisive in scaling up the deployment of renewable energy technologies. I therefore analyse how quantity subsidies affect the dynamics of trade and positive externalities. The model suggests that when consumer subsidies are available as a policy tool, autarky in Stage 1 is always beneficial for the laggard and globally, as competition from the laggard country in Stage 1 no longer provides benefits in terms of constraining the frontier monopolist.

If countries can choose both upstream (producer) and downstream (consumer) subsidies then the laggard country will choose a producer subsidy which is sufficiently high to force the frontier firm to set price equal to marginal cost, but which leaves it to supply the whole market. Both countries subsidise consumers to the point of internalising the domestic part of the positive externality. The outcome is equivalent to the non-cooperative equilibrium obtained under perfect competition. While the first best is not attainable, the 'second best' policy mix which achieves an outcome equivalent to a game with perfect competition thus requires that countries are able to choose a mix of consumer and producer subsidies.

The chapter connects the literature on industrial policy and infant industry protection (e.g. Chang 2003; Krueger and Tuncer 1982; Melitz 2005; Young 1991) to that highlighting increased competition as a cause of gains from trade (Krugman 1979; Markusen 1981) by modelling learning-by-doing in an initially laggard industry as a pre-condition to enable competition

3. Arguably a reasonable assumption for a new industry, see e.g. Fischer (2017) and Fischer et al. (2018)

later on. It also builds on the literature on international collective action problems related to climate change and the environment (see e.g. Barrett 1994a, 2005; Finus 2008; Harstad 2016). The positive global externality arising from consumption of the good implies that the benefits of an infant industry catching up may be global, rather than being limited to the initially laggard country. In contrast, in the absence of positive externalities the advanced country always prefers to retain its ability to extract rents, despite associated losses in consumer surplus.

Previous work on the infant industry argument has emphasised the need for the cost of temporary protection to be outweighed by the benefits of domestic production in a higher value-added industry later (Krueger and Tuncer 1982); for example, because learning-by-doing exhibits spillovers across goods (Young 1991) or domestic and foreign goods are imperfectly substitutable (Melitz 2005). This chapter highlights an additional channel through which infant industry protection may be warranted. I model the maturation of an infant industry as a precondition for allowing gains from trade via increased competition (Krugman 1979; Markusen 1981) to increase in the future.

The model allows me to identify conditions for infant industry protection to improve welfare in the initially laggard country, as well as in the frontier country and globally, even while abstracting from any macroeconomic spillovers or growth effects. I also highlight how the frontier country can, under trade, extract rents from the laggard country, offsetting any losses in consumer surplus from imperfect competition. Finally, introducing a global positive consumption externality implies that infant industry protection can be welfare improving not only for the initially laggard country, but also for the frontier country. The larger the public benefit from consumption becomes relative to the private benefit, the closer countries' interests should align.

Efforts to liberalise trade in 'green' technologies – including, but not limited to, those with the potential to reduce greenhouse gas emissions – have been underway for years. In the 2001 Doha declarations ministers stated their commitment to negotiations on reducing or eliminating tariff and non-tariff barriers to environmental goods and services (Balineau and De Melo 2013; Droege et al. 2016). The Asia-Pacific Economic Cooperation (APEC) countries reached an environmental trade agreement in 2012 (Jacob and Møller 2017; Steenblik 2005; Vossenaar 2016), while negotiations for a World Trade Organisation (WTO)-wide agreement are ongoing (De Melo and Solleder 2020; Monkelbaan 2017). The theoretical rationale for liberalising trade in clean technologies is clear: doing so is expected to facilitate diffusion of such technologies, thereby increasing their deployment, and enabling greater climate change mitigation and other environmentally beneficial outcomes at a lower cost. In practice, however, countries' attitudes towards these technologies have frequently proven to be mercantilist in nature (De Melo and Solleder 2022).

This chapter suggests that while a trade agreement may be beneficial for climate action and global welfare, producer subsidies may be key to realising gains from trade. It further provides intuition for why countries which provide consumer subsidies for renewables often use local content requirements, as well as why early mover countries such as the US or Germany tend to oppose producer subsidies in other countries – even at the expense of their own consumers.[4]

The remainder of the chapter proceeds as follows. Section 2.2 summarises the literatures on trade and international public good games which the chapter builds on. Section 2.3 discusses the evolution of the solar PV sector as a real-world example of the dynamics the model seeks to highlight. Section 2.4 introduces the key tenets of the model and the benchmark 'first best' cooperative outcome, comparing it to a status quo under which countries are in autarky and do not subsidise the technology in any way. Section 2.5.1 analyses the welfare implications of trade when no other climate policy is available, and identifies the conditions under which autarky may be individually or jointly preferable to trade. Section 2.5.2 introduces quantity subsidies and analyses how this changes the dynamics of the game. Section 2.6 concludes.

2.2 Related Literature

Gains From Trade and Infant Industries The trade literature identifies many mechanisms through which gains from trade may materialise. These include the efficiency gains of each country specialising where it has a comparative advantage (Ricardo 1891); increased competition and increasing returns to scale in a larger market (Krugman 1979); and a redistribution of market share towards the most productive firms and the exit of the least productive (Baldwin and Gu 2004; Melitz 2003). A larger potential market might further increase incentives to innovate (Aghion et al. 2018a; Grossman and Helpman 1990) and raise the potential for knowledge spillovers and technology diffusion (Grossman and Helpman 1990; Keller 2004), by making technology more widely and cheaply available (Carbaugh and St Brown 2012; ICTSD 2011).

If comparative advantage and industrial structure are taken as fixed, the benefits of liberalising trade are clear and highly intuitive. However, patterns of comparative advantage are not solely determined by fundamental endowments (Hausmann et al. 2007). In highly complex modern industries in particular, competitiveness is developed over time. Many scholars argue that industries need temporary protection from import competition in order to develop and become competitive (Chang 2003; Hanlon 2017; Juhász 2018). This is known as the 'infant industry argument'. Infant industry protection is usually seen as a strategy for developing countries, but can also play a role in building productive capabilities in developed economies, especially if the industry in question is underdeveloped in a particular country (Andreoni and

4. The expansion of low-cost solar panel manufacturing in China was met with anti-dumping duties by both the United States and the European Union (Hughes and Meckling 2017; Meckling and Hughes 2018; Wu and Salzman 2013). Estimates of the cost of US protective tariffs downstream, both in the solar PV sector and more broadly, include Houde and Wang (2022) and Fajgelbaum et al. (2020).

Chang 2016).

Theoretical models suggest that temporary protection can be beneficial when entry barriers and dynamic learning effects are high (Irwin 2000; Melitz 2005; Young 1991). The temporary costs of protecting the infant industry must be outweighed by the benefits of domestic production in a higher value-added industry later on (Krueger and Tuncer 1982). Empirical evidence on the justifications for and effectiveness of infant industry protection is mixed: Krueger and Tuncer (1982) show that protected industries in Turkey over the period 1963-1976 did not experience faster cost declines than others, and argue that infant industry protection could therefore not be a valid argument for the use of tariffs. Conversely, Hanlon (2017) argues that competition from Britain hindered North American shipbuilders' ability to transition from wood to metal shipbuilding in the late 19th century, while Juhász (2018) shows that the blockade of British imports during the Napoleonic wars enabled more protected French regions to more rapidly transition to mechanised cotton spinning.

Overall, more competition through trade may not necessarily be beneficial during the early stage of developing a new industry. This may provide some justification for the use of instruments such as local content requirements (Johnson 2016). The returns from infant industry protection are usually modelled as greater future growth via the reallocation of output to more rapidly growing industry; inter-industry spillovers enabling learning-by-doing (Young 1991); the result of imperfect substitutability between domestic and foreign goods (Melitz 2005); or protection against a sudden demand-shock favouring a foreign-produced good with non-linearly increasing production cost (Traiberman and Rotemberg 2022). In contrast, this chapter explores the implications of infant industry dynamics for consumer surplus and positive externalities under trade and autarky, and in particular the potential global benefits of temporarily protecting an infant industry through its impact on competition later on. I thereby identify an additional mechanism through which infant industry protection may be beneficial, and explicitly model the rents which the initially frontier country can extract from the initially laggard country under imperfect competition in the absence of any policy supporting the infant industry. The chapter does not explicitly model the source of these dynamics, nor does it consider other, more long-term, implications of competition and market size beyond prices and quantities, such as innovation or learning by the frontier industry.

Climate Change and International Cooperation Climate change is an inherently global problem, which must nevertheless be addressed within the current framework of individual nation-states. Action on climate change and other transboundary environmental problems involves strategic interaction between individual countries, which makes game theory an attractive tool of analysis. In the absence of a supra-national authority which could force countries to act to achieve the global social optimum, incentives to free ride on others' efforts abound, making it extremely difficult for international cooperation to be achieved.

A broad literature has therefore used game theory to formally analyse the mechanisms at play in international climate negotiations. Due to the absence of an authority which could hold countries to a binding agreement, non-cooperative game theory is usually thought most relevant (Barrett 2005; Finus 2008). This literature typically attempts to provide insights on how treaties may improve on the status quo, using two benchmark cases: no agreement with each country only taking into account its own environmental damages and ignoring the transboundary externalities caused by its emissions; and the global 'first-best' or fully cooperative outcome, which would be obtained if a benevolent social planner could set global policy (e.g. Barrett 1994a; Battaglini and Harstad 2016; Harstad 2012b).

Technology as a potential channel for enhancing international cooperation has also been explored. Barrett (2006) discusses if and how a system of two treaties promoting R&D and adoption of a resulting breakthrough technology could enhance cooperation. He argues that the R&D and technology approach faces the same challenges as the Kyoto approach, with the exception of breakthrough technologies with increasing returns to scale. Building on Barrett (2006), Hoel and De Zeeuw (2010) show that when R&D costs affect adoption costs, a large stable coalition is possible and can improve welfare. Harstad (2016), however, points out that in a dynamic setting, green investment may be negatively affected by the hold-up problem identified in earlier literature (Beccherle and Tirole 2011): incentives to invest in green technology may be reduced if countries expect this will force them to agree to abate more in future negotiations, which is especially damaging in the presence of technological spillovers. Conversely, Battaglini and Harstad (2016) present a dynamic model with incomplete contracts, in which the non-contractibility of investments in green technology can help leverage the hold-up problem when agreement duration is endogenous: in their model, a short-term agreement with low investment is used as a credible threat against free-riding, bringing about a longer-term, more comprehensive agreement.

This chapter also relates to a growing body of literature exploring international environmental or climate cooperation in the presence of international trade. Research in this area typically explores the issue of pollution leakage and the potential for border adjustments (e.g. Barrett 1994b; Grubb et al. 2022; Richter et al. 2021); the potential use of trade policy to incentivise cooperation, also referred to as 'issue linkage' (e.g. Barrett 1997; Barrett and Dannenberg 2022; Hagen and Schneider 2021; Nordhaus 2015); or both (e.g. Helm et al. 2012). The chapter departs from most existing research on trade and the environment in that it considers trade in pollution-reducing, rather than polluting, products.[5] Existing work in this vein includes Fischer

5. In reality, of course, the production process itself of so-called 'clean technology' is rarely carbon-neutral. However, for the purposes of this analysis I will focus on the mitigation potential of a clean technology and its resultant positive externalities.

et al. (2017), who compare the relative merits of up- and downstream subsidies when regions set different emission taxes and upstream producers engage in Cournot competition, selling abatement technology to downstream polluting firms in both regions. They find greater emission reductions under upstream subsidies, as a downstream subsidy increases the global price of abatement technology, leading the other region to use less of it. Fischer (2017), building on Spencer and Brander (1983) and Brander and Spencer (1985), shows that when producing countries of an environmental technology have domestic political incentives to increase production, and environmental benefits are large relative to such political distortions, restrictions on upstream subsidies can reduce global welfare.

2.3 Motivation: Solar Photovoltaics

Renewable energy technologies, once considered too expensive to be economically viable, have seen dramatic declines in cost over the past few decades, becoming competitive with traditional fossil fuels in many contexts. The two great success stories are electricity production using wind and solar power. Since the first commercial use of solar PV in 1958, its cost decreased by more than three orders of magnitude (Way et al. 2022). The price of solar panels fell by 75% between 2010 and 2015 (Gerarden 2023).

While about half of these cost declines can be attributed to reductions in material costs, economies of scale, and efficiency-increasing innovation (Nemet 2006), increased competition is thought to be another key driver (Carvalho et al. 2017; Dent 2018; Nemet 2006).

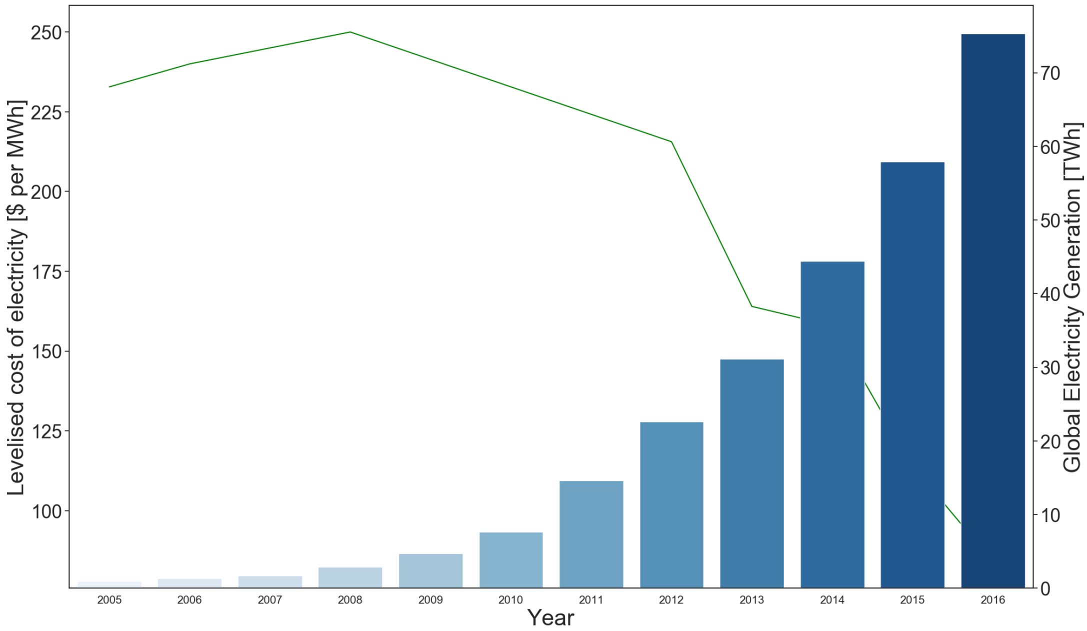
Figure 2.1 shows the levelised cost of electricity[6] in solar PV, as well as global electricity generation from solar, over the period 2000-2016. During this time, the levelised cost of electricity declined from over 0.5 to 0.1 USD per kWh, while global electricity generation increased from virtually nothing to more then 70 TWh per year. Technology innovation support and demand creation through government subsidies around the world, as well as the expansion of Chinese manufacturing – characterised by both supply- and demand-side industrial policy (Chen 2015) – are likely to have played a significant role.[7] Early government policies supporting solar PV include, for example, government R&D support and the founding of the Solar Energy Research Institute in the US in 1974 and the 1990 ‘1000 Roof’ solar deployment program, as well as the 1991 solar feed-in tariff, in Germany (Hansen et al. 2018).

Figure 2.2 illustrates how the share of the top 10 firms in terms of global solar PV shipments declined from 88% in 2000 to 53% in 2015[8] – a period which experienced significant

6. The price per unit of electricity which would be required in order for a project to break even over its lifetime

7. In the context of the model presented in this chapter, measures targeting the supply side (such as R&D support or export subsidies) will be conceptualised as ‘producer subsidies’, while demand-creation policies (such as feed-in tariffs or other deployment programmes) are conceptualised as ‘consumer subsidies’.

8. Note that the data on market concentration displayed in this section was sourced from industry blogs, as it



Note: The green line plots the Levelised Cost of Electricity from solar PV in $ per kWh between 2000 and 2016. The blue bars show global electricity generation from solar PV in TWh over the same period. We see cost declining from over 0.5 to 0.1 $ per kWh, while deployment rose from close to zero to over 70 TWh. Source: Author's calculations based on Way et al. (2022) and Dudley et al. (2018).

FIGURE 2.1
Solar PV Cost and Deployment, 2000-2016

firm entry, in particular by Chinese firms. The Chinese government supported its solar PV industry using a mix of upstream subsidies, including discounts on raw materials, electricity and funding, export subsidies, and technological, infrastructure and personnel support (Chen 2015); and demand-creation measures such as feed-in tariffs and free grid connection services for distributed solar by China's largest state-owned utility (Zhang and He 2013). Chinese solar panel manufacturers reached more than 50% of global revenue share by 2012 (Chen 2015).

In 2012 and 2013, the US and the EU respectively imposed anti-dumping duties on Chinese solar panels, arguing that the latter were unfairly subsidised (Hughes and Meckling 2017; Meckling and Hughes 2018) and thereby retaliating against subsidies which reduced the cost of a low-carbon energy technology for their own utilities and consumers. The model presented below provides intuition for why the loss in profits earned by domestic producers may have outweighed the benefits to consumers and the climate from the perspective of western governments.

Looking forward, technologies which need to decline in cost in order to be economical include carbon capture and storage, green hydrogen, and energy storage. Lithium ion batteries,

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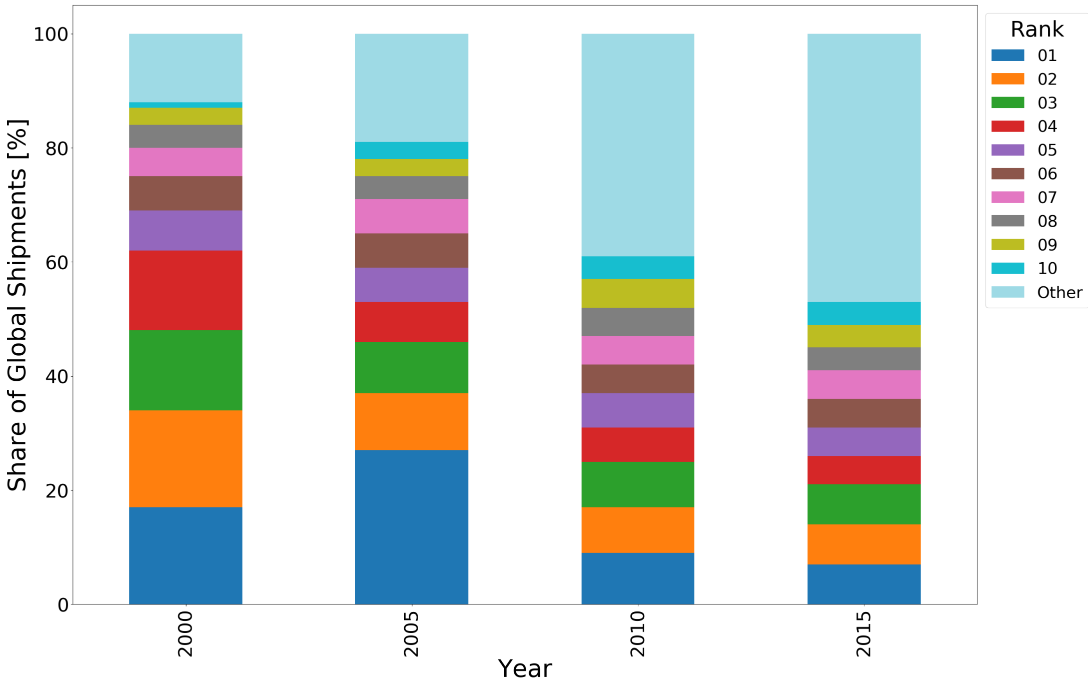
was not possible to obtain data going back further than 2015 and covering more than the top 5 players from more formal data providers.



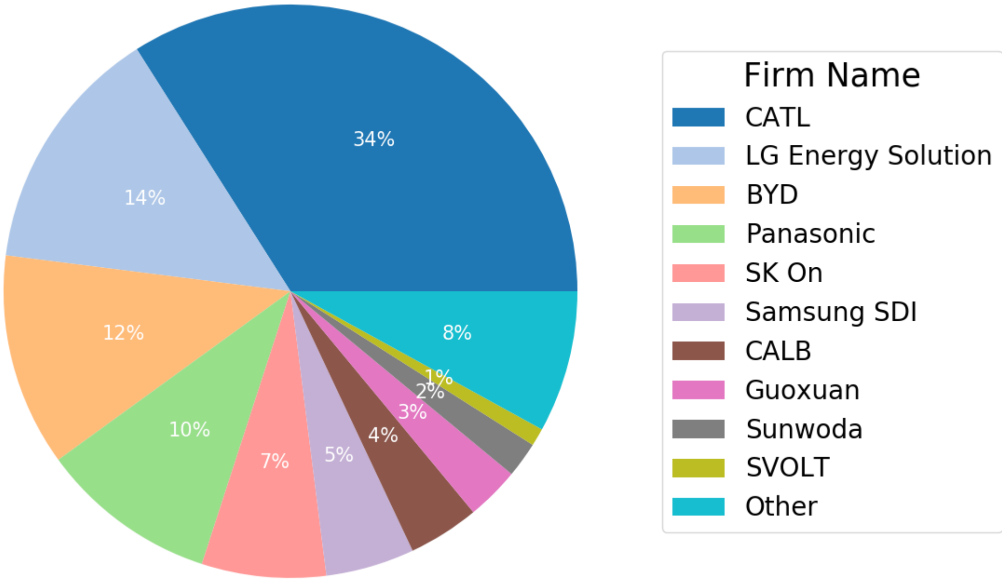
Note: The figure shows the share of the top 10 producers in global shipments of solar PV generation capacity for the years 2000 (when the top 10 captured 88% of global market share), 2005, 2010, and 2015 (when the share of the top 10 had declined to 53%). Source: Author's calculations based on Mints (2016) and Renewable Energy World (2014).

FIGURE 2.2
Market Concentration Over Time (Solar PV)

for example, are currently the most expensive part of electric vehicles, with a heavily concentrated global market. Figure 2.3 plots global market shares in EV batteries in 2022, showing that the top 10 producers currently capture 92% of global market share. Firm entry and competition may be key to driving down cost.

However, it is important to note that competition is only one of many reasons why the solar sector has evolved as it has. Moreover, the ability of Chinese manufacturers to sell at lower prices is likely to be at least in part due to domestic production conditions, rather than rent-seeking by western manufacturers.[9] Finally, the relationship between firm entry and technological maturity is surely bi-directional. While this section has sought to add intuition and real-world context to the theoretical model presented below, it should be interpreted with caution.

9. One seemingly obvious advantage are lower labour costs. However, Chen (2015) argues that labour costs account for only 10% of the cost of solar panel manufacturing, due to the industry's highly capital intensive nature.



Note: The figure shows the global market share of the top 10 firms in EV batteries in 2022. The market is highly concentrated, with the top 10 producers capturing 92% of the global market. Source: Author's calculations based on E-Vehicle Info (2022).

FIGURE 2.3
Market Concentration in 2022 (EV Batteries)

2.4 Model and Preliminaries

I analyse the strategic interactions between two countries, denoted as $i \in \{F, L\}$, over two time periods $t \in \{1, 2\}$. The model is a sequential game, wherein in each period, both countries simultaneously set policy. Both countries face the challenge of climate change and consider supporting the adoption of a climate-friendly technology that mitigates climate damages and negative externalities associated with fossil fuels. This technology is modeled to generate positive global externalities.

The strategic agents in this game are the governments of the two countries, responsible for trade policy and subsidies with the aim of maximising domestic welfare over both periods. For simplicity, I assume there is no discount factor. Each government's welfare function encompasses consumer surplus ($CS_{i,t}$), industry profits ($\Pi_{i,t}$), and positive externalities ($B_{i,t}$) from global technology consumption.

Both governments are assumed to have complete information.

Government Policy To define the action set, it is useful to distinguish between the policy decisions each government can take.

First, in both periods government i chooses whether to trade or not to trade: $T_i = (\tau_{i,1}, \tau_{i,2})$.

$$T_i = \{(\tau_{i,1}, \tau_{i,2}) | (\tau_{i,1}, \tau_{i,2} \in \{0,1\})\}$$

, where $\tau_{i,t} = 0$ means autarky in period t and $\tau_{i,t} = 1$ means trade in period t.

Trade requires mutual agreement, such that it is sufficient for one country to prefer autarky to prevent trade.[10] This implies that countries' decisions with respect to trade map to trade policy outcomes as follows: $A_t = min(\tau_{F,t}, \tau_{L,t})$, where $A_t = 0$ indicates that countries are in autarky in period t, and $A_t = 1$ indicates that they are trading (i.e. there is a trade agreement) in period t. Let the sequence of trade policy outcomes[11] be denoted $A = \{A_1, A_2\}$.

Second, in each period t, governments also set the level of consumer subsidies $s_{i,t}^{cons} \geq 0$ and producer subsidies $s_{i,t}^{prod} \geq 0$. The set of subsidy policy decisions across both periods is

$$S_i = \{(s_{i,1}^{cons}, s_{i,1}^{prod}, s_{i,2}^{cons}, s_{i,2}^{prod}) | (s_{i,1}^{cons}, s_{i,1}^{prod}, s_{i,2}^{cons}, s_{i,2}^{prod} \in \mathbb{R}^+)\}$$

An element $s_i \in S_i$ is therefore 4-dimensional vector with the levels of subsidies for country i in both periods.

The full action set of government i is

$$P_i = T_i \times S_i$$

I assume that the subsidies employed are quantity subsidies, such that the overall cost of a consumer subsidy is $s_{i,t}^{cons} r_{i,t}$, where $r_{i,t}$ represents the quantity demanded by consumers in country i and period t, and that of a producer subsidy is $s_{i,t}^{prod} q_{i,t}$, where $q_{i,t}$ is the quantity produced by the domestic industry in period t. The government's best response will be that which maximises

$$\begin{aligned}
&\Sigma_{t=1}^{2} W_{i,t}(\tau_i, s_i, \tau_{-i}, s_{-i}) = \\
&\Sigma_{t=1}^{2} CS_{i,t}(\tau_i, s_i, \tau_{-i}, s_{-i}) + \Pi_{i,t}(\tau_i, s_i, \tau_{-i}, s_{-i}) + B_{i,t}(\tau_i, s_i, \tau_{-i}, s_{-i}) \\
&- s_{i,t}^{cons} r_{i,t}(\tau_i, s_i, \tau_{-i}, s_{-i}) - s_{i,t}^{prod} q_{i,t}(\tau_i, s_i, \tau_{-i}, s_{-i})
\end{aligned} \tag{2.1}$$

.

Consumer Demand and Externalities In each country and at each stage,[12] private sector demand for the technology is characterised by a linear relationship,[13] where p_i is the domestic

10. In practice, of course, trade policy tends to focus either on import or export barriers. Strategic sectors might be protected from import competition, while key inputs into such sectors might be subject to export restrictions. However, trade barriers do tend to be reciprocal where possible, and free trade agreements require mutual cooperation. I therefore consider this a reasonable simplification.

11. hereafter referred to as a 'trade policy sequence'

12. Time subscripts are dropped where possible to to aid readability.

13. Similarly to Fischer (2017) and Fischer et al. (2018).

price of the technology, and a is the demand curve intercept:

$$r_i = \quad a - (p_i - s_i^{cons}) \tag{2.2}$$

implying that consumer surplus is

$$CS_i = \frac{a - (p_i - s_i^{cons})}{2} r_i = \frac{(a - (p_i - s_i^{cons}))^2}{2} = \frac{r_i^2}{2}$$

I assume that the clean technology replaces a dirty one, thereby avoiding negative externalities from pollution. For ease of exposition, I model this as a public benefit. The positive externality ($B_{i,t}$) from consumption in country i is a linear function[14] of global consumption:

$$B_{i,t} = \frac{b}{2}(r_{F,t} + r_{L,t})$$

The global positive externality is the sum of both countries' externalities, i.e.

$$B_t = b(r_{F,t} + r_{L,t})$$

Production and Market Structure Each country possesses a domestic industry capable of producing any quantity of the technology. The quantity produced in country i is denoted q_i. The cost of production depends on previous experience, with constant marginal cost c if experience exists and dc otherwise, where $d > 1$.

I assume that at the beginning of Stage 1, industry F is at the technology frontier with marginal production cost c, while industry L is lagging behind with marginal production cost dc. The process of the laggard country moving from marginal production cost dc in Stage 1 to marginal production cost c in Stage 2 will hereafter be referred to as 'catching up'. This process is captured by

$$c_{L,2}(q_{L,2}) = \begin{cases} cq_{L,2} & \text{if } q_{L,1} > 0 \\ dcq_{L,2} & \text{if } q_{L,1} = 0 \end{cases} \tag{2.3}$$

Markets are imperfectly competitive, with each country's domestic industry acting as a monopolist under autarky and a Bertrand duopolist under trade. I assume that the leading firm's monopoly price[15] exceeds the marginal cost of the lagging firm, such that trade puts competitive pressure on both firms under all scenarios. This implies that

$$\frac{a+c}{2} > dc \tag{2.4}$$

14. Linear climate damage functions are used in much of the literature on international climate cooperation, e.g. Battaglini and Harstad (2016) and Holtsmark and Midttømme (2021).

15. Firm F's monopoly price is given by Equation 2.6.

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Firms are assumed to be myopic and only take into account the information available in the current period.

Market Equilibrium Under autarky, firm i solves

$$\max_{\{p_i\}} \Pi_i = p_i q_i(p_i) + s_i^{prod} q_i(p_i) - c_i(q_i(p_i)) \tag{2.5}$$

Under trade, both consumers face the same prices – therefore, the firm with the lower price captures the whole market. Firm F's individual demand curve is given by

$$q_F(p_F, p_L) = \begin{cases} 2a - 2p_F + s_F^{cons} + s_L^{cons} & \text{if } p_F < p_L \\ a - p_F + \frac{s_F^{cons} + s_L^{cons}}{2} & \text{if } p_F = p_L \\ 0 & \text{if } p_F > p_L \end{cases}$$

while firm L's demand curve is given by

$$q_L(p_F, p_L) = \begin{cases} 0 & \text{if } p_F < p_L \\ a - p_L + \frac{s_F^{cons} + s_L^{cons}}{2} & \text{if } p_F = p_L \\ 2a - 2p_L + s_F^{cons} + s_L^{cons} & \text{if } p_F > p_L \end{cases}$$

. Let the competitive price faced by the consumer be denoted p. In the absence of producer subsidies, this leads to $p = c$ if the industry is levelled, and $p = dc - \varepsilon$ if it is unlevelled, where ε is an infinitesimal positive number. When producer subsidies are positive they modify firms' marginal costs accordingly.

I further assume that $a > dc$, which ensures consumption in all scenarios.

First Best A benevolent social planner seeking to maximise the sum of both countries' welfare over both periods would set global marginal benefits from consuming the technology, both private and public, equal to marginal cost c.[16] This yields

$$a + b - c = r_i$$

in each stage of the game. Proof: Appendix A.1.

Business As Usual Under autarky and without subsidies, each firm acts as a monopolist, leading to suboptimal outcomes due to monopoly losses, missed trade gains, and uninternalised externalities.

In both Stage 1 and Stage 2, in country F, the representative firm solves

16. Because the frontier country's marginal cost is lower, it is more efficient for the frontier country to supply the whole market in this scenario.

$$\max_{\{p_F\}}[\Pi_F = \quad (a-p_F)p_F-(a-p_F)c]$$

yielding

$$p_{F,1}=p_{F,2}=\frac{a+c}{2};r_{F,1}=r_{F,2}=\frac{a-c}{2} \tag{2.6}$$

In country L,

$$p_{L,1}=\frac{a+dc}{2};p_{L,2}=\frac{a+c}{2};r_{L,1}=\frac{a-dc}{2};r_{L,2}=\frac{a-c}{2}$$

Proof: Appendix A.1.

Subgame Perfect Nash Equilibrium I analyse governments' strategies over trade policy and subsidies. The following analysis will use backward induction to identify Subgame Perfect Nash Equilibria in pure strategies.

2.5 Analysis & Results

In the following, I identify Subgame Perfect Nash Equlibria in pure strategies for different versions of the game and examine their welfare implications. I start by analysing the case in which countries have the option to trade, but do not use any additional policy to correct market failures. I then move on to a scenario in which countries can additionally use quantity subsidies to support the clean technology.

2.5.1 Equilibrium and Welfare without Subsidies

Could a trade agreement on its own (absent other policy to internalise externalities or correct monopoly losses) constitute an improvement over business-as-usual? Proposition 1 discusses countries' welfare payoffs under different trade policy strategies and highlights how these depend on the distance to frontier d. Proposition 2 characterises the pareto optimal Subgame Perfect Nash Equilibrium, and Proposition 3 highlights the global welfare implications of different trade policy sequences.

Proposition 1. *Suppose that no subsidies can be employed, and the government's action set is restricted to T_i. Let T_i^* denote country i's trade policy choice in both periods under its best response. Then,*

i $\Sigma_{t=1}^2 W_{L,t}((\tau_{L,1},1),T_F^*)) > \Sigma_{t=1}^2 W_{L,t}((\tau_{L,1},0),T_F^*))$

ii $\Sigma_{t=1}^2 W_{F,t}((\tau_{F,1},1),T_L^*)) > \Sigma_{t=1}^2 W_{F,t}((\tau_{F,1},0),T_L^*))$

iii *There exists a threshold $\omega = f(a,c,b)$ such that*

- *For $d > \omega$: $\Sigma_{t=1}^{2} W_{L,t}((0,1),T_F^*)) \geq \Sigma_{t=1}^{2} W_{L,t}((1,1),T_F^*))$*
- *For $d < \omega$: $\Sigma_{t=1}^{2} W_{L,t}((0,1),T_F^*)) < \Sigma_{t=1}^{2} W_{L,t}((1,1),T_F^*))$*

iv *There exists a threshold $\gamma = g(a,c,b)$ such that*

- *For $d > \gamma$ and $b > a-c$: $\Sigma_{t=1}^{2} W_{F,t}((0,1),T_L^*)) \geq \Sigma_{t=1}^{2} W_{F,t}((1,1),T_L^*))$*
- *For $d < \gamma$ or $b < a-c$: $\Sigma_{t=1}^{2} W_{F,t}((0,1),T_L^*)) \leq \Sigma_{t=1}^{2} W_{F,t}((1,1),T_L^*))$*

v *For any a,c,b which are consistent with the assumptions of the model, $\omega < \gamma$.*

Proof: Welfare payoffs under trade and autarky and the implied thresholds ω and γ are derived in Appendix A.2.

Proposition 1, parts (i) and (ii) state that both countries are better off if they trade in Stage 2. In Stage 2, if the laggard firm has not caught up with the frontier firm, the frontier firm will dominate the market with a price $p = dc - \varepsilon$. However, if the laggard firm catches up, both firms share the market at a price $p = c$. In either case, trade leads to higher consumer surplus, consumption, and positive externalities compared to autarky.[17] Because trade requires mutual agreement, there are other Nash Equilibria in which there is no trade. Therefore, this implies that trade is a weakly dominant strategy for both countries in Stage 2.

If the laggard country has not caught up, the frontier firm extracts rent from the laggard country amounting to $c(d-1)r_L$. Conversely, if it has caught up, prices are lower, consumption, consumer surplus, and positive externalities are higher, and the deadweight loss of monopoly is eliminated. In order for the laggard country to catch up, countries must remain in autarky in Stage 1.

Proposition 1, part (iii) states that whether the laggard country's welfare over both periods is greater under trade in both periods or autarky in Stage 1, trade in Stage 2, depends on the value of d. As in Stage 2, in Stage 1 welfare is higher under trade than autarky. However, remaining in autarky allows the laggard country to catch up. If countries trade in Stage 1, then the frontier firm supplies the market in both periods. If they remain in autarky in Stage 1, the laggard country trades off welfare losses in Stage 1 for gains in Stage 2. Whether welfare gains in Stage 2 outweigh welfare losses in Stage 1 of remaining in autarky to catch up with the frontier country depends on whether d exceeds some threshold ω.

While the frontier country extracts rents from the laggard country in an unlevelled industry with trade, it also enjoys higher consumer surplus and positive externalities in Stage 2 if the

17. This is not the case when subsidies can be employed to correct for monopoly losses and positive externalities. However, when there are no subsidies, given stated assumptions trade always leads to competitive benefits for both countries.

laggard country has caught up. Proposition 1, part (iv) states that the frontier country's best response is also dependent on the value of d, as well as the level of the positive externality b. If d exceeds a threshold γ and there are positive externalities $b > a - c$, the frontier country's welfare payoff is also higher under the trade policy sequence $A = \{0,1\}$ than under $A = \{1,1\}$. Intuitively, while the intertemporal trade-off for the laggard country depends only on the relative levels of consumer surplus and positive externalities under different trade policy sequences, the frontier country additionally takes into account the rents it can extract from the laggard in an unlevelled industry under trade. In the absence of positive externalities, these rents ensure that the benefits from trading in the first stage (comprising higher consumer surplus in Stage 1, as well as rents collected in both stages) always outweigh the gains in consumer surplus in Stage 2 if the laggard has caught up. However, positive externalities from consumption present an additional gain from fiercer competition in Stage 2, resulting in the conditions presented in (iv).

Part (v) states that the threshold ω is smaller than γ, meaning that there are values of d for which the laggard country's pay-off is higher under $A = \{0,1\}$, while that of the frontier country would be higher under $A = \{1,1\}$.

Following from Proposition 1, we can characterise the pareto-optimal SPNE in pure strategies as follows:

Proposition 2. *If no subsidies can be employed, and the government's action set is restricted to T_i, then*

i There exists a pareto-optimal Subgame Perfect Nash Equilibrium in which the outcome is characterised by

- *Autarky in Stage 1, Trade in Stage 2 if $d > \omega$*
- *Trade in Stage 1, Trade in Stage 2 if $d < \omega$*

ii If $d > \gamma > \omega$ and $b > a - c$ or $d < \omega < \gamma$, this SPNE is pareto superior to any other trade policy sequence, including other Nash Equilibria as well as non-equilibria.

iii If $\omega < d < \gamma$ or $d > \gamma$ and $b < a - c$, the SPNE is pareto optimal, but the frontier country would enjoy a higher welfare payoff under trade in both Stage 1 and Stage 2.

Given that trade requires mutual agreement, it is sufficient for one country to prefer autarky over trade in order to prevent trade. Proposition 2, part (i) therefore describes the equilibrium as determined by the value of d in relation to ω as defined in Proposition 1: the pareto optimal Subgame Perfect Nash Equilibrium involves autarky in Stage 1, trade in Stage 2 if $d > \omega$, and trade in both periods if $d < \omega$.

Proposition 2, part (ii) states that if $d > \gamma$ (as defined in Proposition 1) and $b > a - c$ or if $d < \omega$, the policy outcomes defining the SPNE are associated with the highest possible welfare payoff for both the laggard and the frontier country, and are therefore pareto superior to all other possible outcomes (including both equilibria and non-equilibria). Part (iii) states that if one of these conditions does not hold, the equilibrium is pareto optimal, but it is not the only pareto optimal allocation: the frontier country would enjoy a higher welfare payoff under a different outcome which is, however, not an equilibrium.

As per the reasoning presented above and the welfare payoffs derived in Appendix A.2, if countries trade in Stage 2, neither country can increase its welfare by moving to autarky. In Stage 1, if $d > \omega$, cumulative welfare over both periods in the laggard country is higher by remaining in autarky, and moving to trade will therefore not constitute a welfare improvement. Since trade requires mutual agreement, the frontier country cannot unilaterally bring about trade, even if this would be welfare-improving. Moreover, if $d < \omega$, moving to autarky would be welfare-reducing for both countries, making the mutual decision to trade an equilibrium.

Other Equilibria The Subgame Perfect Nash Equilibrium in pure strategies as outlined in Proposition 2 is pareto optimal, but not unique. Due to the assumption that trade requires mutual agreement, opting for trade affects payoffs only if the other country also opts for trade, while opting for autarky affects payoffs only if the other country does not. This implies that there are additional Subgame Perfect Nash Equilibria which deviate from the equilibrium outlined in Proposition 2, for example because both countries have opted for autarky in Stage 1 despite $d < \omega$ or both countries have opted for autarky in Stage 2. These equilibria are pareto inferior.

Having analysed each individual country's welfare payoffs under different trade policy outcomes and characterised the pareto optimal SPNE, I now turn to global welfare.

Proposition 3. *If the government's action set is restricted to T_i, there exists a threshold $\theta = k(a,c,b)$ such that*

- *For $d > \theta$ and $b > \frac{a-c}{24}$:*

$$\Sigma_{t=1}^{2} W_{F,t}((0,1),(\tau_{L,1},1)) + W_{L,t}((\tau_{L,1},1),(0,1)) =$$
$$\Sigma_{t=1}^{2} W_{F,t}((\tau_{F,1},1),(0,1)) + W_{L,t}((0,1),(\tau_{F,1},1)) > \Sigma_{t=1}^{2} W_{F,t}((1,1),(1,1)) + W_{L,t}((1,1),(1,1))$$

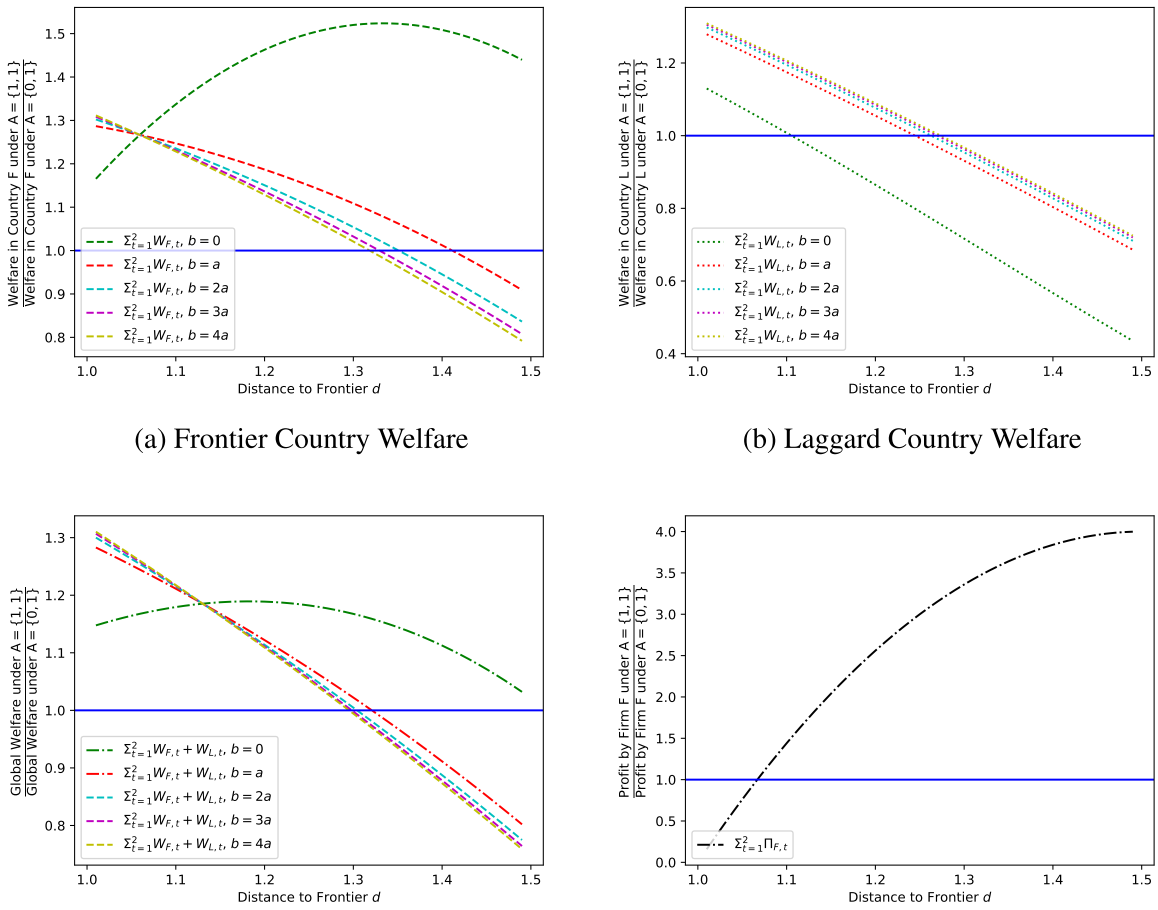
- *For $d < \theta$ or $b < \frac{a-c}{24}$:*

$$\Sigma_{t=1}^{2} W_{F,t}((0,1),(\tau_{L,1},1)) + W_{L,t}((\tau_{L,1},1),(0,1)) =$$
$$\Sigma_{t=1}^{2} W_{F,t}((\tau_{F,1},1),(0,1)) + W_{L,t}((0,1),(\tau_{F,1},1)) < \Sigma_{t=1}^{2} W_{F,t}((1,1),(1,1)) + W_{L,t}((1,1),(1,1))$$

Proof: θ is derived in Appendix A.2.

Proposition 3 states that the presence of positive externalities implies that the policy sequence $A = \{0,1\}$ is associated with greater global welfare than $A = \{1,1\}$ if d exceeds a particular threshold. For any a, c, b which are consistent with the assumptions of the model, $\omega < \theta < \gamma$.

Appendix A.2 derives welfare payoffs for both countries for all possible strategy profiles.



(a) Frontier Country Welfare

(b) Laggard Country Welfare

(c) Global Welfare

(d) Profit by firm F

Note: The figures above plot the ratios of overall (sum of Stage 1 and Stage 2) country welfare, global welfare, and firm F's profit for different values of d under $A = \{1,1\}$ as compared to $A = \{0,1\}$ when $a = 2c$. Figures A.1, A.2 and A.3 (Appendix) show the same plots for different ratios of a to c. Where the ratio falls below 1, the outcome in question is improved by remaining in autarky in Stage 1.

The figures illustrate the opposing effects of trade on profit and welfare: the further country L is from the technological frontier, the more $A = \{1,1\}$ reduces overall welfare as compared to $A = \{0,1\}$, and the more it increases firm F's profits (firm L's profits are not plotted as the ratio is always 0). Figures 2.4a and 2.4c highlight the significance of the positive externality $b(r_F + r_L)$ in the model: for $b = 0$, $A = \{1,1\}$ is always welfare improving for the frontier country, as well as globally, for any value of d which is greater than 1 and satisfies Equation 2.4. However, for sufficiently large positive values of b, trading in both periods can become welfare reducing beyond certain thresholds of d for both countries. Moreover, the greater b becomes relative to a, the more the ratio of individual countries' welfare payoffs should resemble each other.

FIGURE 2.4
Welfare and Profit Under Trade Relative to Autarky

Figure 2.4a plots the ratio of the frontier country's, Figure 2.4b the laggard country's overall (Stage 1 plus Stage 2) welfare under the policy sequence $A = \{1,1\}$ versus $A = \{0,1\}$ for different values of d and b when $a = 2c$. The figures show that for $b = 0$, losses in rents and Stage 1 externalities and consumer surplus outweigh any Stage 2 gains in externalities and consumer surplus from the laggard industry catching up for the frontier country, while ω is much lower than it is at higher values of b. The greater the positive externality b, the more closely aligned countries' preferences for trade or autarky in Stage 1 become: ω and λ converge as b increases. Finally, Figure 2.4c plots the ratios of global welfare for different values of b, showing that in the absence of positive externalities, global welfare implications more closely resemble the frontier country's welfare and make free trade the preferred choice. When a positive externality is present, remaining in autarky in Stage 1 to allow the laggard country to catch up becomes welfare improving globally for sufficiently high values of d.

Finally, Figure 2.4d plots the ratio of profits earned by firm F in the scenario $A = \{1,1\}$ compared to $A = \{0,1\}$.

2.5.2 Optimal Subsidy Mix Under Trade

In the presence of market failures such as consumption externalities and imperfect competition, a policy maker may want to intervene beyond the decision whether or not to trade. In this section, I therefore consider the use of quantity subsidies.

An upstream (producer) subsidy shifts the firm's profit, as in Equation 2.5, while a downstream (consumer) subsidy shifts the demand curve, as shown in Equation 2.2. Under autarky, either subsidy affects quantitites and welfare in the same way. Under trade, the subsidy mix matters.[18]

Let s_i^* denote country i's optimal subsidy mix, with s_i^{prod*} and s_i^{cons*} denoting the optimal producer and consumer subsidy.

Proposition 4. *Suppose both countries can choose a mix of consumer and producer subsidies. In Stage 1, the laggard firm produces at constant marginal cost dc, while the frontier firm produces at constant marginal cost c. Then there exists a pareto-optimal SPNE in pure strategies such that*

i *Countries trade in both periods:* $T_L^* = T_F^* = (1,1)$.

ii *In each period, the laggard country sets its producer subsidy at* $s_L^{prod*} = c(d-1) - \varepsilon$.

iii *The frontier country does not use producer subsidies:* $s_F^{prod*} = 0$

iv *In each period, both countries set consumer subsidies* $s_F^{cons*} = s_L^{cons*} = \frac{b}{2}$.

18. Fischer (2017) highlights how under imperfect competition, an upstream subsidy will enhance the domestic firm's market share, while a downstream subsidy benefits both domestic and foreign firms. Under Cournot competition, a downstream subsidy also tends to increase prices globally, which is not the case here.

Proposition 4, part (i) is based on the observation that if both countries have the flexibility to choose their subsidy mix, the weakly dominant strategy for both is to trade in both periods.[19] Part (ii) states that the laggard country opts for a producer subsidy that enforces marginal cost pricing and prevents the frontier firm from extracting rents:

$$s_L^{prod*} = c(d-1) - \varepsilon$$

Part (iv) states that simultaneously, both countries implement a consumer subsidy equal to

$$s_F^{cons*} = s_L^{cons*} = \frac{b}{2}$$

, thereby internalising domestic positive externalities.

As a result, the frontier firm supplies the global market at a price of $p = c$, with demand (r_F and r_L) equal to $a - c$. The outcome is equivalent to perfect competition. Welfare in each country during each stage of the game can be expressed as:

$$W_F = W_L = \frac{(a-c)^2}{2} + b(a-c)$$

This configuration represents a Subgame Perfect Nash Equilibrium in this model. The equilibrium is pareto-optimal, but not unique. Optimal subsidies and the resulting quantities and welfare payoffs are derived in Appendix A.4.

The laggard country has no incentive to deviate from this equilibrium. Moving to autarky would increase production costs and reduce consumer surplus and positive externalities. Setting a higher upstream subsidy results in either market sharing or the laggard firm monopolising the market, both of which similarly reduce its welfare. Reducing the subsidy would allow the frontier firm to extract rent from its consumers and increase prices while reducing consumer surplus and positive externalities.

Likewise, the frontier country finds no welfare-improving deviations. In autarky, the frontier country would set a subsidy which eliminates the deadweight loss from the monopoly and internalises domestic positive externalities, leading to the same domestic outcome as that which is obtained when countries trade and $s_L^{prod*} = c(d-1) - \varepsilon$ and $s_F^{cons*} = s_L^{cons*} = \frac{b}{2}$. Autarky would reduce welfare in the frontier country by lowering positive externalities from consumption in the laggard country.

Finally, given the price regime and trade conditions, $\frac{b}{2}$ is the optimal consumer subsidy. While positive externalities would increase if the subsidy was higher, each country considers only the marginal benefit to its own population, which equals $\frac{b}{2}$.

19. When both producer and consumer subsidies are available, neither country benefits from allowing the laggard country to catch up. The inter-temporal trade-off therefore becomes irrelevant.

The policy mix countries will choose if they are able to trade and use a combination of producer and consumer subsidies thus delivers the highest cumulative welfare, given the first best is not available. It cannot correct the market failure resulting from the climate externality. However, it yields an outcome equivalent to perfect competition.

Other Equilibria The Subgame Perfect Nash Equilibrium in pure strategies as outlined above is pareto optimal, but not unique. Because trade requires mutual agreement, neither country can unilaterally decide to bring about trade. If one country opts to remain in autarky then the other country is indifferent between trade and autarky, making trade a weakly dominant strategy. This implies that there are additional Subgame Perfect Nash Equilibria in which countries trade only in one period, but not the other, or remain in autarky throughout both periods. In any given stage of the game, such an equilibrium could come about because both countries have opted for autarky. The optimal subsidy for each country becomes that which eliminates the deadweight loss from monopoly and internalises domestic positive externalities. However, both countries are worse off under autarky relative to trade, rendering these other equilibria pareto inferior. For optimal subsidies, quantities and welfare under autarky, see Appendix A.3.

Equilibrium and Welfare without Producer Subsidies In practice, countries have often relied on downstream subsidies to support green industries. This may be due to political acceptability considerations, fiscal constraints, or the dubious status of upstream subsidies under World Trade Organisation rules. This section therefore analyses equilibrium policy and welfare when only consumer subsidies are available.

Proposition 5. *Suppose countries can only use consumer subsidies, and all other assumptions remain unchanged. Then,*

i $\Sigma_{t=1}^{2} W_{L,t}((0,1), s_L^*, T_F^*, s_F^*)) = \Sigma_{t=1}^{2} W_{L,t}((0,0), s_L^*, T_F^*, s_F^*) > \Sigma_{t=1}^{2} W_{L,t}((1,\tau_{L,2}), s_L^*, T_F^*, s_F^*))$. *There are thus two weakly dominant strategies for the laggard country. One strategy involves autarky in both stages, while the other involves autarky in the first and trade in the second stage.*

ii There are eight SPNE in pure strategies. In all of them, the strategy profiles imply autarky in the first stage.

iii For all equilibria, in Stage 1: $s_{F,1}^{cons*} = a + b - c$, $s_{L,1}^{cons*} = a + b - dc$

iv For all equilibria, in Stage 2, both firms produce at constant marginal cost c.

v For the set of SPNE in which countries trade in the second stage, in Stage 2: $s_{F,2}^{cons*} = s_{L,2}^{cons*} = \frac{b}{2}$

vi For the set of SPNE in which countries are in autarky in the second stage, in Stage 2: $s^{cons*}_{F,2} = s^{cons*}_{L,2} = a + b - c$

Proof: Appendix A.4.1.

Proposition 5, part (i) states that the laggard country's overall welfare payoff is higher if countries remain in autarky in Stage 1 than if they trade in Stage 1. Whether countries trade in Stage 2, having remained in autarky in Stage 1, is irrelevant to either country's welfare. Under autarky each government will subsidise in order to eliminate the deadweight loss from the monopoly and internalise the domestic part of the climate externality.

As a result, there are no competitive benefits from trade, and quantities consumed in both countries in any given stage are the same under trade as under autarky. However, remaining in autarky in Stage 1 implies equalised marginal costs in Stage 2, which reduces prices, increases consumer surplus and positive externalities, and eliminates the possibility of rent extraction by the frontier country. The laggard country's (weakly)[20] dominant strategy is therefore to remain in autarky in Stage 1. There is no equlibrium involving trade in Stage 1. In Stage 2, both countries are indifferent between trade and autarky as quantities consumed and welfare payoffs are identical under both scenarios. There are thus eight Subgame Perfect Nash Equilibria in pure strategies, as stated in Proposition 5, part (ii).

Each SPNE involves autarky in Stage 1, with the consumer subsidies given in Proposition 5, part (iii). As a result, the laggard firm catches up and also produces at marginal cost c in Stage 2, as stated in part (iv).

Part (v) states optimal consumer subsidies in Stage 2 of those SPNE which involve trade in the second stage, while part (vi) states optimal consumer subsidies in Stage 2 of the SPNE which involve autarky in the second stage.

To see why these are the only pure strategy Nash Equilibria, suppose countries opted for trade in Stage 1. As shown in Table A.3, Appendix A.4.1, the laggard's welfare in Stage 1 remains the same, while the frontier country's welfare in Stage 1 increases by $c(d-1)r_L$. In Stage 2, following autarky, the laggard is indifferent between trade and autarky. However, its welfare would be higher, had it remained in autarky in Stage 1 and caught up to the technology frontier. Anticipating this, the laggard could increase its Stage 2 welfare by moving to autarky in Stage 1, without sacrificing any Stage 1 welfare. Thus, the laggard's best response if the frontier country opts for trade in Stage 1 is to opt for autarky. Given the laggard's best response, the frontier is indifferent between trade and autarky.

20. Because trade requires mutual agreement, such that the laggard country would be indifferent between trade and autarky if the frontier country had opted for autarky.

2.6 Discussion & Conclusion

Government support for climate change mitigation technologies often goes hand in hand with efforts to promote domestic production, such as in the US Inflation Reduction Act and the EU's Net Zero Industry Act. Meanwhile, foreign subsidies for such technologies have in the past been met with trade restrictions such as anti-dumping measures, as for example in the US- and EU-China solar trade wars in 2012 and 2013. While restrictions on trade increase the cost of deploying green technologies, thereby potentially slowing down climate change mitigation efforts, attempts to reach an environmental trade agreement at the WTO have thus far been unsuccessful.

Promoting domestic green industries could be deemed desirable for many reasons. Underlying factors and objectives could include local job creation and the interests of industry lobby groups, as well as the resilience of domestic supply chains in a key sector such as energy, particularly in the context of a volatile geopolitical environment. Fischer (2017) shows how in the presence of environmental externalities, these individual country objectives can lead to an upstream subsidy race correcting environmental externalities in a framework building on Spencer and Brander (1983) and Brander and Spencer (1985), where two producing countries compete for a third country export market.

This chapter has focused on the implications of environmental externalities in the presence of an infant industry and imperfect competition. In the absence of policy tools such as subsidies to correct for market failures, temporarily protecting an infant industry can be beneficial for the protecting country in the long run. In contrast to other work on infant industries, which typically emphasises intersectoral spillovers and other growth-promoting factors rendering a sector strategically important, these benefits arise because allowing the infant industry to mature increases global competition later on. This prevents rent extraction by the country which was originally at the technology frontier. Moreover, when there are sufficiently large positive externalities from the technology (such as, in this case, avoided climate damages), allowing an infant industry to catch up improves not only the welfare of the initially laggard country, but also global welfare, and sometimes even the welfare of the frontier country.

In contrast, when countries are able to use both up- and downstream subsidies, the laggard can avoid rent extraction by the frontier country and global gains from trade are maximised. Infant industry protection is no longer necessary in this framework and the short-term costs associated with it can be avoided. However, when only downstream subsidies are available, gains from trade disappear. Then, both the laggard country's welfare as well as global welfare are unambiguously higher when the infant industry is allowed to catch up. The frontier country is worse off than under free trade, as it loses the ability to extract rents from the laggard.

The model provides intuition for why it may be optimal that (a) countries supporting clean technology often use trade barriers such as local content requirements, to the extent to which those actually work,[21] and (b) early movers in the global market often oppose production subsidies, as was apparent in the EU and US-China solar trade wars, for example.[22] The results imply that an environmental trade agreement may be desirable from a climate point of view only when production subsidies are available. Global trade law does not currently make allowances for the potential global benefits of producer subsidies for products with positive externalities, which renders such subsidies susceptible to challenge, as exemplified in the US- and EU-China solar trade wars. This relates to the broader challenge of reviewing WTO rules to ensure they are compatible with climate goals, especially given stated plans to introduce a Carbon Border Adjustment Mechanism in the European Union (Grubb et al. 2022).

More broadly, the framework presented here demonstrates that when there are positive externalities, industrial policy can benefit not only the country undertaking it, but also the rest of the world. This is relevant to any technology with positive consumption externalities in addition to those with environmental benefits.

The model presented is very parsimonious and includes a number of limiting assumptions. First, the only mechanism through which an active domestic industry is beneficial for the laggard country is by catching up the technology frontier and thereby avoiding rent extraction by the other country. Once the laggard has caught up, Bertrand competition implies profit dissipation for both countries. The model abstracts from any other potential benefits of having an active domestic industry, such as job creation or inter-sectoral spillovers.

While there may be some differences in quality, the products motivating the chapter – such as solar panels, batteries or vaccines – are homogenous enough for price competition to be a reasonable assumption. The ‘catching up’ process can be conceptualised as implicitly being driven by entry costs or dynamic economies of scale, and, while highly simplified, is sufficient to illustrate the mechanism this chapter has sought to highlight. However, other factors such as capacity constraints on the one hand, economies of scale on the other, are not explicitly considered here and might more appropriately be modelled using Cournot competition.

In a Cournot model, both firms would produce positive quantities even in an unlevelled industry, implying that results would depend on the properties of the learning curve. Here, the learning process is modelled in a very simplistic way: if the laggard country is active, it catches up; otherwise the industry remains unlevelled. The frontier country does not learn. Future work could consider a more sophisticated learning curve, as well as dynamics of innovation in level

21. Recent empirical evidence, however, suggests that local content requirements alone are not sufficient to develop an infant industry, see Scheifele et al. (2022).

22. The inspiration for this chapter comes from China’s entry into the solar PV market, supported by industrial policy, and the resulting increase in competition and reduction in prices. By now, however, China has come to dominate the market for solar PV as well as other clean technologies. One might therefore argue that at this point in time, China has become the frontier country and countries which used to be early movers are lagging behind.

versus uneven global supplier markets. The merits of infant industry protection would then depend on the relative rates of learning, as well as degree to which current market share and competition incentivise learning and innovation.

Chapter 3

Was the Trade War Justified? Solar PV Innovation in Europe and the Impact of the ‘China Shock’

3.1 INTRODUCTION

Preventing the worst effects of climate climate change by limiting global temperature rises (be it to 2°C or even 1.5°C) requires rapid and dramatic reductions in greenhouse gas emissions around the world. In the face of continuing economic and population growth, this implies an even more rapid reduction in the global economy’s emission intensity. Technological change can lead to significant long run cost reductions in clean technologies, thereby altering the presumed trade-off between climate benefits and economic cost in magnitude (Popp et al. 2010) if not removing it entirely. This is rarely more evident than in the case of electricity production from renewable sources, specifically onshore wind and solar power, which saw reductions in the levelised cost of electricity of 23% and 73%, respectively, between 2010 and 2017 alone (Gielen et al. 2019). The main drivers of these trends, in particular with respect to solar technology, are thought to be policy support and the expansion of low cost manufacturing in China. The latter has, however, also resulted in trade tensions, culminating in the US-China solar trade war in 2012 and the EU-China solar trade war in 2013. This chapter adds to the empirical literature on clean technological change by examining whether low wage import competition presented a driver or a barrier to technological progress in solar photovoltaic technology. It also constitutes a case study relating to the wider literatures on the China Shock and on the relationship between competition and innovation in a world of heterogeneous firms.

The effects of competition (through trade or otherwise) on innovation and growth are ambiguous. Trade theory suggests that higher competition through trade leads to a redistribution of market share towards the most productive firms and the exit of the least productive, thereby raising overall productivity (Baldwin and Gu 2004; Melitz 2003). A similar effect could exist for innovation, with the most innovative firms escaping competition through innovation (Bloom et al. 2016), or innovating in order to simply keep up with competitors (Aghion et al. 2005; Baldwin 1992). Trade may further unlock benefits from comparative advantage, knowledge spillovers, and increased incentives to innovate due to a larger market (Grossman and Helpman 1990). On the other hand, more trade and fiercer competition could also harm innovation through a reduction of rents available to invest in it, and by reducing firms' ability to appropriate post-innovation rents (Baldwin 1992).

Empirically, the effect of competition on innovation appears to depend on market structure. Aghion et al. (2005) show that the relationship between product market competition and innovation resembles an inverted U-shape. In a related paper, Aghion et al. (2009) test the effects of entry on incumbent innovation using UK firm-level data, showing that the threat of entry encourages incumbent innovation and productivity growth in sectors close to the technological frontier, but may discourage it in laggard sectors. Schumpeterian growth models, such as the one presented in Aghion et al. (2014), provide a theoretical framework which can explain these empirical patterns. They distinguish between R&D efforts by laggard firms to 'catch up' with the leader, and efforts to innovate by neck-and-neck firms attempting to become a leader, which is more beneficial in a more competitive environment. An increase in product market competition leads to a 'Schumpeterian effect' reducing innovation among laggards, as the benefits of catching up with the leader are reduced when less rent can be extracted; at the frontier, firms may conversely be encouraged to innovate more in order to 'escape competition' (Aghion et al. 2014). Given the very low initial levels of competition identified by Carvalho et al. (2017), we might expect that increased competition would tend to encourage innovation within the solar PV manufacturing sector – in particular in countries which started out as the technological leaders. In line with the theory of international trade with heterogeneous firms, we would also expect to find this effect to be more pronounced among the most technologically advanced firms (Bloom et al. 2016; Melitz 2003).

Existing work on the evolution of the solar value chain includes Carvalho et al. (2017), who argue using descriptive statistics that although the expansion of solar panel manufacturing in China squeezed profit margins and forced many western firms out of the market, innovation became more intensive and radical among survivors. This is in line with some of the more general literature on Chinese import competition: Bloom et al. (2016), using European firm-level data, find that higher import competition from China after its accession to the WTO increased innovation within the most exposed European firms, while employment and survival among low tech firms decreased. In contrast, Autor et al. (2020) estimate the effect of Chinese import competition on US manufacturing innovation and find a significant negative impact on private sector innovation, both at the firm- and technology class-level. Chakravorty et al. (2023) find an inverted U-shaped relationship between innovation by publicly listed US firms and Chinese import competition, wherein the latter increased innovation if it was below 60%, but reduced it above 60%. Further, Acemoglu et al. (2016a) argue that import competition from China has been responsible for significant manufacturing job losses in the US, as well as weak overall employment growth. A systematic review of existing research on this topic by Shu and Steinwender (2019) concludes that the empirical literature finds mixed effects of import competition on firm productivity and innovation in the US in particular, but that positive effects are generally found for developing countries and, to some extent, Europe. The authors posit that perhaps the US are to the right of Aghion's inverted U, whilst Europe and the developing world are to its left.

The lack of consensus emerging from the broader 'China Shock' literature motivates this case study of the solar sector. I carry out a firm-level analysis of the effects of the China shock on firm-level innovation in solar PV and related technologies by 10,137 firms in 15 EU countries between 1999 and 2020. The main challenge to this endeavour is the endogeneity of trade patterns, which I address by instrumenting for country-level Chinese imports (scaled by market absorption) using overall Chinese exports to the rest of the world interacted with start-of-period import competition. Using import penetration in other countries or world exports as an instrument is a widely used approach in the broader China Shock literature. In addition, I interact country-level measures of import competition with a firm-level exposure measure based on the similarity of each firm's patent portfolio to those of Chinese solar innovators, based on Jaffe (1986)'s proposed measure of technological proximity.

The results indicate that firms which were exposed to higher import competition tended to innovate more if they had a low, and less if they had a high, historical stock of innovation – with the exception of the small minority of firms whose knowledge stock fell within the top 1 percentile, which also increased their innovation. Moreover, a high a priori technology stock is negatively associated with future innovation. This suggests that innovation in the solar PV sector was driven by newcomers, rather than incumbents with a large existing knowledge stock. Newer firms appear to have been more adaptive in responding to competition by increasing innovation, while incumbents may have been locked into old technological paradigms. Given that firms with a smaller existing knowledge stock seemed to innovate more overall, the fact that import competition was associated with higher innovation among those firms suggests that China's entry into the sector introduced a healthy dose of competition, calling into question the rationale behind the trade war.

I do, however, find evidence to suggest that import competition increased the odds of firm exit by about 10%. Moreover, I do not consider the effects of Chinese competition on employment or global market share in solar PV, outcomes which policy-makers may have considered to be of greater importance than innovation or market dynamism.

The remainder of the chapter proceeds as follows. Section 3.2 further motivates the case study by providing a brief overview of the literature on clean technological change and the context and significance of the solar trade war. Section 3.3 provides details of the dataset and empirical strategy. Section 3.4 reports results, and section 3.5 concludes.

3.2 Background: Clean Technological Change and the Solar Trade War

There is some empirical evidence that pricing carbon – economists' poster child for a 'first best' policy – can on its own encourage innovation in low carbon technologies, for example in the case of the EU ETS (Calel 2020; Calel and Dechezleprêtre 2016). However, a broader literature on technological change and the environment argues that this is not sufficient: there are multiple externalities at play, including positive knowledge spillovers from R&D, (dynamically) increasing returns to scale, technological lock-in and path-dependency, network effects and learning-by-doing. Energy systems in particular are resistant to change (Neuhoff 2005). This calls for a portfolio of policies, combining environmental regulation legislating for emission reductions with R&D incentives and policies to support diffusion (Acemoglu et al. 2012; Acemoglu et al. 2016b; Jaffe 2012; Jaffe et al. 2005; Popp 2010; Popp et al. 2010). In practice, governments aiming to promote renewable energy technology have deployed a range of demand-pull policies such as feed-in tariffs and renewable energy portfolio standards, as well as supply-push policies like R&D or manufacturing subsidies.

Aside from its importance for climate change mitigation, clean technological change may bring a number of co-benefits. Using citations from clean, grey and dirty transport and electricity generation patents to identify knowledge spillovers from those respective technologies, Dechezleprêtre et al. (2017) find that clean technologies tend to generate larger spillovers than their dirty counterparts (though they acknowledge this may be due to those technologies' novelty more than anything else). Renewable energy technologies are also thought to have particularly large macroeconomic multipliers (Hepburn et al. 2020). Co-benefits such as economic growth and job creation are often brought forward by governments seeking popular support for pro-climate technology support; this strategy, while possibly effective, has also contributed to trade tensions in the renewable energy space (Lewis 2012, 2014).

Gerarden (2023) estimates a dynamic structural model of oligopolistic (Cournot) firm competition to study the effects of consumer subsidies on solar manufacturers. Using data on the electrical conversion efficiency of solar panels as measure of technological innovation, he shows not only that induced innovation significantly increases the social benefits of subsidies (as compared to the benefit of short run mitigation alone), but also that induced innovation may not only occur in the country paying out the subsidies, but spill over to other parts of the world (Gerarden 2023). In addition to potential concerns over where the benefits of domestic subsidies accrue, foreign subsidies are inevitably susceptible to challenge under WTO law, as the case of solar PV demonstrates.

The Evolution of the Solar PV Sector Solar photovoltaics is a technology central to decarbonisation, which has undergone a dramatic evolution since its conception in the 1950s. Its cost has declined by a factor of almost 100 since then, making it a unique historical example in the sphere of energy technologies (Nemet 2006).

Nemet (2006), focusing on the period 1975-2001 (during which the cost of PV modules decreased by a factor of 20), identifies the three largest drivers of cost reductions (out of the seven considered) as being plant size, cell efficiency, and the cost of silicon. However, those seven drivers (which additionally include yield, poly-crystalline share, silicone consumption and wafer size) leave nearly half the change in cost over the period unexplained.

One of the potential explanations for this residual is increased competition (Nemet 2006). Indeed, the dramatic reductions in the cost of solar PV equipment are often attributed to the expansion of low-cost manufacturing in China (Carvalho et al. 2017; Dent 2018), which drastically increased competition in the sector, reducing the share of top 5 producers from about 80% in 2004 to about 30% in 2012 in up- and midstream production (Carvalho et al. 2017). Between 2010 and 2015 alone, the price of solar panels fell by 75% – two thirds of all solar panels were produced by Chinese manufacturers during this period (Gerarden 2023).

Due (at least to a large extent) to these dramatic falls in equipment costs, the levelised cost of electricity (LCOE) has decreased rapidly, making it competitive with fossil fuels in many cases. Figure 3.1 illustrates the rapid reduction in the LCOE from solar PV, falling from about 80,000 USD per MWh in 1965 to just 84 in 2016. The graph also shows how electricity generation using the technology has risen sharply since the turn of the century.

This is good news for the cost of greening the energy sector, which is responsible for two thirds of global greenhouse gas emissions (Gielen et al. 2019). However, the expansion of low-cost manufacturing in China has not only enabled dramatic cost reductions, but has also resulted in trade tensions.

Solar Trade Wars Figure 3.2a graphs the evolution of imports of solar panels from China to France, Germany, the UK, the US, and worldwide. While a notable drop can be observed following the trade dispute in 2012, the global trend mirrors country and regional trends. As figure 3.2b shows, world exports of solar panels also followed a similar trend for the regions shown, with China clearly rising to dominance between 2005 and 2010, but all countries' exports peaking just after 2010. This is likely reflective of the solar panel 'production glut': the global oversupply of solar panels which occurred during this period.

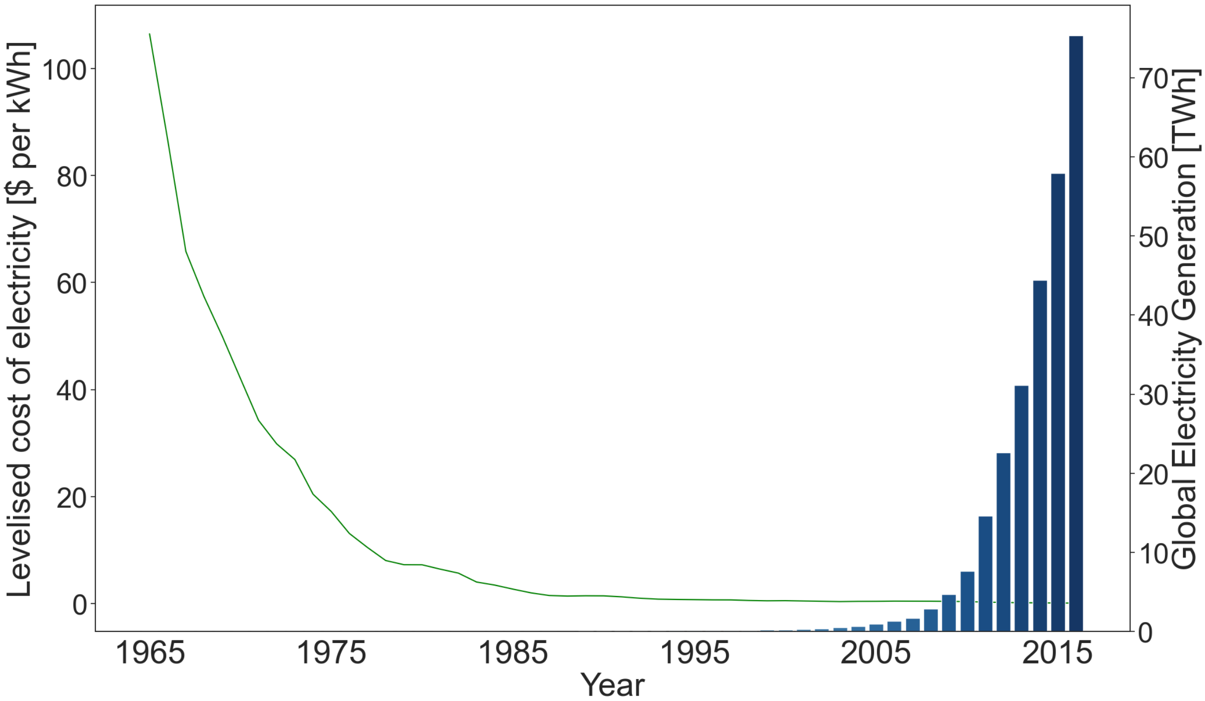


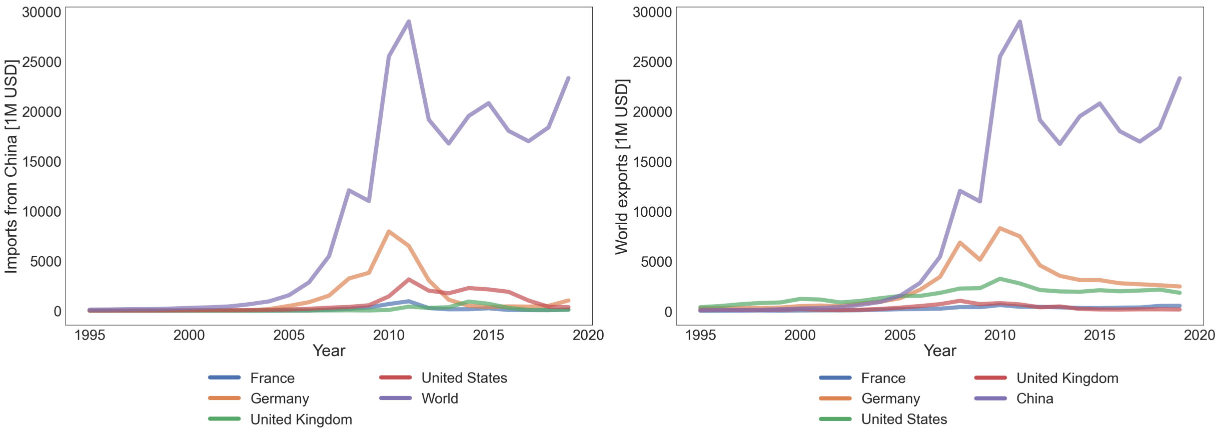
FIGURE 3.1
Solar PV Cost and Deployment Over Time

Note: The figure plots global levelised cost of electricity (LCOE) from solar PV in USD per kWh over time (left axis, green line) against global solar PV electricity generation in TWh (right axis, blue bars). It demonstrates the dramatic fall in costs between the 1960s and early 2000s, as well as the rapid increase in deployment since about 2005. Source: Way et al. (2022), Dudley et al. (2018).

In 2012, the US and China entered into a trade dispute over solar PV subsidies when the US imposed anti-dumping and countervailing duties on Chinese module manufacturers, following a petition led by a subsidiary of the German firm SolarWorld 2011. Tariffs were supported by a coalition of congress members and manufacturing firms despite opposition from a majority of US solar firms. China responded with a WTO complaint and imposed its own anti-dumping duties on US polysilicon (Hughes and Meckling 2017; Stemler et al. 2016).

The EU-China solar trade war started out in a very similar fashion. An industry coalition named ‘Pro Sun’, again led by Solar World, called for anti-dumping and anti-subsidy investigations. In September 2012, the European Comission launched investigations and imposed provisional tariffs on Chinese solar panel imports in 2013, despite opposition by a number of other industry coalitions. The dispute was resolved when the European Commission and China agreed on a minimum price for imports, as well as restrictions on export volumes (Meckling and Hughes 2018).

The extant literature studying the effects of these trade disputes suggests that the US and European anti-dumping measures reduced stock market valuations of Chinese solar companies (Crowley et al. 2019; Huang et al. 2016), as well as those of European manufacturers (Mc-



(a) Chinese Imports

(b) World Exports

FIGURE 3.2
Regional and Global Trends in Solar PV Trade

Note: Figure 3.2a plots Chinese imports of solar panels by a subset of countries and worldwide over time. Figure 3.2b plots the same countries' global exports of solar panels. Both graphs show a peak in solar panel trade around 2010, which led to the global production glut.

carthy 2016), and that they reduced demand for solar in the US and were generally damaging to downstream utilities and consumers (Houde and Wang 2022). More generally, anti-dumping measures are thought to have heterogeneous effects on firms in the protected market. Using European firm-level data and a distance-to-frontier measure, Konings and Vandenbussche (2008) find that laggard firms experience productivity gains and frontier firms experience productivity losses during periods of protection. Jabbour et al. (2019) distinguish between importing and import-competing firms when analysing the effect of EU anti-dumping measures on total factor productivity, employment, exports and investment in R&D over the period 1999-2007, and estimate a negative net effect on French employment and exports.

There are a number of competing claims surrounding the solar trade war, its justifications and its effects. On the one hand, US and EU trade defence measures against China were opposed by many domestic firms, whose position in the international supply chain meant that they could be adversely affected by the anti-dumping measures (Curran 2015; Meckling and Hughes 2018; Wu and Salzman 2013). On the other hand, the narrative supporting trade remedies held that China was utilising unfair public subsidies to drive out foreign competition and establish a monopoly by 'dumping' underpriced solar panels on the European market. Ensuring a competitive solar industry in the future would in such a case require trade defence (Goron 2018). Gaining better insight into how China's manufacturing expansion affected the solar sector, and thus, potentially, the energy transition, is crucial in order to evaluate the decision to impose trade defence measures.

3.3 Data & Empirical Strategy

This chapter combines firm-level patent data with country-level trade and production data. Data on patent families, representing inventions, was obtained from the EPO's PATSTAT Global Database (2023 spring edition). Patents and their respective patent families were selected using a list of technology codes from the Cooperative Patent Classification (see Table B.1 for the list of codes used). The technology categories included are solar photovoltaic cells; production equipment and inputs; storage; energy systems which include solar cells; enabling technologies; and hybrid technologies such as solar PV-thermal or solar-wind hybrids. Codes were selected via a keyword search and manual checks on the descriptions of codes within the Cooperative Patent Classification. Furthermore, patents related to solar cells were identified as belonging to generation 1, 2 or 3 as set out in Table B.2 (Appendix B.2).[1] [2]

Patent families were matched to patent applicants and inventors, identified by their *psn_id*. *psn_id* records were retained if the assignee's country code was among the sample of countries studied, and if the variable *psn_sector* identified them as a company. In addition, patents were matched to firms in Bureau Van Dijk's ORBIS database, using ORBIS IP as a crosswalk. This allows me to include firm-level financials, such as turnover, assets and employment, as control variables. However, the ORBIS-based firm panel results in a significantly smaller sample size (8,475 firms in the ORBIS versus 10,137 in the PATSTAT-derived final dataset, with the overall number of observations in the baseline regression using the ORBIS dataset amounting to only a third of those using the PATSTAT dataset). About 31.49% of all patent families (across all relevant technologies) could be matched to ORBIS. The analysis therefore relies primarily on companies from PATSTAT, using ORBIS as a robustness check.

The ORBIS dataset allows for the construction of a *survival* indicator, based on its status variable. The *survival* variable is assigned as 1 (indicating survival) if a firm is active for at least three years post the reference year, or if its last observed year is at least three years after the reference year. A value of 0 (indicating exit) is assigned to inactive firms whose final status is recorded within less than three years from the reference year. The variable is set to missing for years beyond 2018 or when the survival status is indeterminate.

Bilateral trade data was acquired from CEPII's BACI database (Gaulier and Zignago 2010). The database contains annual bilateral trade values and volumes for all countries at the Harmonised System 6 digit code level. This data was used to compile a panel of Chinese exports

1. My thanks to Professor Dr Ulf Blieske from the Cologne Institute for Renewable Energy for his help in categorising the set of solar photovoltaic codes into 'generations'.

2. Note that only two technology codes from the cooperative patent classification were categorised as falling under generation three; the categorisation does not consider tandem, triple junction, perovskites or quantum dot solar cells, as no technology codes relating specifically to these third generation technologies could be found.

to each of the countries in the sample at HS 1992 code 854140[3] and 854150[4]. Country-level production, overall import and export data at Prodcom code 26112240[5] and 26114070[6] was obtained from Eurostat's Prodcom database and combined with bilateral trade data to construct country-level import penetration measures. Country-level exposure to Chinese import competition at the start of the study period was proxied using trade and production in semi-conductors.[7] The sample includes the 15 countries for which Prodcom data was available from the start of the study period, 1999.[8]

TABLE 3.1
Summary Statistics

	mean	sd	min	max
Patent Family Count, Weighted by Size	0.20	1.97	0.00	143.04
Patent Family Count	0.19	1.66	0.00	79.00
Patent Family Stock, Weighted by Size	0.95	8.80	0.00	508.35
Patent Family Stock	0.87	7.29	0.00	295.01
Hirschmann-Herfindahl Index (Weighted Family Stock)	0.09	0.10	0.00	1.00
Import Penetration	0.09	1.20	-1.49	23.69
Exports (USD 100M)	16.67	21.80	0.00	84.36
Chinese Imports (USD 100M)	9.48	17.72	0.00	79.63
Market Size (USD 100M)	24728.24	37137.04	-1501.20	153435.19
Observations	91820			

Note: The table shows the mean, standard deviation and range of key firm- and country-level variables. While the regression uses size-weighted patent family counts and stocks, the table also includes simple counts as a point of comparison. Import Penetration is defined as $IMP_{it} = 100 * \frac{imp\_CHN_{it}}{prod_{it} + imp_{it} - exp_{it}}$, where imp_CHN_{it} is the value of solar panel imports from China in country i at time t, $prod_{it}$ is country i's production of solar panels at t, and imp_{it} are imports and exp_{it} exports of solar panels from country i at t.

3.3.1 Empirical Strategy

Definition of Key Variables The main dependent variable is each firm's new patent counts. To avoid double-counting the same invention, these counts are constructed at the patent family level, rather than the patent level. A patent family is a group of patents which relate to the same invention, but are filed in multiple patent offices for commercial purposes. Firm-level patent family counts are weighted by the size of the patent family. Weighting accounts for the fact that not all patents contain the same amount of innovative novelty – patents which have been filed in

3. Electrical apparatus; photosensitive, including photovoltaic cells, whether or not assembled in modules or made up into panels, light emitting diodes

4. Electrical apparatus; photosensitive semi-conductor devices n.e.s. in heading no. 8541, including photovoltaic cells, whether or not assembled in modules or made up into panels

5. Photosensitive semi-conductor devices; solar cells, photo-diodes, photo-transistors, etc.

6. Parts of diodes, transistors and similar semi-conductor devices, photosensitive semi-conductor devices and photovoltaic cells, light-emitting diodes and mounted piezo-electric crystals

7. Trade in semi-conductors was identified using HS92 codes 854110, 854121, 854129, 854130, 854140, 854150, 854160, and 854190, while domestic production data from Prodcom is based on Prodcom codes 26112280, 27902050, 26112260, 27115023, 26112240, 26112180, 26112150, 26114070, 26112120, and 26112220.

8. Austria, Belgium, Luxembourg, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the United Kingdom.

a larger number of countries are likely to be more valuable (Harhoff et al. 2003; Lanjouw and Schankerman 1999).

In addition, patent stocks for each firm j were computed as a measure of accumulated past innovation, where $FamStock_{jt} = FamStock_{jt-1} * 0.85 + FamCount_{jt}$, starting from 1980. Following convention (Hall et al. 2005), patents are discounted at an annual rate of 15% to account for the decay in their value over time. The patent stock variable aims to capture firms' heterogeneity in terms of their previously accumulated stock of knowledge. How much a firm has innovated in the past may affect its propensity to further innovate in solar PV and could alter the effects of import competition on the firm's innovative efforts. Theory and empirical evidence tend to suggest that firms which are more productive and/or innovative will be more likely to increase innovation (or at least reduce it to a lesser degree) in response to heightened competition, while the opposite is the case for firms that are further away from the technological frontier. Conversely, firms with a higher a priori patent stock may be more locked into old technological paradigms and therefore less able to innovate in more disruptive technologies.

Import penetration in country i and year t is defined as Chinese imports divided by market absorption:

$$IMP_{it} = 100 * \frac{imp\_CHN_{it}}{prod_{it} + imp_{it} - exp_{it}} \tag{3.1}$$

where imp_CHN_{it} is the value of solar panel imports from China in country i at time t, $prod_{it}$ is country i's production of solar panels at t, and imp_{it} are imports and exp_{it} exports of solar panels from country i at t. To aid interpretation as a percentage, the fraction is multiplied by 100.[9] [10] As an alternative to import penetration, some of the regressions use overall Chinese imports as the variable of interest (while controlling for market size).

The China Shock literature traditionally exploits sectoral variation in import penetration. Because I analyse trade and innovation in only one product, only geographical variation in trade is available. To obtain additional variation, I interact country-level import penetration and overall imports with a firm-level exposure variable based on the similarity of firms' patent portfolios to Chinese firms and inventors. For each sampled firm and each Chinese inventor associated with a solar patent, I collect all other patents in PATSTAT and their IPC codes. I then construct the share of each IPC class in the knowledge stock (calculated iteratively from 1980 and

9. The measure, being a percentage, is robust to price fluctuations which would affect both the numerator and the denominator. The sharp decline in solar panel prices during the period is therefore no cause for concern.

10. There are a few instances in which market absorption, and thus also import penetration, are smaller than zero. This may happen for a number of reasons related to the construction of Prodcom and external trade statistics by Eurostat. The production data is derived from the PRODCOM survey, while the trade data originally comes from external trade surveys. These surveys differ in a few respects, such as the sampling procedure, the product classification used originally, and the fact that Prodcom accounts for sales, while external trade statistics record the value of goods passing a border and estimate this value if no sale takes place, etc. Furthermore, Prodcom does not identify whether a product sold is consumed, or added to an inventory; for this reason, positive exports may be observed during a year when no production appears to have taken place.

discounted at 15% per year) of each sampled firm, as well as the share of each IPC class in the knowledge stock of Chinese inventors and applicants overall. Following Jaffe (1986), I use these shares to compute the cosine similarity of each firm's patent portfolio to the patent portfolios of Chinese solar inventors. This firm-level exposure variable is bounded between 0 and 1, with higher levels indicating higher similarity and therefore exposure to Chinese inventors.

Instrumental Variable Estimation Any attempt to study the effects of an increase in trade on an economy must contend with endogeneity issues. Import penetration in a given market at a given time is likely to be correlated with numerous factors which could affect, or be affected by, the innovativeness of the local industry – for example, local demand, the ability of the local industry to meet demand, its competitiveness in terms of quality and price, etc. However, import penetration in other, similar countries or overall Chinese export growth are more likely to be externally driven by China, rather than each country's endogenous characteristics and capabilities.

The main regression specification therefore uses exposure-weighted Chinese export growth in solar panels as an instrument for import penetration in each country. The instrumental variable is 3-, 4- and 5-year averages in overall Chinese exports to the rest of the world times a given country's import penetration in semi-conductors at the start of the study period (1999).

Prior research within the China shock literature tends to consider multiple industrial sectors, rather than just one. Because this is a case study focusing on a single technology, the only sources of variation in import competition are time and geography. While other work within the China Shock literature has constructed Bartik-style instruments exploiting the share of a given industry in regional employment, for instance (Autor et al. 2013), this chapter therefore uses start-of-period import competition in semi-conductors as a measure of 'exposure'. In addition, I interact import competition with firm-level technological similarity to obtain a more granular measure of exposure. The analysis further accounts for unobserved firm characteristics and time shocks by using year and firm fixed effects.

The validity of the instrumental variable rests on the assumption that it is a) relevant and b) exogenous. Relevance is easily verified using the results of the first stage regression reported in Table 3.2. The instrument is highly relevant, with a first stage F-statistic of 22.6 for regressions using import penetration and 98909 when using overall Chinese imports.

The exclusion restriction for Bartik-style instruments requires that the shares used to construct them are uncorrelated with the error term of the main regression, given controls (Goldsmith-Pinkham et al. 2020). The validity of the instrumental variable used here therefore rests on the assumption that the share of Chinese imports in each country's market for semi-conductors in 1999 does not affect innovation in solar panels through any channels other than its implications for import competition in solar panels (given controls, which include firm fixed effects). I argue that this is a reasonable assumption, given that China did not accede to the WTO until 2001 and did not account for a significant share of semi-conductor trade in 1999. In the dataset used in this analysis, the highest level of import penetration in semi-conductors in 1999 was observed in Belgium, amounting to 0.01%. By 2012, semi-conductor import penetration in Belgium had risen tenfold to 0.11%, with the highest levels observed in the Netherlands at 0.69%.

Estimation Strategy The system of equations used to estimate the relationship of interest is

$$\begin{cases} \sum_{k=t}^{t+3} FamCount_{j,k} = & \exp(\beta_1 \overline{IMP}_{i,t-4,t-3,t-2,t-1} * \overline{Exposure}_{j,t-4,t-3,t-2,t-1} \\ & + \beta_2 \overline{FamStock}_{j,t-4,t-3,t-2,t-1} + \gamma_j + \delta_t + \varepsilon + u_{FirstStage}) \\ \overline{IMP}_{i,t-4,t-3,t-2,t-1} = & b_1 \overline{CHNExports^{ROW}}_{i,t-4,t-3,t-2,t-1} * IMP_{i,1999}^{semi-conductors} + \\ & b_2 \overline{Exports}_{i,t-4,t-3,t-2,t-1} + b_3 \overline{Absorption}_{i,t-4,t-3,t-2,t-1} + \\ & \gamma_j + \delta_t + u \end{cases} \tag{3.2}$$

where $\sum_{k=t}^{t+3} FamCount_{j,k}$ is the sum of quality adjusted patent families by firm j during the current year and the following 3 years; $\overline{IMP}_{i,t-4,t-3,t-2,t-1}$ is import penetration in country i (where firm j is based) , averaged over the preceeding 4 years; $\overline{Exposure}_{j,t-4,t-3,t-2,t-1}$ is firm-level proximity to the Chinese knowledge stock, $\overline{FamStock}_{j,t-4,t-3,t-2,t-1}$ is firm j's weighted, discounted patent family stock, $\overline{CHNExports^{ROW}}_{i,t-4,t-3,t-2,t-1}$ are Chinese exports to the rest of the world (excluding country i), $\overline{Exports}_{i,t-4,t-3,t-2,t-1}$ are country i's exports, and $\overline{Absorption}_{i,t-4,t-3,t-2,t-1}$ is market absorption in country i, all averaged over the preceeding 4 years. $IMP_{i,1999}^{semi-conductors}$ is import competition in semi-conductors in country i at the start of the period; γ_j are firm fixed effects; δ_t are year dummies; u and ε are error terms. Forward looking sums for the dependent variable and backward looking averages for the regressors are used to account for the fact that innovation is a prolonged process and any changes therein are likely to occur over a timespan of several years. Complete patent data from the PATSTAT 2023 edition is available until 2020, implying that 4-year forward looking sums effectively limit the analysis to 2017 and earlier.

Due to the count nature of the dependent variable, the relationship is estimated using a poisson fixed effects model, with the instrumental variable strategy implemented using the control function method. The residuals from the first stage are included in the second stage regression to control for the endogenous part of the main regressor.

Theory suggests that competition is more likely to induce innovation among firms which are at the technological frontier, while discouraging it among those which are lagging behind. To account for the potential heterogeneity of the relationship under investigation, some regression include interactions of the main regressor with two binary variables indicating whether the firm's historical patent family stock is in the top or bottom 1%, 5%, 10% or 20% of the sample for a given year.

Other variations of the regression model include 3- and 5-year sums and averages, and substituting overall Chinese imports for import penetration.

TABLE 3.2
First Stage Regression

	(1) Import Penetration	(2) Chinese Imports
Chinese Exports (ROW) × Semiconductor IMP˙1999	0.086***	0.738***
	(0.010)	(0.080)
Market Size (USD 100M)	-0.000***	0.000***
	(0.000)	(0.000)
Exports (USD 100M)	0.002***	0.372***
	(0.000)	(0.008)
Constant	0.015	-1.959***
	(0.015)	(0.110)
F Stat	22.62	98909.26
Observations	15356	15356

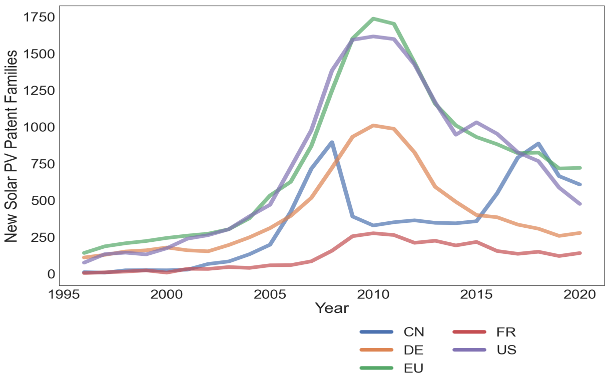
First Stage Regression on Estimation Sample.
All Variables are Averaged Over the Preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: The table shows the results of the first stage regression, using either import penetration or overall Chinese import volume as the endogenous regressor. The first stage includes year and firm fixed effects.

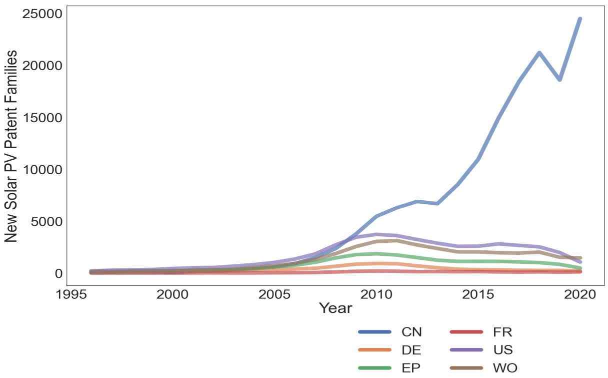
3.4 EMPIRICAL RESULTS

Trends in Solar PV and Related Patenting Figure 3.3a plots the number of new solar PV patent families over time by country of inventor or applicant. Patenting by Chinese inventors shows two peaks: one around 2007 and the other arond 2017. In contrast, figure 3.3b shows that the number of new patent families filed in the Chinese Patent Office, while stagnant in other authorities, has risen continuously and steeply since the early 2000s. Figure 3.4a plots new patent families filed anywhere in the world by generation of solar cell over time, showing a clear dominance of 2nd and 3rd generation over 1st generation solar cells since the 1990s. Figure 3.4b plots new patent families in solar PV and related technologies filed at any patent authority. While there appears to have been a slight dip in patenting in upstream production equipment and inputs, as well as solar cells and solar thermal, following the trade disputes in 2012/2013, overall trends for all technologies continue to increase.

Effect of Import Competition on Firm Innovation Table 3.3 reports regression results of overall solar cell innovation on imports, with and without the inclusion of the instrumental variable estimation. While the coefficient on Chinese Import Penetration, as well as overall Chinese

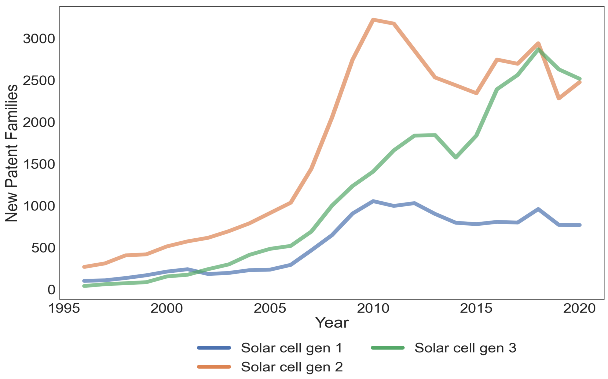


(a) Country of Inventor

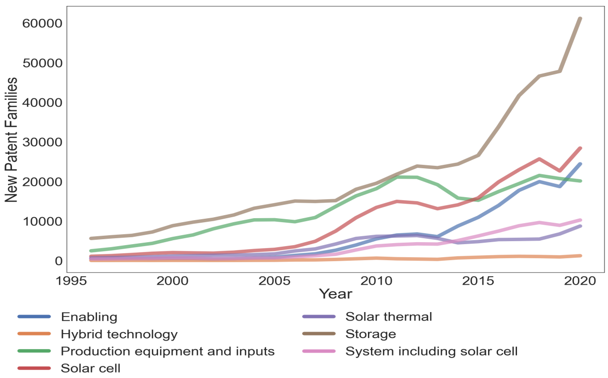


(b) Patent Office

FIGURE 3.3
Global Patenting Trends in Solar Cell Generations and Related Technologies



(a) New Solar PV Patent Families by Generation



(b) New Solar Related Patent Families

FIGURE 3.4
Regional Trends in Solar PV Patenting

Note: Figure 3.3a plots new solar PV patent families by country of inventor, while figure 3.3b plots families by patent authority, showing that while few new families were attributed to Chinese inventors after a small peak in the early 2000s, patents filed in the Chinese patent office are on a steep upward trend. Figure 3.3 plots new families filed at any patent office by generation of solar cell and for related technologies.

imports, interacted with firm-level exposure, is negative and significant when no instrumental variable and no other interactions are included (Models (1) and (5)), it becomes insignificant when using an instrumental variable design. The coefficient on import penetration remains insignificant when interaction terms accounting for heterogeneity in firms' existing patent stocks are introduced. However, Models (7) and (8) suggest that overall Chinese imports (controlling for market size) affect solar cell innovation differently for different firms. Firms whose patent stocks are in the bottom 10th percentile (which make up the majority – about 70% of observations) increase their quality-adjusted patenting by a factor of $e^{0.109} \approx 1.115$ for each unit of exposure weighted imports (100M USD times the cosine similarity to Chinese inventors). Firms whose stocks are in the top 10th percentile, conversely, reduce patenting by a factor of $e^{-0.026} \approx 0.974$. The coefficient on the historical stock of patent families is consistently negative and significant (though small in size), indicating that firms with a large historical knowledge stock tend to innovate less in general.

There is some nuance to this result. Table B.8 (Appendix) carries out the same analysis, but uses the top and bottom 1 percentile, instead of the 10th percentile, of accumulated patent stocks. Firms in the top 1 percentile make up only 0.8% of observations, while those in the top 10 percentile account for 6.57%.[11] The results in column (8) of Table B.8 indicate that firms in the top 1 percentile increase quality-adjusted patenting by a factor of $e^{0.012} \approx 1.01$ for each unit of exposure weighted imports. No significant results are found for the top 5 percentile (Appendix Table B.9), which account for 3.88% of observations, while the top 20 percentile (Appendix Table B.10, 9.91% of observations) show a similar pattern to the top 10 percentile.

TABLE 3.3
Effects of Chinese Imports on Solar Cell Innovation

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import Penetration × Exposure	-0.081**	-0.045	-0.122	-0.064				
	(0.032)	(0.060)	(0.126)	(0.141)				
Import Penetration × Exposure × Bottom 10%			0.091	0.084				
			(0.174)	(0.181)				
Import Penetration × Exposure × Top 10%			0.040	0.019				
			(0.127)	(0.123)				
Chinese Imports (USD 100M) × Exposure					-0.013**	-0.007	0.011	0.020
					(0.005)	(0.006)	(0.013)	(0.013)
Chinese Imports (USD 100M) × Exposure × Bottom 10%							0.108***	0.109***
							(0.023)	(0.024)
Chinese Imports (USD 100M) × Exposure × Top 10%							-0.023**	-0.026**
							(0.012)	(0.012)
Fam Stock	-0.001**	-0.001**	-0.001***	-0.001**	-0.002***	-0.002***	-0.001**	-0.001**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market Size (USD 100M)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.009***	-0.009***	-0.009***	-0.009***	-0.007**	-0.006*	-0.007**	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
IV regression		X		X		X		X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X
Observations	15356	15356	15356	15356	15356	15356	15356	15356

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in solar cells on Chinese import penetration and overall Chinese imports. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 1000 repetitions. Models 2, 4, 6 and 8 use an instrumental variables regression, implemented using the control function method.

Table 3.4 reports results separately for different generations of solar cells. While the co-

11. As the distribution is heavily skewed towards 0, the choice of percentile makes little difference as far as the lowest category is concerned (always about 70%).

efficients on exposure-weighted import penetration and its interactions remain insignificant for patenting in 2nd-generation solar cells, columns (2) and (4) suggest that a larger share of Chinese imports in overall market absorption is associated with higher patenting in generation 1 and 3 technologies for firms in the bottom 10th percentile of historical patenters. Meanwhile, higher levels of overall Chinese imports are associated with an increase in generation 2 patent counts by a factor of $e^{0.166} \approx 1.18$ for firms in the middle 80 percentile, and a reduction by a factor of $e^{-0.156} \approx 0.86$ for firms in the top 10th percentile. Patenting in generation 1 solar cells increases for the bottom 10th percentile only, while patenting in generation 3 declines by a factor of $e^{-0.019} \approx 0.98$ for the middle 80 percentile but increases by a factor of $e^{0.124} \approx 1.13$ for the bottom 10th percentile of historical patent stocks. These results broadly hold when controlling for market concentration using the Hirschmann-Herfindahl Index (calculated based on firms' shares in overall patent stocks within their countries) – results reported in Table B.4 (Appendix).

Results differ slightly when using the ORBIS firm sample (Appendix Table B.12): higher levels of import penetration are significantly associated with higher patenting in solar cells overall for the middle 80 percentile and negatively for the top 10th percentile, while no significant effect is observed for individual generations of solar cells. Meanwhile, Chinese imports overall seem to reduce innovation in the middle 80 percentile, while increasing it in the bottom 10th percentile, for generations 1, 3 and overall. As in the PATSTAT sample, a higher historical patent stock is associated with lower levels of future patenting.

Repeating the baseline regression separately for the periods before and after the trade war yields interesting effects: until 2012, both import penetration and increases in import volume increase patenting for firms with historical stocks in the bottom 10th, but reduce it for firms with a historical stock within the top 10th percentile. After 2013, all coefficients become insignificant (this can be observed both during the immediate aftermath, as well as the post-trade-war period overall). Results are reported in Appendix Table B.5.

I also examine the effects of Chinese imports on patenting in related technologies (results reported in Appendix Tables B.6 and B.7). Import penetration is negatively and significantly associated with patenting in storage technologies for the top 10th percentile and positively for patenting in production equipment for the bottom 10th percentile of historical innovators, while no significant effect is found for any other technologies. The volume of imports, on the other hand, is significantly associated with an increase in patenting for the bottom 10 and/or middle 80 percentiles in solar thermal, production equipment, storage, enabling, and systems related technologies. It is negatively and significantly associated in patenting in solar thermal, production equipment, storage, and enabling technologies for the top 10th percentile of historical patent stocks.

TABLE 3.4
Effects of Chinese Imports on Solar Cell Innovation by Generation

	(1) Solar cells	(2) Gen 1	(3) Gen 2	(4) Gen 3	(5) Solar cells	(6) Gen 1	(7) Gen 2	(8) Gen 3
Import Penetration × Exposure	-0.064	-0.363	9.714	-0.057				
	(0.134)	(0.221)	(17.086)	(0.161)				
Import Penetration × Exposure × Bottom 10%	0.084	0.916***	-9.049	0.275**				
	(0.174)	(0.214)	(17.104)	(0.136)				
Import Penetration × Exposure × Top 10%	0.019	0.000	-9.501	0.000				
	(0.119)	(0.000)	(17.088)	(0.000)				
Chinese Imports (USD 100M) × Exposure					0.020	-0.002	0.166*	-0.019**
					(0.013)	(0.014)	(0.092)	(0.010)
Chinese Imports (USD 100M) × Exposure × Bottom 10%					0.109***	0.163***	-0.018	0.124***
					(0.023)	(0.030)	(0.090)	(0.025)
Chinese Imports (USD 100M) × Exposure × Top 10%					-0.026**	0.000	-0.156*	0.000
					(0.011)	(0.000)	(0.090)	(0.000)
Fam Stock	-0.001**	-0.002	-0.039***	-0.001	-0.001**	-0.002	-0.038***	-0.001
	(0.001)	(0.003)	(0.005)	(0.001)	(0.001)	(0.002)	(0.005)	(0.001)
Market Size (USD 100M)	0.000	-0.000	0.000***	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.009***	-0.011	-0.013***	0.006	-0.006*	-0.007	-0.013***	0.011
	(0.003)	(0.007)	(0.004)	(0.007)	(0.003)	(0.008)	(0.005)	(0.008)
IV regression	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X
Observations	15356	2612	5855	3105	15356	2612	5855	3105

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in different generations of solar cells on Chinese import penetration and overall Chinese imports. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among during that year. Standard errors are heteroskedasticity robust and bootstrapped with 1000 repetitions. All regressions use an instrumental variables regression, implemented using the control function method.

3.4.1 Effect of Import Competition on Firm Survival

Finally, I use the ORBIS sample to estimate the effects of Chinese import penetration and import volume on the probability of firm survival, using a logistic regression reported in Table 3.5. The instrumental variable regression is once again implemented using the control function method. Results suggest that accounting for heterogeneity in firm patent stocks is not appropriate here. Model (2) indicates that a unit increase in exposure-weighted import penetration is associated with an $e^{-1.205} \approx 0.3$ factor reduction in the odds of a firm surviving over the next 3 years. Model (6) suggests that a unit increase in exposure-weighted import volumes reduces the same odds by a factor of $e^{-0.105} \approx 0.9$.

3.4.2 Robustness and Limitations

The baseline analysis relies on forward-looking sums (for the dependent variable) and backward-looking averages (for the explanatory variables) over 4 years. As a robustness check, I carry out the same analysis using 3- and 5-year sums and averages. Results are reported in

TABLE 3.5
Effects of Chinese Imports on Firm Survival

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import Penetration × Exposure	-0.818*	-1.205**	-1.451	-1.567				
	(0.465)	(0.548)	(2.949)	(2.991)				
Import Penetration × Exposure × Bottom 10%			0.974	0.697				
			(3.205)	(3.174)				
Import Penetration × Exposure × Top 10%			1.500	1.199				
			(3.049)	(3.067)				
Chinese Imports (USD 100M) × Exposure					-0.107***	-0.105***	-0.092	-0.090
					(0.034)	(0.035)	(0.340)	(0.295)
Chinese Imports (USD 100M) × Exposure × Bottom 10%							0.001	0.001
							(0.345)	(0.303)
Chinese Imports (USD 100M) × Exposure × Top 10%							-0.063	-0.063
							(0.342)	(0.297)
Fam Stock	0.120	0.119	0.106	0.108*	0.120	0.120	0.162*	0.162*
	(0.082)	(0.078)	(0.071)	(0.065)	(0.076)	(0.079)	(0.084)	(0.084)
Total Assets (USD 100M)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Number of Employees	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Size (USD 100M)	0.000	0.000	0.000	0.000	0.000**	0.000**	0.000**	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.023	-0.021	-0.022	-0.021	-0.021	-0.021	-0.021	-0.021
	(0.020)	(0.019)	(0.020)	(0.020)	(0.022)	(0.021)	(0.022)	(0.022)
IV regression		X		X		X		X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs								
Observations	25772	25772	25772	25772	25772	25772	25772	25772

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm Survival over 3 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: The table reports the results of a logistic regression of firm survival on Chinese import competition and overall imports. The dependent variable takes the value 1 if a firm is still active within 3 years, and 0 if it is not. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 1000 repetitions. IV regressions are implemented using the control function method.

Appendix Table B.3. Using 3-year sums and averages yields a qualitatively similar result in terms of the coefficient on exposure-weighted Chinese imports for firms whose patent stocks fall within the bottom 10 percentile, while there is no significant effect for the top 10 percentile. Over 5 years, on the other hand, qualitatively similar results are observed as over 4 years; however, there is an additionally significant positive effect of imports on innovation for the middle 80 percentile. All significant coefficients also increase in magnitude. This suggests that changes in innovation in response to competition tend to take place over longer time periods.

I further carry out two placebo tests.

First, I repeat the baseline regressions using randomised exposure variables. Firm-level exposure is randomised using a beta distribution, with the α and β parameters estimated using the real mean and variance of the distribution. Import penetration is randomised using Kernel Density estimation, and import volume is randomised using a log-normal distribution. Results are reported in Appendix Table B.13. All coefficients related to import competition are insignificant, lending credence to the validity of the baseline model.

Second, I construct a sample of firms patenting in dentistry prosthetics (IPC Class A61C/13). Dentistry prosthetics were chosen as innovation dynamics therein are arguably unlikely to be correlated with innovation in the solar sector (to the extent that this is ever the case where the evolution of different technologies is concerned). Results are reported in Appendix Table B.14. All patent-based variables, as well as exposure to Chinese firms, are constructed in the same way as in the main sample. This time, both the interaction of import volume (in solar PV) and with the bottom 10th percentile and that with the top 10th percentile of historical patent stocks are positive and significant (recall that in the main analysis, the first tended to be positive, the second negative and significant). This suggests that the effect of historical patenting dynamics may be the main driver of these results.

Results differ somewhat between the PATSTAT and ORBIS samples. No significant effect of import penetration on overall solar PV innovation was found in the PATSTAT sample, while in the ORBIS sample I observe a significant positive effect on firms with knowledge stocks within the middle 80 percentile and a significant negative effect on firms within the top 10 percentile. For overall Chinese imports I observe the same positive significant effect on firms within the bottom 10 percentile as in the PATSTAT sample; however, the coefficient becomes significant (and negative) for the middle 80 percentile, but insignificant for the top 10 percentile. There are some further differences when analysing different generations of solar cells separately, as discussed above.

While these results can be interpreted similarly, it is interesting that ORBIS firms display a similar response to import penetration as PATSTAT firms do to overall imports. The differences observed particularly between different levels of historical knowledge stocks could potentially be due to the characteristics of the ORBIS sample. Only about 31.49% of all patent families identified in PATSTAT could be matched to ORBIS. Moreover, other research has highlighted that larger, more productive firms tend to be overrepresented in ORBIS data (Bajgar et al. 2020). The PATSTAT sample is therefore more likely to be representative of the population of patenting firms. On the other hand, the ORBIS sample does allow for the inclusion of firm-level controls which may increase confidence in the results.

The exclusion of tandem, triple junction, perovskites and quantum dot solar cells from the category of generation 3 solar cells presents an additional limitation of the analysis. Finally, the analysis considers innovation as the only outcome of interest. Employment and market share, including in upstream and downstream sectors, are not taken into account here.

3.5 Discussion & Conclusion

Transitioning to cleaner energy sources is crucial in the fight against climate change. The expansion of low cost manufacturing of solar panels in China is credited with contributing strongly to the rapid decrease in the cost of producing electricity from solar photovoltaic technology. However, it has not been popular with some Western producers, and led to the imposition of anti-dumping duties against Chinese solar panels by the European Commission in 2013 (following a similar move in the US the previous year). In order to justify trade defence measures under WTO law, the member imposing them must argue convincingly that the other member is harming its industry by flooding its market with an unfairly subsidised or otherwise underpriced product.

This chapter provides an investigation of the effect of the 'China Shock' on solar PV innovation using a causal inference estimation strategy. I combine patent data from the EPO's PATSTAT database with country-level trade and production data from UN Comtrade and Eurostat, as well as firm level financials and status information from Bureau van Dijk's ORBIS database. Innovation is measured using patent family counts, weighted by family size to account for quality, and import competition instrumented using changes in overall Chinese solar PV exports to the rest of the world interacted with start-of-period import competition in semiconductors. I also interact import penetration and import volumes with a firm-level measure of similarity to Chinese innovators.

I find that an increase in exposure-weighted imports from China is associated with an increase in patenting for firms with a small existing patent stock and a reduction for firms with a relatively high patent stock, where the latter is defined as falling within the top 10th or 20th percentile for a given year. Conversely, firms whose accumulated knowledge stock falls within the top 1 percentile increase their patenting in response to an increase in imports. The effect of import penetration (the share of Chinese imports in overall market absorption) is statistically significant only for innovation in generation 1 and 3 solar cell technology, leading to an increase in patenting among firms with a relatively small historical stock of innovation. Firms with a large existing patent stock generally innovate less, which may be a sign of technological lock-in. Similar findings are obtained using a smaller sample of ORBIS firms with assets and employment as additional control variables.

The theoretical frameworks discussed in Section 3.1 indicate that firms at the technological frontier are likely to innovate more in response to an increase in competition, while laggards are likely to innovate less. The findings in this chapter are consistent with this prediction if we consider – somewhat counter-intuitively – firms with a small historical knowledge stock to be among the most innovative firms in the sample. This proposition seems reasonable given the consistently negative relationship between the historical knowledge stock and future patenting observed in this chapter. The small minority of firms with an accumulated stock within the top 1 percentile also increased their innovation in response to heightened competition, while the remainder of those within the top 20 percentile reduced patenting.

The empirical literature on the effect of Chinese import competition on innovation overall has yielded mixed results for the US, but broadly positive ones for Europe (Shu and Steinwender 2019). The results presented here are also consistent with Carvalho et al. (2017)'s observation that levels of competition in the solar sector were quite low prior to China's entry.

Given China's manufacturing dominance in primarily crystalline solar PV, we would expect that firms might attempt to compete by moving into 2nd or 3rd generation solar cells. However, when analysing the effects of Chinese imports on innovation within each generation separately I do not observe much of a difference, except that the positive effect of overall imports is observed for the middle 80 percentile of historical innovators for generation 2 and the bottom 10 percentile for generation 1 and 3. I also find a significant positive effect of import penetration on innovation among firms within the bottom 10 percentile in generation 1 and 3. These dynamics could be a reflection of the technology lifecycle, wherein more established as well as very novel technologies benefit from competition which is particularly driven by newcomers. Firms with a 'medium-sized' knowledge stock seem to have been more important in driving innovation in generation 2 solar technologies in response to import competition.

Overall we may infer that competition in the solar PV sector in the European countries studied, prior to China's entry into the sector, was low enough for competition to be conducive to innovation. The firms which responded by innovating more appear to have included relative newcomers to solar PV innovation, as well as very large incumbents with extremely high accumulated knowledge stocks. Other incumbents with large knowledge stocks, which were however not at the very top, seem to have been less able to adapt.

I further study the effects of import competition on innovation in related technologies. Import penetration appears to be negatively associated with patenting in storage technologies for firms with a large existing stock of innovation, while an increase in import volume increases patenting among firms with a low historical knowledge stock and reduces it among firms with a high knowledge stock for solar thermal, production equipment, storage, and enabling technologies. Finally, I use status information from ORBIS to compute a variable indicating firm survival over 3 years, and find that an increase in both import penetration and import volume, weighted by exposure, reduced the odds of firm survival considerably.

Overall, the fact that innovation appeared to be driven mostly by firms with a lower existing patent stock, and that those firms tended to innovate more in response to competition from China, suggests that the overall impact of import competition on innovation pre-trade war was likely positive. Trade defence measures appear to have been mainly in the interest of incumbents which were unable to adapt to a more competitive environment. Future trade policy should more carefully consider the competitive environment and whether more competition could be beneficial in incentivising incumbents to innovate more. Alternative measures for supporting domestic industries, such as R&D support, could also be considered.

However, the role of import competition in driving firm exit has implications for outcomes not explicitly studied here, such as employment or global market share in solar PV. Policymakers may have considered these to be of greater importance than innovation or market dynamism. Further research could explore the effects of Chinese import competition on other outcomes of interest. A focus on solar panel manufacturers more broadly, as well as firms operating in upstream and downstream industries, would be beneficial for this purpose.

Chapter 4

Stranded Nations? Transition Risks and Opportunities Towards a Clean Economy

4.1 INTRODUCTION

As the world transitions from dirty to clean energy sources and modes of production, some countries will be affected more than others. Previous research has explored which countries have the know-how, skills and innovative drive that makes them likely leaders in the 'race' towards green competitiveness (Fankhauser et al. 2013; Mealy and Teytelboym 2020). However, there has been less work to better understand the characteristics of countries that could get left behind. Are all exporters of 'brown' (or emissions intensive) products likely to face significant transition risk, or are some brown export industries more challenging to transition from than others? While recent literature has studied transition risks to companies (e.g. Bolton and Kacperczyk 2021) and financial systems (e.g. Semieniuk et al. 2021), quantitative estimates at the country-level are lacking. This chapter fills this gap by estimating the degree to which countries' productive capabilities are 'locked-in' to sectors that are at risk of stranding.

A rich literature in economic geography has shown that industrial development in countries and regions is path dependent (Hausmann and Klinger 2006). Places are more likely to diversify into new activities that are similar to those they already have an advantage in (Frenken et al. 2007; Hausmann and Klinger 2006; Hidalgo et al. 2007; Neffke et al. 2011). This, alongside the fact that exporting more technologically sophisticated products tends to be associated with higher income and growth (Hausmann et al. 2007; Hidalgo and Hausmann 2009), has given rise to the 'Smart Specialisation Policy' paradigm. The latter emphasises place-based industrial policy which targets complex new economic activities that are also related to existing regional capabilities, thereby increasing the likelihood of success (Balland et al. 2019; Boschma and Gianelle 2013). Path dependency implies that existing productive capabilities are important drivers of countries' ability to seize opportunities emerging in the green economy (Mealy and

Teytelboym 2020). It also creates the potential for countries to be locked-in to brown industries, possibly resulting in stranded assets, stranded jobs and the risk of economic decline.

Fossil fuel resources may become effectively worthless as countries around the world take action to mitigate climate change (Caldecott 2015; Cust et al. 2017), with significant implications for the companies and countries owning them. While the literature on asset stranding often focuses on carbon lock-in through long-lived physical infrastructure (e.g. Fisch-Romito et al. 2021; Pfeiffer et al. 2018), a broader definition beyond the risk to fossil fuel companies includes the risks to countries which are heavily dependent on fossil fuel exports, as well as workers whose skills are specific to declining activities (Van Der Ploeg and Rezai 2020). Country-level vulnerability to the transition will be governed both by their exposure to declining sectors, and their flexibility to adapt and change their economic structure accordingly (Zenghelis et al. 2018).

Here, we quantify the degree to which countries' productive capabilities are tied up in declining sectors and identify viable transition paths, which is crucial to achieving a just transition. With the exception of Jee and Srivastav (2022), there has been limited research on this issue. Jee and Srivastav (2022) use patent data to show that direct knowledge spillovers between green and brown technologies are limited, but most green patents are connected to a brown patent through two or more degrees of separation. However, the ability of different energy-related inventions to build on one another need not directly translate into the ease with which a country's productive capabilities as a whole may transition to new activities. Moreover, mitigating transition risk need not require moving into green sectors, but rather moving out of brown ones.

We leverage methods introduced by Hidalgo and Hausmann (2009) and Hidalgo et al. (2007); and Mealy and Teytelboym (2020) to develop indicators of country-level lock-in to brown sectors and transition opportunities into activities which require similar capabilities. First, we compile a list of traded 'brown' products that are likely to see reduced global demand in a green economy. Drawing on the product space approach developed by Hidalgo et al. (2007), we explore transition possibilities out of each brown product, and rank them in terms of their product complexity and transition outlook. While some products like coal or crude oil appear to have relatively limited diversification opportunities, other products such as engines, pumps and hydrocarbon-derived chemicals involve a wider variety of skills, capabilities and factors of production that could be used to diversify into other industries.

We then turn to countries and develop several novel metrics to explore the extent to which countries may be locked-in to brown exports. We show that countries exporting a high number of brown products, especially technologically sophisticated ones, may not only find it relatively easy to transition, but could also position themselves to play a key role in the production of green technologies and products. Conversely, countries with export baskets concentrated in few, low-complexity brown products have much more limited diversification opportunities into green or other exports. Their areas of specialisation are heavily concentrated in the periphery of the product space, with few 'nearby' areas to move into. This is due to the peripheral location of extractive industries such as oil, gas and mining in the product space. Affected countries have few adjacent areas to move into and are therefore unlikely to adapt to a net zero future without policy to enable path-breaking diversification. Our findings are evocative of the 'resource curse' literature which emphasises the difficulties resource-rich countries face in diversifying their economies (e.g. Krugman 1987; Manzano 2014).

Our results suggest that export complexity and diversity play a key role in mitigating transition risk and could potentially be more important than the 'brown-ness' of a country's export profile on its own. Early and pro-active policy interventions will likely be necessary to ensure a just and inclusive transition.

4.2 METHOD

4.2.1 Data

We construct our dataset using CEPII's BACI database (Gaulier and Zignago 2010), which is a global database of bilateral trade flows at the HS 6-digit level, spanning the period from 1995 to 2020. To ensure our results are not skewed by short-term trade fluctuations, we average country-product export values over 5-year periods. This results in a panel dataset of 5 distinct periods: 1996-2000, 2001-2005, 2006-2010, 2011-2015, and 2016-2020. Our panel includes 228 countries and territories. We collect control variables from the World Bank's World Development Indicators Database and OECD Stat's Environment Indicators.[1] Table C.5 (Appendix) displays summary statistics.

4.2.2 List of 'Brown' Products

We develop a new list of 'brown' products which are likely to decline in demand as the world decarbonises. Because our focus is on economic competitiveness in a low carbon global economy, we focus on products which are brown in *use* rather than brown in *production*. We create a narrow and a broad list based on an initial keyword search on product descriptions and then validate these lists with key subject experts. We also draw on lists of green (Mealy and Teytelboym 2020) and carbon capture and storage related (Serin et al. 2021) products used in prior research. More detail about the construction of this list can be found in Appendix Section C.1.

4.2.3 Measuring Dependence on Brown Exports

The Green Complexity Index (GCI) introduced in Mealy and Teytelboym (2020) provides a measure of the degree to which countries are able to capitalise on the opportunities the green

1. Variables from OECD Stat are available only for varying subsets of countries in our export dataset.

economy brings, by measuring their export competitiveness in technologically sophisticated green products. A key aim of this chapter is to construct a 'brown' counterpart to the GCI: a measure of dependence on brown activities which provide fewer and fewer opportunities to the economy as the green transition progresses. Intuitively, the GCI is a complexity-weighted count of a country's competitive green exports. It therefore has a strong relationship with a country's diversity (the number of products exported competitively) and especially its *green* diversity (the number of green products exported competitively). Table C.8 (Appendix) documents this relationship.

When it comes to measuring brown lock-in, however, we find that countries which depend on brown products for a large share of their export value or export diversity tend to have low diversity overall. That is, major hydrocarbon exporters, for example, with up to 90% of export value composed of brown products, have few other competitive exports – including, in many cases, brown competitive exports, as *brown* diversity and *overall* diversity are in turn positively correlated (Table C.8, Appendix). As Revealed Comparative Advantage (RCA) in brown exports for major fossil fuel exporters will in many cases be enormous, a binary measure of whether or not a country is competitive in brown products will not necessarily capture the degree of lock-in very well. On the other hand, exporting a large number of technologically sophisticated brown products implies that many pockets of competitiveness in high value-added activities are at risk of stranding. We therefore compute two indices capturing these different aspects of brown lock-in.

Our baseline measure of country lock-in to low-complexity, brown exports is the 'Brown Lock-in Index' (BLI), which we compute as:

$$BLI_c = \Sigma_b \frac{exports_b}{\Sigma_p exports_p} * (1 - \tilde{PCI}). \tag{4.1}$$

Here $\frac{exports_b}{\Sigma_p exports_p}$ is the share of each brown product in overall export values, and $\tilde{PCI}$ is the Product Complexity Index normalised to take a value between 0 and 1. Intuitively, the BLI measures the share of brown exports in a country's export volume, weighted by the inverse of PCI such that less technologically sophisticated products (which tend to be associated with lower income and growth compared to more complex ones, and open up fewer diversification paths) carry a larger weight.

We also construct a more obvious brown equivalent to the GCI: the Brown Complexity Index (BCI), calculated as

$$BCI_c = \Sigma_b \rho_b^c * \tilde{PCI}. \tag{4.2}$$

This index counts the number of competitive brown exports, weighted by each product's complexity (as opposed to the BLI, which measures their share in exports and gives a greater weight to less complex brown products). Export capabilities in more technologically sophisticated activities may take longer to develop, involve more specialised equipment, and tend to bring greater benefits to the economy in terms of growth and income. On the other hand, countries with high overall complexity tend to have higher income, rendering them more adaptable to climate- and transition risks. Finally, more complex products are located in the denser core of the product space (see Figure 4.1 for an illustration), implying a greater number of other, nearby diversification opportunities. Despite these benefits, countries must move out of brown areas of comparative advantage if we are to transition to a greener production system.

4.2.4 Measuring Transition Outlook

Due to the path dependency of industrial development, countries are more likely to develop future competitive advantages in products which require similar capabilities to the ones they already produce. Recall that Hidalgo et al. (2007) measure the similarity or 'pairwise proximity' of two products as the probability that a country has $RCA > 1$ in one if it does in the other. We use this insight to develop measures aiming to capture the ease of transitioning out of brown activities.

While country proximity to non-brown products would be a measure of climate compatible diversification options more generally, there may be physical, institutional and human capital within a country which specialises in a declining sector and cannot easily transition into those new activities – in other words, even if activity in declining sectors were balanced out, or even exceeded, by new opportunities within the same country, the firms and individuals facing the highest transition risk may not be the same as those benefiting from opportunities in the green economy. We therefore aim to measure the proximity of each particular declining activity to other, climate compatible activities.

For each brown product, we compute the average proximity to products in a non-brown list (green or any non-brown), divided by the product's average proximity to all products, as follows:

$$TransitionOutlook_b = \frac{\Sigma_q^Q \Omega_{b,q}}{Q} / \frac{\Sigma_p^P \Omega_{b,p}}{P} \tag{4.3}$$

where $\Omega_{b,q}$ is the pairwise proximity between brown product b and climate-compatible (green or non-brown) product q; Q is the total number of products of type q; $\Omega_{b,p}$ is the pairwise proximity between product b and product p; and P is the set of all traded products.

We then compute the *Country Transition Outlook* as the average of product-level transition possibilities from brown products which the country exports with $RCA > 1$ to products in a non-brown list (green/any non-brown):

$$TransitionOutlook_c = \frac{\Sigma_b \rho_b^c * TO_b}{\Sigma_b \rho_b^c} \tag{4.4}$$

where ρ_b^c indicates whether the country has RCA in product b, and TO_b denotes the product's Transition Outlook to list q.

All indices are standardised to mean 0 and standard deviation 1. Table C.4 (Appendix) provides an overview over the measures we construct using trade data, some of which are derived from prior literature.

4.3 RESULTS

4.3.1 Are Brown Products Different From Other Exports?

Following the methodology originally used to create the product space (Hidalgo et al. 2007), Figure 4.1 plots the network of all products at the 6-digit level, highlighting those categorised as green or brown. In this network, traded products are represented as nodes, linked to each other on the basis of their product-to-product proximity. This provides some visual intuition for where green and brown products are located in the broader product space. Some brown products (such as conventional vehicles) are located within the dense core of the product space, close to many non-brown products, including green ones (such as electric or hybrid vehicles). Others, such as bovine meat or crude oil, are located in the periphery and mostly near other brown products. Petroleum is a particularly interesting case: while refined oil is arguably still within the core and near a good number of other products, crude oil is very peripheral. This would suggest that countries engaged in petroleum refining may find it easier to transition than those mostly exporting crude oil.

Overall, we find that brown products tend to be less complex than green products (see Figure 4.2). We also find that brown products tend to be closer to green products in the product space than they are to other products. This suggests that countries which export these products may find it relatively easy to shift towards greener activities.

Figure 4.2 plots the distribution of the Product Complexity Index (hereafter PCI) for products on our narrow brown list (in brown), compared to the distribution of PCI for all products (in blue). The PCI distribution for brown products is not statistically different to the PCI distribution for all products, suggesting brown products are no more or less complex than average.[2] Brown products thus tend to be less complex than green products, the latter on average being more complex than other products (Mealy and Teytelboym 2020).

Tables C.10 and C.11 (Appendix) list the 20 brown products with the highest and the lowest

2. The two sampled Kolmogorov–Smirnov test statistic is 0.0499 and the p-value is 0.816.

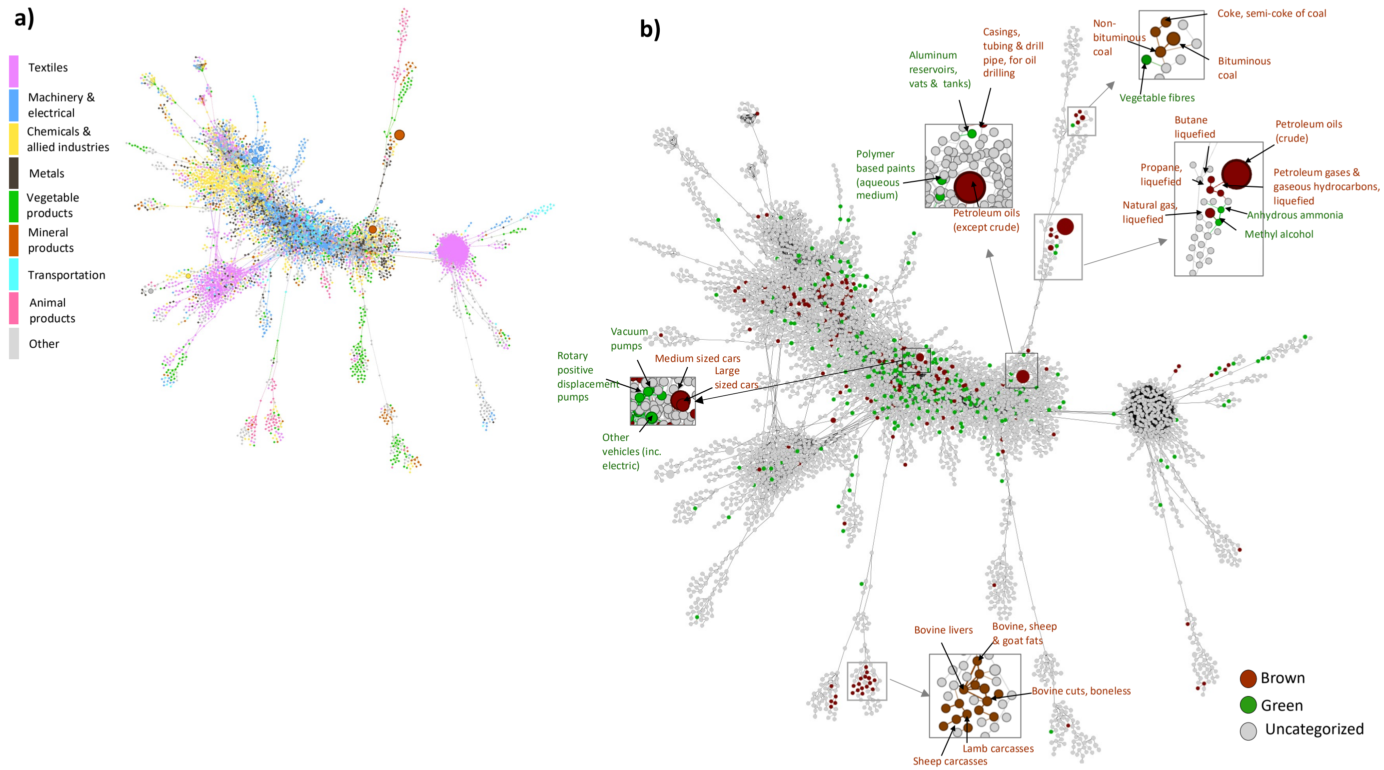


FIGURE 4.1
Brown and Green Products in the Product Space

Note: The product space at the 6-digit level. Nodes are products linked to each other based on their product-to-product proximity. Panel a) shows products colored by key broad (2-digit) HS categories, while panel b) shows products colored by their green, brown and uncategorised classification. Nodes are sized by their total trade volume. Visualisation created from trade data averaged over the period 2016-2020.

PCI, respectively. Brown products which are high in complexity include engines, pumps and various hydrocarbon-derived chemicals, while low-complexity brown products more prominently feature unprocessed hydrocarbons.

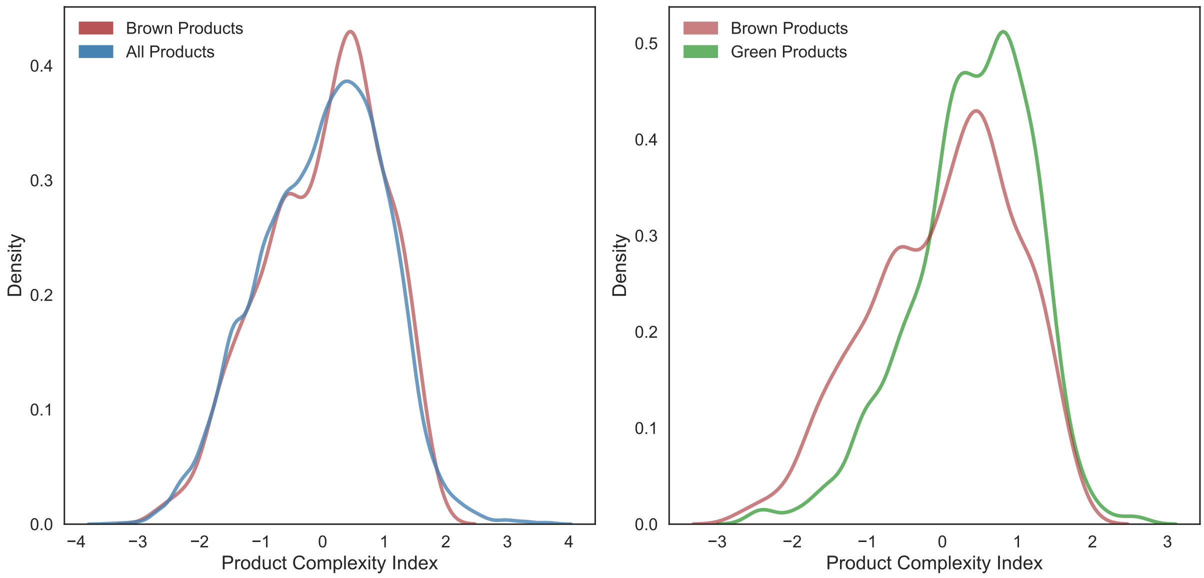


FIGURE 4.2
Distribution of Product Complexity Index for Brown Products

Note: The figure plots the distribution of brown products' PCI against that of all products (left), as well as green products (right). Visualisation created from trade data averaged over the period 2016-2020.

Figure 4.3 plots the distribution of Product Transition Outlook to green products for the period 2016-2020. Transition opportunities for brown to green products tend to be above average, as indicated by the higher density of products with transition possibilities above 1. This suggests that there are proximate green transition opportunities for many brown exports.

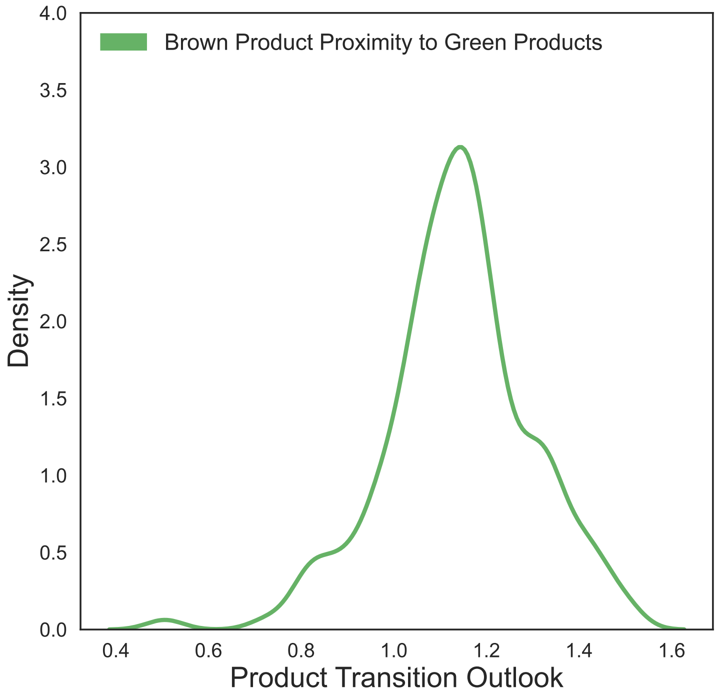


FIGURE 4.3
Distribution of normalised proximity from brown to green products

Note: Density of normalised proximity from brown to green products, which we interpret as a proxy for the ease of transitioning from brown to green products. To obtain normalised proximity ('Product Transition Outlook'), we compute a brown product's average proximity to green or non-brown products, divided by its average proximity to all products. Visualisation created from trade data averaged over the period 2016-2020.

Section C.4 (Appendix) reports global trends in exports of brown and green products. We find that trade in brown products is currently much larger than trade in green products, but has declined slightly in recent years, while trade in green products shows a steady increase.

4.3.2 Country Dependence on Brown Exports and Transition Possibilities

Our results indicate that countries which rely on low complexity brown products for a large share of their exports face very different challenges in the transition to those exporting more sophisticated brown products. For the latter group, we find that brown exports tend to be close to non-brown diversification opportunities in the product space. By contrast, the former group, and petrostates in particular, have low transition opportunities and could find it more difficult to adjust to a low carbon global economy.

Tables 4.1 and 4.2 show the 20 countries ranking most highly on the Brown Lock-in Index and Brown Complexity Index, respectively.[3] As we have alluded to, they paint two very different pictures. The countries ranking highest on the BLI include South Sudan, Iraq, and Libya, followed by a number of mostly other petrostates including Venezuela, Kuwait, Saudi Arabia,

3. Tables C.6 and C.7, Appendix, extend these tables, showing the 50 highest ranking countries.

TABLE 4.1
Countries Ranking Most Highly on the Brown Lock-in Index

Country	BLI	Brown exports [1M USD]	Brown Export Share [%]	GDP per capita [USD]	Transition Outlook	Green TO
South Sudan	3.57	13.49	94.82	NaN	-4.42	-2.39
Iraq	3.48	634.12	94.50	5115.69	-0.30	-0.55
Libya	3.29	193.89	90.92	5810.85	-2.45	-2.21
Angola	3.27	307.13	88.99	3095.46	-1.58	-1.67
Equatorial Guinea	3.21	38.62	88.80	8897.39	-1.87	-2.03
Azerbaijan	3.19	148.20	89.41	4358.97	-0.99	-0.55
Nigeria	3.18	449.05	87.69	2099.86	-1.51	-1.84
Brunei Darussalam	3.02	56.55	91.51	29177.48	-0.73	-0.21
Chad	2.98	11.30	81.44	690.87	-4.42	-2.39
Venezuela	2.92	178.51	84.28	NaN	-0.31	-0.47
Kuwait	2.92	479.84	90.00	29599.34	-0.75	-0.76
Algeria	2.91	299.23	93.75	3898.94	-1.27	-1.28
Qatar	2.77	571.76	86.98	58919.32	-1.71	-1.19
Turkmenistan	2.49	71.46	87.21	6888.55	-0.17	-0.86
Saudi Arabia	2.42	1592.41	74.14	21453.67	-1.04	-0.40
Timor-Leste	2.25	0.63	69.09	1385.77	-2.05	-0.05
Gabon	2.19	32.41	64.23	7364.51	-2.51	-1.02
Oman	2.16	240.97	69.68	17047.08	-1.22	-0.73
Kazakhstan	2.09	343.43	63.78	9141.98	-1.18	-1.21
Iran	1.99	369.01	63.00	3981.87	-0.85	-0.77

Note: The Brown Lock-in Index (BLI) constitutes our baseline measure of lock-in to brown exports. It is computed as $BLI_c = \Sigma_b \frac{exports_b}{\Sigma_p exports_p} * (1 - \tilde{PCI})$ where $\frac{exports_b}{\Sigma_p exports_p}$ is the share of each brown product in overall export values, and $\tilde{PCI}$ is the Product Complexity Index normalised to take a value between 0 and 1. The table shows the 20 countries with the highest BLI.

and Iran.

The BCI yields very different results. The country with the highest ranking of BCI, shown in Table 4.2, is the United States, followed by Japan, Germany, and predominantly other industrialised nations, as well as emerging economies such as India and China. The BCI correlates possitively with the GCI, indicating that countries which competitively export complex products, even if many of them are classed as 'brown', also tend to have strong capabilities to export complex green products. Table C.8 (Appendix) reports correlations between these and other indices.

Which countries enjoy proximate transition opportunities? Table 4.3 reports the results of a regression estimating the relationship

$$\begin{aligned} TransitionOutlook_{c,t} = &\beta_0 + \beta_1 Index_{c,t} + \beta_2 GDP_{c,t} + \beta_3 CoalRents_{c,t} + \\ &\beta_4 OilRents_{c,t} + \beta_5 GasRents_{c,t} + \beta_6 CO_2Emissions_{c,t} + \delta_t + \varepsilon \end{aligned} \tag{4.5}$$

where $Index_{c,t}$ denotes BLI, BCI or GCI, δ_t are year dummies, and ε is the error term. Standard errors are clustered at the country level.[4]

Results indicate that the BLI is negatively and significantly associated with the ease of

4. Note that this and other regression analyses in this chapter are intended to identify correlations. We cannot claim identification of any causal relationships. Instead, our aim is to highlight how the measures we develop relate to one another and, where applicable, whether they are useful in predicting probable future trends.

TABLE 4.2
Countries Ranking Most Highly on the Brown Complexity Index

Country	BCI	Brown exports [1M USD]	Brown Export Share [%]	GDP per capita [USD]	Transition Outlook	Green TO
USA	4.93	2462.74	17.11	62013.69	-0.52	0.14
Japan	4.27	1257.50	18.67	39814.17	-0.24	0.31
Germany	3.95	1824.49	13.21	45520.66	0.02	0.68
Belgium	3.73	460.61	14.92	45068.76	-0.41	0.14
Netherlands	3.67	718.24	14.26	50490.97	-0.44	-0.24
France	3.24	468.56	8.99	39380.82	0.27	0.65
United Kingdom	3.03	802.30	19.29	42026.79	-0.05	0.77
Rep. of Korea	2.84	871.01	15.49	31579.38	-0.19	0.07
Thailand	2.76	321.74	13.03	6977.58	0.07	0.31
India	2.48	488.12	15.91	1947.72	0.43	-0.33
Spain	2.39	534.73	17.27	28314.84	0.14	0.02
Italy	2.22	434.85	8.74	32645.50	0.92	0.97
Austria	2.02	147.49	9.11	48550.29	0.30	1.15
China	1.91	652.10	2.60	9479.06	0.88	-0.59
Poland	1.67	189.41	7.87	14646.76	0.74	0.77
Finland	1.62	98.55	14.24	47483.98	0.54	1.43
Canada	1.62	1269.66	31.52	44725.29	-0.85	0.33
Singapore	1.61	507.49	16.89	62028.43	-0.47	0.04
Turkey	1.44	222.47	12.58	9719.31	0.80	0.46
Portugal	1.40	76.23	11.80	22094.78	0.48	0.18

Note: The Brown Complexity Index (BCI) forms a direct counterpart to the Green Complexity Index (GCI) and measures the number and complexity of brown products a country is competitive in. It is computed as $BCI_c = \Sigma_b \rho_b^c * \tilde{PCI}$. Export capabilities in more technologically sophisticated activities may take longer to develop and bring greater benefits to the economy. However, by opening up a greater number of diversification paths they are likely associated with easier transition pathways. The table shows the 20 countries with the highest BCI.

transitioning to green or overall non-brown products. The BCI is negatively associated with transition opportunities to non-brown products overall, but positively with transition opportunities to green products, which tend to be more complex.

We also explore the relationship between natural resource rents and CO2 emissions and the ease of transitioning away from brown areas of competitive advantage. Most coefficients estimated are not statistically significant. Both coal and oil rents (as a % of GDP) seem to be negatively associated with transition possibilities (significant in most specifications), while natural gas rents are negatively associated with transition possibilities to non-brown products overall, but insignificant when it comes to transitioning to green. The coefficient on logged CO2 emissions per capita is insignificant.

We carry out robustness checks computing our baseline measures of BLI and BCI for the longer list of brown products, which includes in particular cattle and sheep farming exports, as discussed in Section C.1 (Appendix). Appendix Section C.5 shows that our baseline results are broadly robust to this alternative definition of ‘brown’.

4.3.3 Validation

We take several steps to ensure our measures are meaningful. First, we regress the Brown Lock-in Index and the Brown Complexity Index on a number of potentially relevant covariates, such

TABLE 4.3
Correlates of Country Transition Outlook Measures

	(1) Overall	(2) Overall	(3) Overall	(4) Green	(5) Green	(6) Green
Brown Lock-in Index	-0.518***			-0.550***		
	(0.068)			(0.063)		
GDP per capita (current USD) (log)	-0.051	-0.028	-0.073	0.074	0.038	-0.030
	(0.058)	(0.066)	(0.066)	(0.068)	(0.072)	(0.063)
Coal rents (% of GDP)	-0.066**	-0.083**	-0.083***	-0.151***	-0.172***	-0.165***
	(0.030)	(0.038)	(0.030)	(0.041)	(0.057)	(0.062)
Oil rents (% of GDP)	0.006	-0.044***	-0.038***	0.005	-0.039***	-0.031***
	(0.007)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)
Natural gas rents (% of GDP)	-0.021**	-0.041**	-0.038***	-0.001	-0.017	-0.015
	(0.009)	(0.016)	(0.013)	(0.015)	(0.018)	(0.016)
CO2 emissions (metric tons per capita, log)	0.042	0.065	-0.005	0.176	0.061	0.053
	(0.099)	(0.114)	(0.106)	(0.110)	(0.125)	(0.106)
Brown Complexity Index		-0.115***			0.208***	
		(0.041)			(0.052)	
Green Complexity Index			0.082			0.360***
			(0.050)			(0.049)
Year FEs	X	X	X	X	X	X
Observations	854	854	854	854	854	854
R2	.267	.21	.204	.318	.274	.335

Linear regression. Cluster-Robust Standard Errors in Parentheses.
Dependent Variables are Country-Level Transition Opportunities from Brown to the List Stated.
The label (log) refers to the natural logarithm of 1 + the variable in question.

Note: The table reports the results of a regression of Green and Overall Transition Outlook on the a number of potential explanatory variables.

as income, natural resource rents, and Revealed Technological Advantage[5] (RTA) in climate-relevant technologies. While there is no statistically significant relationship between the BLI and income, our results suggest high BCI-countries also have higher GDP per capita. The BLI is positively and significantly, the BCI negatively and significantly associated with higher oil rents. The BLI is also positively associated with natural gas rents and patenting in carbon capture and storage (CCS), but negatively with patenting in transport-related mitigation technologies. There is no significant association between BLI and per capita CO2 emissions; however, countries which score highly in BCI have higher CO2 emissions. By contrast, Mealy and Teytelboym (2020) find that countries with high green complexity have lower per capita emissions.

We also test the relevance of our Transition Outlook measures. We first regress BLI and BCI on lagged Green and Overall Transition Outlook, as well as their own lagged values, GDP per capita and other covariates. Results suggest that the Green Transition Outlook is a statistically significant predictor of future reductions in Brown Complexity Index, but not Brown Lock-in Index.[6] The Overall Transition Outlook, on the other hand, is significantly associated

5. An index computed in a similar fashion as Revealed Comparative Advantage, but based on country-level patenting, rather than exports (e.g. Montresor and Quatraro 2017).

6. This is consistent with our finding in 4.3.1 that the proximity of many brown to green products is higher

with reductions in future BLI but not BCI.[7]

Regression tables can be found in Appendix Section C.2.

4.4 DISCUSSION

Mitigating climate change requires a systemic technological transformation which is historically unparalleled in speed and scale. This transition is likely to leave large swaths of previously productive and profitable assets stranded. While the transition risk facing oil exporting countries has been noted (e.g. Manley et al. 2017; Zenghelis et al. 2018), quantitative measures of transition risk at the level of nations' productive structures have been lacking – a gap this chapter has endeavoured to fill. Our estimates of current lock-in to declining sectors, as well as the ease of transitioning to climate-compatible activities, highlight the isolated nature of extractive industries and the importance of diverse productive assets and capabilities in adapting to global economic shifts (Zenghelis et al. 2018). We also map the similarity of brown products to green products within the product space, and find that many brown products seem to require similar productive capabilities as green products – in line with a recent finding by Jee and Srivastav (2022) that most clean patents are at least indirectly connected to a dirty patent in the technology space. This suggests many productive assets currently devoted to brown activities may shift to emerging green ones with relative ease. We find a similar pattern at the country level, with countries exporting a diverse number of sophisticated brown products often being well-positioned to shift into green technologies. Countries depending on a small number of fossil fuel exports, however, face significant transition risk.

There is an ongoing policy debate about transition opportunities for the fossil fuel industry. Suggested possibilities include green hydrogen and other low carbon fuels, ammonia, and products used in carbon capture and storage. These tend to co-occur with high-carbon products, as CO2 captured and stored with the respective technology can be utilised in a synthesis of methanol, for example (Collodi et al. 2017). Hydrogen is primarily an energy carrier, which can be transformed to ammonia for easier transport, another net-zero relevant energy carrier. As the global market for hydrogen still needs to be scaled up, one can expect initially grey hydrogen to increasingly transform into blue and eventually green, as large-scale production facilities in countries such as Namibia, Morrocco, Chile and Australia come on-stream (Eicke and De Blasio 2022; International Energy Agency 2021).[8]

than average, as well as the intuition that countries scoring high on BLI are specialised in a small number of low-complexity brown products located at the periphery of the product space.

7. This suggests that countries scoring high in BCI tend to move away from brown and into green activities, while those high in BLI find it easier to transition into undefined areas.

8. Both hydrogen and ammonia are labelled based on the type of energy used to produce then, which is green for renewable energy, blue for fossil-based production with carbon-capture and storage, grey for fossil-based pro-

Our methodological approach has some potential to validate these largely anecdotal accounts. While the above considerations are mostly strategic and forward-looking, and trends in such directions therefore unlikely to feature prominently in historical data, there are some encouraging individual country examples. Saudi Arabia is the world's largest exporter of anhydrous ammonia,[9] accounting for 23% of world exports, followed by Russia and Trinidad and Tobago. Trinidad and Tobago and Saudi Arabia are further the largest exporters of methanol[10] at 13% of world exports each, followed by Iran at 11%. Drawing on the list of products related to carbon capture, utilisation and storage (CCUS) compiled by Serin et al. (2021), we find that declines (increases) in the share of refined oil, natural gas (liquefied or piped) and coal are all significantly associated with increases (reductions) in revealed comparative advantage in carbon capture and storage technologies, as well as – with the exception of LNG – export share of CCUS. There is, however, no correlation between changes in the share of crude and CCUS.

Despite these encouraging examples, however, our results highlight the limitations of exploiting 'latent comparative advantage' in countries which score highly on our Brown Lock-in Index measure. Countries which have reduced their BLI have tended to reduce reliance on coal or crude oil, but have usually done this either by increasing reliance on other hydrocarbon exports, like refined oil or natural gas, or by increasing exports of unrelated products. Pathways for 'related diversification' for these 'locked-in' countries are thus very limited. For example, the United Arab Emirates, whose BLI rank fell from 19 in 1996-2000 to 32 in 2016-2020, reduced the share of crude oil in its exports from 56.24% to 21.42% during the same period.[11] Meanwhile, the share of refined oil almost doubled, from 6.97% to 12.23%. The country further increased its exports of diamonds, metals and gold, jewellery and radio transmissions apparatus.

Overall, our results suggest that the complexity of a nation's exports could be more important to mitigating transition risk than the 'brown-ness' of those exports on its own. The related diversification approach is of limited use to countries which have few areas of latent comparative advantage in sectors that are likely to remain viable in the green economy. The question then becomes: how can countries break out of low complexity, low diversity specialisation paths?

There is significantly less quantitative evidence on how regions may break out of path dependent trajectories than there is for the importance of relatedness in driving industrial development. Studies which do engage with this question suggest that the capacity to invest in innovation may play an important role in reducing the constraints of existing capabilities and enabling regions to jump into less related areas of specialisation (e.g. Xiao et al. 2018; Zhu

duction without CCS, and so on.

9. Ammonia has pairwise proximity 0.27 to crude oil
10. Methanol has pairwise proximity 0.37 to crude oil, making it crude's closest non-hydrocarbon export
11. Note, however, that absolute export volumes continued to increase.

et al. 2017). Xiao et al. (2018), in their study of Chinese regions' diversification into related and unrelated new industries over the period 2002-2011, further find a significant and positive effect of factors such as extra-regional linkages (proxied by FDI and imports), human capital and 'open-minded social-institutional contexts' in enabling regions to jump further within the industry space. This suggests that promoting extra-regional knowledge exchange and fostering healthy innovation ecosystems (see e.g. Brown and Mawson 2019; Gomes et al. 2018; Leendertse et al. 2021) may be key strategies for countries locked-in to low-complexity, declining industrial sectors.

4.5 CONCLUSION

This chapter estimates the extent to which countries' productive capabilities are specialised in both complex and non-complex brown exports. We make three contributions to the literature. First, we develop novel measures of country-level transition risk that account for the ability of countries with brown exports to transition into more climate-compatible areas of comparative advantage. Second, we develop a list of traded 'brown' products, which provides a previously missing counterpart to the WTO's 'green' list used in prior research. Third, we locate declining brown products within the product space and measure their proximity to climate-compatible products.

Compared to the average exported product, brown products tend to be more proximate to green products. This is an encouraging finding, as it suggests that factors of production currently devoted to many brown activities could be redeployed towards climate compatible alternatives relatively easily. However, the picture is bleaker for major hydrocarbon exporters that score low on diversity, complexity, and have low proximity between their brown areas of comparative advantage and non-brown products within the product space. While smart specialisation policies and relatedness measures can highlight the most proximate products for brown activities to shift into, this is less helpful for countries specialised in brown products at the periphery of the product space that have very few proximate diversification opportunities. As the difficulty fossil fuel exporters face in adapting to a low carbon future presents a threat to effective global climate action, there is an urgent need to find viable development pathways for these countries. Further research on how to achieve path-breaking diversification, particularly for low complexity regions, should be a high priority.

While our chapter provides trade-based measures of transition risk and opportunities across nations, we recognise that transition risk will also vary within countries. Although our measures are agnostic regarding the underlying mechanisms of relatedness,[12] the ability of workers to

12. which likely include the traditional drivers of agglomeration economies: knowledge spillovers, labour market

move into new activities as some sectors decline is key to achieving a just transition. Existing research has examined the similarity of green skills to non-green skills (e.g. Consoli et al. 2016; Saussay et al. 2022). Saussay et al. (2022) identify the skills intensities required for low- and high-carbon jobs using job ads data, and find evidence to suggest that differences between high- and low-carbon jobs tend to be smaller than those between generic and low-carbon jobs, but that high and low-carbon jobs in the US tend not to be spatially co-located. However, granular evidence on the transferability of skills used in declining sectors to climate compatible ones (green or not) is currently lacking and should be a priority for future research.

More broadly, our measures are based on historical patterns of co-exporting. The low carbon transition requires shifts in global trade, as well as changes in technologies themselves. Such dynamics are likely to transform the product space network and alter the relatedness between different economic activities. The implications of such changes in the network of economic activities for economic development are another important avenue for future inquiry.

pooling, and input-output linkages

Chapter 5

Directed Technological Change and General Purpose Technologies: Can AI Accelerate Clean Energy Innovation?

5.1 Introduction

Directing technological change away from polluting technologies and towards cleaner options is central to addressing global environmental problems such as climate change. Prior work has shown that a combination of taxes and research subsidies can effectively level the playing field between clean and dirty technologies (Acemoglu et al. 2012; Aghion et al. 2016). Those policies incentivise the development and adoption of environmentally friendly technologies, which allows clean sectors' productivity to catch up to their dirty counterparts in the longer term.

However, the race between clean and dirty technologies is taking place against a backdrop of improvements in information and communication technologies (ICT) and artificial intelligence (AI). Some highlight the positive impact those technological developments may have in helping solve environmental problems.[1] But are low-carbon technologies surfing the AI wave better than dirty technologies? AI and ICT, in some respect, resemble the textbook case of general-purpose technologies in that they have the potential to be applied in many, if not most, areas of the economy, including in high-carbon energy industries (Brynjolfsson et al. 2021; Crafts 2021; Trajtenberg 2018). 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 productivity.

This chapter investigates how a new general-purpose technology (GPT) affects the direction of technological change and, in particular, the competition between clean and dirty tech-

1. See, for example, Rolnick et al. (2019) or private sector initiatives such as Microsoft's 'AI for the Planet'.

nologies. 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 R&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 equilibrium is made easier if clean technologies have a higher capacity to absorb the GPT than dirty technologies. The absorptive capacity of a technology is shaped both by characteristics intrinsic to the technology and previous exposure to the GPT: both can make it easier to apply the GPT in that particular technological field.

We then study the absorptive capacities of clean and dirty technologies empirically. To do so, we analyse citations between energy patents and AI (or ICT) patents and show 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 capacities and characteristics intrinsic to the technologies (i.e. technological 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 chapter 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. 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 chapter 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 analyse environmentally beneficial innovations in isolation from other technological developments. Here, we extend it by studying the interaction with a general-purpose technology. In doing so, we also contribute to the economic literature on GPTs (Helpman and Trajtenberg 1994, 1996; Lipsey et al. 2005; Rosenberg and Trajtenberg 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 infrastructure, production methods, lifestyles and consumption habits (**Fouquet2008**; Dosi 1982; Grübler et al. 1999; 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. 2016b; 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 chapter proceeds as follows. Section 5.2 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 5.3 analyses a model of green directed technological change in which we add a GPT. Section 5.4 describes the construction of our global dataset of 2,545,063 electricity and transport patent families and the extent to which they have absorbed AI and ICT knowledge. Section 5.5 presents our key result about clean technologies' greater ability to absorb the GPT as compared to dirty technologies. Section 5.6 presents the results of the firm-level analysis, while section 5.7 discusses the implications of our results for the low-carbon transition.

5.2 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 optimisation, 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. (2018b) 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 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 and Khosravi 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 performance checks (Bose 2017). Lee (2020) has analysed patent citations and found that AI has contributed to improving battery performance and optimising cars' energy management systems 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 and Liu (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. Crucially, there are numerous potential applications for AI not just in clean but also in dirty energy. For example, AI can increase the efficiency of fossil fuel exploration (such as through well logging or geological mapping), field development and engineering, and other parts of the value chain (Koroteev and Tekic 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 and Trajtenberg (1994) and Helpman and Trajtenberg (1996), the economic benefits from a new GPT may accrue only after a lag because advances in the GPT do not diffuse spontaneously: adoption requires complementary co-invention in application sectors typically happening via R&D investments. Helpman and Trajtenberg (1996) model the diffusion of a new GPT, allowing for both early and late adopters, and the extent to which application sectors innovate to make use of the GPT depends on four key factors: their capacity to absorb the GPT (that is to learn from it to create large productivity gains in their sector); their 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 and Levinthal (1990) in considering 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).

Finally, 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 modeling the diffusion of a GPT, Helpman and Trajtenberg (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.

5.3 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 this 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. Endogenising absorptive capacity also yields comparative statics that we use as hypotheses to explain the observed empirical variation in the extent to which 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 or material):

$$Y = (Y_{ct}^{\frac{\varepsilon-1}{\varepsilon}} + Y_{dt}^{\frac{\varepsilon-1}{\varepsilon}})^{\frac{\varepsilon}{1-\varepsilon}} \tag{5.1}$$

We assume that clean and dirty inputs are highly substitutable ($\varepsilon > 1$)[2]. Sector $j \in \{c, d\}$ produces input Y_j competitively using a combination of labour and sector-specific machines:

$$Y_{jt} = L_{jt}^{1-\alpha} \int_0^1 A_{jit}^{1-\alpha} x_{jit}^{\alpha} di \tag{5.2}$$

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, scientists successfully innovate on machine i with probability η_j. If successful, the machine's productivity gets an incremental increase, denoted γ. Formally:

$$A_{jit} = (1+\gamma)A_{jit} \tag{5.3}$$

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 5.3) 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 by boosting the the machines' productivity.[3] Formally, we write:

$$A_{jit} = (1+\gamma+\beta_j GPT_t)A_{jit} \tag{5.4}$$

This modeling choice is supported by Table 5.4 in Section 5.5, which shows that the value of an energy patent (as measured by the citations it receives) is greater for those patents that

2. This is a key assumption in Acemoglu et al. (2012), which is arguably plausible in the sectors we analyse. Electricity from renewable energy sources can be used in much the same way as electricity from a coal power plant, just as an electric vehicle is a good substitute for an internal combustion engine powered one. For a more detailed discussion of this assumption and its justification, please refer to Acemoglu et al. (2012), page 135, footnote 6.

3. 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 $\eta_j \propto \beta_j GPT_t$. But this does not change the results of our analysis.

draw on the GPT. Equation 5.4 also implies that the spillovers from the GPT depend only on absorptive capacity β_j, and is therefore the same for any machine within the sector j.

Next, we focus on characterising the profitability of research in each sector to understand how the GPT affects the direction of technological change.[4] The average productivity of sector j is:

$$A_{jt} = \int_0^1 A_{jit} di \tag{5.5}$$

It evolves over time according to the following equation:

$$A_{jt} = (1 + (\gamma + \beta_j GPT_t)\eta_j s_j)A_{j,t-1}, \tag{5.6}$$

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

$$\pi_{jit} = (1-\alpha)\alpha p_{jt}^{\frac{1}{1-\alpha}} L_{jt} A_{jit} \tag{5.7}$$

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

$$\Pi_{jt} = \eta_j(1 + \gamma + \beta_j GPT_t)(1-\alpha)\alpha p_{jt}^{\frac{1}{1-\alpha}} L_{jt} A_{jt-1} \tag{5.8}$$

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:

$$\frac{\Pi_{ct}}{\Pi_{dt}} \equiv f(s_c, s_d) = \frac{\eta_c}{\eta_d} \frac{1 + \gamma + \beta_c GPT_t}{1 + \gamma + \beta_d GPT_t} \left(\frac{1 + (\gamma + \beta_c GPT_t)\eta_c s_c}{1 + (\gamma + \beta_d GPT_t)\eta_d s_d} \right)^{-\phi-1} \left(\frac{A_{ct-1}}{A_{dt-1}} \right)^{-\phi} \tag{5.9}$$

Equation 5.9 allows us to study how the GPT affects the direction of technological change. 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 of $A_{c,t-1}$ where $f(1,0) = 1$. This is the minimum value that $A_{c,t-1}$ must take, given $A_{d,t-1}$, so that a clean equilibrium becomes possible. Conversely, denote $\bar{A}_{d,t-1}(A_{c,t-1})$ the value of $A_{d,t-1}$ where $f(0,1) = 1$. This is the minimum value that $A_{d,t-1}$ must take, given $A_{c,t-1}$, so that a dirty equilibrium becomes possible. These two functions, depicted in Figure 5.1, delineate the area in the $(A_{c,t-1}, A_{d,t-1})$ space where we ob-

4. Appendix D.1 provides the step by step derivation of the equilibrium equations.

tain a clean equilibrium, a dirty equilibrium, or multiple equilibria. Result 1 below summarises the impact of the GPT on the direction of technological change.[5]

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.

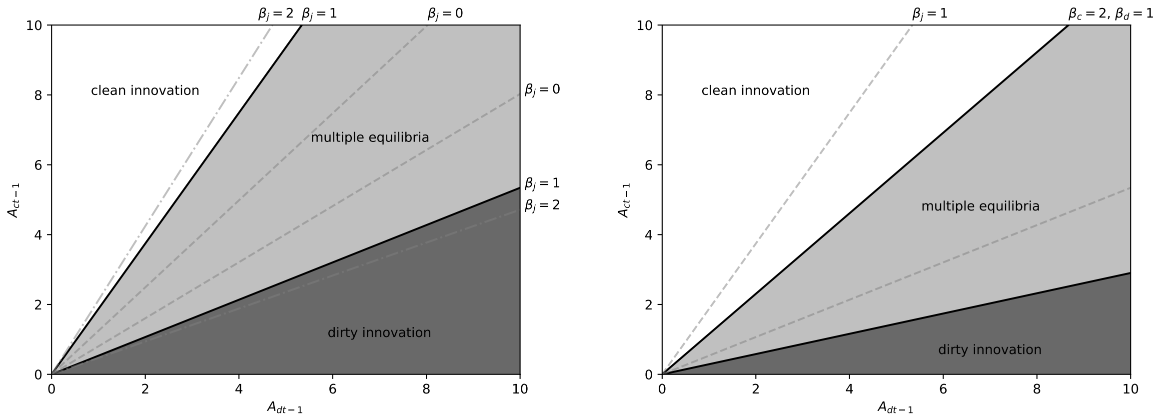
Figure 5.1 illustrates Result 1. As a baseline, consider $\beta_c = \beta_d = 0$ which corresponds to the case where neither sector can absorb the GPT, making it irrelevant and equivalent to the original model by Acemoglu et al. (2012). In Figure 5.1a, we see that, in this case, technological change 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 5.1b, 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 5.1 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 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.

5. The proof is shown in Appendix D.1.2.



(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 5.1
Direction of Technological Change With a GPT

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:

$$\beta_j = b_j B_j, \tag{5.10}$$

where b_j is exogenous (coming from the characteristics 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:

$$\Pi_{jt} = \eta_j(1+\gamma+b_j B_j GPT_t)\alpha(1-\alpha)p_{jt}^{1/(1-\alpha)} L_{jt} A_{j,t-1} - \psi B_j^2 \tag{5.11}$$

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

$$B_j^* = (\eta_j b_j GPT_t)\frac{(1-\alpha)\alpha}{2\psi} p_{jt}^{1/(1-\alpha)} L_{jt} A_{j,t-1} \tag{5.12}$$

Using Equation 5.12 in combination with the other equations that characterise the equilibrium, we obtain Result 2 below.[6]

6. The proof is shown in Appendix D.1.3.

Result 2. *In equilibrium, investments in absorbing the GPT in a given sector increase with the existing accessible stock of the GPT 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, regions 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 application sector's productivity A_{jt}. We now write the absorptive capacity β_j as a function of A_{jt}:

$$\beta_j = b_j B_j A_{jt-1}^{-\delta}, \tag{5.13}$$

where $\delta \geq 0$ represents an aging factor. The idea is that more mature technologies are less able to undergo radical changes, or in other words, aging 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* $\delta < 1$

Result 3 shows that the maturity of the technology in the application sector can impact the endogenous part of absorptive capacity.[7] If the aging factor is large ($\delta > 1$), then when the technology matures and becomes more productive, fewer investments are made which leads

7. The proof is shown in Appendix D.1.4.

to lower absorptive capacity. On the contrary, when the impact of aging is minimal ($\delta < 1$), an increase in the productivity of technology j leads to more investment and higher absorptive capacity.

5.4 DATA

Patent Data. Our next steps focus on measuring the extent to which clean and dirty technologies absorb spillovers from AI and ICT. To do so, we use data on patent applications from PATSTAT and obtain a full coverage of patents filed around the world up until 2018.[8] 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.[9] 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.[10] 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 5.1 summarises 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 Appendix Table D.1 and D.2.

We keep all energy families with a priority year between 1990 and 2018. For this period, we find a total of 1,674,751 electricity families (809,327 clean, 257,490 grey, 607,934 dirty) and 1,300,651 transport patent families (795,408 clean, 298,645 grey, 206,598 dirty). Figure 5.2a and 5.2b show that the number of energy families have been going up both for electricity and transport. In transport, clean vastly outpaces dirty and grey throughout most of the period,

8. 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 2018 onwards are severely truncated.

9. 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. We include patent families of all sizes (i.e., including size 1) and with patent applications filed in any jurisdictions. This approach allows us to capture global trends in clean and dirty innovation without restrictions on where the invention happened and how many jurisdictions the assignees deemed interesting to file in. Some regressions will only use triadic granted families as a way to narrow down the analysis to potentially more valuable inventions.

10. We use both classifications in order to capture as many relevant families as possible. Using IPC codes is necessary to capture many families from the Chinese, Japanese and Russian patent offices which do not use the CPC. A family is assigned to a category if at least one patent within it has been assigned a relevant technology code.

TABLE 5.1
Technology Categories

	Electricity	Transport
Clean	Renewable Energy (Wind, Solar, Geothermal, Hydro, Marine), Nuclear Energy, Enabling technologies (e.g., smart grids)	Electric, Hybrid, or Hydrogen vehicles, Fuel cells, Batteries, Enabling technologies (e.g., charging stations)
Grey	Efficiency, Biomass and waste	Efficiency of internal combustion engines
Dirty	Combustion of traditional fossil fuels (Oil, Natural Gas and Coal), Hydrofracturing	Internal combustion engines

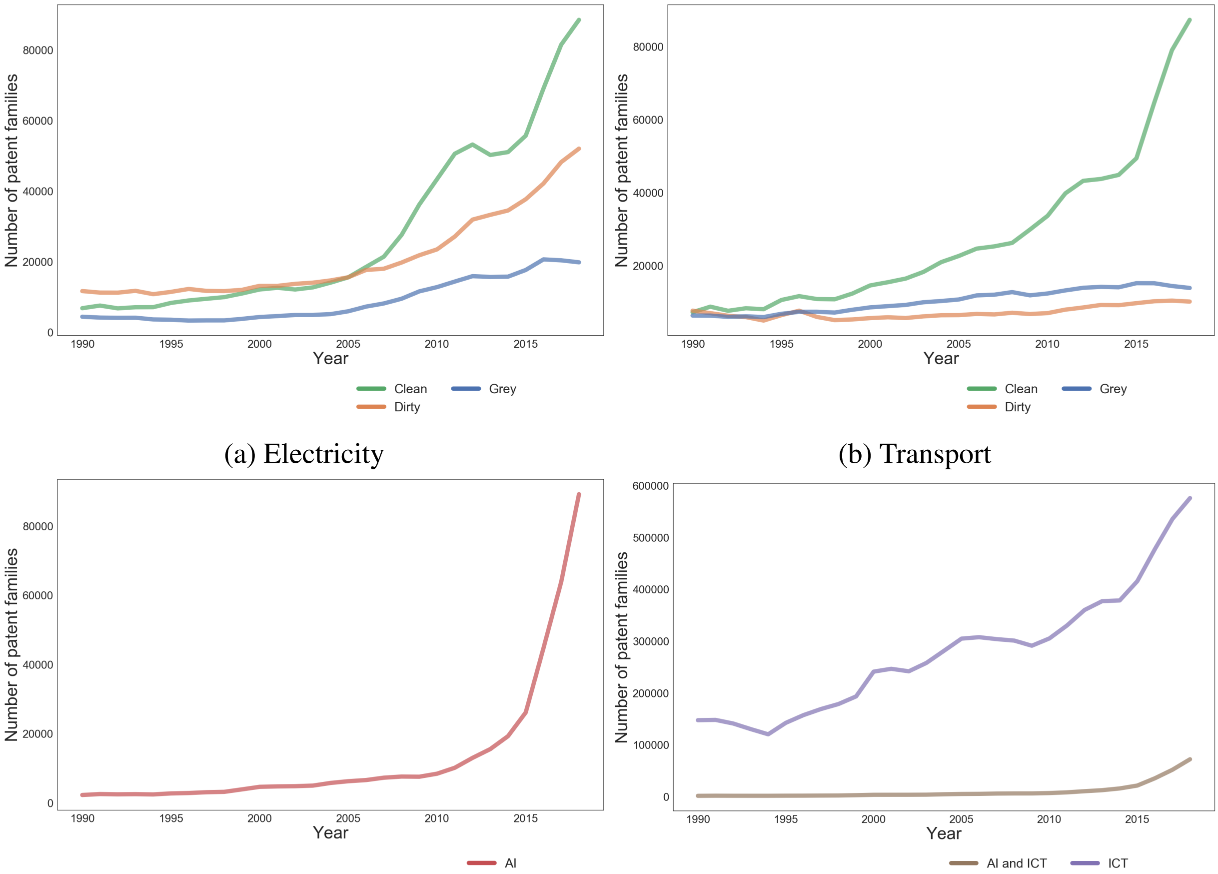
Note: The table shows the technologies we include as clean, grey or dirty electricity and/or transport. We identify patent families related to those technologies based on codes from the Cooperative Patent Classification (CPC) and the International Patent Classification (IPC). We use both classifications in order to capture as many relevant families as possible. Using IPC codes is necessary to capture many families from the Chinese, Japanese and Russian patent offices which do not use the CPC. A family is assigned to a category if at least one patent within it has been assigned a relevant technology code.

while in electricity clean innovation has exceeded dirty and grey since the early 2000s.

AI and ICT Inventions. To identify patents related to AI, we follow the methodology developed by WIPO (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 and Squicciarini (2017). These codes include inventions classified as related to the 'transmission of digital information', 'self-organising networks, e.g. ad hoc networks or sensor networks' or 'high speed computing'. In the end, this procedure identifies 548,641 AI families and 10,883,849 ICT families. We note that, to this day, the stock of ICT knowledge is vastly greater than that of AI. Figures 5.2c and 5.2d 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 have been filed each year since the early 1990s. We also find that a majority of AI families also qualify as ICT: this implies that, to some degree, AI can be thought of as a sub-field of ICT (see Appendix Figure D.1).

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 backward citations that each energy family makes to AI or ICT patent families.[11] In our sample, the average energy family cites about 3.8 patent families with 0.3% going to AI and 4.3% 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 5.2 provides examples of energy patents with high reliance on AI. The first patent in the table, for instance,

11. PATSTAT provides information about citations at the family level, meaning if two patents in the same family cite the same AI patent, that patent counts only as one citation.



(a) Electricity (b) Transport

(c) AI (d) ICT

Note: The figure plots the total number of patent families over time filed worldwide for each of the following categories: a) electricity, b) transport, c) AI and d) ICT. The year used is the priority year of the family. We note that AI patenting has seen a sharp increase since 2010. Source: Authors' calculations based on PATSTAT 2021.

FIGURE 5.2
Patenting Trends Over Time by Family Type

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 by using the number of citations received (a.k.a. forward citations) as a proxy of patent quality (Jaffe and De Rassenfosse 2017; Jaffe et al. 2000). The number of times a particular family is cited by other families, however, heavily depends on the number of years since it was first filed: the older the family, the more opportunities there have been for other families to cite it. It is therefore inappropriate to compare families filed in different years since the younger ones would mechanically have fewer citations. To avoid this problem, our main measure is the number of forward citations received within 3

TABLE 5.2
Examples of Energy Innovations Citing AI Patents

Patent 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 optimisation	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

Note: The table illustrates how AI may be applied to energy technologies by showing examples of energy patent families with a high number of citations to AI.

years. [12] 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). 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.[13] The end result is a dataset of 1,460,034 observations covering 21,046 firms over 1990 to 2018.

5.5 AI and ICT Absorption 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 5.3, we plot trends over time in the

12. We also use the number of forward citations received within 5 years as a robustness check where appropriate. Since we use forward citations here to make statements about families relative to other families within a particular time window, the particular time window used should not matter (assuming that there is not much variation in how citations appear over time across families). In any case, we find that citations peak after 4 years, and so, our robustness checks using citations received within 5 years ensure that our measures cover the majority of citations.

13. We use the following vintages: 201709, 201812, 201912, 202012, and 202106. Please refer to the Appendix to Chapter 3 (B.1) for more details on the data cleaning process.

percentage of backward citations going to AI or ICT for different types of energy families. A key take-away is that, in the transport sector, clean patents build on AI and ICT more than dirty and grey, while, in the electricity sector, grey slightly leads clean. On Figure 5.3a, we see that, overall, the average percentage of backward 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 5.2c. We also note that AI absorption is higher in clean than in grey or dirty (especially since 2010) and that it is higher in transport than in electricity.

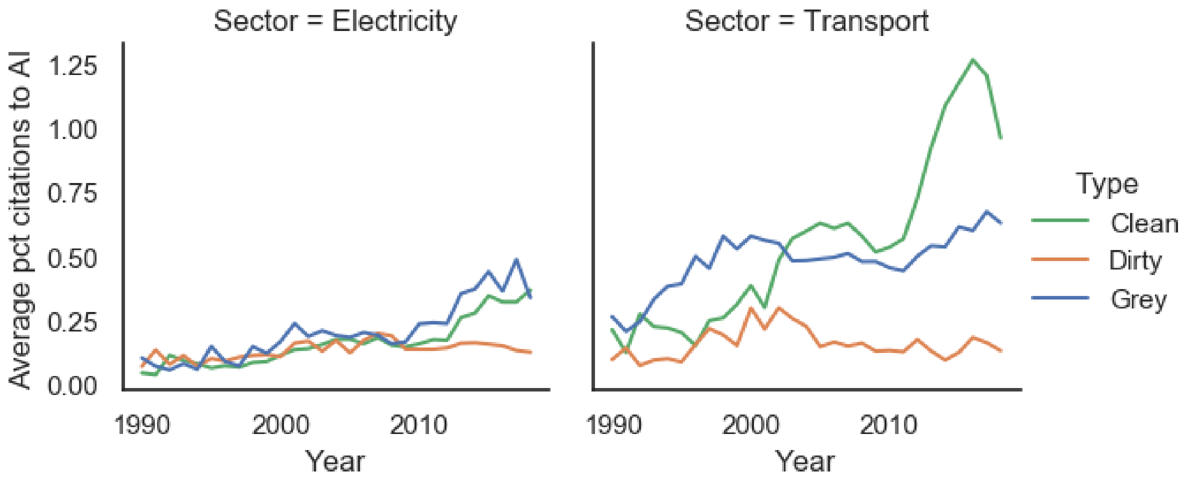
Figure 5.3b shows that, similar to the case of AI, the percentage of backward citations going to ICT is higher in clean than in grey or in dirty. The magnitude of ICT absorption in clean electricity is particularly high: the average percentage of citations going to ICT reached nearly 20% in the late 2000s, while other technology groups have remained below 10% 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.

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:

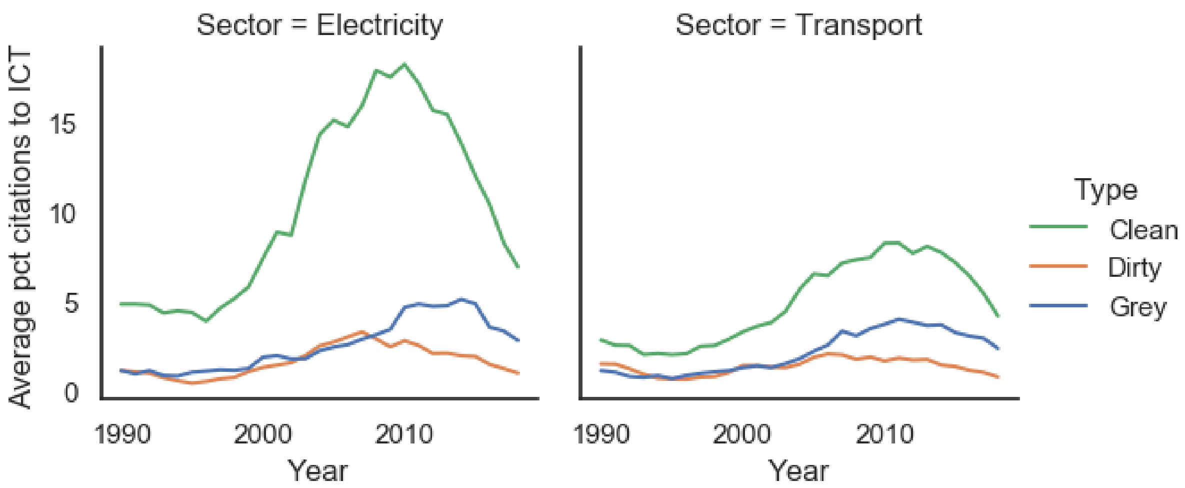
$$Absorption_{ijt} = \beta_0 + \beta_c Clean_i + \beta_g Grey_i + \mathbf{b}\mathbf{X}_i + \delta_t + \delta_j + \varepsilon_{ijt} \tag{5.14}$$

$Absorption_{ijt}$ 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_0 is the intercept. $\mathbf{X}_i$ 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 5.3 presents the regression results. Column 1 to 4 focus on AI, Column 5 to 8 on ICT. Column 1 and 5 show specifications with year fixed effects but without firm fixed effects; this allows us to document the size of the effect in the whole sample of families without any controls. As we move from Column 1 to Column 4, we add more restrictions on the sample and on the specifications such as firm fixed effects and quality controls. Whether the coefficients on 'Clean' and 'Grey' change at all from Column 1 and Column 4 is instructive in understanding what may or not be driving the effect. In particular, showing the difference between results with and without firm fixed effects illustrates that the magnitude of the overall trends can be driven, to a large extent, by differences between firms (rather than within).

Consistent with Figure 5.3, the coefficients on 'Clean' are positive and statistically significant, indicating that clean families rely more on AI and ICT than their dirty counterparts. To



(a) Citations to AI



(b) Citations to ICT

Note: The figure shows the percentage of citations going to AI (a) and ICT (b) for the average electricity (left) and transport (right) family over time. The year used is the priority year of the family. Since 2010, AI clearly makes up a greater share of backward citations in clean transport families than in grey and dirty families. For electricity the picture is less clear. The share of ICT in backward citations is higher for clean families throughout the period in both electricity and transport. Source: Authors' calculations based on PATSTAT 2021.

FIGURE 5.3
Percentage of Citations to AI and ICT Over Time

allow for an easier interpretation of the main effect captured by β_c, the line 'Ratio Clean/Dirty' in Table 5.3 expresses the magnitude of the effect in percentage term relative to dirty and can be interpreted as the relative absorptive capacity of clean vs dirty. Formally, it corresponds to $\frac{100\times\beta_c}{mean_d}$, where $mean_d$ is the average percentage of backward citations going to AI (or ICT) in the average dirty family. For example, Column 1 indicates that the absorptive capacity for AI is 304% higher in clean than in dirty. It is 502% higher for ICT (see Column 5).

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 being 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 energy 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 changes little for AI but decreases for ICT, highlighting that firms may play a larger role for ICT than AI. The ratio remains high showing that, even within the same firm, clean inventions cite more than 300% as much AI than dirty ones. Section 5.6 explores the role of firm-level characteristics in more depth.

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 while limiting the sample to triadic patent families that have been granted.[14] 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 in those specifications too.[15] When running regressions separately for transport and electricity families, we find that the AI absorption gap between clean and dirty is stronger in transport than in electricity. The reverse is true for ICT: clean electricity is much more ahead in absorbing ICT than dirty.[16]

Next, we examine how the relative absorptive capacity of clean vs dirty has changed over time by running a similar regressions as Column 1 and 2 for AI (and Column 4 and 5 for ICT)

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

15. All coefficients excluded from the main tables are shown in the long version of the same table in Appendix Table D.3. The number of patents in the family and the number of countries in the family are not significant. The number of citations received (within 3 years) is positive and significant at the 10% level for AI and at the 5% level for ICT. They do seem to add some explanatory power to the model since the R squared goes from 0.058 to 0.060 for AI and from 0.441 to 0.445 for ICT.

16. Those regressions are shown on Appendix Tables D.6 and D.7. For AI, the coefficients on Clean are lower in Electricity compared to Transport. When controlling for quality proxies, the coefficients become insignificant. This indicates that among high-quality electricity families, there is no difference between the ability of clean and dirty technologies to absorb AI. The same coefficient for ICT remains strongly significant however.

TABLE 5.3
Estimating the Absorptive Capacity of Clean, Grey and Dirty Technologies

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Clean Family	0.437***	0.530**	0.463**	0.420**	8.243***	7.071**	10.329***	9.951***
	(0.024)	(0.069)	(0.077)	(0.070)	(0.263)	(0.943)	(0.951)	(0.947)
Grey Family	0.264***	0.040	-0.124	-0.151	0.894**	0.432	0.443	0.196
	(0.001)	(0.105)	(0.098)	(0.103)	(0.142)	(0.255)	(0.211)	(0.208)
Nbr Citations Made (1000s)	8.134***	3.081**	0.177	-0.434	103.298***	47.204**	3.524*	-3.953
	(0.497)	(0.610)	(0.302)	(0.235)	(9.297)	(7.022)	(1.124)	(1.487)
Constant	0.121***	0.245**	0.575***	0.624***	1.402***	4.591***	7.691***	9.157**
	(0.010)	(0.042)	(0.033)	(0.030)	(0.107)	(0.461)	(0.443)	(1.172)
Ratio Clean/Dirty	304.35***	212.71**	94.15**	85.39**	501.72***	239.56**	229.29***	220.91***
	(16.63)	(27.86)	(15.77)	(14.24)	(16.00)	(31.96)	(21.11)	(21.02)
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	0.043	0.058	0.060	0.067	0.312	0.441	0.445
Observations	2,550,428	1,495,048	131,564	131,564	2,550,428	1,495,048	131,564	131,564

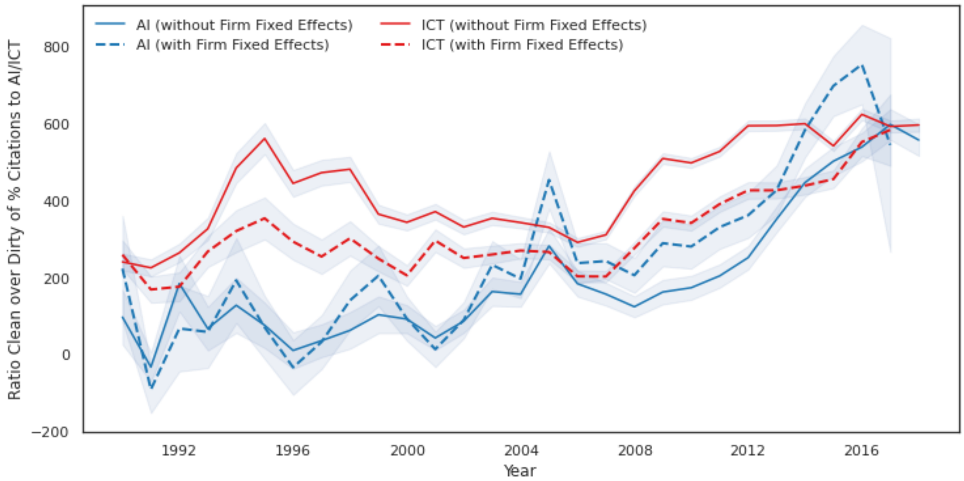
Linear Regression.
Standard Errors in Parentheses. Clustered at the type and firm level.
Dependent Variable: Percentage of backward citations going to AI or ICT

Note: To allow for an easier interpretation of the main effect captured by β_c, the line 'Ratio Clean/Dirty' expresses the magnitude of the effect in percentage term relative to dirty and can be interpreted as the relative absorptive capacity of clean vs dirty. Formally, it corresponds to $\frac{100\times\beta_c}{mean_d}$, where $mean_d$ is the average percentage of backward citations going to AI (or ICT) in the average dirty family. 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. Column 1 and 5 use observations at the family level while the other columns use observations at the family-firm level. Some families are associated with several firms, implying that those families appear multiple times in the data. For this reason, the number of observations in Columns 2 (and 6) could in theory be larger than Columns 1 (and 5). All coefficients excluded from the main tables are shown in the long version of the same table in Appendix Table D.3.

but for each year separately. We then plot the yearly estimated 'Ratio Clean/Dirty' either with or without firm fixed effects on Figure 5.4. 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).

We see that the relative absorptive capacity for AI has increased over the years: it is fairly noisy up until around 2002, then becomes positive, and reaches close to 600% in 2018. For most years, it is very similar whether or not firm fixed effects are used in the estimation. Since 2008, however, the within-firm absorptive capacity is consistently higher. This means that AI did not diffuse through all firms at the same pace.[17] We further explore heterogeneity along firm characteristics in the next section.

17. The specifications using firm fixed effects mechanically drop the families filed by firms that do not have both clean and dirty families. As a result, those specifications capture only the relative absorptive capacity in the context of firms that do both clean and dirty patenting. Intuitively, we can expect those to be large diversified firms. Conversely, the specifications without firm fixed effects contain families associated to any kind of firms: either firms filing both clean and dirty, firms specialising in dirty patenting only, or firms specialising in clean patenting.



Note: The figure examines how the relative absorptive capacity of clean vs dirty has changed over time. To do so, we run similar regressions as Column 1 and 2 for AI (and Column 4 and 5 for ICT) but for each year separately. We then plot the yearly estimated 'Ratio Clean/Dirty' either with or without firm fixed effects. 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). 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. The differences between the solid and dotted lines indicate that firm-level characteristics are playing a significant role, which we further investigate in Section 5.6. Source: Authors' calculations based on PATSTAT 2021 and BvD Orbis.

FIGURE 5.4
Relative Absorptive Capacity of Clean vs. Dirty Over Time

For ICT, the story differs slightly. The relative absorption is positive and significantly higher for ICT than for AI for most years. 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 the relative absorptive capacity estimated with and without firm fixed effects is larger for ICT than for AI. But, this time, the line without firm fixed effects is on top. This means that firms specialising in clean patenting have an easier time absorbing ICT, compared to other firms.

Finally, in Table 5.4, we explore whether inventions relying on AI or ICT generate greater value. For this purpose, we proxy 'value' by the number of citations received within 3 years of the priority year.[18] First, in Column 1, we see clean families receive about 66% more citations then dirty.[19] 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 27% more citations.[20] The effect of citing AI declines somewhat when firm fixed

18. We run a similar analysis using citations received within 5 years in Appendix Table D.10 and find similar results.

19. The specification is log-linear, hence we convert the coefficients in the following way: $100 * (e^{0.508} - 1) = 66.2\%$.

20. Similarly: $100 * (e^{0.240} - 1) = 27.1\%$.

TABLE 5.4
Do Families Citing AI or ICT Receive More Forward Citations?

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Clean Family	0.508***	0.497***	0.413***	0.394***	0.508***	0.480***	0.413***	0.377***
	(0.024)	(0.022)	(0.042)	(0.041)	(0.024)	(0.040)	(0.042)	(0.042)
Grey Family	0.324***	0.322***	0.265***	0.262***	0.324***	0.342***	0.265***	0.262***
	(0.019)	(0.017)	(0.032)	(0.030)	(0.019)	(0.022)	(0.032)	(0.027)
AI Citing		0.240***		0.130***				
		(0.046)		(0.026)				
Clean X Citing AI		0.061***		0.119***				
		(0.014)		(0.022)				
Grey X Citing AI		0.008		0.042				
		(0.017)		(0.028)				
ICT Citing						0.335***		0.156***
						(0.047)		(0.039)
Clean X Citing ICT						-0.111***		0.007
						(0.005)		(0.020)
Grey X Citing ICT						-0.126***		-0.022
						(0.016)		(0.027)
Constant	-1.407***	-1.385***	-0.960***	-0.945***	-1.407***	-1.401***	-0.960***	-0.957***
	(0.088)	(0.093)	(0.090)	(0.095)	(0.088)	(0.090)	(0.090)	(0.091)
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	0.282	0.284	0.338	0.339	0.282	0.285	0.338	0.340
Observations	2.55e+06	2.55e+06	1.47e+06	1.47e+06	2.55e+06	2.55e+06	1.47e+06	1.47e+06

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. All coefficients excluded from the main tables are shown in the long version of the same table in Appendix Table D.9.

effects are included, but the magnitude remains relatively high at around 14%. The interaction between being clean and citing AI is positive and significant implying that the effect of citing AI on forward citations is stronger for clean than dirty inventions. This interaction effect is much greater when firm fixed effects are included.

5.6 Firm-Level Mechanisms

In this section, we examine cross-firm variation in the capacity to absorb AI and ICT spillovers into energy inventions. In the previous section, family-level analyses highlighted the role of firms' characteristics in determining relative absorptive capacity. In addition, recall that our theoretical results show that spillovers from a GPT knowledge stock should be an important determinant of 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 or ICT (see Appendix Figure D.2).

To estimate the role of GPT spillovers within firms, we construct a dataset at the firm-year-

TABLE 5.5
Examples of Top Energy Patenting Firms

Firm Type	Name	Count Energy	% Clean	% Dirty	% Clean Families Citing AI	% Dirty Families Citing AI
Electricity	Sharp Corporation	256	87	8	1	0
Electricity	GE	115	8	45	14	5
Electricity	Kobe Steel,Ltd.	92	22	56	2	0
Transport	Toyota	3259	54	11	5	1
Transport	Bosch	1215	33	9	11	3
Transport	Denso	1108	30	27	9	1
Both	Panasonic	1096	85	10	2	0
Both	Sanyo Electric Co.,Ltd.	651	97	2	0	0
Both	Toshiba	615	80	8	2	1

Note: The table shows the number of energy patent families, the percentage of families which are clean or dirty, and the percentage of each which cite AI, for some of the top patenting firms. The values correspond to averages over the period 1990-2018. To classify firms, we calculate the following ratio: $\frac{CountTransport-CountElectricity}{CountTransport+CountElectricity}$, where *Count* refers to the number of family in the category. We define firms as 'Transport' if this ratio is greater than 0.5; 'Electricity' if it is smaller than -0.5; and 'Both' if it ranges from -0.5 to 0.5.

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.

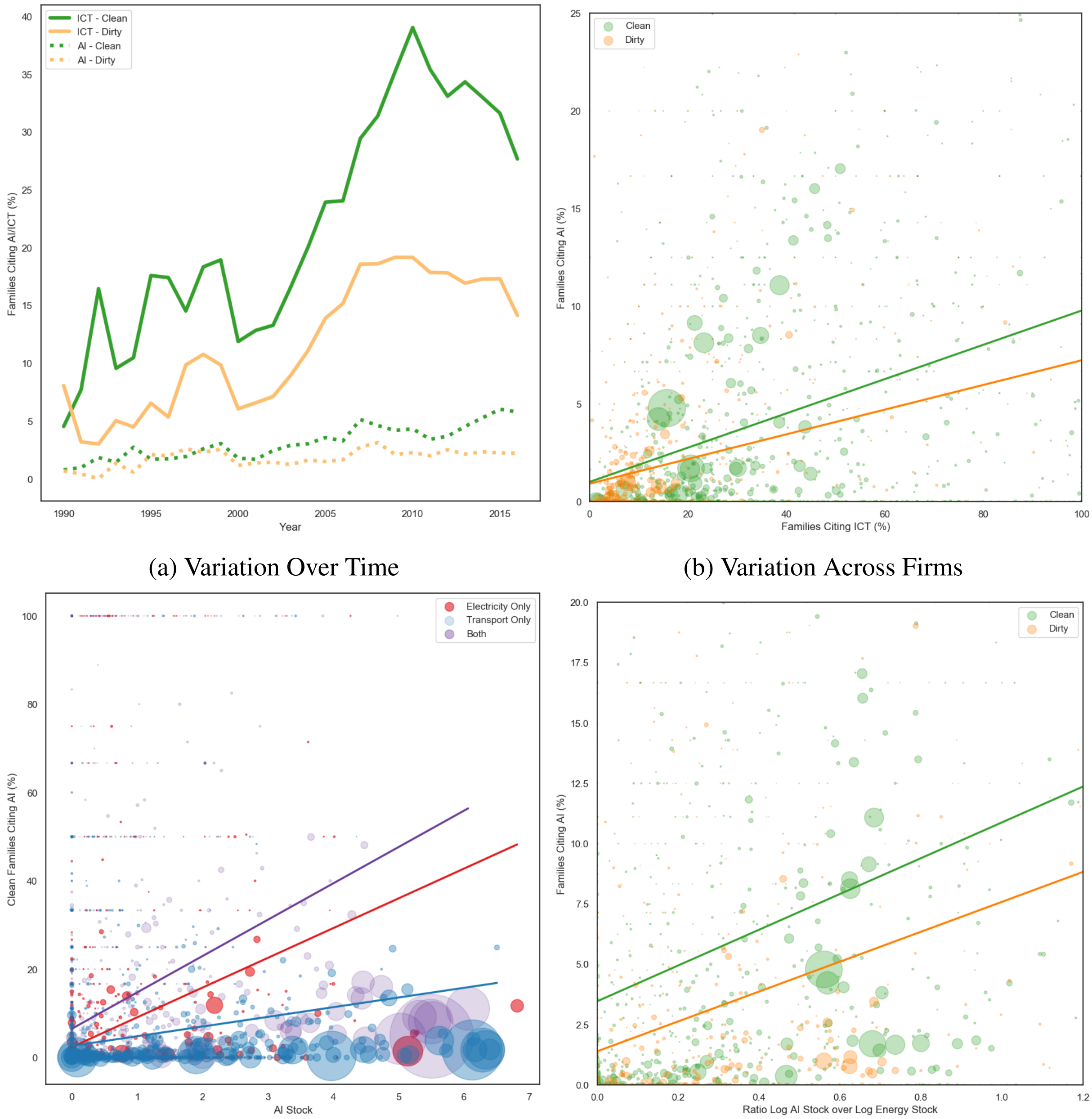
Table 5.5 provides some examples of top patenting firms, together with the average annual number of clean and dirty families and the percentage citing AI. For clarity, we group firms into three types: those that mostly patent electricity-related inventions, those that patent mostly transport-related inventions and those that do both.[21] We note that the percentage of families citing AI is always higher in clean portfolios than in dirty but the percentage can go from 3% (e.g., Panasonic) to 11% (e.g., Vestas, a leading wind energy firm).

Figure 5.5 provides more evidence of firm-level variation in absorption capacity. First, on Figure 5.5a, we see that, the average firm's clean portfolio always relies more on AI and ICT than dirty.[22] For AI, we also note that the gap between clean and dirty has somewhat been widening over time, and especially since 2010. These trends are consistent with what we observed at the family level on Figure 5.4. We note, however, that ICT absorption has been going down since 2010. This is almost coincidental with the temporary slowdown in clean patenting observed on Figure 5.2a and 5.2b.

Figures 5.5b, 5.5c and 5.5d illustrate the variation across firms. On these graphs, each

21. To classify firms, we calculate the following ratio: $\frac{CountTransport-CountElectricity}{CountTransport+CountElectricity}$, where *Count* refers to the number of family in the category. This ratio spans values from -1 to $+1$, where -1 corresponds to firms doing 100% electricity and $+1$ 100% transport. We define firms as 'Electricity' if the ratio is smaller than -0.5; 'Transport' if it is greater than 0.5; and 'Both' if it ranges from -0.5 to 0.5.

22. To be exact, Figure 5.5a plots the *weighted* mean share of families that cite AI or ICT in a given portfolio. The mean is weighted by the size of the portfolio so that firms with larger portfolios weigh more in the calculation.



(a) Variation Over Time

(b) Variation Across Firms

(c) Correlation with AI Stock

(d) Correlation with AI to Energy Stock

Note: Figure 5.5a plots the weighted mean share of families that cite AI or 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. On the other figures, each bubble represents a firm-year-portfolio observation and the bubble's size is proportional to the number of families in the portfolio in that year. The values are calculated for the years 2005 to 2015. Source: Authors' calculations based on PATSTAT 2021 and BvD Orbis.

FIGURE 5.5

Variation Over Time and Across Firms in the Percentage of Families Citing AI and ICT bubble represents a firm-year-portfolio observation where the bubble's size is proportional to the number of families in the portfolio in that year. The values are calculated for the years 2005 to 2015. First, Figure 5.5b shows the variation across firms in the percentage of families in clean and dirty portfolios that cite AI or ICT. Unsurprisingly, portfolios rely on ICT in larger proportions than for AI (the y-axis' scale is larger than that of the x-axis). The solid lines further show that, for a given level of ICT absorption, AI absorption is typically higher in clean portfolios compared to dirty. Again, this is consistent with what we saw in the previous section.

Next, we examine whether firm-level stock of AI knowledge is an important predictor of absorptive capacity. In other words, do firms that filed more AI patent families in the past rely more on AI in their clean portfolios? According to Figure 5.5c, the answer is a tentative yes. The solid lines highlight that firms patenting in both sectors (purple) or mostly in transport (red) have a higher level of absorption on average. The correlation seems also stronger for those firms relative to those patenting mostly in electricity.

Finally, we explore whether energy incumbents may be at a disadvantage relative to new entrants. To do so, we calculate firms' energy stock as the sum of clean, grey and dirty electricity/transportation patent stocks. Figure 5.5d shows there is a positive relationship between firm-level AI absorption and the ratio of the firm's AI stock to Energy stock. This suggests that firms with a very high energy stock relative to their AI stock are less able to apply AI to energy technologies, which would be consistent with new or smaller energy firms being better able to absorb AI and ICT into their inventions.

We probe those relationships further using linear regressions. First, we check whether clean portfolios absorb more AI and ICT than dirty ones. The first specification is, therefore, as follows:

$$\begin{aligned} FamilyCountCitingGPT_{jtk} = \beta_0 + \beta_1 FamilyCount_{jtk} + \beta_c Clean_k + \beta_g Grey_k \\ + \mathbf{bX}_{jt} + \delta_t + \delta_j + \varepsilon_{jtk} \end{aligned} \tag{5.15}$$

$FamilyCountCitingGPT_{jtk}$ is the count of families in portfolio k filed in year t by firm j that cite some AI or ICT patents. $FamilyCount_{jtk}$ is the total number of families in portfolio k (filed in year t by firm j). $Clean_k$ and $Grey_k$ are binary variables equal to 1 if the portfolio is clean or grey. We run separate regressions for the transport and 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.

To examine more closely how absorption varies by type of firms, we also include two other control variables interacted with Clean and Grey. The first, 'Firm Sectoral Focus', is a variable with values between -1 and 1 that captures the degree of sectoral specialisation. It equals to -1 when the firm's energy families are all in electricity, and to 1 when they are all in transport. Specifically, it is equal to $\frac{CountTransport-CountElectricity}{CountTransport+CountElectricity}$, where *Count* refers to the number of families in the category (for firm j in year t). Second, we include variables that capture specialisation within the clean-grey-dirty space. In particular, 'Firm Clean Focus' is the percentage of clean families out of all energy families (in year t) and allows us to explore whether the propensity to absorb AI and ICT is higher or lower in firms that specialise in clean energy inventions.

Next, we examine 1) whether higher stocks of AI or ICT facilitate AI and ICT absorption, and 2) whether there is a negative incumbent effect such that a higher stock of energy patents correlates with lower levels of absorption. To do so, we study a regression similar to the one above, but adding terms for the AI, ICT and energy stocks:

$$\begin{aligned} FamilyCountCitingGPT_{jtk} = \beta_0 &+ \beta_1 FamilyCount_{jtk} + \beta_c Clean_k + \beta_g Grey_k \\ &+ \beta_2 StockGPT_{jt-1} + \beta_3 StockEnergy_{jt-1} \\ &+ \mathbf{bX}_{jt} + \delta_t + \delta_j + \varepsilon_{jtk} \end{aligned} \tag{5.16}$$

$StockGPT_{jt-1}$ is the discounted cumulative count of AI or ICT families firm j filed up to time $t-1$. $StockEnergy_{jt-1}$ is the discounted cumulative count of energy families (of any type) firm j filed up to time $t-1$. We also include interactions between the stock variables and $Clean_k$ and $Grey_k$. Table 5.6 and 5.7 present the regression results. In both Tables, Column 1 to 4 focus on AI, Column 5 to 8 on ICT. Columns 1-2 and 5-6 examine 'Transport' portfolios, while Columns 3-4 and 7-8 examine 'Electricity' portfolios.

First, Columns 1, 3, 5 and 7 in Table 5.6 show that clean portfolios typically absorb more AI or ICT than dirty: in all columns, the coefficient on Clean is positive and significant at the 1% level, except for AI in electricity.[23] This is indicative that clean technologies have a greater *intrinsic* capacity to use AI in transport, and ICT in both transport and electricity. On the other hand, it seems unlikely that clean technologies in electricity have a much higher intrinsic absorptive capacity for AI than dirty.

Results shown in Columns 2, 4, 6, and 8, however, highlight that the lead of clean over dirty is significantly different for firms with different specialisations. For transport portfolios, the lead of clean over dirty in absorbing AI and ICT is mostly present when firms' patenting concentrates on clean transport.

In electricity, the story is different. First, clean portfolios do not appear to absorb significantly more AI, and, in fact, dirty may lead slightly when firms concentrate on dirty electricity. Indeed, in Column 4, the coefficient on 'Clean Portfolio' is negative and significant at the 10%

23. This is consistent with our family-level results presented in Section 5.5.

TABLE 5.6
Do Firms' Clean Portfolios Rely More on AI and ICT Than Dirty Portfolios?

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Family Count (log)	0.944***	0.974***	0.979***	0.997***	0.888***	0.921***	0.979***	0.970***
	(0.049)	(0.050)	(0.040)	(0.055)	(0.038)	(0.042)	(0.026)	(0.030)
Clean Portfolio	1.471***	-0.020	0.156	-0.599*	0.904***	0.176	0.495***	0.188
	(0.098)	(0.297)	(0.123)	(0.363)	(0.062)	(0.182)	(0.057)	(0.154)
Firm Sectoral Focus		-0.028		-0.101		-0.046		-0.091
		(0.194)		(0.167)		(0.117)		(0.099)
Firm Clean Focus		-0.004		-0.005		-0.001		-0.003*
		(0.004)		(0.003)		(0.002)		(0.002)
Clean X Firm Sectoral Focus		0.523***		0.179		0.201*		-0.142
		(0.195)		(0.162)		(0.115)		(0.111)
Clean X Firm Clean Focus		0.012***		0.012**		0.006**		0.003
		(0.005)		(0.005)		(0.003)		(0.002)
Portfolio Type	Transport	Transport	Electricity	Electricity	Transport	Transport	Electricity	Electricity
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	X	X	X	X
Firm level controls	X	X	X	X	X	X	X	X
Observations	10,733	10,733	10,082	10,082	17,310	17,310	22,476	22,476
R2	0.738	0.740	0.450	0.455	0.835	0.836	0.732	0.733

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.

Note: Firm Sectoral Focus is a variable from -1 to 1 that captures the degree of specialisation (in year t). It equals to -1 when the firm's energy families are all in electricity; it equals to 1 when they are all in transport. Specifically, it is equal to $\frac{CountTransport - CountElectricity}{CountTransport + CountElectricity}$, where *Count* refers to the number of families in the category. Firm Clean Focus is the percentage of clean families out of all energy families (in year t). 'Grey' and interactions with 'Grey' are included in the regressions but left out of the table for clarity. All coefficients shown in the longer version of the same table in Appendix Table D.11.

level.

ICT absorption in electricity also presents a mixed picture. Although Column 7 shows that clean indeed leads over dirty, the effect mostly disappears (but remains positive) when controlling for firms' sectoral and clean specialisations. The coefficients are not significant for those variables, but qualitatively, their signs indicate that that the gap between clean and dirty is stronger when firms specialise in electricity.

Next, on Table 5.7, we find that firms with higher AI (resp. ICT) stocks cite more AI (resp. ICT) patents in their inventions (Columns 1, 3, 5 and 7). This is consistent with the earlier theoretical result 2a) which stated that GPT absorption will increase with the existing accessible GPT stock.

When adding firm fixed effects, however, the coefficients on AI stock is no longer significant (Columns 2). In other words, the variation over time within firms in the size of the AI stock explains little of the variation in absorptive capacity. The coefficient on the interaction, however, remains significant at the 10% level.

The interaction between the AI stock and Clean is also positive and significant for transport (at the 10% level). It indicates that a higher AI stock facilitates AI absorption more so for clean than dirty portfolios. This is consistent with our theoretical result 2c), which predicted a positive interaction between the intrinsic absorption capacity of a technology and the GPT stock (for the technology which is chosen as the direction of technological change).

The story of AI absorption in 'Electricity' portfolios is similar but weaker. Column 3 indicates that firms with a higher AI stock cite more AI in both their clean and dirty portfolios. Coefficients lose significance once adding firm fixed effects (Column 4) highlighting that the correlations in Column 3 were driven by variation across firms.

ICT absorption also seems to increase when firms have a higher stock of ICT patents. However, now the coefficient on the interaction between Clean and ICT Stock is negative and significant, highlighting that the facilitating effect of the ICT stock is stronger for dirty than clean portfolios. Interestingly, those results hold also when including firm fixed effects, thus using only variation over time within firms. This indicates that, as firms grow their stock of ICT, they also increase the proportion of their energy patents absorbing ICT.

Last but not least, we explore whether experience in energy patenting accelerates or slows down absorption in the GPT. Here, the coefficients on 'Stock Energy' are negative and almost always strongly significant. This indicates that firms with many energy patents (e.g., incumbents) tend to absorb the GPT less. The coefficients on the interaction 'Clean X Stock Energy' are generally not significant, highlighting that this effect is similar for both clean and dirty portfolios. Importantly, this negative incumbent effect is consistent with our theoretical result 3 assuming an aging parameter δ greater than 1; in other words, mature application sectors are less able to absorb the GPT.

TABLE 5.7
Does Experience in AI, ICT and/or Energy Patenting Facilitate AI/ICT Absorption?

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Family Count (log)	0.982***	0.922***	1.064***	1.017***	0.939***	0.887***	1.032***	1.016***
	(0.044)	(0.045)	(0.126)	(0.042)	(0.030)	(0.044)	(0.036)	(0.026)
Clean Portfolio	0.750***	1.014***	0.350***	0.006	0.680***	0.697***	0.903***	0.476***
	(0.147)	(0.273)	(0.112)	(0.184)	(0.075)	(0.126)	(0.064)	(0.102)
Stock AI (log, t-1)	0.273***	0.020	0.333***	-0.067				
	(0.066)	(0.096)	(0.082)	(0.087)				
Clean X Stock AI (log, t-1)	0.138*	0.137*	-0.030	-0.014				
	(0.073)	(0.074)	(0.101)	(0.047)				
Stock Energy (log, t-1)	-0.199***	-0.186**	-0.136***	-0.048	-0.169***	-0.244***	-0.250***	-0.183***
	(0.045)	(0.083)	(0.051)	(0.063)	(0.026)	(0.049)	(0.023)	(0.045)
Clean X Energy Stock (log, t-1)	-0.029	-0.007	-0.112*	0.033	0.109***	0.093***	0.017	0.101***
	(0.046)	(0.065)	(0.068)	(0.042)	(0.025)	(0.026)	(0.033)	(0.032)
Stock ICT (log, t-1)					0.231***	0.197***	0.305***	0.083*
					(0.022)	(0.060)	(0.019)	(0.049)
Clean X Stock ICT (log, t-1)					-0.121***	-0.072***	-0.099***	-0.084***
					(0.027)	(0.024)	(0.023)	(0.023)
Portfolio Type	Transport	Transport	Electricity	Electricity	Transport	Transport	Electricity	Electricity
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	26,810	9,610	41,591	9,097	26,810	15,604	41,591	20,266
R2	0.660	0.742	0.335	0.449	0.769	0.836	0.639	0.726

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.

Note: Stock Energy corresponds to the firm's total stock of energy patents (i.e., the sum of clean, grey and dirty electricity/transportation patent stocks). We add interactions between the portfolio type and the GPT stock but only show the interaction for 'Clean'. 'Grey' is included in the regressions but left out of the table for clarity. All coefficients excluded from the main tables are shown in longer versions of the same table in Appendix Table D.18 and D.19.

5.7 Discussion and Conclusion

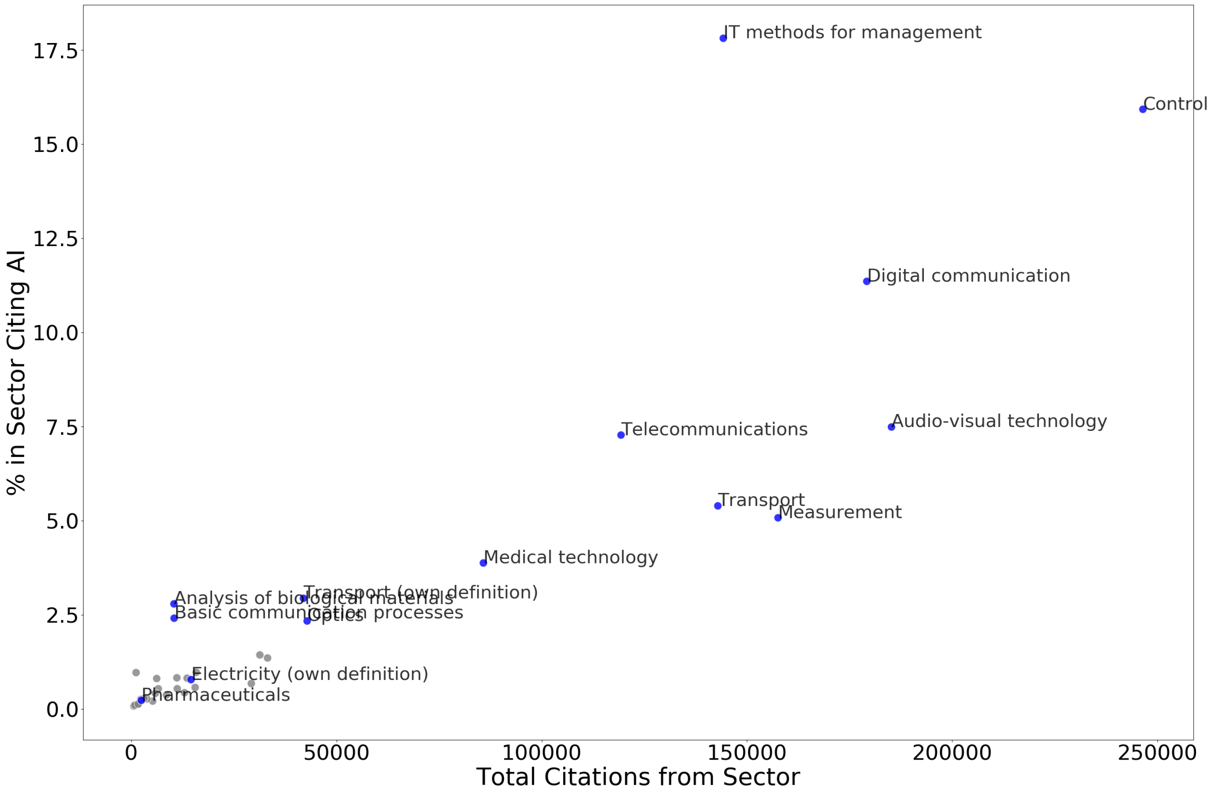
This chapter explores theoretically and empirically whether AI has the potential to accelerate clean energy innovation. We first examine how a GPT can affect the race between clean and dirty in a model of directed technological change. We find that, depending on the relative absorptive capacity of clean and dirty, the GPT can break path dependency and help clean technologies compete with dirty. We then use 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 a 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 not only holds, but increases within firms, suggesting that clean tech has a higher intrinsic absorptive capacity and is now the preferred direction of technological change.[24] 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. 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 0.3% of backward citations that energy patents make go to AI inventions. Similarly, only about 9% of firms' patents cite any AI invention. These figures are much lower than the trends for ICT between 1990 and 2010. Figure 5.6 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.

24. 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.



Note: The figure illustrates variation in the propensity to absorb AI across sectors in the economy. The x-axis shows the total number of families in sector j; the y-axis shows the percentage of families in sector j that cite AI. We identify sector-specific families using the technical field classification in PATSTAT's Table 230. We also add on the graph dots representing the electricity and transport sectors as defined in this chapter, that is, based on the sets of CPC and IPC codes detailed in Appendix Table D.1 and D.2. These are different because the PATSTAT technical field are typically broader. For transport, for example, it includes any family related to non-road transport and other aspects of transport innovation, such as automated driving. For readability, we have excluded computer technology from the graph because it is a strong outlier in both the x and y-axes. The sample used consists of families filed between 1980 and 2018, in any country. For the y-axis we only consider citations made within three years of an AI family being filed to control for potentially differing levels of maturity across sectors. Source: Authors' calculations based on PATSTAT 2021.

FIGURE 5.6
AI Absorption Across the Economy

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 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). Analysing the heterogeneous impact on different technologies is important to better understand 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 the same. 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, or indeed if and how fast new technologies drawing on AI actually make it to market. Does the integration of AI make technologies more productive and does it accelerate the rate of subsequent innovation? Are there barriers to deployment which mean that many of these technologies are not actually being used? To answer these questions, future research could look at the impact of AI-based energy innovation on firm productivity, sales and subsequent rate of innovation, as well as the degree to which such innovation leads to technology adoption in markets in which it could be most useful.

Despite its limitations, this chapter provides the first empirical analysis of innovation spillovers from AI and ICT to clean and dirty technologies on a global scale. Although policymakers often recognise 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 catalysing spillovers (universities, startups, large firms, regional clusters).

Chapter 6

Conclusion

The transition to greener technologies is key to meeting the world's climate and other environmental challenges. This transition is bound to create winners and losers, and is taking place in the context of broader geopolitical and often mercantilist competition between nations on the global stage, as well as broader technological shifts.

This thesis has considered the shift towards green technologies and its relationship with the broader global landscape of trade, economic competitiveness and competition, as well as other technological transitions, from a number of different angles and using several different methods. In doing so, I have drawn on both theory (Chapters 2 and 5) and empirical analyses using patent, trade and firm-level data combined with empirical approaches from standard econometrics (Chapters 3 and 5) and economic geography and complexity (Chapter 4).

Chapters 2 and 3 both studied the issue of protectionism in the renewable energy sector with a focus on solar photovoltaics (PV), albeit from different angles. Chapter 2 presented an analytical framework highlighting the potential for infant industry maturation in a product with positive externalities to yield global benefits through increased gains from trade via competition long term, even at the cost of temporary protection from trade. The chapter used solar PV as a real world case study, illustrating how China's entry into solar manufacturing dramatically increased global competition and drove down costs. Chapter 3 then turned to the 2013 EU-China solar trade war, investigating whether Chinese import competition was beneficial or harmful to firm-level solar PV innovation in Europe. It has argued that competition from China seems to have in fact increased innovation by European firms.

Both chapters add evidence to the literature arguing that environmental and trade policies need to be designed jointly (De Melo and Solleder 2022; Grubb et al. 2022; Jakob et al. 2022; Messerlin 2010), substantiating the case for greater integration of climate-trade regimes. They highlight the importance of competition for market share in green technologies to feature in this discourse, which currently focuses heavily on carbon border adjustments (e.g. Barrett 1994b; Grubb et al. 2022; Richter et al. 2021) and issue linkage (e.g. Barrett 1997; Barrett and Dannenberg 2022; Hagen and Schneider 2021; Helm et al. 2012; Nordhaus 2015). Chapter 3 further presents a case study in the 'China Shock' literature (e.g. Autor et al. 2013; Autor et al. 2016; Bloom et al. 2016; Bloom et al. 2021), examining this issue from a 'green' angle.

Chapter 4 turned away from countries' attempts to seize opportunities in the green economy and towards the issues facing countries whose production capabilities are heavily concentrated in declining, brown sectors. The chapter has provided quantitative estimates of country transition risk and highlighted the limitations of the 'smart specialisation policy' paradigm. The level of difficulty fossil fuel exporters face in adapting to a low carbon future presents a threat to effective global climate action and raises the contentious issue of compensation or buy-outs (e.g. Collier and Venables 2014; Harstad 2012a). In the case of low income fossil fuel exporters, compensation could be considered consistent with the moral imperative of a just transition, and possibly be used to fund policies to support economic diversification (Steckel and Jakob 2022).

Finally, the transition is taking place in the context of broader technological shifts which may have implications for policy, as well as for the 'green race'. Chapter 5 therefore analysed how the technological competition between clean and dirty energy and transport technologies may be affected by advances in artificial intelligence (AI) technology. It has argued, using theory and empirics, that the arrival of a new General Purpose Technology such as AI can reduce the path dependency currently favoring incumbent fossil fuel technologies (Acemoglu et al. 2012; Aghion et al. 2016), and that clean innovations seem to more intensely draw on AI technology than dirty ones.

More broadly, I hope that this thesis has contributed to demonstrating the value of breaking out of the intellectual niches we can sometimes be locked into and investigate a topic from multiple angles and methodological approaches.

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Appendix A

Industrial Policy and Global Public Goods Provision: Rethinking the Environmental Trade Agreement

A.1 Model Preliminaries

First Best Note that because production costs are lower in the frontier country, welfare would be higher if all production took place there, provided other market failures such as those arising from imperfect competition can be corrected.

In each stage, a benevolent social planner maximises global welfare by setting the marginal benefit of consumption equal to the marginal cost.

From the demand curve we deduce that the marginal private benefit from consumption (given by the marginal willingness to pay price p_i, $p_i = a - r_i$) is equal to $a - r_i$ in each country $i \in \{F, L\}$. The global public benefit from consumption is equal to $B = b(r_F + r_L)$, implying that the marginal public benefit from each additional unit consumed is b. Finally, the marginal cost of production in the frontier country is c. Thus, the social planner sets

$$a - r_i + b = c$$

such that

$$r_F = r_L = a + b - c$$

However, due to misalignment of countries' incentives this outcome cannot be sustained as an equilibrium. Neither country has an incentive to pay the subsidies required to achieve the first best outcome, because the marginal public benefit from consumption in each country is only $\frac{b}{2}$.

Business as Usual Let a business-as-usual scenario be one where countries are in autarky and no subsidies are employed. Then, in the frontier country the monopolist sets prices or quantities to solve

$$\max_{\{p_F\}} \Pi_F = r_F(p_F - c) = (a - p_F)(p_F - c)$$
$$= ap_F - p_F^2 - ac + p_F c$$

The first order condition is:

$$\frac{\delta \Pi_F}{\delta p_F} = a + c - 2p_F = 0$$

It is satisfied at

$$p_F = \frac{a+c}{2}; r_F = \frac{a-c}{2}$$

The second order condition is always satisfied as

$$\frac{\delta^2 \Pi_F}{\delta p_F} = -2 < 0$$

The monopolist in the laggard country solves an equivalent problem, substituting dc for c in Stage 1. Thus

$$\begin{aligned} p_{L,1} &= \frac{a+dc}{2}; r_{L,1} = \frac{a-dc}{2} \\ p_{L,2} &= \frac{a+c}{2}; r_{L,2} = \frac{a-c}{2} \end{aligned} \tag{A.1}$$

A.2 EQUILIBRIUM WITH NO SUBSIDIES

In a business-as-usual scenario in which countries are in autarky and no subsidies are used, each firm acts as a monopolist, with prices and quantities given by Equation A.1.

Let ε be an infinitesimal positive number. Under trade and in the absence of subsidies, the competitive price and resultant quantities are given by $p_1 = p_{F,1} = dc - \varepsilon$, $q_{F,1} = r_{F,1} + r_{L,1}; q_{L,1} = 0$ and $r_{F,1} = r_{L,1} = a - dc$ in Stage 1. In Stage 2,

$$p_2 = \begin{cases} p_{F,2} = dc - \varepsilon & \text{if } q_{L,1} = 0 \\ p_{F,2} = p_{L,2} = c & \text{if } q_{L,1} > 0 \end{cases}$$

implying that

$$\begin{cases} q_{F,2} = r_{F,2} + r_{L,2}; q_{L,2} = 0 \text{ if } q_{L,1} = 0 \\ q_{F,2} = q_{L,2} = \frac{r_{F,2}+r_{L,1}}{2} \qquad \text{if } q_{L,1} > 0 \end{cases}$$

and

$$\begin{cases} r_{F,2} = r_{L,2} = a - dc \text{ if } q_{L,1} = 0 \\ r_{F,2} = r_{L,2} = a - c \quad \text{if } q_{L,1} > 0 \end{cases}$$

Welfare payoffs for each strategy profile in the game without subsidies are given in Table A.1.

In Stage 2, trade is a weakly dominant strategy for both countries. The following analysis will therefore focus on characterising the Subgame-Perfect Nash Equilibrium in which countries trade in Stage 2, and determine which Stage 1 strategy is welfare maximising across both periods.

It is clear that Stage 1 welfare in both countries is greater under trade, while the laggard country's and collective Stage 2 welfare are greater following autarky in Stage 1.[1] Each government must therefore trade off the welfare losses from Stage 1 autarky against the welfare gains derived from the frontier firm's ability to catch up.

Proof of Proposition 1 Using the welfare payoffs presented in Table A.1, we see that

$$\Sigma_{t=1}^{2} W_{L,t}((0,1), T_F^*)) > \Sigma_{t=1}^{2} W_{L,t}((1,1), T_F^*))$$

requires

$$\frac{3}{8}(a-dc)^2 + \frac{(a-c)^2}{2} + \frac{b}{4}(6a - c(5+d)) > (a-dc)^2 + 2b(a-dc)$$

which holds for

$$d > \frac{5a+7b}{5c} - \frac{1}{5}\sqrt{\frac{20a^2+50ab+49b^2-40ac-50bc+20c^2}{c^2}}$$

. We therefore define the threshold ω as

$$\omega = \frac{5a+7b}{5c} - \frac{1}{5}\sqrt{\frac{20a^2+50ab+49b^2-40ac-50bc+20c^2}{c^2}}$$

.

$$\Sigma_{t=1}^{2} W_{F,t}((0,1), T_L^*)) \geq \Sigma_{t=1}^{2} W_{F,t}((1,1), T_L^*))$$

1. The frontier country's welfare may be higher or lower in Stage 2 following autarky in Stage 1, depending on whether the increases in consumer surplus and positive externalities are greater or lower than the loss in rents extracted from the laggard country's consumers.

TABLE A.1
Payoff Matrix (No Subsidies)

	Laggard: (1, 1)	Laggard: (1, 0)	Laggard: (0, 1)	Laggard: (0, 0)
Frontier: (1, 1)	$\Big(2(a-dc)(\frac{a-dc}{2} + 2c(d-1)+b), (a-dc)^2+2b(a-dc)\Big)$	$\Big((a-dc)(\frac{a-dc}{2} + 2c(d-1)+b)+\frac{3}{8}(a-c)^2 + \frac{b}{2}(a-\frac{c(1+d)}{2}), \frac{7}{8}(a-dc)^2 + \frac{b}{4}(6a-c(1+5d)\Big)$	$\Big(\frac{7}{8}(a-c)^2+\frac{b}{4}(6a-c(5+d)), \frac{3}{8}(a-dc)^2+\frac{(a-c)^2}{2} + \frac{b}{4}(6a-c(5+d)\Big)$	$\Big(\frac{3}{4}(a-c)^2+\frac{b}{4}(4a-c(3+d)), \frac{3}{8}(a-dc)^2+\frac{3}{8}(a-c)^2 + \frac{b}{4}(4a-c(3+d))\Big)$
Frontier: (1, 0)	$\Big((a-dc)(\frac{a-dc}{2} + 2c(d-1)+b)+\frac{3}{8}(a-c)^2 + \frac{b}{2}(a-\frac{c(1+d)}{2}), \frac{7}{8}(a-dc)^2 + \frac{b}{4}(6a-c(1+5d)\Big)$	$\Big((a-dc)(\frac{a-dc}{2} + 2c(d-1)+b)+\frac{3}{8}(a-c)^2 + \frac{b}{2}(a-\frac{c(1+d)}{2}), \frac{7}{8}(a-dc)^2 + \frac{b}{4}(6a-c(1+5d)\Big)$	$\Big(\frac{3}{4}(a-c)^2+\frac{b}{4}(4a-c(3+d)), \frac{3}{8}(a-dc)^2+\frac{3}{8}(a-c)^2 + \frac{b}{4}(4a-c(3+d))\Big)$	$\Big(\frac{3}{4}(a-c)^2+\frac{b}{4}(4a-c(3+d)), \frac{3}{8}(a-dc)^2+\frac{3}{8}(a-c)^2 + \frac{b}{4}(4a-c(3+d))\Big)$
Frontier: (0, 1)	$\Big(\frac{7}{8}(a-c)^2+\frac{b}{4}(6a-c(5+d)), \frac{3}{8}(a-dc)^2+\frac{(a-c)^2}{2} + \frac{b}{4}(6a-c(5+d)\Big)$	$\Big(\frac{3}{4}(a-c)^2+\frac{b}{4}(4a-c(3+d)), \frac{3}{8}(a-dc)^2+\frac{3}{8}(a-c)^2 + \frac{b}{4}(4a-c(3+d))\Big)$	$\Big(\frac{7}{8}(a-c)^2+\frac{b}{4}(6a-c(5+d)), \frac{3}{8}(a-dc)^2+\frac{(a-c)^2}{2} + \frac{b}{4}(6a-c(5+d)\Big)$	$\Big(\frac{3}{4}(a-c)^2+\frac{b}{4}(4a-c(3+d)), \frac{3}{8}(a-dc)^2+\frac{3}{8}(a-c)^2 + \frac{b}{4}(4a-c(3+d))\Big)$
Frontier: (0, 0)	$\Big(\frac{3}{4}(a-c)^2+\frac{b}{4}(4a-c(3+d)), \frac{3}{8}(a-dc)^2+\frac{3}{8}(a-c)^2 + \frac{b}{4}(4a-c(3+d))\Big)$	$\Big(\frac{3}{4}(a-c)^2+\frac{b}{4}(4a-c(3+d)), \frac{3}{8}(a-dc)^2+\frac{3}{8}(a-c)^2 + \frac{b}{4}(4a-c(3+d))\Big)$	$\Big(\frac{3}{4}(a-c)^2+\frac{b}{4}(4a-c(3+d)), \frac{3}{8}(a-dc)^2+\frac{3}{8}(a-c)^2 + \frac{b}{4}(4a-c(3+d))\Big)$	$\Big(\frac{3}{4}(a-c)^2+\frac{b}{4}(4a-c(3+d)), \frac{3}{8}(a-dc)^2+\frac{3}{8}(a-c)^2 + \frac{b}{4}(4a-c(3+d))\Big)$

requires that

$$\frac{3}{8}(a-c)^2+\frac{b}{2}(\frac{a-dc}{2}+\frac{a-c}{2})+\frac{(a-c)^2}{2}+b(a-c)>2\left[(a-dc)\left(\frac{a-dc}{2}+2c(d-1)+b\right)\right]$$

which holds for

$$d>\frac{8a-7b+16c}{24c}+\frac{1}{24}\sqrt{\frac{88a^2-16ab+49b^2-176ac+16bc+88c^2}{c^2}}$$
$$b>a-c$$

leading us to define γ as

$$\gamma=\frac{8a-7b+16c}{24c}+\frac{1}{24}\sqrt{\frac{88a^2-16ab+49b^2-176ac+16bc+88c^2}{c^2}}$$

.

Proof of Proposition 3 Defining trade policy in terms of outcomes $A=\{A_1,A_2\}$ rather than strategies for ease of exposition,

$$\Sigma_{t=1}^2 W_{F,t}(\{0,1\})+W_{L,t}(\{0,1\}))>\Sigma_{t=1}^2 W_{F,t}(\{1,1\})+W_{L,t}(\{1,1\})$$

requires that

$$\frac{11}{8}(a-c)^2+\frac{3}{8}(a-dc)^2+b\left(3a-\frac{c(5-d)}{2}\right)>2(a-dc)^2+4(a-dc)(c(d-1)+b)$$

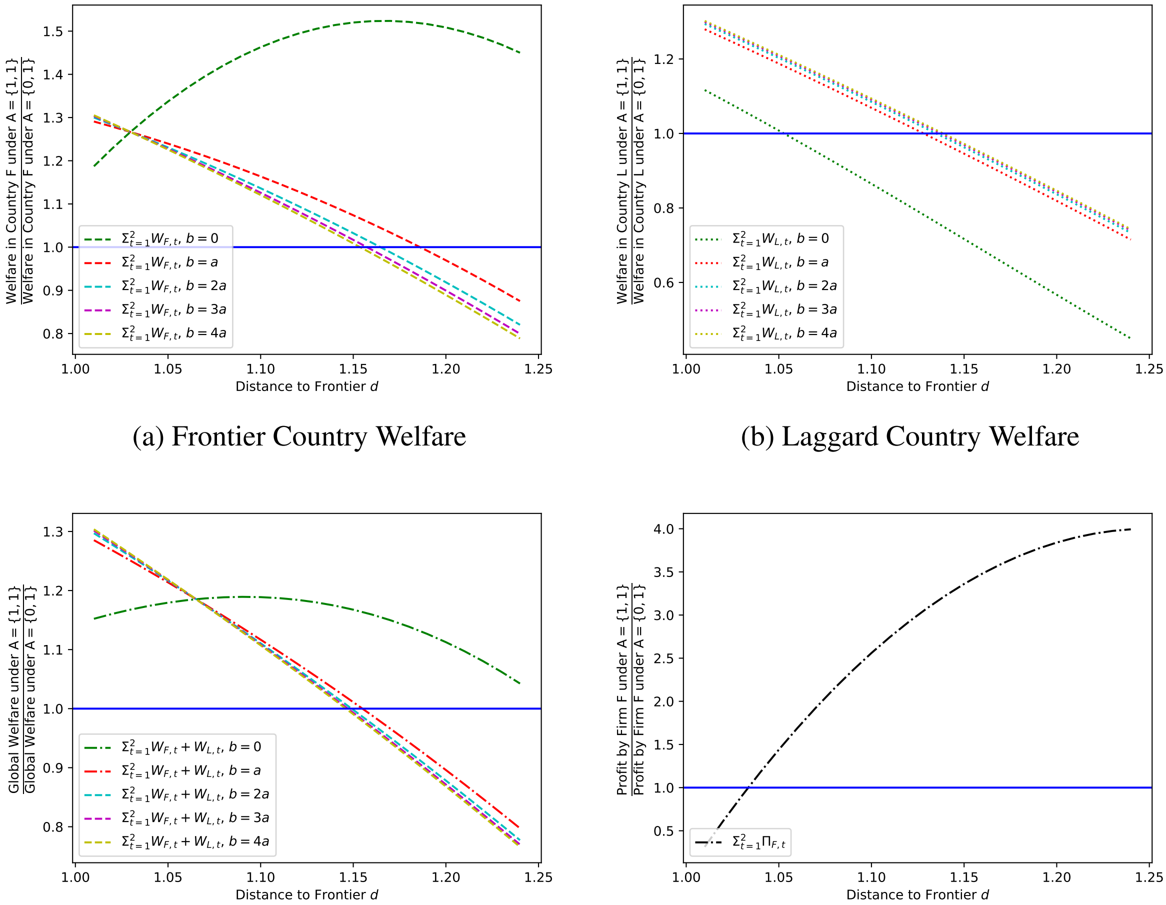
which holds for

$$d>\frac{3a-14b+16c}{19c}+\frac{1}{19}\sqrt{\frac{47a^2+68ab+196b^2-94ac-68bc+47c^2}{c^2}}$$
$$b>\frac{a-c}{24}$$

. This leads us to define

$$\theta=\frac{3a-14b+16c}{19c}+\frac{1}{19}\sqrt{\frac{47a^2+68ab+196b^2-94ac-68bc+47c^2}{c^2}}$$

.



(a) Frontier Country Welfare

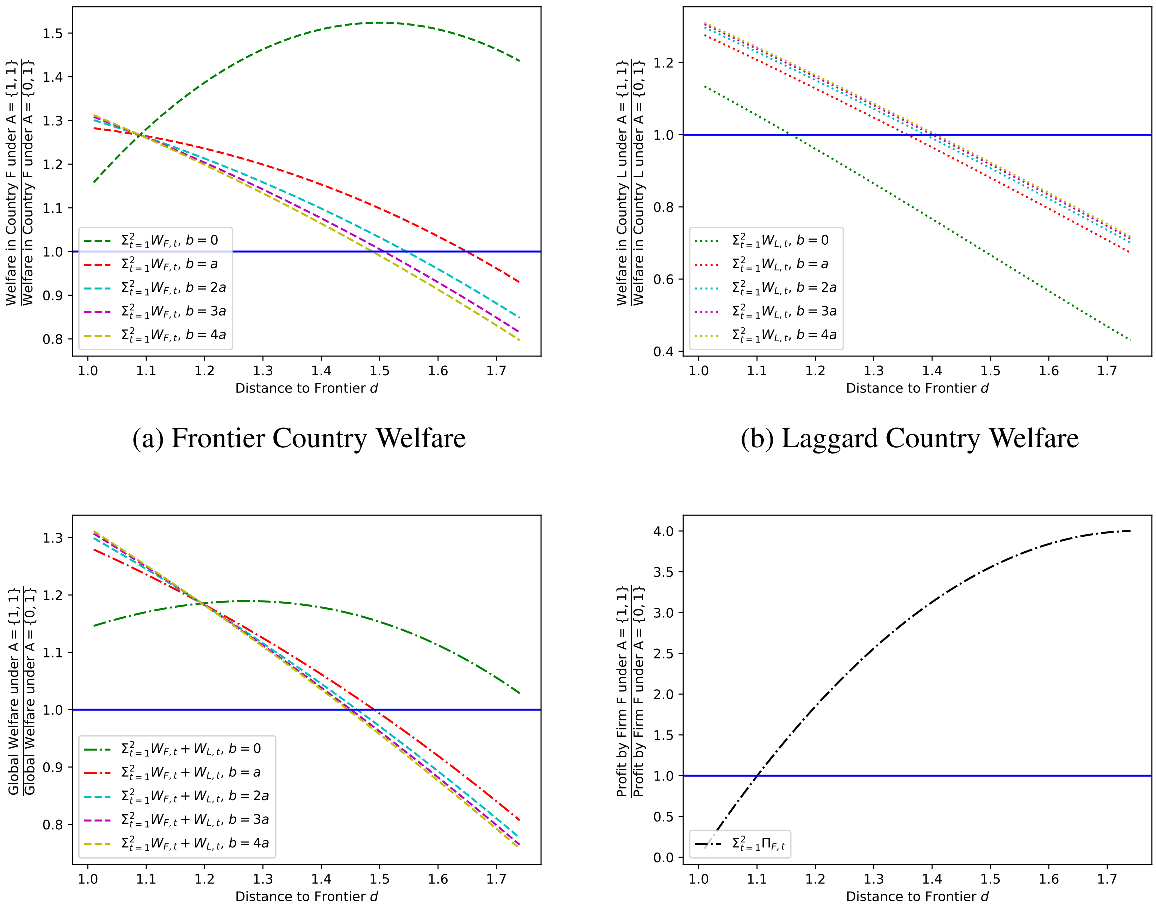
(b) Laggard Country Welfare

(c) Global Welfare

(d) Profit by firm *F*

Note: Like Figure 2.4, but with $a = 1.5c$.

FIGURE A.1
Welfare and Profit Under Trade Relative to Autarky, Using $a = 1.5c$



(a) Frontier Country Welfare

(b) Laggard Country Welfare

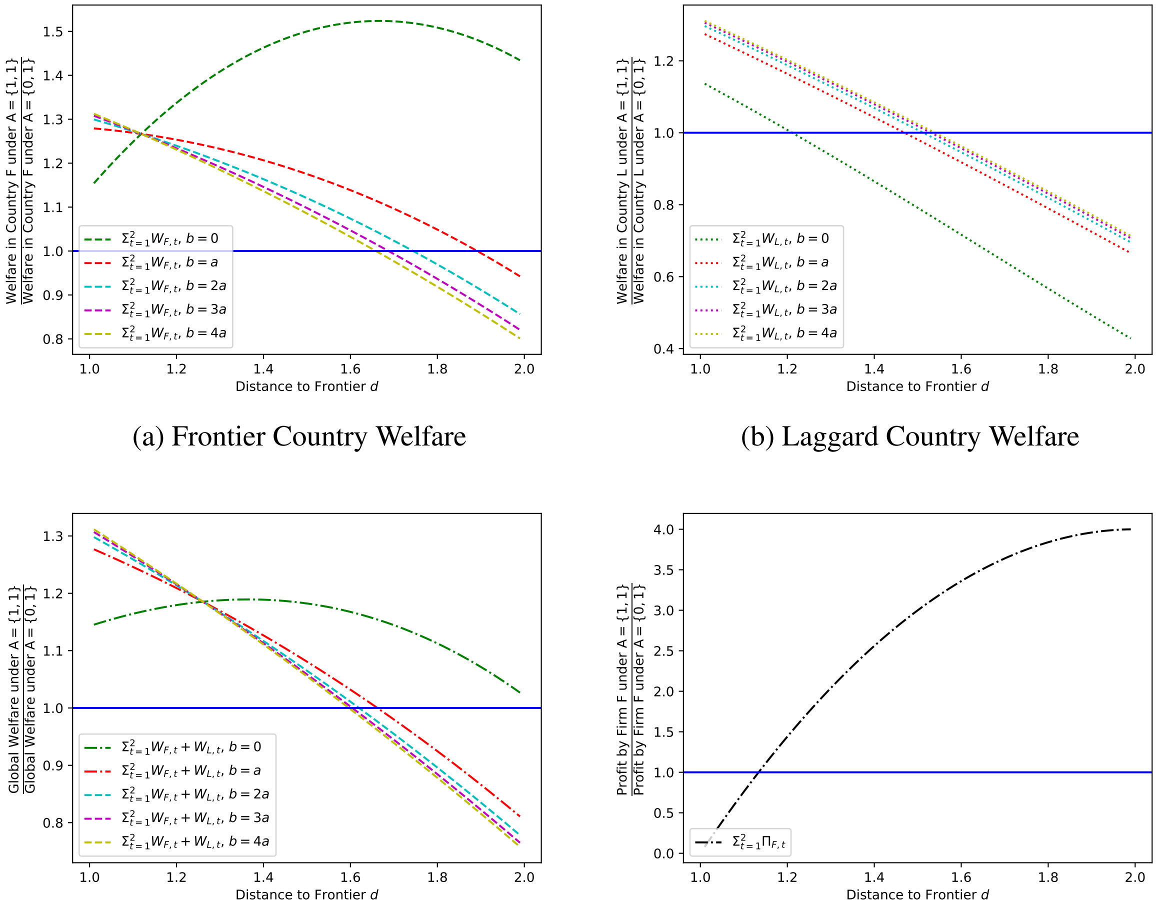
(c) Global Welfare

(d) Profit by firm F

Note: Like Figure 2.4, but with $a = 2.5c$.

FIGURE A.2

Welfare and Profit Under Trade Relative to Autarky, Using $a = 2.5c$



(a) Frontier Country Welfare

(b) Laggard Country Welfare

(c) Global Welfare

(d) Profit by firm F

Note: Like Figure 2.4, but with $a = 3c$.

FIGURE A.3
Welfare and Profit Under Trade Relative to Autarky, Using $a = 3c$

A.3 Optimal Subsidies under Autarky

In any stage of the game, the optimal subsidy under autarky corrects monopoly losses and internalises positive externalities which are realised locally. It does not matter whether the government subsidises the consumer or the producer.[2]

Consider a consumer subsidy in country i. A quantity subsidy s_i^{cons} shifts consumer demand such that

2. To see this, consider how a producer subsidy would shift the monopolist's profit maximisation problem. Profit in the frontier country would become $\Pi_F = (a - p_F)p_F + (a - p_F)s_F^{prod} - (a - p_F)c$, which is equivalent to Equation A.2. The laggard firm's profit maximisation function is modified in the same way, substituting dc for c.

$$r_i = a - p_i + s_i^{cons}$$

The monopolist in the frontier country now maximises

$$\Pi_F = (a - p_F + s_F^{cons})(p_F - c) \tag{A.2}$$

such that

$$p_F = \frac{a + s_F^{cons} + c}{2}; r_F = \frac{a + s_F^{cons} - c}{2}$$

The government thus faces the objective function

$$\begin{aligned}
\max_{\{s_F^{cons}\}} W_F(s_F^{cons}) &= ar_F - \frac{r_F^2}{2} - (p_F - s_F^{cons})r_F + p_F r_F - cr_F + \frac{b}{2}(r_F + r_L) - s_F^{cons} r_F \\
&= (a - c + \frac{b}{2})r_F - \frac{r_F^2}{2} + \frac{b}{2}r_L \\
&= (a - c + \frac{b}{2})(\frac{a + s_F^{cons} - c}{2}) - \frac{(\frac{a + s_F^{cons} - c}{2})^2}{2} + \frac{b}{2}r_L
\end{aligned}$$

From the first order condition we get the optimal consumer subsidy

$$s_F^{cons*} = a + b - c$$

which yields

$$r_F = a - c + \frac{b}{2}; p_F = a + \frac{b}{2}$$

Unlevelled industry In an unlevelled industry, country L solves a similar problem, substituting dc for c. The optimal consumer subsidy is

$$s_L^{cons*} = a + b - dc$$

leading to quantity and price

$$r_L = a - dc + \frac{b}{2}; p_L = a + \frac{b}{2}$$

Therefore, welfare in the frontier country is

$$W_F = \frac{r_F^2}{2} + r_F(a + \frac{b}{2} - c) + \frac{b}{2}(r_F + r_L) - r_F(a + b - c)$$
$$= \frac{r_F^2}{2} + \frac{b}{2} r_L = \frac{(a - c + \frac{b}{2})^2}{2} + \frac{b}{2}(a - dc + \frac{b}{2})$$

.

Similarly, welfare in the laggard country is

$$W_L = \frac{r_L^2}{2} + \frac{b}{2} r_F = \frac{(a - dc + \frac{b}{2})^2}{2} + \frac{b}{2}(a - c + \frac{b}{2})$$

.

Levelled industry In a levelled industry, subsidies, prices and quantities in the frontier country are the same as in the unlevelled case. In the laggard country,

$$s_L^{cons*} = a + b - c; r_L = a - c + \frac{b}{2}; p_L = a + \frac{b}{2}$$

Therefore, welfare in both countries is

$$W_F = W_L = \frac{(a - c + \frac{b}{2})^2}{2} + \frac{b}{2}(a - c + \frac{b}{2})$$

.

A.4 OPTIMAL SUBSIDIES UNDER TRADE

Unlevelled industry Let ε be an infinitesimal positive number. In each period, the competitive price facing the consumer is defined by

$$p = \begin{cases} p_F = dc - s_L^{prod} - \varepsilon & \text{if } p_F < p_L \\ p_F = p_L = dc - s_L^{prod} = c - s_F^{prod} & \text{if } p_F = p_L \\ p_L = c - s_F^{prod} - \varepsilon & \text{if } p_F > p_L \end{cases}$$

Quantities demanded are

$$\{r_F, r_L\} = \{a - p + s_F^{cons}, a - p + s_L^{cons}\}$$

.

Quantities produced by each firm are given by

$$\{q_F, q_L\} = \begin{cases} \{r_F + r_L, 0\} & \text{if } p_F < p_L \\ \{\frac{(r_F+r_L)}{2}, \frac{(r_F+r_L)}{2}\} & \text{if } p_F = p_L \\ \{0, r_F + r_L\} & \text{if } p_F > p_L \end{cases}$$

Welfare in the frontier country is defined as follows

$$W_F = \begin{cases} \frac{r_F^2}{2} + (p + s_F^{prod} - c)(r_F + r_L) + \frac{b}{2}(r_F + r_L) - s_F^{cons} r_F - s_F^{prod}(r_F + r_L) & \text{if } p_F < p_L \\ \frac{r_F^2}{2} + (p + s_F^{prod} - c)\frac{(r_F+r_L)}{2} + \frac{b}{2}(r_F + r_L) - s_F^{cons} r_F - s_F^{prod}\frac{(r_F+r_L)}{2} & \text{if } p_F = p_L \\ \frac{r_F^2}{2} + \frac{b}{2}(r_F + r_L) - s_F^{cons} r_F & \text{if } p_F > p_L \end{cases}$$

While welfare in the laggard country is

$$W_L = \begin{cases} \frac{r_L^2}{2} + \frac{b}{2}(r_F + r_L) - s_L^{cons} r_L & \text{if } p_F < p_L \\ \frac{r_L^2}{2} + (p + s_L^{prod} - dc)\frac{(r_F+r_L)}{2} + \frac{b}{2}(r_F + r_L) - s_L^{cons} r_L - s_L^{prod}\frac{(r_F+r_L)}{2} & \text{if } p_F = p_L \\ \frac{r_L^2}{2} + (p + s_L^{prod} - dc)(r_F + r_L) + \frac{b}{2}(r_F + r_L) - s_L^{cons} r_L - s_L^{prod}(r_F + r_L) & \text{if } p_F > p_L \end{cases}$$

Optimal subsidies if $p_F < p_L$ First, note that $p_F < p_L$ implies $c - s_F^{prod} < dc - s_L^{prod}$. The first order condition on s_F^{cons} is given by

$$\frac{\delta W_F}{\delta s_F^{cons}} = r_F + (p + s_F^{prod} - c) + \frac{b}{2} - r_F - s_F^{cons} - s_F^{prod} = 0$$
$$= p - c + \frac{b}{2} - s_F^{cons} = 0$$

therefore

$$s_F^{cons} = c(d-1) + \frac{b}{2} - s_L^{prod}$$

The second order condition is trivially satisfied with

$$\frac{\delta^2 W_F}{\delta s_F^{cons}} = -1 < 0$$

The first order condition on s_F^{prod} is

$$\frac{\delta W_F}{\delta s_F^{prod}} = (r_F + r_L) - (r_F + r_L) = 0$$

and is satisfied at any value of s_F^{prod}, implying that s_F^{prod} is solely defined by $c - s_F^{prod} < dc - s_L^{prod}$.

Solving for the laggard's optimal subsidies gives

$$\frac{\delta W_L}{\delta s_L^{cons}} = r_L + \frac{b}{2} - s_L^{cons} - r_L = 0$$

therefore

$$s_L^{cons*} = \frac{b}{2}$$

with the second order condition trivially satisfied at

$$\frac{\delta^2 W_L}{\delta s_L^{cons}} = -1 < 0$$

When solving for the optimal level of s_L^{prod},

$$\frac{\delta^2 W_L}{\delta s_L^{prod}} = 1$$

indicates that the laggard's welfare is strictly increasing in s_L^{prod} as long as $c - s_F^{prod} < dc - s_L^{prod}$ is satisfied and all production takes place in the frontier country.

In equilibrium, the frontier country's producer subsidy will therefore equal zero, while $s_L^{prod*} = c(d-1) - \varepsilon$. To see this, consider the case where $s_L^{prod} = c(d-1) - \lambda$, where $\lambda > \varepsilon$ is a non-negligible positive number, and $c - s_F^{prod} < dc - s_L^{prod}$. Welfare in the frontier country is

$$\begin{aligned} W_F &= \frac{r_F^2}{2} + (p + s_F^{prod} - c)(r_F + r_L) + \frac{b}{2}(r_F + r_L) - s_F^{cons} r_F - s_F^{prod}(r_F + r_L) \\ &= \frac{r_F^2}{2} + (p - c)(r_F + r_L) + \frac{b}{2}(r_F + r_L) - s_F^{cons} r_F \\ &= \frac{r_F^2}{2} + (dc - s_L^{prod} - c)(r_F + r_L) + \frac{b}{2}(r_F + r_L) - s_F^{cons} r_F \end{aligned} \tag{A.3}$$

The second term in the above equation becomes negative, as $dc - c(d-1) - \lambda - c = -\lambda$. This implies that there is a profitable unilateral deviation for the frontier country. By reducing its own production subsidy such that $c - s_F^{prod} = dc - s_L^{prod} + \varepsilon$ it can shift all production to the laggard country and increase its welfare by $\lambda(r_F + r_L)$ while retaining the same level of consumption and positive externalities.

Similarly, if $s_F^{prod} > 0$ there would be a profitable unilateral deviation for the laggard country, which could reduce prices and increase its own welfare by raising s_L^{prod} to $c(d-1) + \lambda$. Finally, if $s_L^{prod} < c(d-1) - \varepsilon$ the frontier country would extracts rents amounting to $(dc - s_L^{prod} - c)r_L > 0$ from the laggard country and consumer surplus and positive externalities would be lower in both countries. This implies a profitable unilateral deviation for the laggard country, which increases s_L^{prod} until all rents have dissipated.

Given $s_F^{prod*} = 0$, $s_L^{prod*} = c(d-1) - \varepsilon$, and $s_F^{cons*} = s_L^{cons*} = \frac{b}{2}$, the price facing the consumer is $p = p_F = c$ and quantities demanded in both countries are $r_F = r_L = a - c + \frac{b}{2}$.

Welfare is equal in both countries:

$$W_F = \frac{r_F^2}{2} + \frac{b}{2}(r_F + r_L) - \frac{b}{2}r_F = \frac{(a-c+\frac{b}{2})^2}{2} + \frac{b}{2}(a-c+\frac{b}{2})$$
$$W_L = \frac{r_L^2}{2} + \frac{b}{2}(r_F + r_L) - \frac{b}{2}r_L = \frac{(a-c+\frac{b}{2})^2}{2} + \frac{b}{2}(a-c+\frac{b}{2})$$

Optimal subsidies if $p_F = p_L$ $p_F = p_L$ implies that $p = c - s_F^{prod} = dc - s_L^{prod}$. Since $p + s_F^{prod} - c = 0$ and $p + s_L^{prod} - dc = 0$, the frontier country maximises

$$W_F = \frac{r_F^2}{2} + \frac{b}{2}(r_F + r_L) - s_F^{cons} r_F - s_F^{prod}\frac{(r_F + r_L)}{2}$$

where $r_F = a - c + s_F^{prod} + s_F^{cons}$ and $r_L = a - c + s_F^{prod} + s_L^{cons}$.

The laggard country maximises

$$W_F = \frac{r_L^2}{2} + \frac{b}{2}(r_F + r_L) - s_L^{cons} r_L - s_L^{prod}\frac{(r_F + r_L)}{2}$$

where $r_F = a - dc + s_L^{prod} + s_F^{cons}$ and $r_L = a - dc + s_L^{prod} + s_L^{cons}$.

Taking partial derivatives with respect to s_F^{cons}, s_F^{prod}, s_L^{cons}, and s_L^{prod} yields the first and second order conditions

$$\frac{\delta W_F}{\delta s_F^{prod}} = b - s_F^{prod} - \frac{s_F^{cons} + s_L^{cons}}{2} = 0; \frac{\delta^2 W_F}{\delta s_F^{prod}} = -1$$

$$\frac{\delta W_F}{\delta s_F^{cons}} = \frac{b}{2} - s_F^{cons} - \frac{s_F^{prod}}{2} = 0; \frac{\delta^2 W_F}{\delta s_F^{cons}} = -1$$

$$\frac{\delta W_L}{\delta s_L^{prod}} = b - s_L^{prod} - \frac{s_F^{cons} + s_L^{cons}}{2} = 0; \frac{\delta^2 W_L}{\delta s_F^{prod}} = -1$$

$$\frac{\delta W_L}{\delta s_L^{cons}} = \frac{b}{2} - s_L^{cons} - \frac{s_L^{prod}}{2} = 0; \frac{\delta^2 W_L}{\delta s_L^{cons}} = -1$$

Solving this system of equations yields

$$s_F^{prod} = b, s_L^{prod} = b, s_F^{cons} = 0, s_L^{cons} = 0 \tag{A.4}$$

Since $dc - b = c - b$ requires that $d = 1$, this implies that a market sharing equilibrium is not possible in an unlevelled industry. Moreover, $s_F^{prod} = s_L^{prod} = b$ is not a Nash Equilibrium even when $d = 1$, as will be argued in the paragraph below denoted 'Levelled industry'.

Optimal subsidies if $p_F > p_L$ $p_F > p_L$ implies that $c - s_F^{prod} > dc - s_L^{prod}$. The price faced by the consumer is defined by $c - s_F$.

No subsidy mix satisfying this condition can be a Nash equilibrium. To see this, assume that $c - s_F^{prod} > dc - s_L^{prod}$ holds. Suppose that $s_F^{prod} = 0$ and $s_L^{prod} = c(d-1) + \varepsilon$. Now, the laggard country's welfare is

$$\begin{aligned}
W_L &= \frac{r_L^2}{2} + (p + s_L^{prod} - dc)(r_F + r_L) + \frac{b}{2}(r_F + r_L) - s_L^{cons} r_L - s_L^{prod}(r_F + r_L) \\
&= \frac{r_L^2}{2} + (p - dc)(r_F + r_L) + \frac{b}{2}(r_F + r_L) - s_L^{cons} r_L \\
&= \frac{r_L^2}{2} + (c - s_F^{prod} - dc)(r_F + r_L) + \frac{b}{2}(r_F + r_L) - s_L^{cons} r_L
\end{aligned}$$

The second term in the above equation is negative as $c - dc < 0$ for any $d > 1$. Thus, by reducing s_L^{prod} to $c(d-1) - \varepsilon$ the laggard can shift all production to the frontier country and retain the same prices, consumer surplus and positive externalities, while increasing its welfare by $c(d-1)(r_F + r_L)$. The laggard will therefore not be willing to support at producer subsidy greater than $s_L^{prod} = c(d-1) - \varepsilon$.

Levelled industry In a levelled industry, prices, quantities and welfare are defined as in the unlevelled case, where $d = 1$. The unique Nash Equilibrium is characterised by $s_F^{prod*} = s_L^{prod*} = 0, s_F^{cons*} = s_L^{cons*} = \frac{b}{2}$.

To see this, suppose first that $p_F < p_L$, which requires that $c - s_F^{prod} < c - s_L^{prod}$, thus $s_F^{prod} > s_L^{prod}$. Assume that $s_F^{prod} > s_L^{prod}$ and $s_L^{prod} = \lambda$.

Welfare in the frontier country is given by Equation A.3, with $d = 1$. The frontier country can profitably deviate by reducing its s_F^{prod} to $\lambda - \varepsilon$ and shifting all production to the other country without lowering consumption and positive externalities in a meaningful way. This increases its welfare by $\lambda(r_F + r_L)$. By the same logic, $s_F^{prod} < s_L^{prod}$ cannot be sustained as a Nash Equilibrium either. Thus, the Nash Equilibrium will involve a market sharing equilibrium, with $s_F^{prod} = s_L^{prod} = s^{prod}$ and $p = p_F = p_L = c - s^{prod}$.

Equation A.4 implies that $s^{prod} = b$ and $s_F^{cons} = s_L^{cons} = s^{cons} = \frac{b}{2} - \frac{s^{prod}}{2} = 0$. While these subsidies are optimal as long as $s_F^{prod} = s_L^{prod}$, either country can increase its welfare by unilaterally reducing its producer subsidy to $b - \varepsilon$, thereby shifting all production and the burden of subsidising to the other country. As demonstrated previously, such a move increases the deviating country's welfare by $b\frac{(r_F + r_L)}{2}$ and reduces the other country's welfare by the same amount. The other country can then do the same by reducing its producer subsidy to $b - 2\varepsilon$.

In conclusion, profitable deviations are possible for any positive producer subsidy. Thus, $s_F^{prod*} = s_L^{prod*} = 0, s_F^{cons*} = s_L^{cons*} = \frac{b}{2}$ in equilibrium. Prices are $p_F = p_L = c$ and quantities $r_F = r_L = a - c + \frac{b}{2}$. Welfare in both countries is $W_F = W_L = \frac{(a-c+\frac{b}{2})^2}{2} + \frac{b}{2}(a - c + \frac{b}{2})$.

Table A.2 lays out welfare payoffs for both countries under all trade strategy profiles given the prices, quantities and optimal subsidies derived in this section. Since $dc > c$ by assumption, these payoffs imply that trade is a weakly dominant strategy for both countries in both stages of the game. The pareto-optimal Subgame Perfect Nash Equilibrium is one in which

i Countries trade in both periods.

ii The laggard country sets $s_L^{prod*} = c(d-1)$.

iii Both countries set their consumer subsidies, s_F^{cons*} and s_L^{cons*} equal to $\frac{b}{2}$.

A.4.1 Equilibrium without Producer Subsidies

Optimal consumer subsidies in autarky are derived in Appendix A.3.

Under trade, again assuming that dc is below the frontier country's monopoly price, only the frontier firm is active and supplies the market at global price $p = p_F = dc - \varepsilon$. Dropping ε for simplicity, the frontier country's government sets a subsidy to optimise

$$W_F = ar_F - \frac{r_F^2}{2} - (dc - s_F^{cons})r_F + (dc - c)(r_F + r_L) - r_F s_F^{cons} + \frac{b}{2}(r_F + r_L)$$

Given that $r_F = a - dc + s_F^{cons}$ and r_L is not affected by the domestic subsidy, the first order condition implies that

$$s_F^{cons*} = c(d-1) + \frac{b}{2}$$

The laggard country's government solves

$$maxW_L = ar_L - \frac{r_L^2}{2} - dcr_L + \frac{b}{2}(r_F + r_L)$$

yielding

$$s_L^{cons*} = \frac{b}{2}$$

These subsidies lead to quantities

$$r_F = a - c + \frac{b}{2}; r_L = a - dc + \frac{b}{2}$$

and welfare

TABLE A.2
Payoff Matrix (Optimal Subsidies)

	Laggard: (1, 1)	Laggard: (1, 0)	Laggard: (0, 1)	Laggard: (0, 0)
Frontier: (1, 1)	$\Big((a-c+\frac{b}{2})^2+b(a-c+\frac{b}{2}), (a-c+\frac{b}{2})^2+b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$
Frontier: (1, 0)	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$
Frontier: (0, 1)	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$
Frontier: (0, 0)	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$	$\Big((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(1+d)+b), \frac{(a-c+\frac{b}{2})^2}{2} + \frac{(a-dc+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\Big)$

$$\begin{aligned}
W_F &= \frac{r_F^2}{2} + c(d-1)(r_F + r_L) + \frac{b}{2}(r_F + r_L) - (c(d-1) + \frac{b}{2})r_F \\
&= \frac{r_F^2}{2} + (c(d-1) + \frac{b}{2})r_L \\
&= \frac{(a-c+\frac{b}{2})^2}{2} + (c(d-1) + \frac{b}{2})(a - dc + \frac{b}{2})
\end{aligned}$$

$$\begin{aligned}
W_L &= \frac{r_L^2}{2} + \frac{b}{2}(r_F + r_L) - \frac{b}{2}r_L \\
&= \frac{r_L^2}{2} + \frac{b}{2}r_F \\
&= \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{b}{2}(a - c + \frac{b}{2})
\end{aligned}$$

The frontier country extracts rent amounting to

$$Rent_F = c(d-1)r_L$$

Table A.3 shows the welfare payoff matrix in the version of the game with consumer subsidies only. While country F weakly prefers trade in Stage 2, country L's Stage 2 pay-offs depend solely on the strategy chosen in Stage 1. The laggard country's welfare in Stage 1 is the same whether countries trade or remain in autarky. However, its welfare in Stage 2 – and therefore its cumulative welfare – is higher if countries are in autarky in Stage 1. As trade requires mutual agreement, there is no equilibrium under which countries trade in Stage 1. There are eight SPNE in pure strategies, which are characterised by the following optimal trade decisions:

(1) $T_L^* = (0,1)$ and $T_F^* = (1,1)$

(2) $T_L^* = (0,1)$ and $T_F^* = (0,1)$

(3) $T_L^* = (0,1)$ and $T_F^* = (1,0)$

(4) $T_L^* = (0,1)$ and $T_F^* = (0,0)$

(5) $T_L^* = (0,0)$ and $T_F^* = (1,1)$

(6) $T_L^* = (0,0)$ and $T_F^* = (0,1)$

(7) $T_L^* = (0,0)$ and $T_F^* = (1,0)$

(8) $T_L^* = (0,0)$ and $T_F^* = (0,0)$

TABLE A.3
Payoff Matrix (Consumer Subsidies)

	Laggard: (1, 1)	Laggard: (1, 0)	Laggard: (0, 1)	Laggard: (0, 0)
Frontier: (1, 1)	$\left((a-c+\frac{b}{2})^2 +2(c(d-1)+\frac{b}{2})(a-dc+\frac{b}{2}), (a-dc+\frac{b}{2})^2+b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 +(c(d-1)+b)(a-dc+\frac{b}{2}), (a-dc+\frac{b}{2})^2+b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$
Frontier: (1, 0)	$\left((a-c+\frac{b}{2})^2 +(c(d-1)+b)(a-dc+\frac{b}{2}), (a-dc+\frac{b}{2})^2+b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 +(c(d-1)+b)(a-dc+\frac{b}{2}), (a-dc+\frac{b}{2})^2+b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$
Frontier: (0, 1)	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$
Frontier: (0, 0)	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$	$\left((a-c+\frac{b}{2})^2 + \frac{b}{2}(2a-c(d+1)+b), \frac{(a-dc+\frac{b}{2})^2}{2} + \frac{(a-c+\frac{b}{2})^2}{2} + b(a-c+\frac{b}{2})\right)$

Appendix B

Was the Trade War Justified? Solar PV Innovation in Europe and the Impact of the 'China Shock'

B.1 Data Cleaning Procedure for BvD Orbis

Following Kalemli-Ozcan et al. (2015), observations were assigned to the reporting year if the financial data was reported during or after June 1st (as indicated by the variable 'closing date'), and the previous year if the report was made before June. In order to avoid duplication, all observations with consolidation code C2 (consolidated account, when there is an unconsolidated companion) were dropped, as were observations with consolidation code LF (limited financial information available). To address quality issues, observations were dropped if total assets, operating revenue, sales and employment were simultaneously missing. Furthermore, the whole company was dropped if

- employment, sales, total assets or tangible fixed assets were negative in any year;
- the ratio of employment/sales was larger than the 99.9th percentile in any year and vice versa;
- employment/total assets was larger than 99.9 pct in any year and vice versa;
- employment/revenue larger was larger than 99.9 pct in any year and vice versa;
- the value of sales to total assets was larger than 99.9 pct in any year.

To deal with sudden jumps, observations were set to missing if assets or employment changed by more than 100% upwards or 50% downwards one year and the reverse the following year.

Following this cleaning procedure, financials data and patenting indicators were matched. Where a particular firm was missing in Orbis during a period lying between the year it was first and last observed, a firm-year observation was created, but all control variables derived from Orbis missing. Patent-based innovation counts were set to 0 when no patent was associated with the firm during a particular period.

B.2 TECHNOLOGY CODES

TABLE B.1
Solar Related CPC Codes

Technology	CPC Codes
Enabling	H02J 2300/22, H02J 2300/24, H02J 2300/26, H02J 3/383, H02J 3/385, H02S 20, H02S 20/10, H02S 20/20, H02S 20/21, H02S 20/22, H02S 20/23, H02S 20/24, H02S 20/25, H02S 20/26, H02S 20/30, H02S 20/32, H02S 30, H02S 30/10, H02S 40, H02S 40/10, H02S 40/12, H02S 40/20, H02S 40/22, H02S 40/30, H02S 40/32, H02S 40/34, H02S 40/345, H02S 40/36, H02S 40/40, H02S 40/42, H02S 40/425, H02S 50, H02S 50/10, H02S 50/15, H02S 99/00, Y02E 10/56, Y04S 10/123
Hybrid technology	H02S 10/12, H02S 40/44, Y02E 10/60
Production equipment and inputs	H01L 31, H01L 51
Solar cell	H01G 9/20, H01L 51/42, H02S 10/30, H02S 30/20, Y02E 10/50, Y02E 10/52, Y02E 10/541, Y02E 10/542, Y02E 10/543, Y02E 10/544, Y02E 10/545, Y02E 10/546, Y02E 10/547, Y02E 10/548, Y02E 10/549
Solar thermal	Y02E 10/40
Storage	H01M 10, H01M 12, H01M 14, H01M 16, H01M 2200, H01M 2250/40, H01M 2300, H01M 4, H01M 50, H01M 8, H02J 15, H02S 40/38, Y04S 10/14
System including solar cell	F03G 6/0001, H02J 2300/24, H02J 2300/26, H02J 3/383, H02J 3/385, H02S 10, H02S 10/10, H02S 10/40, Y02B 10/10
System including solar cell; Storage	H02S 10/20

Note: The table lists the technology codes from the Cooperative Patent Classification (CPC) used to identify Solar PV and related patents. For maximum coverage I also search for the equivalent codes from the International Patent Classification (IPC). I identify a patent family as belonging to a given category if it has at least one patent with a relevant technology code.

TABLE B.2
Generations of Solar Cells

Generation	CPC Code	Description
Any	Y02E 10/50	Photovoltaic [PV] energy
1	Y02E 10/544	Solar cells from Group III-V materials
	Y02E 10/545	Microcrystalline silicon PV cells
	Y02E 10/546	Polycrystalline silicon PV cells
	Y02E 10/547	Monocrystalline silicon PV cells
2	H01G 9/20	Electrolytic light sensitive devices, e.g. dye sensitized solar cells
	H02S 10/30	Thermophotovoltaic systems
	H02S 30/20	Collapsible or foldable PV modules
	Y02E 10/52	PV systems with concentrators
	Y02E 10/541	CuInSe2 material PV cells
	Y02E 10/542	Dye sensitized solar cells
	Y02E 10/543	Solar cells from Group II-VI materials
	Y02E 10/548	Amorphous silicon PV cells
3	H01L 51/42	Solid state devices using organic materials as the active part, or using a combination of organic materials with other materials as the active part;specially adapted for sensing infra-red radiation, light, electro-magnetic radiation of shorter wavelength or corpuscular radiation and adapted for the conversion of the energy of such radiation into electrical energy or for the control of electrical energy by such radiation
	Y02E 10/549	Organic PV cells

Note: The table lists the technology codes from the Cooperative Patent Classification (CPC) used to identify Solar PV patents, classified into 'generations'.

B.3 ADDITIONAL REGRESSION TABLES

B.3.1 PATSTAT Firm Dataset

TABLE B.3
Effects of Chinese Imports on Solar Cell Innovation, Using 3, 4 and 5-year sums and averages

	(1) 3 Years	(2) 4 Years	(3) 5 Years	(4) 3 Years	(5) 4 Years	(6) 5 Years
Import Penetration × Exposure	-0.009	-0.064	-0.133			
	(0.121)	(0.148)	(0.181)			
Import Penetration × Exposure × Bottom 10%	-0.105	0.084	0.234			
	(0.217)	(0.170)	(0.175)			
Import Penetration × Exposure × Top 10%	-0.009	0.019	0.001			
	(0.107)	(0.130)	(0.156)			
Chinese Imports (USD 100M) × Exposure				0.012	0.020	0.032**
				(0.012)	(0.013)	(0.014)
Chinese Imports (USD 100M) × Exposure × Bottom 10%				0.072***	0.109***	0.158***
				(0.017)	(0.022)	(0.041)
Chinese Imports (USD 100M) × Exposure × Top 10%				-0.017	-0.026**	-0.038***
				(0.011)	(0.011)	(0.012)
Fam Stock	-0.001**	-0.001***	-0.002**	-0.001**	-0.001**	-0.002**
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Market Size (USD 100M)	0.000**	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.009***	-0.009***	-0.008**	-0.007**	-0.006*	-0.005
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
IV regression	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X
Observations	19283	15356	12077	19283	15356	12077

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 3, 4 or 5 Years.
Independent Variables are Averaged over the preceeding 3, 4 or 5 Years.
Robust Standard Errors in Parentheses.

Note: The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in solar cells on Chinese import penetration and overall Chinese imports. The dependent variable is the sum of quality-adjusted patent families over 3, 4 and 5 years in the future. All independent variables are averaged over the preceeding 3, 4 and 5 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 3, 4 or 5 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. All regressions use an instrumental variables regression, implemented using the control function method.

TABLE B.4
Effects of Chinese Imports on Solar Cell Innovation by Generation, Including HHI

	(1) Solar cells	(2) Gen 1	(3) Gen 2	(4) Gen 3	(5) Solar cells	(6) Gen 1	(7) Gen 2	(8) Gen 3
Import Penetration × Exposure	-0.106	-0.363*	8.620	-0.057				
	(0.156)	(0.211)	(18.472)	(0.164)				
Import Penetration × Exposure × Bottom 10%	0.083	0.907***	-7.933	0.275*				
	(0.168)	(0.208)	(18.464)	(0.150)				
Import Penetration × Exposure × Top 10%	0.046	0.000	-8.402	0.000				
	(0.133)	(0.000)	(18.478)	(0.000)				
Chinese Imports (USD 100M) × Exposure					0.022*	-0.002	0.164*	-0.019**
					(0.013)	(0.015)	(0.084)	(0.009)
Chinese Imports (USD 100M) × Exposure × Bottom 10%					0.103***	0.163***	-0.016	0.124***
					(0.024)	(0.029)	(0.081)	(0.025)
Chinese Imports (USD 100M) × Exposure × Top 10%					-0.026**	0.000	-0.154*	0.000
					(0.011)	(0.000)	(0.082)	(0.000)
Fam Stock	-0.001**	-0.002	-0.040***	-0.001	-0.001**	-0.001	-0.039***	-0.001
	(0.001)	(0.003)	(0.005)	(0.001)	(0.001)	(0.002)	(0.004)	(0.001)
Hirschman-Herfindahl Index	-0.626*	-1.076	1.021**	-0.458	-0.738**	-2.546**	1.206***	-0.412
	(0.360)	(1.418)	(0.477)	(0.649)	(0.343)	(1.136)	(0.466)	(0.587)
Market Size (USD 100M)	0.000	-0.000	0.000***	-0.000	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.008**	-0.008	-0.014***	0.005	-0.005	-0.002	-0.015***	0.010
	(0.003)	(0.008)	(0.004)	(0.008)	(0.003)	(0.008)	(0.005)	(0.007)
IV regression	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X
Observations	14602	2612	5854	3097	14602	2612	5854	3097

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: Like Table 3.4, with the additional inclusion of the Hirschmann-Herfindahl Index (HHI) as an indicator overall market competitiveness. The HHI is calculated based on each firm's historical patent stock's share in the sum of knowledge stocks within the sample, by country and year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions.

TABLE B.5
Effects of Chinese Imports on Solar Cell Innovation, Pre- and Post-2013

	(1) 2000-2012	(2) 2014-2015	(3) 2014-2017	(4) 2000-2012	(5) 2014-2015	(6) 2014-2017
Import Penetration × Exposure	0.077	10.602	0.953			
	(0.114)	(15.820)	(4.118)			
Import Penetration × Exposure × Bottom 10%	0.316***	28.097	15.860			
	(0.120)	(28.238)	(11.677)			
Import Penetration × Exposure × Top 10%	-0.242**	1.069	0.777			
	(0.099)	(12.908)	(3.280)			
Chinese Imports (USD 100M) × Exposure				0.053***	-0.015	-0.018
				(0.019)	(0.047)	(0.028)
Chinese Imports (USD 100M) × Exposure × Bottom 10%				0.217***	0.022	0.012
				(0.044)	(0.058)	(0.029)
Chinese Imports (USD 100M) × Exposure × Top 10%				-0.059***	0.015	0.020
				(0.017)	(0.040)	(0.022)
Fam Stock	-0.002	-0.007	-0.008**	-0.001	-0.007	-0.008***
	(0.001)	(0.014)	(0.003)	(0.001)	(0.015)	(0.003)
Market Size (USD 100M)	0.000	-0.000	-0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.006	0.005	0.003	-0.005	0.007	0.005
	(0.005)	(0.014)	(0.007)	(0.005)	(0.017)	(0.008)
IV regression	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X
Observations	9320	908	2044	9320	908	2044

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in different generations of solar cells on Chinese import penetration and overall Chinese imports. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. All regressions use an instrumental variables regression, implemented using the control function method.

TABLE B.6
Effects of Chinese Imports on Solar Cell and Related Innovation

	(1) Solar cells	(2) Hybrid	(3) Solar thermal	(4) Production	(5) Storage	(6) Enabling	(7) Systems
Import Penetration × Exposure	-0.064	-0.657	0.351	-0.036	0.080	-0.139	0.165
	(0.139)	(0.408)	(0.409)	(0.208)	(0.125)	(0.571)	(0.795)
Import Penetration × Exposure × Bottom 10%	0.084	0.200	0.655	0.428*	0.097	0.162	-0.182
	(0.187)	(0.442)	(0.788)	(0.249)	(0.244)	(0.566)	(0.778)
Import Penetration × Exposure × Top 10%	0.019	0.000	-0.294	-0.024	-0.252**	0.143	-0.184
	(0.123)	(0.000)	(0.410)	(0.176)	(0.114)	(0.566)	(0.780)
Fam Stock	-0.001**	-0.336***	-0.015***	0.001	0.000	-0.002***	-0.002***
	(0.001)	(0.104)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Market Size (USD 100M)	0.000	-0.000**	-0.000	0.000	-0.000***	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.009***	0.011	-0.002	-0.003	0.019***	-0.009***	-0.002
	(0.003)	(0.008)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
IV regression	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X
Observations	15356	1648	9604	14766	20256	11297	8876

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in solar cells and related technologies on Chinese import penetration. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. All regressions use an instrumental variables regression, implemented using the control function method.

TABLE B.7
Effects of Chinese Import Penetration on Solar Cell and Related Innovation

	(1) Solar cells	(2) Hybrid	(3) Solar thermal	(4) Production	(5) Storage	(6) Enabling	(7) Systems
Chinese Imports (USD 100M) × Exposure	0.012	0.022	0.078***	-0.010	0.032***	0.038**	0.036*
	(0.012)	(0.021)	(0.022)	(0.011)	(0.009)	(0.016)	(0.019)
Chinese Imports (USD 100M) × Exposure × Bottom 10%	0.108***	0.059	0.123**	0.117***	-0.057	0.070***	0.076***
	(0.023)	(0.039)	(0.054)	(0.021)	(0.059)	(0.018)	(0.021)
Chinese Imports (USD 100M) × Exposure × Top 10%	-0.024**	0.000	-0.060***	-0.019**	-0.017*	-0.029**	-0.023
	(0.011)	(0.000)	(0.020)	(0.009)	(0.009)	(0.014)	(0.018)
Fam Stock	-0.001**	-0.319***	-0.016***	0.000	0.000	-0.002***	-0.003***
	(0.001)	(0.103)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
Market Size (USD 100M)	0.000	-0.000**	-0.000	0.000*	-0.000***	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.007**	0.006	-0.004	0.002	0.016***	-0.010***	-0.004
	(0.004)	(0.009)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
IV regression	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X
Observations	15356	1648	9604	14766	20256	11297	8876

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in solar cells and related technologies on overall Chinese imports. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. All regressions use an instrumental variables regression, implemented using the control function method.

TABLE B.8
Effects of Chinese Imports on Solar Cell Innovation,
Top/Bottom 1st Percentile of Patent Stocks

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import Penetration × Exposure	-0.081***	-0.045	-0.084**	-0.042				
	(0.030)	(0.057)	(0.038)	(0.070)				
Import Penetration × Exposure × Bottom 1%			0.056	0.065				
			(0.138)	(0.136)				
Import Penetration × Exposure × Top 1%			0.002	-0.004				
			(0.059)	(0.059)				
Chinese Imports (USD 100M) × Exposure					-0.013**	-0.007	-0.026***	-0.017**
					(0.006)	(0.007)	(0.008)	(0.008)
Chinese Imports (USD 100M) × Exposure × Bottom 1%							0.131***	0.131***
							(0.021)	(0.023)
Chinese Imports (USD 100M) × Exposure × Top 1%							0.015**	0.012*
							(0.007)	(0.007)
Fam Stock	-0.001**	-0.001***	-0.001**	-0.001**	-0.002***	-0.002***	-0.002***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market Size (USD 100M)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.009***	-0.009***	-0.009***	-0.009***	-0.007*	-0.006*	-0.007**	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
IV regression		X		X		X		X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X
Observations	15356	15356	15356	15356	15356	15356	15356	15356

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: Like Table 3.3, but using the 1st and 99th percentile of accumulated patent family stocks. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions.

TABLE B.9
Effects of Chinese Imports on Solar Cell Innovation,
Top/Bottom 5th Percentile of Patent Stocks

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import Penetration × Exposure	-0.081**	-0.045	-0.038	0.023				
	(0.034)	(0.058)	(0.069)	(0.083)				
Import Penetration × Exposure × Bottom 5%			0.015	0.016				
			(0.154)	(0.152)				
Import Penetration × Exposure × Top 5%			-0.050	-0.067				
			(0.075)	(0.076)				
Chinese Imports (USD 100M) × Exposure					-0.013**	-0.007	-0.017	-0.007
					(0.006)	(0.005)	(0.011)	(0.011)
Chinese Imports (USD 100M) × Exposure × Bottom 5%							0.128***	0.128***
							(0.025)	(0.020)
Chinese Imports (USD 100M) × Exposure × Top 5%							0.005	0.001
							(0.010)	(0.009)
Fam Stock	-0.001**	-0.001**	-0.001**	-0.001***	-0.002***	-0.002**	-0.002**	-0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market Size (USD 100M)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.009***	-0.009***	-0.009***	-0.009***	-0.007**	-0.006*	-0.007**	-0.006*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
IV regression		X		X		X		X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X
Observations	15356	15356	15356	15356	15356	15356	15356	15356

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: Like Table 3.3, but using the 5th and 95th percentile of accumulated patent family stocks. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions.

TABLE B.10
Effects of Chinese Imports on Solar Cell Innovation,
Top/Bottom 20th Percentile Percentile of Patent Stocks

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import Penetration × Exposure	-0.081**	-0.045	-0.084	0.026				
	(0.031)	(0.060)	(1.825)	(1.721)				
Import Penetration × Exposure × Bottom 20%			0.056	-0.004				
			(1.836)	(1.728)				
Import Penetration × Exposure × Top 20%			0.001	-0.071				
			(1.821)	(1.718)				
Chinese Imports (USD 100M) × Exposure					-0.013**	-0.007	0.018	0.029
					(0.006)	(0.006)	(0.018)	(0.019)
Chinese Imports (USD 100M) × Exposure × Bottom 20%							0.096***	0.094***
							(0.025)	(0.024)
Chinese Imports (USD 100M) × Exposure × Top 20%							-0.030*	-0.035**
							(0.017)	(0.017)
Fam Stock	-0.001***	-0.001***	-0.001**	-0.001***	-0.002**	-0.002***	-0.001***	-0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Market Size (USD 100M)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	-0.009***	-0.009***	-0.009***	-0.009***	-0.007**	-0.006*	-0.007*	-0.006**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
IV regression		X		X		X		X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X
Observations	15356	15356	15356	15356	15356	15356	15356	15356

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: Like Table 3.3, but using the 20th and 80th percentile of accumulated patent family stocks. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions.

B.3.2 ORBIS Firm Dataset

TABLE B.11
Effects of Chinese Imports on Solar Cell Innovation, Using ORBIS Firms

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import Penetration × Exposure	-0.080	-0.002	0.869**	1.252*				
	(0.145)	(0.181)	(0.379)	(0.649)				
Import Penetration × Exposure × Bottom 10%			-0.797	-0.994				
			(0.548)	(0.842)				
Import Penetration × Exposure × Top 10%			-0.955*	-1.231**				
			(0.518)	(0.591)				
Chinese Imports (USD 100M) × Exposure					-0.050***	-0.056***	-0.034	-0.041*
					(0.014)	(0.015)	(0.021)	(0.023)
Chinese Imports (USD 100M) × Exposure × Bottom 10%							0.129***	0.130***
							(0.037)	(0.038)
Chinese Imports (USD 100M) × Exposure × Top 10%							-0.023	-0.022
							(0.020)	(0.020)
Fam Stock	-0.007***	-0.007**	-0.007**	-0.007**	-0.008***	-0.008***	-0.008***	-0.008***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Total Assets (USD 100M)	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of Employees	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Size (USD 100M)	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	0.003	0.003	0.003	0.003	0.009*	0.009*	0.011**	0.011*
	(0.006)	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)	(0.005)	(0.006)
IV regression		X		X		X		X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X
Observations	5617	5617	5617	5617	5617	5617	5617	5617

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in solar cells on Chinese import penetration and overall Chinese imports, using the sample of firms from ORBIS. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. Models 2, 4, 6 and 8 use an instrumental variables regression, implemented using the control function method.

TABLE B.12
Effects of Chinese Imports on Solar Cell Innovation by Generation, Using ORBIS Firms

	(1) Solar cells	(2) Gen 1	(3) Gen 2	(4) Gen 3	(5) Solar cells	(6) Gen 1	(7) Gen 2	(8) Gen 3
Import Penetration × Exposure	1.252**	-0.402	0.105	-0.117				
	(0.596)	(1.725)	(1.454)	(2.233)				
Import Penetration × Exposure × Bottom 10%	-0.994	0.730	0.542	32.281				
	(1.024)	(5.107)	(43.788)	(25.680)				
Import Penetration × Exposure × Top 10%	-1.231**	0.000	0.000	0.000				
	(0.568)	(0.000)	(0.000)	(0.000)				
Chinese Imports (USD 100M) × Exposure					-0.041*	-0.084***	-0.017	-0.124***
					(0.022)	(0.031)	(0.024)	(0.027)
Chinese Imports (USD 100M) × Exposure × Bottom 10%					0.130***	0.155***	0.073	0.140**
					(0.033)	(0.049)	(0.123)	(0.067)
Chinese Imports (USD 100M) × Exposure × Top 10%					-0.022	0.000	0.000	0.000
					(0.019)	(0.000)	(0.000)	(0.000)
Fam Stock	-0.007**	-0.040*	-0.064***	-0.026***	-0.008***	-0.041	-0.064***	-0.027***
	(0.003)	(0.021)	(0.013)	(0.005)	(0.003)	(0.027)	(0.011)	(0.004)
Total Assets (USD 100M)	0.002***	0.002	0.005***	0.002***	0.002***	0.001	0.005***	0.002*
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Number of Employees	0.000	-0.000	-0.000	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Market Size (USD 100M)	-0.000	-0.000	-0.000**	-0.000	-0.000	0.000	-0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	0.003	-0.021*	0.002	0.026***	0.011**	-0.009	0.005	0.033***
	(0.006)	(0.011)	(0.008)	(0.010)	(0.005)	(0.012)	(0.009)	(0.011)
IV regression	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X
Observations	5617	944	1929	989	5617	944	1929	989

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: The table reports the results of a poisson pseudo-likelihood regression of firm-level patenting in different generations of solar cells on Chinese import penetration and overall Chinese imports, using the sample of firms from ORBIS. The dependent variable is the sum of quality-adjusted patent families over 4 years in the future. All independent variables are averaged over the preceeding 4 years. Firm-level exposure is based on the technological proximity of firms' patent portfolios to the average Chinese firm's patent portfolio. 'Bottom 10%' and 'Top 10%' are binary variables indicating whether a firm's quality-adjusted patent family stock over the preceeding 4 years falls in the top or bottom 10th percentile among firms during that year. Standard errors are heteroskedasticity robust and bootstrapped with 200 repetitions. All regressions use an instrumental variables regression, implemented using the control function method.

B.3.3 Placebo Regressions

TABLE B.13
Placebo Test: Randomised Exposure

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import Penetration × Exposure	0.388	-0.061	-2.597	-3.350				
	(2.383)	(2.966)	(2.770)	(3.039)				
Import Penetration × Exposure × Bottom 10%			6.153	6.150				
			(4.237)	(3.879)				
Import Penetration × Exposure × Top 10%			3.613	3.913				
			(4.681)	(4.693)				
Chinese Imports (USD 100M) × Exposure					0.034	0.042	-0.086	-0.080
					(0.108)	(0.125)	(0.516)	(0.551)
Chinese Imports (USD 100M) × Exposure × Bottom 10%							0.183	0.179
							(0.548)	(0.579)
Chinese Imports (USD 100M) × Exposure × Top 10%							0.017	0.021
							(0.517)	(0.562)
Fam Stock	0.030**	0.031**	0.030**	0.031**	0.032**	0.033**	0.029**	0.030*
	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
Market Size (USD 100M)	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Exports (USD 100M)	0.011	0.010	0.013	0.012	0.010	0.009	0.011	0.011
	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)	(0.017)	(0.018)
IV regression		X		X		X		X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X
Observations	581	581	581	581	581	581	581	581

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: Like Table 3.3, but using randomised exposure variables. Firm-level exposure is randomised using a beta distribution, with the α and β parameters estimated using the real mean and variance of the distribution. Import penetration is randomised using Kernel Density estimation, and import volume is randomised using a log-normal distribution.

TABLE B.14
Placebo: Innovation in Dental Prosthetics

	(1) No IV	(2) IV	(3) No IV	(4) IV	(5) No IV	(6) IV	(7) No IV	(8) IV
Import Penetration × Exposure	-0.162 (0.165)	0.192 (0.259)	-0.126 (0.145)	0.056 (0.368)				
Import Penetration × Exposure × Bottom 10%			-3.537 (2.834)	-2.660 (2.934)				
Import Penetration × Exposure × Top 10%			-0.517 (1.728)	-0.573 (1.831)				
Chinese Imports (USD 100M) × Exposure					-0.017 (0.014)	-0.013 (0.014)	-0.023 (0.015)	-0.021 (0.015)
Chinese Imports (USD 100M) × Exposure × Bottom 10%							0.277*** (0.056)	0.278*** (0.059)
Chinese Imports (USD 100M) × Exposure × Top 10%							0.023** (0.011)	0.025** (0.011)
Fam Stock	-0.013* (0.007)	-0.013* (0.007)	-0.013* (0.007)	-0.013* (0.007)	-0.013* (0.007)	-0.011 (0.007)	-0.013* (0.007)	-0.010 (0.007)
Market Size (USD 100M)	-0.000* (0.000)	-0.000* (0.000)	-0.000* (0.000)	-0.000* (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000* (0.000)
Exports (USD 100M)	0.019*** (0.007)	0.019*** (0.007)	0.019** (0.007)	0.018*** (0.007)	0.019*** (0.007)	0.018*** (0.007)	0.019*** (0.007)	0.018*** (0.007)
IV regression		X		X		X		X
Year FEs	X	X	X	X	X	X	X	X
Firm FEs	X	X	X	X	X	X	X	X
Observations	2804	2804	2804	2804	2804	2804	2804	2804

Poisson Pseudo-Likelihood Estimation.
Dependent Variable: Firm-Level Patenting over 4 Years.
Independent Variables are Averaged over the preceeding 4 Years.
Robust Standard Errors in Parentheses.

Note: Like Table 3.3, but using a sample of firms patenting in dentistry prosthetics (IPC Class A61C/13), with all patent-based variables constructed using patent families from IPC Class A61C/13.

Appendix C

Stranded Nations? Transition Risks and Opportunities Towards a Clean Economy

C.1 List of 'Brown' Products

To identify specialisations in 'brown' products, we first define and identify such products within trade data, as no such list exists to date. Prior research analysing patenting trends in clean and dirty technologies has compiled various lists of dirty patent codes, which tend to focus primarily on the energy and transport sectors (e.g. Aghion et al. 2016; Dechezleprêtre et al. 2017; Johnstone et al. 2010; Popp et al. 2020; Verdolini and Galeotti 2011). Much of our list is in the spirit of this work. While the capacity to innovate is likely geographically correlated with production capabilities in a particular sector, exports are a more direct proxy of a country's actual manufacturing and other production capacity, as well as the jobs and capital tied up therein. They also have significant implications for overall economic viability and terms of trade. We therefore measure productive capabilities using export, rather than patent, data.

Since the goal of this chapter is to assess transition risks and transition possibilities for countries, we focus specifically on developing a list of brown products for which global demand is likely to decline as the world decarbonises. We maintain a focus on products which are mostly brown in *use*, rather than production. As such, we do not consider products where current production processes are polluting, but which can be expected to form part of the low carbon economy.[1] Moreover, our focus on the transition to a low carbon economy results in a narrower classification than a broader definition of 'brown' might.

We first conduct a keyword search on the descriptions of 6-digit codes within the Harmonised System,[2] aiming to create a 'narrow' and a 'broad' list. The narrow list focuses on

1. Examples would include hard to decarbonise sectors, such as heavy industry. Steel, for example, is an essential input into many green products, such as wind turbine towers.

2. In line with Mealy and Teytelboym (2020), we use the 1992 edition of the Harmonised System to permit us to use the full time series of trade data available from UN Comtrade.

fossil fuels and includes the following keywords: 'coal', 'petro', 'hydrocarbon', 'internal combustion engine', 'gas', 'combustion'. Fossil fuels are the biggest contributors to climate change, and their use must decline most substantially to reach net zero CO2 emissions (IPCC 2019, 2022). The burning of coal, for example, accounts for 26% of global greenhouse gas emissions and needs to decline by 20-70% by 2030 in order to reach the goals of the Paris agreement (Steckel and Jakob 2022), and coal consumption without carbon capture and storage needs to fall by 67-82% by 2030 to limit global warming to 1.5°C. Oil and gas consumption need to decline less abruptly. Overall, 30% of oil, 50% of gas and 80% of coal reserves are unburnable if we are to limit global warming to 2° Celsius (IPCC 2022). Coal, oil and gas patents codes are also classified as dirty in the respective patent-literature (e.g. Aghion et al. 2016; Dechezleprêtre et al. 2017).

The broad list additionally includes the keywords 'bovine' (relating to cattle) and 'sheep'. Meat consumption, particularly beef and mutton, is particularly emission intensive and consumption reductions can reduce emissions substantially (Funke et al. 2021; IPCC 2019). While they are brown in production, rather than in use, a more sustainable diet requires a shift away from these agricultural products. Hence we include both in our broader list, which is used for robustness checks.

To validate this keyword search-based classification into brown product categories and respective lists, we elicited feedback from five policy, chemicals and green innovation and growth experts. We approached experts based on their technical ability to assess the implications of the transition for relevant economic sectors. Whenever more than one expert disagreed with our classification, say to classify a product as brown, we followed that suggestion and reclassified the product. Upon cross-checking the proposed new list with the WTO's original green list we found that 7 products to be moved to the brown list were on the WTO's list of green products and should therefore remain excluded. In the end, only one additional product was added to the brown list and another removed. We also matched our list to the green list used in prior research (Mealy and Teytelboym 2020) and excluded products which appeared on the green list from the brown list. Following this validation process, 144 products constitute the narrow brown list vis-a-vis 171 products in the full brown list. The revised green list includes 299 products, which includes carbon capture, utilisation and storage products listed in Serin et al. 2021[3]. For consistency with prior research, the Green Complexity Index is computed based on the list used in Mealy and Teytelboym 2020 and does not include additional products from the CCUS list.

We initially approached experts to also review a list of grey products designed to deal with controversial cases – specifically, the small set of products which appeared on both our brown and the WTO's green list, as well as steel, cement and plastic products. Steel, cement and plastic

3. Excluding those previously identified as potentially 'brown'.

are particularly difficult cases to contend with: they are essential inputs into many sectors of the economy, including clean infrastructure. However, the emissions involved in their production process are very large, and not easily mitigated with available technology. Nevertheless, the fact that demand for some of these products such as cement and steel might increase as a result of the net zero transition, and that there was no clear rationale for including or excluding a product from the grey list given that most fossil-energy based production processes are polluting and need cleaning up, led us to eventually drop the list. Instead, we focus on brown goods which are both brown in use and likely to decline in demand in net zero scenarios.

There are many possible approaches which could be taken, such as selecting products based on embodied emissions (e.g. Broner et al. 2012), and we therefore cannot claim this list to be exhaustive or authoritative. We have selected products which we consider uncontroversial in their status as 'highly likely to see demand declines in the green transition', as this approach is best suited to our aim of capturing transition risk. Other research on 'brown trade' (for example, work which focuses on exposure to carbon border adjustments) may be better served by a different list (for example, one which is based on embodied carbon emissions).

C.2 VALIDATION

Table C.1 reports our estimates of

$$\begin{aligned} BLI_{c,t} =& \beta_0 + \beta_1 GDP_{c,t} + \beta_2 CoalRents_{c,t} + \beta_3 OilRents_{c,t} + \beta_4 GasRents_{c,t} + \\ & \beta_5 CO_2 Emissions_{c,t} + \beta_6 RTA\_Climate_{c,t} + \delta_t + \varepsilon \end{aligned} \tag{C.1}$$

and

$$\begin{aligned} BCI_{c,t} =& \beta_0 + \beta_1 GDP_{c,t} + \beta_2 CoalRents_{c,t} + \beta_3 OilRents_{c,t} + \beta_4 GasRents_{c,t} + \\ & \beta_5 CO_2 Emissions_{c,t} + \beta_6 RTA\_Climate_{c,t} + \delta_t + \varepsilon \end{aligned} \tag{C.2}$$

where $RTA\_Climate_{c,t}$ is a vector of Revealed Technological Advantage (RTA) values in climate-related technologies, δ_t are year dummies, and ε is the error term. Standard errors are clustered at the country level.

TABLE C.1
Correlates of Brown Dependence Measures

	(1) BLI	(2) BLI	(3) BLI	(4) BCI	(5) BCI	(6) BCI
GDP per capita (current USD) (log)	0.045	-0.004	0.057	0.321***	0.180*	0.204
	(0.041)	(0.049)	(0.083)	(0.055)	(0.100)	(0.159)
Coal rents (% of GDP)		0.035			0.008	
		(0.022)			(0.086)	
Oil rents (% of GDP)		0.090***			-0.025***	
		(0.006)			(0.005)	
Natural gas rents (% of GDP)		0.036**			-0.017	
		(0.014)			(0.015)	
CO2 emissions (metric tons per capita, log)		0.050			0.421***	
		(0.098)			(0.159)	
RTA, Environment-related Technologies			1.939			1.271
			(1.198)			(1.809)
RTA, Energy-related Mitigation Technologies			-0.425			-3.280**
			(1.210)			(1.498)
RTA, Carbon Capture and Storage			3.658***			-4.977*
			(0.688)			(2.660)
RTA, Climate Change Adaptation Technologies			0.765			-1.061*
			(0.646)			(0.556)
RTA, Transport-related Mitigation Technologies			-2.525**			2.730
			(1.066)			(2.748)
Year FEs	X	X	X	X	X	X
Observations	933	854	222	933	854	222
R2	.00453	.767	.203	.212	.324	.171

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
Dependent Variables Relate to Brown List (Narrow).

Note: We regress the Brown Lock-in Index and the Brown Complexity Index on a number of potentially relevant covariates, such as income, natural resource rents, and Revealed Technological Advantage in climate-relevant technologies.

Table C.2 reports our estimates of

$$BLI_{i,t} = \beta_0 + \beta_1 BLI_{i,t-1} + \beta_2 GreenTransitionOutlook_{i,t-1} + \beta_3 X_{i,t-1} + \delta_t + \varepsilon \tag{C.3}$$

and

$$BCI_{i,t} = \beta_0 + \beta_1 BCI_{i,t-1} + \beta_2 GreenTransitionOutlook_{i,t-1} + \beta_3 X_{i,t-1} + \delta_t + \varepsilon \tag{C.4}$$

while Table C.3 reports estimates of

TABLE C.2
Predictive Power of Green Transition Outlook

	(1) BLI	(2) BLI	(3) BCI	(4) BCI
Brown Lock-in Index (t-1)	0.957***	0.949***		
	(0.017)	(0.034)		
Green Transition Outlook (t-1)	-0.006	-0.001	-0.027***	-0.024**
	(0.018)	(0.019)	(0.010)	(0.011)
GDP per capita (current USD, log, t-1)	-0.002	-0.015	0.023***	0.021
	(0.009)	(0.016)	(0.007)	(0.017)
Coal rents (% of GDP, t-1)		0.026***		0.001
		(0.009)		(0.010)
Oil rents (% of GDP, t-1)		0.002		-0.002
		(0.003)		(0.001)
Natural gas rents (% of GDP, t-1)		0.004*		-0.001
		(0.002)		(0.001)
CO2 emissions (metric tons per capita, log, t-1)		0.024		0.021
		(0.027)		(0.027)
Brown Complexity Index (t-1)			0.955***	0.947***
			(0.014)	(0.016)
Year FEs	X	X	X	X
Observations	715	661	715	661
R2	.931	.943	.926	.93

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
t-1 refers to the previous period's value.

Note: Country Transition Outlook is calculated as $TransitionOutlook_c = \frac{\Sigma_b \rho_b^c * TO_b}{\Sigma_b \rho_b^c}$, where ρ_b^c indicates whether the country has RCA in product b, and TO_b denotes the product's Transition Outlook to list q (more intuitively called Normalised Product Proximity). $TO_b = \frac{\Sigma_q^Q \Omega_{b,q}}{Q} / \frac{\Sigma_p^P \Omega_{b,p}}{P}$ with $\Omega_{b,q}$ being the pairwise proximity between brown product b and climate-compatible (green or non-brown) product q; Q the total number of products of type q; $\Omega_{b,p}$ the pairwise proximity between product b and product p; and P the set of all traded products. The table reports the results of a regression of the BLI and BCI on their lagged values, lagged Green Transition Outlook and several covariates, showing that a higher Green Transition Outlook predicts future decreases in BCI, but has no statistically significant association with BLI.

$$BLI_{i,t} = \beta_0 + \beta_1 BLI_{i,t-1} + \beta_2 TransitionOutlook_{i,t-1} + \beta_3 X_{i,t-1} + \delta_t + \varepsilon \quad \text{(C.5)}$$

and

$$BCI_{i,t} = \beta_0 + \beta_1 BCI_{i,t-1} + \beta_2 TransitionOutlook_{i,t-1} + \beta_3 X_{i,t-1} + \delta_t + \varepsilon \quad \text{(C.6)}$$

where $X_{i,t-1}$ is a vector of controls, δ_t are year dummies, and ε is the error term. Standard errors are clustered at the country level.

TABLE C.3
Predictive Power of Overall Transition Outlook

	(1) BLI	(2) BLI	(3) BCI	(4) BCI
Brown Lock-in Index (t-1)	0.941***	0.939***		
	(0.018)	(0.030)		
Overall Transition Outlook (t-1)	-0.042***	-0.024*	0.005	0.010
	(0.016)	(0.013)	(0.009)	(0.012)
GDP per capita (current USD, log, t-1)	-0.005	-0.016	0.022***	0.020
	(0.008)	(0.016)	(0.007)	(0.017)
Coal rents (% of GDP, t-1)		0.025***		0.005
		(0.009)		(0.011)
Oil rents (% of GDP, t-1)		0.002		-0.000
		(0.003)		(0.001)
Natural gas rents (% of GDP, t-1)		0.004*		-0.000
		(0.002)		(0.001)
CO2 emissions (metric tons per capita, log, t-1)		0.023		0.019
		(0.026)		(0.027)
Brown Complexity Index (t-1)			0.948***	0.943***
			(0.015)	(0.016)
Year FEs	X	X	X	X
Observations	715	661	715	661
R2	.932	.943	.926	.93

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
t-1 refers to the previous period's value.

Note: Like C.2, but using overall, instead of green, Transition Outlook.

C.3 Supplementary Tables

TABLE C.4
Measures Derived From Trade Data

Name	Formula	Source
Revealed Comparative Advantage (RCA)	$RCA = \frac{p_c}{\Sigma_p p_c} / \frac{\Sigma_c p_c}{\Sigma_p \Sigma_c p_c}$	Balassa 1965
Product-to-Product Proximity	$\Omega_{p,p'} = \min(\frac{\Sigma \rho_p^c * \rho_{p'}^c}{\Sigma \rho_p^c}, \frac{\Sigma \rho_p^c * \rho_{p'}^c}{\Sigma \rho_{p'}^c})$	Hidalgo et al. 2007
Country-to-Product Proximity (Proximity Density)	$\omega_p^c = \frac{\Sigma_{p'} \rho_p^c * \Omega_{p,p'}}{\Sigma_{p'} \Omega_{p,p'}}$	Hidalgo et al. 2007
Diversity	$\Sigma_p \rho_p^c$	Hidalgo and Hausmann 2009
Economic Complexity Index (ECI)	Eigenvector associated with the second largest right eigenvalue of the matrix given by $D^{-1}MU^{-1}M'$ where D is the diagonal matrix formed from the vector of countries' diversity values, U is the diagonal matrix formed from the vector of product ubiquity values and M is a binary matrix where rows correspond to countries, columns correspond to products and M_{cp} = 1 if country c's RCA in product p is > 1 and 0 otherwise.	Hidalgo and Hausmann 2009
Product Complexity Index (PCI)	Eigenvector associated with the second largest right eigenvalue of the matrix given by $U^{-1}M'D^{-1}M$	Hidalgo and Hausmann 2009
Green Complexity Index (GCI)	$GCI_c = \Sigma_g \rho_g^c * \tilde{PCI}$	Mealy and Teytelboym 2020
Brown Lock-in Index (BLI)	$BLI_c = \Sigma_b \frac{exports_b}{\Sigma_p exports_p} * (1 - \tilde{PCI})$	This Chapter
Brown Complexity Index (BCI)	$BCI_c = \Sigma_b \rho_b^c * \tilde{PCI}$	This Chapter
Brown Lock-in Index (binary)	$\tilde{BLI}_c = \Sigma_b \rho_b^c * (1 - \tilde{PCI})$	This Chapter
Product Transition Outlook (Normalised Proximity)	$TransitionOutlook_b = \frac{\Sigma_q^Q \Omega_{b,q}}{Q} / \frac{\Sigma_p^P \Omega_{b,p}}{P}$	This Chapter
Country Transition Outlook	$TransitionOutlook_c = \frac{\Sigma_b \rho_b^c * TO_b}{\Sigma_b \rho_b^c}$	This Chapter

Note: Notation: $\frac{exports_b}{\Sigma_p exports_p}$ is the share of each brown product in overall export values. ρ_p^c is a binary variable taking the value 1 if a country exports the product in question with $RCA > 1$. $\tilde{PCI}$ is the Product Complexity Index normalised to take a value between 0 and 1. $\Omega_{b,q}$ is the pairwise proximity between brown product b and climate-compatible (green or non-brown) product q; Q is the total number of products of type q; $\Omega_{b,p}$ is the pairwise proximity between product b and product p; and P is the set of all traded products.

Table C.9 reports estimates of the relationships

TABLE C.5
Summary Statistics for Trade and Policy Variables

	mean	sd	min	max
Brown Export Volume (1,000 USD)	1.13e+07	3.08e+07	11.94	2.88e+08
% Share of Brown in Export Volume	19.90	26.66	0.07	99.70
Number of Competitive Brown Products	11.89	12.83	1.00	76.00
% Share of Brown in Export Diversity	3.45	4.67	0.14	50.00
Green Export Volume (1,000 USD)	5.19e+06	2.22e+07	0.00	3.30e+08
% Share of Green in Export Volume	4.27	4.35	0.00	29.01
Number of Competitive Green Products	31.32	35.89	0.00	200.00
% Share of Green in Export Diversity	5.82	2.98	0.00	16.67
CO2 emissions (metric tons per capita)	4.50	5.44	0.00	42.74
GDP per capita (current USD)	12597.35	18127.71	124.93	116072.05
Coal rents (% of GDP)	0.14	0.65	0.00	10.63
Oil rents (% of GDP)	3.79	9.43	0.00	66.21
Natural gas rents (% of GDP)	0.66	3.25	0.00	57.32
RTA, Climate Change Adaptation Technologies	0.68	1.27	0.00	15.62
RTA, Energy-related Mitigation Technologies	0.50	0.82	0.03	8.81
RTA, Environment-related Technologies	0.81	0.87	0.08	5.38
RTA, Carbon Capture and Storage	0.06	0.18	0.00	1.75
RTA, Transport-related Mitigation Technologies	0.26	0.58	0.01	5.26
Observations	1051			

Note: The table displays summary statistics for some of the indices we compute, as well as policy and control variables. Export-based indicators are computed using data from CEPII's BACI database (Gaulier and Zignago 2010). Revealed Technological Advantage (RTA) in different low carbon technologies is derived from OECD Stat. All other variables are collected from the World Bank's World Development Indicators.

$$\begin{aligned}\Delta ExportShare_{c,t}^{CCS} =& \beta_0 + \beta_1 \Delta ExportShare_{c,t}^{RefinedOil} + \\ & \beta_2 \Delta ExportShare_{c,t}^{NaturalGas} + \beta_3 \Delta ExportShare_{c,t}^{LNG} + \\ & \beta_4 \Delta ExportShare_{c,t}^{Coal} + \beta_5 \Delta ExportShare_{c,t}^{CrudeOil} + \delta_t + \varepsilon\end{aligned} \tag{C.7}$$

$$\begin{aligned}\Delta RCA_{c,t}^{CCS} =& \beta_0 + \beta_1 \Delta ExportShare_{c,t}^{RefinedOil} + \\ & \beta_2 \Delta ExportShare_{c,t}^{NaturalGas} + \beta_3 \Delta ExportShare_{c,t}^{LNG} + \\ & \beta_4 \Delta ExportShare_{c,t}^{Coal} + \beta_5 \Delta ExportShare_{c,t}^{CrudeOil} + \delta_t + \varepsilon\end{aligned} \tag{C.8}$$

where δ_t are year dummies, and ε is the error term. Standard errors are clustered at the country level.

TABLE C.6
Countries Ranking Most Highly on the Brown Lock-in Index (Top 50)

Country	BLI	Brown exports [1M USD]	Brown Export Share [%]	GDP per capita [USD]	Transition Outlook	Green TO
South Sudan	3.57	13.49	94.82	NaN	-4.42	-2.39
Iraq	3.48	634.12	94.50	5115.69	-0.30	-0.55
Libya	3.29	193.89	90.92	5810.85	-2.45	-2.21
Angola	3.27	307.13	88.99	3095.46	-1.58	-1.67
Equatorial Guinea	3.21	38.62	88.80	8897.39	-1.87	-2.03
Azerbaijan	3.19	148.20	89.41	4358.97	-0.99	-0.55
Nigeria	3.18	449.05	87.69	2099.86	-1.51	-1.84
Brunei Darussalam	3.02	56.55	91.51	29177.48	-0.73	-0.21
Chad	2.98	11.30	81.44	690.87	-4.42	-2.39
Venezuela	2.92	178.51	84.28	NaN	-0.31	-0.47
Kuwait	2.92	479.84	90.00	29599.34	-0.75	-0.76
Algeria	2.91	299.23	93.75	3898.94	-1.27	-1.28
Qatar	2.77	571.76	86.98	58919.32	-1.71	-1.19
Turkmenistan	2.49	71.46	87.21	6888.55	-0.17	-0.86
Saudi Arabia	2.42	1592.41	74.14	21453.67	-1.04	-0.40
Timor-Leste	2.25	0.63	69.09	1385.77	-2.05	-0.05
Gabon	2.19	32.41	64.23	7364.51	-2.51	-1.02
Oman	2.16	240.97	69.68	17047.08	-1.22	-0.73
Kazakhstan	2.09	343.43	63.78	9141.98	-1.18	-1.21
Iran	1.99	369.01	63.00	3981.87	-0.85	-0.77
Br. Indian Ocean Terr.	1.73	0.16	54.42	NaN	-0.90	0.25
Congo	1.53	49.64	49.38	2208.69	-2.32	-0.93
Norway	1.52	580.71	55.28	74254.91	-0.90	-0.44
Russian Federation	1.47	2130.54	57.93	10467.39	-0.78	-0.63
Yemen	1.44	6.89	46.56	958.38	-1.41	-1.79
Trinidad and Tobago	1.40	46.02	53.31	16305.01	-1.61	-1.20
Colombia	1.38	203.33	54.26	6147.32	-1.12	-0.82
Bonaire	1.13	0.12	66.64	NaN	-0.53	-0.23
Cameroon	1.12	17.64	40.52	1507.63	-1.43	-1.18
Papua New Guinea	1.11	41.80	42.63	2716.75	-1.55	-2.06
Ecuador	0.88	72.13	35.01	6078.49	-0.92	-0.53
United Arab Emirates	0.84	932.20	41.47	40322.40	-0.09	-0.21
Aruba	0.62	0.83	39.63	29352.08	-0.13	-0.11
Curaçao	0.60	3.60	44.28	19018.16	-0.37	-0.43
Saint Vincent and the Grenadines	0.59	0.63	29.35	7277.43	0.52	-0.43
Mozambique	0.55	24.90	37.38	469.77	-0.90	-1.78
Mongolia	0.54	25.93	34.84	3993.63	-0.82	-2.19
Bolivia (Plurinational State of)	0.54	26.19	31.54	3332.31	-2.18	-1.06
Myanmar	0.50	55.89	29.30	1255.32	-0.60	-1.11
Australia	0.48	774.30	30.92	53512.98	-0.87	-1.07
Togo	0.46	9.45	37.88	868.74	0.95	0.27
Bahrain	0.35	43.99	35.98	22879.85	0.13	-0.16
Canada	0.30	1269.66	31.52	44725.29	-0.85	0.33
Gibraltar	0.28	1.08	47.31	NaN	-0.17	1.54
Ghana	0.26	34.82	19.78	2151.85	-0.93	-0.31
Dem. People's Rep. of Korea	0.22	3.18	29.77	NaN	0.57	0.36
Egypt	0.22	76.91	22.34	3017.92	-0.34	-0.50
Greece	0.16	100.15	28.84	18590.33	0.34	-0.24
Maldives	0.13	0.57	21.76	9310.32	0.01	-0.10
Sudan	0.12	7.55	16.78	783.89	-2.48	-2.01

Note: The Brown Lock-in Index (BLI) constitutes our baseline measure of lock-in to brown exports. It is computed as $BLI_c = \Sigma_b \frac{exports_b}{\Sigma_p exports_p} * (1 - \tilde{PCI})$ where $\frac{exports_b}{\Sigma_p exports_p}$ is the share of each brown product in overall export values, and $\tilde{PCI}$ is the Product Complexity Index normalised to take a value between 0 and 1. The table shows the 50 countries with the highest BLI.

TABLE C.7
Countries Ranking Most Highly on the Brown Complexity Index (Top 50)

Country	BCI	Brown exports [1M USD]	Brown Export Share [%]	GDP per capita [USD]	Transition Outlook	Green TO
USA	4.93	2462.74	17.11	62013.69	-0.52	0.14
Japan	4.27	1257.50	18.67	39814.17	-0.24	0.31
Germany	3.95	1824.49	13.21	45520.66	0.02	0.68
Belgium	3.73	460.61	14.92	45068.76	-0.41	0.14
Netherlands	3.67	718.24	14.26	50490.97	-0.44	-0.24
France	3.24	468.56	8.99	39380.82	0.27	0.65
United Kingdom	3.03	802.30	19.29	42026.79	-0.05	0.77
Rep. of Korea	2.84	871.01	15.49	31579.38	-0.19	0.07
Thailand	2.76	321.74	13.03	6977.58	0.07	0.31
India	2.48	488.12	15.91	1947.72	0.43	-0.33
Spain	2.39	534.73	17.27	28314.84	0.14	0.02
Italy	2.22	434.85	8.74	32645.50	0.92	0.97
Austria	2.02	147.49	9.11	48550.29	0.30	1.15
China	1.91	652.10	2.60	9479.06	0.88	-0.59
Poland	1.67	189.41	7.87	14646.76	0.74	0.77
Finland	1.62	98.55	14.24	47483.98	0.54	1.43
Canada	1.62	1269.66	31.52	44725.29	-0.85	0.33
Singapore	1.61	507.49	16.89	62028.43	-0.47	0.04
Turkey	1.44	222.47	12.58	9719.31	0.80	0.46
Portugal	1.40	76.23	11.80	22094.78	0.48	0.18
Hungary	1.34	165.05	14.31	15374.97	0.36	1.55
Russian Federation	1.31	2130.54	57.93	10467.39	-0.78	-0.63
Czechia	1.26	220.90	11.88	21844.52	0.63	1.22
Indonesia	1.25	392.90	21.41	3859.81	-0.52	-0.65
Slovenia	1.21	38.85	10.97	24536.80	0.89	1.42
United Arab Emirates	1.07	932.20	41.47	40322.40	-0.09	-0.21
South Africa	1.05	177.88	16.75	6346.73	-0.24	-0.07
Saudi Arabia	1.03	1592.41	74.14	21453.67	-1.04	-0.40
Sweden	1.01	214.53	14.07	52911.91	0.52	1.62
Brazil	0.95	314.56	14.47	8696.90	-0.58	-0.13
Iran	0.92	369.01	63.00	3981.87	-0.85	-0.77
Slovakia	0.91	202.41	23.43	18389.28	0.08	1.27
Mexico	0.84	959.84	22.13	9199.81	0.26	1.70
Romania	0.81	65.12	8.68	11710.00	0.30	1.00
Lithuania	0.80	43.68	14.10	18165.61	0.41	0.93
Grenada	0.67	0.01	3.81	10067.39	0.61	0.97
Belarus	0.66	71.87	24.71	6089.46	-0.07	0.62
Israel	0.62	29.40	4.99	41657.61	-0.12	0.01
Denmark	0.61	50.99	5.14	58941.02	0.71	0.87
Philippines	0.52	16.98	1.99	3246.64	0.40	-0.55
Brunei Darussalam	0.49	56.55	91.51	29177.48	-0.73	-0.21
Oman	0.48	240.97	69.68	17047.08	-1.22	-0.73
Ukraine	0.43	11.92	2.42	3061.80	0.52	0.28
Norway	0.40	580.71	55.28	74254.91	-0.90	-0.44
Argentina	0.39	78.12	13.07	11566.82	-0.77	-0.12
Latvia	0.35	9.55	6.47	16697.55	0.40	0.17
Egypt	0.33	76.91	22.34	3017.92	-0.34	-0.50
Guam	0.31	0.02	5.78	36407.51	-0.06	0.07
Cyprus	0.27	7.67	16.63	27456.57	-0.02	-0.24
Serbia	0.25	13.92	7.34	6889.57	0.54	1.17

Note: The Brown Complexity Index (BCI) forms a direct counterpart to the Green Complexity Index (GCI) and measures the number and complexity of brown products a country is competitive in. It is computed as $BCI_c = \Sigma_b \rho_b^c * \tilde{PCI}$. Export capabilities in more technologically sophisticated activities may take longer to develop and bring greater benefits to the economy. However, by opening up a greater number of diversification paths they are likely associated with easier transition pathways. The table shows the 50 countries with the highest BCI.

TABLE C.8
Key Relationships

Variable 1	Variable 2	Correlation
Brown Complexity Index	Brown Diversity Share	0.04
Brown Complexity Index	Brown Export Diversity	0.99
Brown Complexity Index	Brown Export Share [%]	0.00
Brown Complexity Index	Diversity	0.78
Brown Complexity Index	Economic Complexity Index	0.62
Brown Complexity Index	GDP per capita [USD]	0.39
Brown Complexity Index	Green Complexity Index	0.80
Brown Diversity Share	Diversity	-0.26
Brown Export Diversity	Diversity	0.77
Brown Export Share [%]	Diversity	-0.25
Brown Lock-in Index	Brown Diversity Share	0.72
Brown Lock-in Index	Brown Export Diversity	0.00
Brown Lock-in Index	Brown Export Share [%]	0.98
Brown Lock-in Index	Diversity	-0.30
Brown Lock-in Index	Economic Complexity Index	-0.33
Brown Lock-in Index	GDP per capita [USD]	-0.03
Brown Lock-in Index	Green Complexity Index	-0.25
Green Complexity Index	Diversity	0.88
Green Complexity Index	Green Export Diversity	0.99
Green Export Diversity	Diversity	0.91

Note: The table shows correlation coefficients between our key indices, as well as the indices and other relevant measures such as export diversity and GDP per capita.

TABLE C.9
Changes in the Relative Share of Carbon Capture and Storage Technologies

	(1) ΔExport Share	(2) ΔRCA
Δ Export Share, Refined (%)	-0.005*	-0.005*
	(0.003)	(0.003)
Δ Export Share, Natural Gas (%)	-0.004**	-0.004**
	(0.002)	(0.002)
Δ Export Share, LNG (%)	-0.003	-0.003*
	(0.002)	(0.002)
Δ Export Share, Coal (%)	-0.017***	-0.016***
	(0.005)	(0.004)
Δ Export Share, Crude (%)	-0.000	-0.000
	(0.002)	(0.002)
Year FEs	X	X
Observations	823	823
R2	.00599	.00457

Linear Regression. Dependent Variables Relate to Carbon Capture and Storage.
Cluster-Robust Standard Errors in Parentheses.

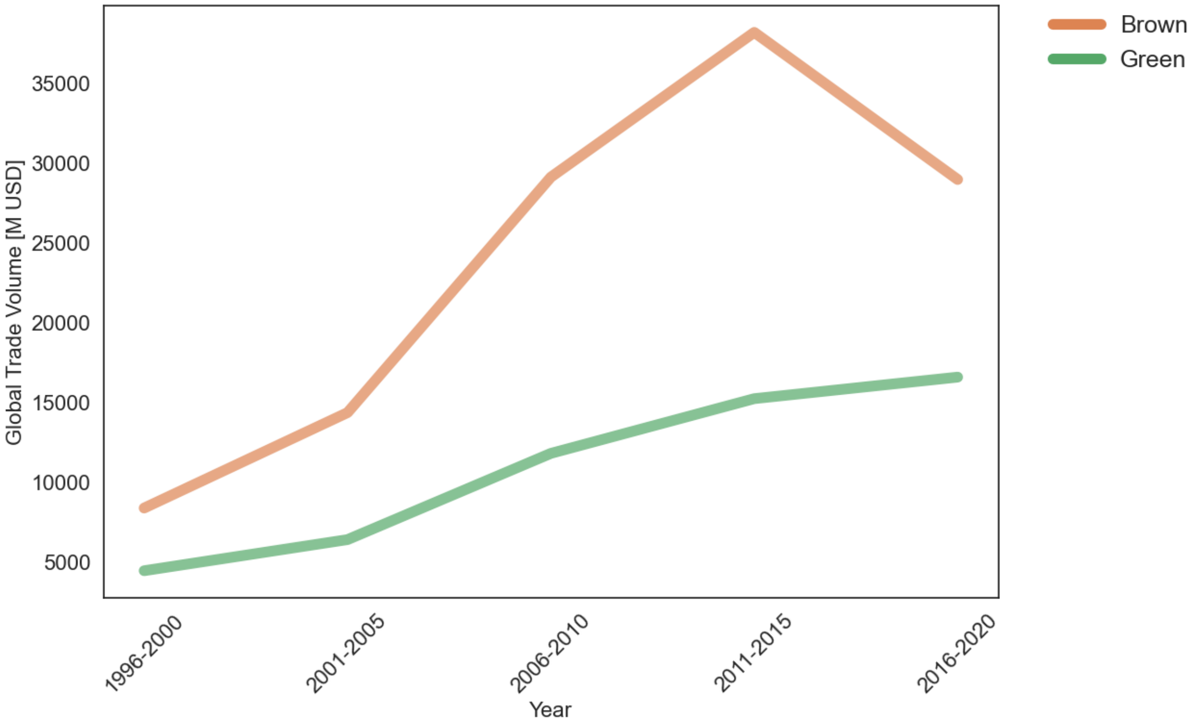
Note: The table reports results of a linear regression of changes in the export share and revealed comparative advantage in CCUS products on changes in the shares of selected fossil fuels. Standard errors are clustered at the country level.

C.4 Supplementary Figures

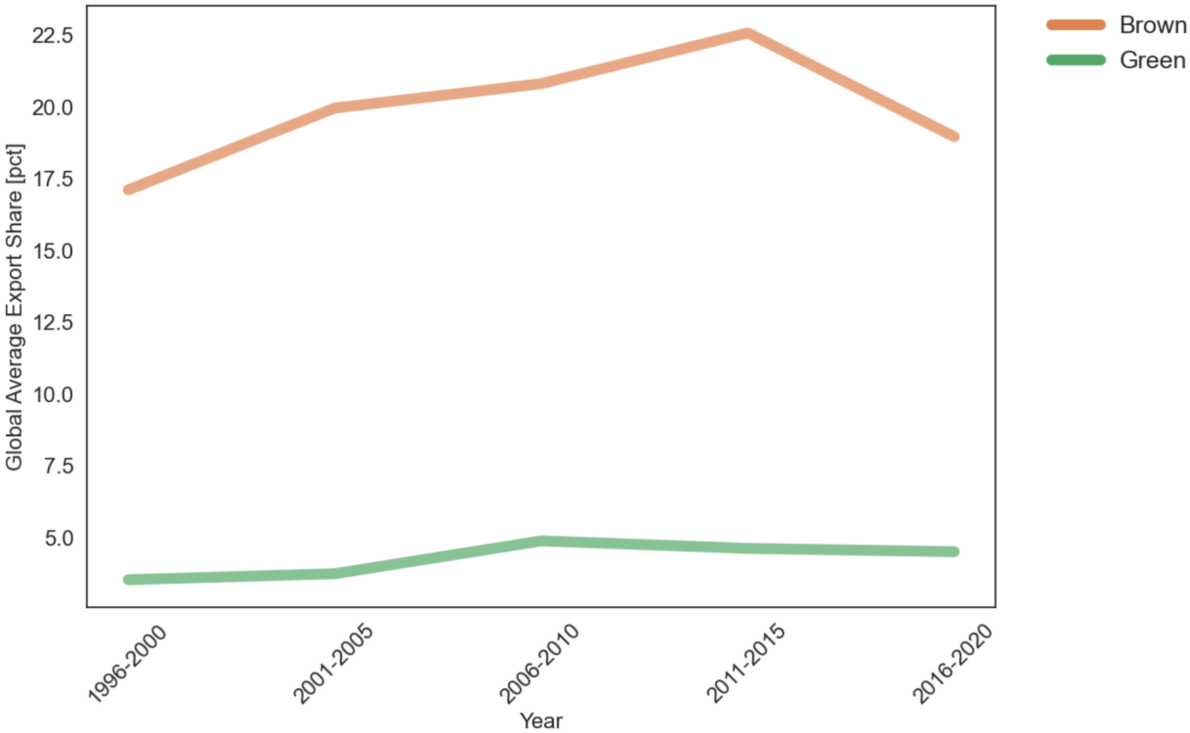
Products on our brown list account for a significantly larger share of global trade than green products. However, our results suggest that trade in brown products declined somewhat in the last period (2016-2020) compared to the penultimate period (2011-2015). Figure C.1 indicates that 'brown' trade peaked at close to 40 billion USD (about 22% of global trade) during the 2011-2015 period and declined slightly thereafter. While this may be partly attributable to the global covid-19 pandemic, it is noteworthy that volumes of green trade continued to rise during the same time period.

Figure C.2 plots the top 10 exporters in terms of trade values for green and brown products. Strikingly, China rose to the top of this ranking for green products during the early 2000s, but does not appear within the top 10 exporters of brown products - unlike the United States, Germany, Japan, the United Kingdom, Canada, South Korea and Mexico, all of which appear alongside petrostates such as Russia, Saudi Arabia and the UAE.

Table C.10 lists the 20 brown products with the highest PCI and their descriptions, while Table C.11 shows those with the lowest PCI. Brown products which are high in complexity include engines, pumps and various hydrocarbon-derived chemicals, while low-complexity brown products more prominently feature unprocessed hydrocarbons.



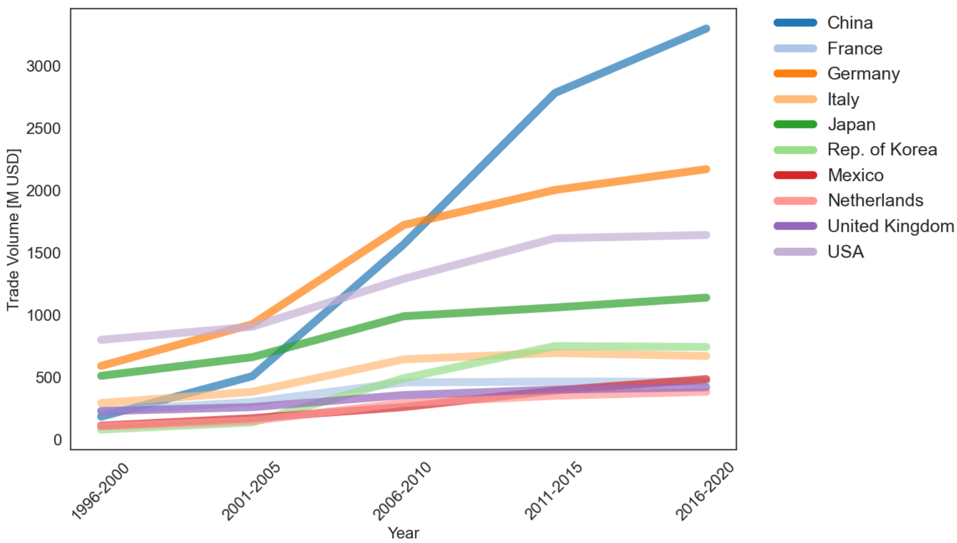
(a) Global Volume of Trade



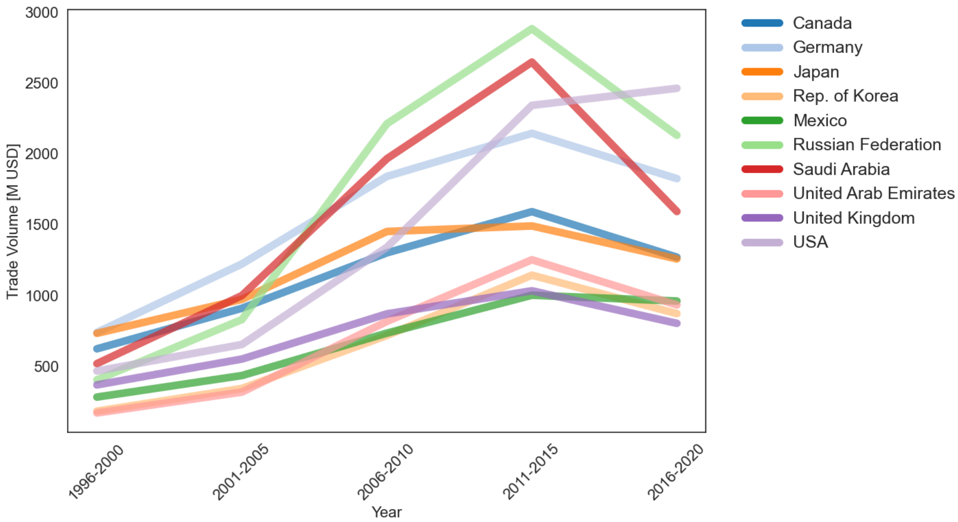
(b) Global Average Share in Exports

FIGURE C.1
Global Trends in Green and Brown Trade

Note: The figure plots total trade volume in each product group (brown and green) and their shares of global trade over time.



(a) Top 10 Green Exporters



(b) Top 10 Brown Exporters

FIGURE C.2
Top 10 Exporters of Green and Brown Products

Note: The figure plots total export volumes in green and brown products by the top 10 exports of such products over time.

TABLE C.10
Top 20 Brown Products in Terms of PCI

HS 1992	Description	PCI	Transition Outlook	Green TO
290270	Cyclic hydrocarbons; cumene	1.75	0.99	1.01
290323	Unsaturated chlorinated derivatives of acyclic hydrocarbons; tetrachloroethylene (perchloroethylene)	1.66	0.99	1.17
340319	Lubricating preparations; (other than for the treatment of textile and similar materials), containing less than 70% (by weight) of petroleum oils or oils obtained from bituminous minerals	1.62	1.00	1.36
290314	Saturated chlorinated derivatives of acyclic hydrocarbons; carbon tetrachloride	1.59	1.00	1.02
391110	Petroleum resins, coumarone, indene or coumarone-indene resins and polyterpenes; in primary forms	1.53	1.00	1.08
840790	Engines; rotary internal combustion piston engines, for other than aircraft or marine propulsion	1.41	1.00	1.14
270720	Oils and products of the distillation of high temperature coal tar; toluole	1.41	0.99	1.02
870323	Vehicles; spark-ignition internal combustion reciprocating piston engine, cylinder capacity exceeding 1500cc but not exceeding 3000cc	1.41	0.99	1.48
290123	Acyclic hydrocarbons; unsaturated, butene (butylene) and isomers thereof	1.38	0.99	1.10
290313	Saturated chlorinated derivatives of acyclic hydrocarbons; chloroform (trichloromethane)	1.37	0.99	1.11
290315	Saturated chlorinated derivatives of acyclic hydrocarbons; 1,2-dichloroethane (ethylene dichloride)	1.36	0.99	1.08
841690	Furnaces; parts of furnace burners, for liquid fuel, pulverized solid fuel or gas, mechanical stokers, grates, ash dischargers and the like	1.31	1.00	1.43
840820	Engines; compression-ignition internal combustion piston engines (diesel or semi-diesel engines), of a kind used for the propulsion of vehicles of chapter 87	1.27	1.00	1.40
290312	Saturated chlorinated derivatives of acyclic hydrocarbons; dichloromethane (methylene chloride)	1.27	1.00	1.11
840890	Engines; compression-ignition internal combustion piston engines (diesel or semi-diesel engines), of a kind used for other than marine propulsion or the vehicles of chapter 87	1.27	1.00	1.37
841620	Furnaces; furnace burners, for pulverized solid fuel or gas, including combination burners	1.23	1.00	1.47
290260	Cyclic hydrocarbons; ethylbenzene	1.22	0.99	1.25
270730	Oils and products of the distillation of high temperature coal tar; xylole	1.21	0.99	1.01
290330	Fluorinated, brominated or iodinated derivatives of acyclic hydrocarbons	1.21	0.99	1.04
290361	Halogenated derivatives of aromatic hydrocarbons; chlorobenzene, o-dichlorobenzene and p-dichlorobenzene	1.17	1.00	1.04

Note: The table lists the 20 products with the highest PCI across the (narrow) brown list.

TABLE C.11
Bottom 20 Brown Products in Terms of PCI

HS 1992	Description	PCI	Transition Outlook	Green TO
270900	Oils; petroleum oils and oils obtained from bituminous minerals, crude	-2.60	0.98	0.95
271111	Petroleum gases and other gaseous hydrocarbons; liquefied, natural gas	-2.29	0.99	0.84
271129	Petroleum gases and other gaseous hydrocarbons; in gaseous state, other than natural gas	-2.14	1.00	0.91
271121	Petroleum gases and other gaseous hydrocarbons; in gaseous state, natural gas	-1.79	0.98	0.81
271119	Petroleum gases and other gaseous hydrocarbons; liquefied, n.e.s. in heading no. 2711	-1.74	0.99	1.02
270119	Coal; (other than anthracite and bituminous), whether or not pulverised but not agglomerated	-1.62	0.99	0.79
270500	Gases; coal, water, producer and similar gases (excluding petroleum and other gaseous hydrocarbons)	-1.59	1.00	1.01
271113	Petroleum gases and other gaseous hydrocarbons; liquefied, butanes	-1.58	0.99	1.15
271112	Petroleum gases and other gaseous hydrocarbons; liquefied, propane	-1.49	0.98	1.03
270740	Oils and products of the distillation of high temperature coal tar; naphthalene	-1.41	1.00	1.10
270112	Coal; bituminous, whether or not pulverised, but not agglomerated	-1.30	0.98	0.91
870432	Vehicles; spark-ignition internal combustion piston engine, for transport of goods, (of a g.v.w. exceeding 5 tonnes), nes in item no 8704.1	-1.29	1.00	1.35
271311	Petroleum coke; (not calcined), obtained from bituminous minerals	-1.26	0.99	1.01
270111	Coal; anthracite, whether or not pulverised, but not agglomerated	-1.04	1.00	0.88
840710	Engines; for aircraft, spark-ignition reciprocating or rotary internal combustion piston engines	-0.99	1.00	1.04
271210	Petroleum jelly	-0.88	1.00	1.14
271000	Oils; petroleum oils and oils obtained from bituminous minerals, not crude; preparations n.e.s., containing by weight 70% or more of petroleum oils or oils obtained from bituminous minerals	-0.82	1.00	1.13
850212	Electric generating sets; with compression-ignition internal combustion piston engines (diesel or semi-diesel engines), of an output exceeding 75kva but not exceeding 375kva	-0.81	1.00	1.10
850213	Electric generating sets; with compression-ignition internal combustion piston engines (diesel or semi-diesel engines), of an output exceeding 375kva	-0.79	1.00	1.15
843039	Coal or rock cutters and tunnelling machinery; not self-propelled	-0.66	1.00	1.36

Note: The table lists the 20 products with the lowest PCI across the brown (narrow) list.

TABLE C.12
Correlates of Brown Dependence Measures, Using the Long List of Brown Products

	(1) BLI (Full)	(2) BLI (Full)	(3) BLI (Full)	(4) BCI (Full)	(5) BCI (Full)	(6) BCI (Full)
GDP per capita (current USD) (log)	0.078*	-0.056	0.068	0.325***	0.219**	0.216
	(0.041)	(0.066)	(0.079)	(0.054)	(0.098)	(0.165)
Coal rents (% of GDP)		0.006			0.047	
		(0.032)			(0.089)	
Oil rents (% of GDP)		0.070***			-0.026***	
		(0.006)			(0.005)	
Natural gas rents (% of GDP)		0.050**			-0.019	
		(0.024)			(0.015)	
CO2 emissions (metric tons per capita, log)		0.228*			0.366**	
		(0.127)			(0.158)	
RTA, Environment-related Technologies			1.661			1.029
			(1.114)			(1.660)
RTA, Energy-related Mitigation Technologies			-0.500			-3.077**
			(1.133)			(1.412)
RTA, Carbon Capture and Storage			3.476***			-4.730*
			(0.711)			(2.533)
RTA, Climate Change Adaptation Technologies			0.805			-1.070*
			(0.676)			(0.555)
RTA, Transport-related Mitigation Technologies			-2.500**			2.399
			(0.992)			(2.627)
Year FEs	X	X	X	X	X	X
Observations	933	854	222	933	854	222
R2	.0139	.659	.186	.22	.347	.191

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
Dependent Variables Relate to Brown List (Narrow).

Note: Like Table C.1, but using the long list of brown products.

C.5 Extension: Long List of Brown Products

TABLE C.13
Predictive Power of Green Transition Outlook, Using the Long List of Brown Products

	(1) BLI (Full)	(2) BLI (Full)	(3) BCI (Full)	(4) BCI (Full)
Brown Lock-in Index (full list, t-1)	0.911***	0.903***		
	(0.024)	(0.031)		
Green Transition Outlook (t-1)	-0.036*	-0.019	-0.019*	-0.014
	(0.019)	(0.019)	(0.010)	(0.011)
GDP per capita (current USD, log, t-1)	0.008	-0.005	0.025***	0.025
	(0.010)	(0.018)	(0.007)	(0.018)
Coal rents (% of GDP, t-1)		0.026*		-0.001
		(0.014)		(0.009)
Oil rents (% of GDP, t-1)		0.004**		-0.001
		(0.002)		(0.001)
Natural gas rents (% of GDP, t-1)		0.010***		-0.001
		(0.003)		(0.001)
CO2 emissions (metric tons per capita, log, t-1)		0.025		0.020
		(0.029)		(0.028)
Brown Complexity Index (t-1)			0.950***	0.938***
			(0.013)	(0.015)
Year FEs	X	X	X	X
Observations	715	661	715	661
R2	.86	.884	.922	.926

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
t-1 refers to the previous period's value.

Note: Like Table C.2, but using the long list of brown products.

TABLE C.14
Predictive Power of Overall Transition Outlook, Using the Long List of Brown Products

	(1) BLI (Full)	(2) BLI (Full)	(3) BCI (Full)	(4) BCI (Full)
Brown Lock-in Index (full list, t-1)	0.902***	0.901***		
	(0.024)	(0.030)		
Overall Transition Outlook (t-1)	-0.060***	-0.029*	0.006	0.009
	(0.019)	(0.017)	(0.009)	(0.012)
GDP per capita (current USD, log, t-1)	0.000	-0.007	0.024***	0.024
	(0.008)	(0.018)	(0.007)	(0.018)
Coal rents (% of GDP, t-1)		0.027**		0.001
		(0.013)		(0.010)
Oil rents (% of GDP, t-1)		0.004**		-0.000
		(0.002)		(0.001)
Natural gas rents (% of GDP, t-1)		0.009***		-0.000
		(0.003)		(0.001)
CO2 emissions (metric tons per capita, log, t-1)		0.021		0.018
		(0.029)		(0.028)
Brown Complexity Index (t-1)			0.945***	0.937***
			(0.014)	(0.015)
Year FEs	X	X	X	X
Observations	715	661	715	661
R2	.862	.884	.922	.926

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
t-1 refers to the previous period's value.
Note: Like Table C.3, but using the long list of brown products.

C.6 Extension: Alternative BLI Using Binary RCA

As an extension of our baseline analysis, we compute the Brown Lock-in Index using binary RCA, instead of product shares in country exports. This alternative version of BLI is calculated as

$$B\tilde{L}I_c = \Sigma_b \rho_b^c * (1 - P\tilde{C}I) \tag{C.9}$$

.

This is a more direct inverse of the GCI: it is computed in exactly the same manner, but using brown instead of green products and attributing greater weight to less, rather than more, complex products. The index is positively associated with overall export diversity and a larger number of diversification paths, making our baseline BLI the preferred measure for brown lock-in.

Our key result here is that when BLI is computed in this manner, it displays a strong positive correlation to BCI – which, as we have shown, correlates positively with GCI, a relationship

TABLE C.15
Alternative BLI Top 20

Country	GDP per capita [USD]	BLI (binary)	Brown exports [1M USD]	Brown Export Share [%]	Transition Outlook	Green TO
USA	62013.69	4.39	2462.74	17.11	-0.52	0.14
India	1947.72	2.93	488.12	15.91	0.43	-0.33
Spain	28314.84	2.89	534.73	17.27	0.14	0.02
Japan	39814.17	2.86	1257.50	18.67	-0.24	0.31
Russian Federation	10467.39	2.69	2130.54	57.93	-0.78	-0.63
Netherlands	50490.97	2.65	718.24	14.26	-0.44	-0.24
United Kingdom	42026.79	2.53	802.30	19.29	-0.05	0.77
Belgium	45068.76	2.53	460.61	14.92	-0.41	0.14
United Arab Emirates	40322.40	2.48	932.20	41.47	-0.09	-0.21
France	39380.82	2.32	468.56	8.99	0.27	0.65
Germany	45520.66	2.31	1824.49	13.21	0.02	0.68
Thailand	6977.58	2.12	321.74	13.03	0.07	0.31
Indonesia	3859.81	2.09	392.90	21.41	-0.52	-0.65
Canada	44725.29	2.06	1269.66	31.52	-0.85	0.33
Turkey	9719.31	1.94	222.47	12.58	0.80	0.46
Rep. of Korea	31579.38	1.94	871.01	15.49	-0.19	0.07
Saudi Arabia	21453.67	1.83	1592.41	74.14	-1.04	-0.40
Iran	3981.87	1.82	369.01	63.00	-0.85	-0.77
South Africa	6346.73	1.77	177.88	16.75	-0.24	-0.07
Italy	32645.50	1.77	434.85	8.74	0.92	0.97

Note: The Brown Lock-in Index is here computed as $\tilde{BLI}_c = \Sigma_b \rho_b^c * (1 - \tilde{PCI})$.

apparently driven by higher export diversity and the 'weighted count' nature of these indices. Figure C.3 plots our baseline and alternative measures of BLI against the BCI, underscoring this finding. The correlation between BCI and the alternative measure of BLI indicates that the weighting by either PCI or inverse PCI plays a secondary role to the diversity aspect (the number of competitive exports within a product group) when a country's rank is computed. Countries with an unusually high share of brown exports in overall export volumes tend to have low export diversity, including within the group of brown products, as well as low export complexity. In contrast, countries which score high on our alternative BLI or BCI measures export a greater *number* of brown products with $RCA > 1$, and the ranking of countries is similar regardless of whether we give a higher relative weight to products with high or low complexity, as Tables C.7 and C.15 show. In both cases, the United States score most highly and a number of industrialised countries feature among the top 20 countries. However, some petrostates – such as Russia, the UAE, Saudi Arabia and Iran – score highly on our alternative BLI, but not BCI, suggesting that these countries export a variety of low-complexity brown products, but not high-complexity ones.

TABLE C.16
Correlates of Brown Dependence Measures, Using Alternative BLI

	(1) BLI (binary)	(2) BLI (binary)	(3) BLI (binary)	(4) BCI	(5) BCI	(6) BCI
GDP per capita (current USD) (log)	0.297***	0.040	0.070	0.321***	0.180*	0.204
	(0.047)	(0.090)	(0.153)	(0.055)	(0.100)	(0.159)
Coal rents (% of GDP)		0.049			0.008	
		(0.127)			(0.086)	
Oil rents (% of GDP)		-0.011**			-0.025***	
		(0.005)			(0.005)	
Natural gas rents (% of GDP)		-0.016			-0.017	
		(0.016)			(0.015)	
CO2 emissions (metric tons per capita, log)		0.636***			0.421***	
		(0.145)			(0.159)	
RTA, Environment-related Technologies			0.926			1.271
			(1.792)			(1.809)
RTA, Energy-related Mitigation Technologies			-2.166			-3.280**
			(1.398)			(1.498)
RTA, Carbon Capture and Storage			-3.453			-4.977*
			(2.370)			(2.660)
RTA, Climate Change Adaptation Technologies			-0.564			-1.061*
			(0.595)			(0.556)
RTA, Transport-related Mitigation Technologies			0.261			2.730
			(2.101)			(2.748)
Year FEs	X	X	X	X	X	X
Observations	933	854	222	933	854	222
R2	.194	.32	.0924	.212	.324	.171

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
Dependent Variables Relate to Brown List (Narrow).

Note: Like Table C.1, except that the Brown Lock-in Index is here computed as $B\tilde{L}I_c = \Sigma_b \rho_b^c * (1 - P\tilde{C}I)$.

TABLE C.17
Predictive Power of Green Transition Outlook, Using Alternative BLI

	(1) BLI (binary)	(2) BLI (binary)	(3) BCI	(4) BCI
Brown Lock-in Index (binary RCA, t-1)	0.895***	0.881***		
	(0.021)	(0.024)		
Green Transition Outlook (t-1)	-0.019	-0.005	-0.027***	-0.024**
	(0.012)	(0.014)	(0.010)	(0.011)
GDP per capita (current USD, log, t-1)	0.039***	0.037*	0.023***	0.021
	(0.011)	(0.022)	(0.007)	(0.017)
Coal rents (% of GDP, t-1)		0.028		0.001
		(0.019)		(0.010)
Oil rents (% of GDP, t-1)		0.001		-0.002
		(0.001)		(0.001)
Natural gas rents (% of GDP, t-1)		0.001		-0.001
		(0.002)		(0.001)
CO2 emissions (metric tons per capita, log, t-1)		0.023		0.021
		(0.037)		(0.027)
Brown Complexity Index (t-1)			0.955***	0.947***
			(0.014)	(0.016)
Year FEs	X	X	X	X
Observations	715	661	715	661
R2	.843	.849	.926	.93

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
t-1 refers to the previous period's value.

Note: Like Table C.2, except that the Brown Lock-in Index is here computed as $B\tilde{L}I_c = \Sigma_b \rho_b^c * (1 - P\tilde{C}I)$.

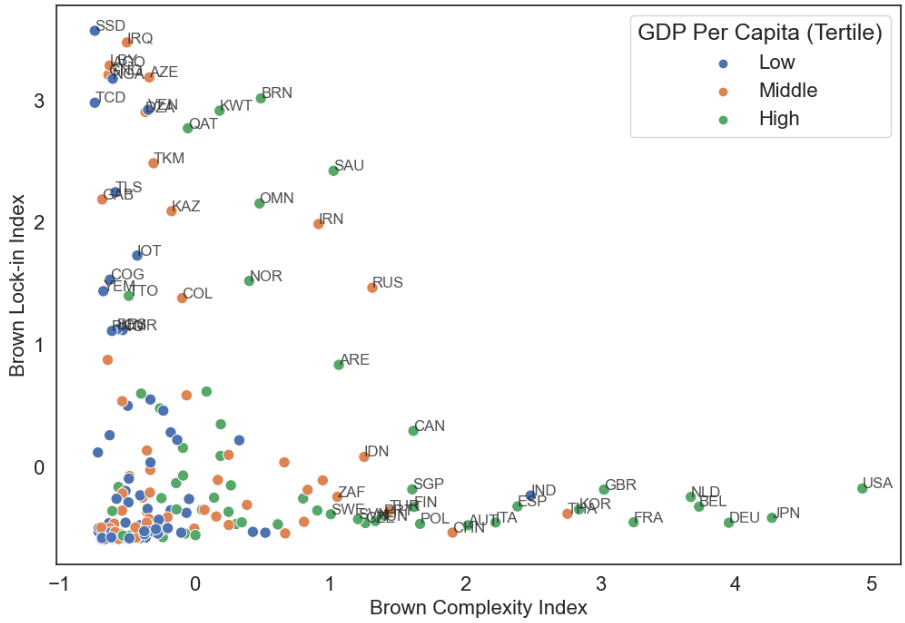
TABLE C.18
Predictive Power of Overall Transition Outlook, Using Alternative BLI

	(1) BLI (binary)	(2) BLI (binary)	(3) BCI	(4) BCI
Brown Lock-in Index (binary RCA, t-1)	0.891***	0.881***		
	(0.022)	(0.024)		
Overall Transition Outlook (t-1)	-0.009	0.003	0.005	0.010
	(0.013)	(0.017)	(0.009)	(0.012)
GDP per capita (current USD, log, t-1)	0.037***	0.037*	0.022***	0.020
	(0.011)	(0.022)	(0.007)	(0.017)
Coal rents (% of GDP, t-1)		0.029		0.005
		(0.019)		(0.011)
Oil rents (% of GDP, t-1)		0.001		-0.000
		(0.001)		(0.001)
Natural gas rents (% of GDP, t-1)		0.001		-0.000
		(0.002)		(0.001)
CO2 emissions (metric tons per capita, log, t-1)		0.023		0.019
		(0.037)		(0.027)
Brown Complexity Index (t-1)			0.948***	0.943***
			(0.015)	(0.016)
Year FEs	X	X	X	X
Observations	715	661	715	661
R2	.843	.849	.926	.93

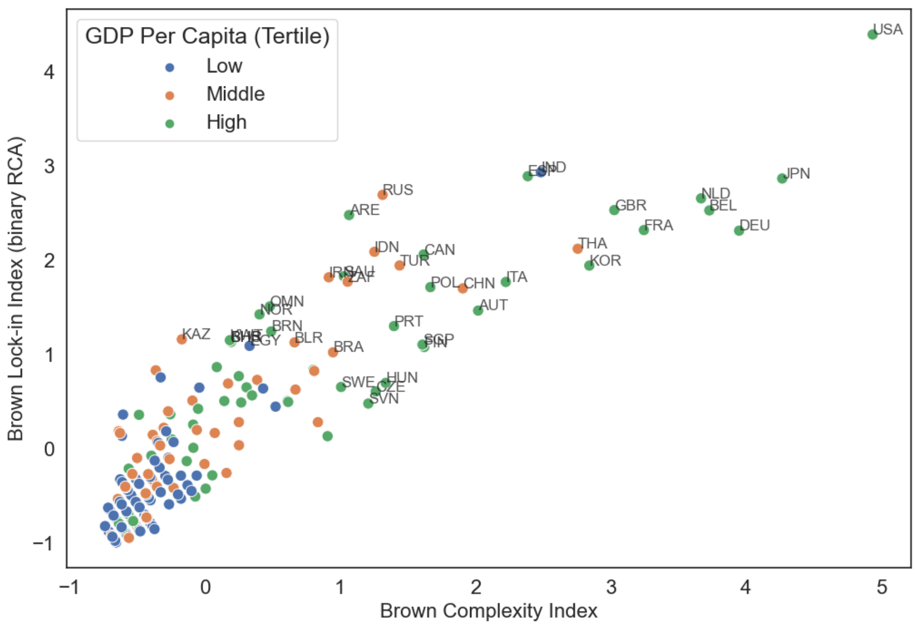
Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
t-1 refers to the previous period's value.

Note: Like Table C.3, except that the Brown Lock-in Index is here computed as $\tilde{BLI}_c = \Sigma_b \rho_b^c * (1 - \tilde{PCI})$.

Tables C.17 and C.18 show that our Transition Outlook measures are not predictive of future changes in binary BLI.



(a) Baseline BLI



(b) Binary BLI

FIGURE C.3

Baseline and alternative measures of BLI, plotted against BCI

Note: The baseline BLI is computed as $BLI_c = \Sigma_b \frac{exports_b}{\Sigma_p exports_p} * (1 - \tilde{PCI})$. The alternative binary version is computed as $BLI_c = \Sigma_b \rho_b^c * (1 - \tilde{PCI})$. Our baseline measure is more appropriate as a measure of lock-in. Visualisation created from trade data averaged over the period 2016-2020.

C.7 Extension: Alternative Averaging Procedure

The BACI database only records strictly non-negative trade flows to save space. For this reason we assume that missing exporter-year-product observations are 0 and include these in the 5-year averages used in our baseline estimates. As a robustness checks, we also compile an alternative dataset in which missing exporter-year-product observations are treated as missing. This section reports key results using this procedure and shows that our country rankings and key regression results change only very marginally when doing so.

TABLE C.19

Countries Ranking Most Highly on the Brown Lock-in Index, Excluding Missing Trade Values

Country	BLI	Brown exports [1M USD]	Brown Export Share [%]	GDP per capita [USD]	Transition Outlook	Green TO
Iraq	3.43	635.06	94.34	5115.69	-0.48	-0.45
South Sudan	3.37	13.49	91.06	NaN	-4.67	-2.48
Libya	3.26	195.45	90.71	5810.85	-2.46	-2.39
Angola	3.20	307.47	87.87	3095.46	-1.74	-1.85
Equatorial Guinea	3.18	38.68	87.98	8897.39	-2.15	-2.21
Azerbaijan	3.16	148.25	88.81	4358.97	-1.00	-0.61
Nigeria	3.11	449.44	86.35	2099.86	-1.49	-2.13
Brunei Darussalam	2.93	60.42	91.25	29177.48	-0.81	-0.24
Algeria	2.92	301.82	93.26	3898.94	-1.47	-1.42
Chad	2.89	11.30	80.07	690.87	-4.67	-2.48
Kuwait	2.86	481.19	88.85	29599.34	-1.14	-0.86
Venezuela	2.82	178.86	82.68	NaN	-0.35	-0.53
Qatar	2.81	571.86	86.56	58919.32	-1.63	-1.10
Br. Indian Ocean Terr.	2.56	0.77	73.49	NaN	-0.87	0.05
Turkmenistan	2.52	71.58	83.74	6888.55	-0.20	-0.97
Saudi Arabia	2.39	1595.39	74.05	21453.67	-1.13	-0.50
Gabon	2.13	32.43	63.37	7364.51	-2.15	-1.04
Oman	2.12	241.70	68.81	17047.08	-1.26	-0.83
Kazakhstan	2.07	344.28	63.60	9141.98	-1.40	-1.14
Iran	1.97	375.71	63.13	3981.87	-0.91	-0.84
Timor-Leste	1.87	0.77	62.43	1385.77	-2.11	-0.10
Norway	1.56	580.79	55.25	74254.91	-0.99	-0.52
Bonaire	1.55	0.44	78.77	NaN	-0.77	-0.32
Congo	1.49	49.69	48.83	2208.69	-1.59	-0.68
Russian Federation	1.46	2130.54	57.91	10467.39	-0.87	-0.60
Trinidad and Tobago	1.43	46.66	53.38	16305.01	-1.57	-1.66
Colombia	1.37	203.38	54.13	6147.32	-1.20	-0.87
Yemen	1.37	7.02	45.37	958.38	-1.33	-2.15
Papua New Guinea	1.14	42.12	42.48	2716.75	-1.76	-2.20
Cameroon	1.13	19.04	41.27	1507.63	-1.61	-1.26
Guyana	1.09	11.75	38.82	6329.52	-2.10	-1.30
Ecuador	0.85	72.18	34.89	6078.49	-0.96	-0.60
United Arab Emirates	0.82	932.20	41.46	40322.40	-0.19	-0.23
Dem. People's Rep. of Korea	0.67	7.57	38.52	NaN	0.45	0.15
Curaçao	0.62	4.02	44.30	19018.16	-1.12	-0.70
Myanmar	0.61	61.47	30.68	1255.32	-0.83	-0.96
Bolivia (Plurinational State of)	0.59	26.19	31.26	3332.31	-2.06	-1.34
Mozambique	0.55	24.98	36.21	469.77	-0.78	-1.56
Mongolia	0.53	25.96	34.38	3993.63	-1.08	-2.26
Australia	0.50	774.31	30.89	53512.98	-0.95	-1.16
Aruba	0.47	1.15	33.84	29352.08	-0.21	-0.34
Togo	0.43	9.47	37.42	868.74	0.96	0.02
Maldives	0.42	0.93	29.46	9310.32	0.12	-0.16
Saint Vincent and the Grenadines	0.39	0.64	23.99	7277.43	0.13	-0.43
American Samoa	0.32	0.24	27.39	11824.79	-0.26	-0.81
Bahrain	0.31	44.12	35.40	22879.85	0.08	-0.30
Canada	0.28	1269.67	31.51	44725.29	-0.92	0.42
Ghana	0.24	34.84	19.65	2151.85	-0.68	0.33
Egypt	0.22	78.75	22.67	3017.92	-0.49	-0.79
Greece	0.14	100.18	28.82	18590.33	0.14	-0.36

Note: Like Table C.6, but using an alternative averaging procedure.

TABLE C.20
Countries Ranking Most Highly on the Brown Complexity Index, Excluding Missing Trade Values

Country	BCI	Brown exports [1M USD]	Brown Export Share [%]	GDP per capita [USD]	Transition Outlook	Green TO
USA	4.97	2462.74	17.11	62013.69	-0.56	0.22
Japan	4.27	1257.50	18.67	39814.17	-0.25	0.40
Germany	3.93	1824.49	13.20	45520.66	-0.04	0.77
Belgium	3.78	460.61	14.90	45068.76	-0.48	0.21
Netherlands	3.64	718.24	14.25	50490.97	-0.51	-0.24
France	3.28	468.56	8.98	39380.82	0.19	0.73
United Kingdom	3.04	802.30	19.28	42026.79	-0.15	0.80
Rep. of Korea	2.80	871.01	15.49	31579.38	-0.24	0.11
Thailand	2.80	321.74	13.02	6977.58	-0.01	0.41
India	2.39	488.12	15.91	1947.72	0.24	-0.34
Italy	2.33	434.90	8.74	32645.50	0.83	1.16
Spain	2.29	534.73	17.26	28314.84	0.12	0.09
Austria	2.02	147.49	9.10	48550.29	0.23	1.27
China	1.74	652.10	2.60	9479.06	0.77	-0.46
Poland	1.66	189.41	7.87	14646.76	0.69	0.87
Canada	1.62	1269.67	31.51	44725.29	-0.92	0.42
Finland	1.58	98.56	14.22	47483.98	0.51	1.54
Singapore	1.57	507.52	16.88	62028.43	-0.52	0.08
Turkey	1.43	222.47	12.58	9719.31	0.73	0.52
Portugal	1.38	76.24	11.80	22094.78	0.40	0.23
Hungary	1.37	165.06	14.30	15374.97	0.31	1.70
Czechia	1.30	220.90	11.86	21844.52	0.57	1.39
Slovenia	1.21	38.85	10.95	24536.80	0.84	1.60
Russian Federation	1.20	2130.54	57.91	10467.39	-0.87	-0.60
Indonesia	1.18	393.05	21.39	3859.81	-0.61	-0.62
Grenada	1.07	0.02	4.26	10067.39	0.51	1.18
Saudi Arabia	1.05	1595.39	74.05	21453.67	-1.13	-0.50
United Arab Emirates	1.03	932.20	41.46	40322.40	-0.19	-0.23
South Africa	0.99	177.88	16.74	6346.73	-0.36	-0.09
Sweden	0.91	214.53	14.04	52911.91	0.56	1.69
Slovakia	0.91	202.41	23.41	18389.28	-0.02	1.40
Brazil	0.88	314.64	14.46	8696.90	-0.61	-0.14
Mexico	0.88	960.02	22.13	9199.81	0.26	1.83
Iran	0.82	375.71	63.13	3981.87	-0.91	-0.84
Romania	0.78	65.18	8.68	11710.00	0.26	1.07
Lithuania	0.77	43.72	14.07	18165.61	0.34	1.00
Oman	0.63	241.70	68.81	17047.08	-1.26	-0.83
Saint Lucia	0.60	0.37	25.76	10629.27	0.64	0.51
Belarus	0.59	71.98	24.62	6089.46	-0.09	0.66
Denmark	0.57	50.99	5.13	58941.02	0.68	0.89
Israel	0.54	29.41	4.98	41657.61	-0.18	-0.10
Guam	0.54	0.03	8.54	36407.51	-0.14	-0.13
Brunei Darussalam	0.52	60.42	91.25	29177.48	-0.81	-0.24
Philippines	0.49	17.23	1.98	3246.64	0.20	-0.53
Ukraine	0.35	12.07	2.45	3061.80	0.43	0.32
Argentina	0.32	78.28	13.00	11566.82	-0.78	-0.13
Norway	0.31	580.79	55.25	74254.91	-0.99	-0.52
Estonia	0.31	18.53	11.22	21629.33	0.28	0.38
Latvia	0.28	9.62	6.49	16697.55	0.32	0.16
Egypt	0.25	78.75	22.67	3017.92	-0.49	-0.79

Note: Like Table C.7, but using an alternative averaging procedure.

TABLE C.21
Correlates of Country Transition Outlook Measures, Excluding Missing Trade Values

	(1) Overall	(2) Overall	(3) Overall	(4) Green	(5) Green	(6) Green
Brown Lock-in Index	-0.606***			-0.586***		
	(0.068)			(0.062)		
GDP per capita (current USD) (log)	-0.060	-0.027	-0.071	0.100	0.064	-0.006
	(0.050)	(0.060)	(0.059)	(0.064)	(0.069)	(0.057)
Coal rents (% of GDP)	-0.088***	-0.108***	-0.105***	-0.130***	-0.145***	-0.136**
	(0.023)	(0.034)	(0.028)	(0.037)	(0.052)	(0.057)
Oil rents (% of GDP)	0.008	-0.050***	-0.044***	0.007	-0.039***	-0.029***
	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)
Natural gas rents (% of GDP)	-0.011	-0.035*	-0.031*	-0.001	-0.017	-0.014
	(0.010)	(0.019)	(0.016)	(0.014)	(0.018)	(0.016)
CO2 emissions (metric tons per capita, log)	0.001	0.016	-0.061	0.142	-0.004	-0.010
	(0.082)	(0.108)	(0.098)	(0.109)	(0.125)	(0.104)
Brown Complexity Index		-0.140***			0.248***	
		(0.037)			(0.055)	
Green Complexity Index			0.065			0.403***
			(0.048)			(0.050)
Year FEs	X	X	X	X	X	X
Observations	873	873	873	873	873	873
R2	.356	.276	.263	.332	.291	.36

Linear regression. Cluster-Robust Standard Errors in Parentheses.
Dependent Variables are Country-Level Transition Opportunities from Brown to the List Stated.
The label (log) refers to the natural logarithm of 1 + the variable in question.

Note: Like Table 3, but using an alternative averaging procedure.

TABLE C.22
Correlates of Brown Dependence Measures, Excluding Missing Trade Values

	(1) BLI	(2) BLI	(3) BLI	(4) BCI	(5) BCI	(6) BCI
GDP per capita (current USD) (log)	0.048	-0.013	0.059	0.316***	0.179*	0.212
	(0.040)	(0.050)	(0.084)	(0.055)	(0.099)	(0.159)
Coal rents (% of GDP)		0.031			-0.009	
		(0.023)			(0.078)	
Oil rents (% of GDP)		0.089***			-0.025***	
		(0.006)			(0.005)	
Natural gas rents (% of GDP)		0.035**			-0.017	
		(0.015)			(0.016)	
CO2 emissions (metric tons per capita, log)		0.072			0.420***	
		(0.099)			(0.158)	
RTA, Environment-related Technologies			1.956			1.364
			(1.204)			(1.836)
RTA, Energy-related Mitigation Technologies			-0.439			-3.384**
			(1.221)			(1.520)
RTA, Carbon Capture and Storage			3.726***			-4.899*
			(0.695)			(2.620)
RTA, Climate Change Adaptation Technologies			0.775			-1.150**
			(0.653)			(0.556)
RTA, Transport-related Mitigation Technologies			-2.569**			2.936
			(1.079)			(2.792)
Year FEs	X	X	X	X	X	X
Observations	961	873	222	961	873	222
R2	.00524	.758	.203	.209	.324	.173

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
Dependent Variables Relate to Brown List (Narrow).

Note: Like Table C.1, but using an alternative averaging procedure.

TABLE C.23
Predictive Power of Green Transition Outlook

	(1) BLI	(2) BLI	(3) BCI	(4) BCI
Brown Lock-in Index (t-1)	0.949***	0.921***		
	(0.017)	(0.035)		
Green Transition Outlook (t-1)	-0.007	-0.006	-0.023**	-0.023*
	(0.015)	(0.016)	(0.010)	(0.012)
GDP per capita (current USD, log, t-1)	-0.002	-0.017	0.029***	0.028
	(0.009)	(0.017)	(0.007)	(0.018)
Coal rents (% of GDP, t-1)		0.025**		0.000
		(0.010)		(0.011)
Oil rents (% of GDP, t-1)		0.005		-0.002*
		(0.003)		(0.001)
Natural gas rents (% of GDP, t-1)		0.002		-0.003**
		(0.003)		(0.001)
CO2 emissions (metric tons per capita, log, t-1)		0.028		0.021
		(0.027)		(0.028)
Brown Complexity Index (t-1)			0.947***	0.938***
			(0.015)	(0.016)
Year FEs	X	X	X	X
Observations	749	687	749	687
R2	.92	.932	.917	.922

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
t-1 refers to the previous period's value.

Note: Like Table C.2 but using an alternative averaging procedure.

TABLE C.24
Predictive Power of Overall Transition Outlook, Excluding Missing Trade Values

	(1) BLI	(2) BLI	(3) BCI	(4) BCI
Brown Lock-in Index (t-1)	0.930***	0.907***		
	(0.019)	(0.034)		
Overall Transition Outlook (t-1)	-0.044***	-0.032**	0.001	0.004
	(0.014)	(0.013)	(0.009)	(0.012)
GDP per capita (current USD, log, t-1)	-0.006	-0.019	0.028***	0.027
	(0.007)	(0.016)	(0.008)	(0.018)
Coal rents (% of GDP, t-1)		0.023**		0.003
		(0.010)		(0.012)
Oil rents (% of GDP, t-1)		0.005		-0.001
		(0.003)		(0.001)
Natural gas rents (% of GDP, t-1)		0.002		-0.003
		(0.003)		(0.002)
CO2 emissions (metric tons per capita, log, t-1)		0.026		0.021
		(0.027)		(0.029)
Brown Complexity Index (t-1)			0.940***	0.933***
			(0.015)	(0.016)
Year FEs	X	X	X	X
Observations	749	687	749	687
R2	.921	.933	.916	.922

Linear regression. Cluster-Robust Standard Errors in Parentheses.
The label (log) refers to the natural logarithm of 1 + the variable in question.
t-1 refers to the previous period's value.

Note: Like Table C.3, but using an alternative averaging procedure.

Appendix D

Directed Technological Change and General Purpose Technologies: Can AI Accelerate Clean Energy Innovation?

D.1 Theoretical Derivations

D.1.1 Model Derivation

The equilibrium must satisfy the following equations:

1. Competitive equilibrium for the two inputs used in producing the final good. Since the final good is produced competitively, the inputs' relative price must satisfy:

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

   In addition, we normalise the final good's price to 1:

$$\left(p_{ct}^{1-\varepsilon} + p_{dt}^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}} = 1 \tag{D.2}$$

2. Profit maximisation for input j. This determines labour demand L_{jt} and the inverse demand curve of machine x_{jit}. Specifically, labour demand in each sector must satisfy:

$$(1-\alpha)p_{jt}L_{jt}^{-\alpha}\int_0^1 A_{jit}^{1-\alpha}x_{jit}^{\alpha}di = w_t \tag{D.3}$$

And the inverse demand for x_{jit} must satisfy:

$$x_{jit} = \frac{\alpha p_{jt}}{p_{jit}}^{\frac{1}{1-\alpha}} A_{jit} L_{jt} \tag{D.4}$$

3. Profit maximisation for the machine producer. The machine producer is a monopolist maximising $\pi_{jit} = (p_{jit} - \psi)x_{jit}$ where x_{jit} is given by Equation D.4. This gives $p_{jit} = \psi/\alpha$. We follow the original model in normalising $\psi = \alpha^2$, which yields the following relations:

$$p_{jit} = \alpha \tag{D.5}$$

$$x_{jit} = p_{jt}^{\frac{1}{1-\alpha}} L_{jt} A_{jit} \tag{D.6}$$

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

4. Profit maximisation for research scientists who decide which sector to work in.

Using Equation D.6, we obtain the following equilibrium production level of input j:

$$\begin{aligned} Y_{jt} &= L_{jt}^{1-\alpha} \int_0^1 A_{jit}^{1-\alpha} (p_{jt}^{\frac{1}{1-\alpha}} L_{jt} A_{jit})^{\alpha} di \\ &= (p_{jt})^{\frac{\alpha}{1-\alpha}} LjtA_{jt} \end{aligned} \tag{D.8}$$

Using Equations D.6 and D.3, we derive an expression for the relative price of clean and dirty inputs as a function of the relative productivities of the two sectors:

$$\frac{p_{ct}}{p_{dt}} = \left(\frac{A_{ct}}{A_{dt}}\right)^{-(1-\alpha)} \tag{D.9}$$

Using Equations D.8, D.1 and D.9, we obtain an equation for relative employment in each sector:

$$\frac{L_{ct}}{L_{dt}} = \left(\frac{A_{ct}}{A_{dt}}\right)^{-\phi} \tag{D.10}$$

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 D.7):

$$\Pi_{jt} = \eta_j (1 + \gamma + \beta_j GPT_t) \alpha(1-\alpha) p_{jt}^{1/(1-\alpha)} L_{jt} A_{jt-1} \tag{D.11}$$

Using Equation D.11 with Equation D.9 and D.10, we get the ratio of expected profit from doing research in the clean versus dirty sector given by Equation 5.9.

Next, we obtain a system of equation to solve to obtain the equilibrium by combining Equations D.9, D.2 and D.10 with market clearing $L_{ct} + L_{dt} = 1$, and the expressions for the advancement of the technology frontier in each sector.

D.1.2 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 $\frac{d\bar{A}_{dt-1}}{dGPT_t} < 0$.

$$
\begin{aligned}
f(1,0) &= \frac{\eta_c}{\eta_d}\frac{1+\gamma+\beta_c GPT_t}{1+\gamma+\beta_d GPT_t}\Big(1+(\gamma+\beta_c GPT_t)\eta_c\Big)^{-\phi-1}\left(\frac{\bar{A}_{ct-1}}{A_{dt-1}}\right)^{-\phi} = 1 \\
\Rightarrow \bar{A}_{ct-1} &= A_{dt-1}\left(\frac{\eta_c}{\eta_d}\frac{1+\gamma+\beta_c GPT_t}{1+\gamma+\beta_d GPT_t}\right)^{1/\phi}\Big(1+(\gamma+\beta_c GPT_t)\eta_c\Big)^{-\frac{\phi+1}{\phi}} \\
\frac{d\bar{A}_{ct-1}}{dGPT_t} &= \frac{1}{\phi}\bar{A}_{ct-1}\Bigg(\underbrace{\frac{\eta_c}{\eta_d}\frac{(\beta_c-\beta_d)(1+\gamma)}{(1+\gamma+\beta_c GPT_t)(1+\gamma+\beta_d GPT_t)}}_{\sim 0}\underbrace{-(\phi+1)\frac{\eta_c\beta_c}{1+(\gamma+\beta_c GPT_t)\eta_c}}_{<0}\Bigg)
\end{aligned}
$$

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 if and only if $\phi < 1$. 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:

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

D.1.3 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 behavior with respect to GPT_t.

$$\frac{dB_j^*}{dGPT_t} = (\eta_j b_j \frac{\alpha(1-\alpha)}{2\psi} p_{jt}^{1/(1-\alpha)} L_{jt} A_{jt-1})\left(1 + \frac{1}{1-\alpha}\frac{GPT_t}{p_{jt}}\frac{dp_{jt}}{dGPT_t} + \frac{GPT_t}{L_{jt}}\frac{dL_{jt}}{dGPT_t}\right) \tag{D.12}$$

WLOG, we describe what happens in the clean equilibrium $s_c = 1$ (the dirty equilibrium can then be analyzed symmetrically). Using Equation D.9 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, we already know that $\frac{dA_{ct}}{dGPT_t} \geq 0$. 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 $\frac{dp_{jt}}{dA_{ct}}$, take Equation D.2 (the normalisation 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 D.10, 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} increases. Hence, $\frac{dL_{jt}}{dGPT_t} \to 0$.

Thus, Equation D.12 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 so 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 favored 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 $L_{dt} \to 0$.

D.1.4 Proof of Result 3

We now consider the role of the energy stock in investments towards absorptive capacity, allowing for an aging 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 aging paramter.

$$\frac{dB_j^*}{dA_{jt-1}} = (\eta_j b_j GPT_t (1-\delta) \frac{\alpha(1-\alpha)}{2\psi} p_{jt}^{1/(1-\alpha)} L_{jt} A_{jt-1}^{-\delta}) \left(1 + \frac{1}{1-\alpha}\frac{A_{jt-1}}{p_{jt}}\frac{dp_{jt}}{dA_{jt-1}} + \frac{A_{jt-1}}{L_{jt}}\frac{dL_{jt}}{dA_{jt-1}}\right) \tag{D.13}$$

The reasoning we developed in proof D.1.3 regarding the derivatives of prices and labour with respect to GPT_t and their limiting behavior carries over to the behavior of these derivatives and limits with respect to A_{jt-1}. Hence, in the clean equilibrium, we have:

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

Clearly, if $\delta = 0$, this derivative is positive. However, if $\delta > 1$, then the aging 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.

TABLE D.1
Electricity Codes

Type	Sub-sector	Codes
Clean	Biomass and waste	F02B43/08
Clean	Enabling technologies Systems integration	Y02E40/70, Y04S
Clean	Nuclear Energy	Y02E30
Clean	Renewable Energy	Y02E10
Clean	Renewable Energy Geothermal	F03G7/04, Y02E10/10
Clean	Renewable Energy Hydro	Y02E10/20
Clean	Renewable Energy Marine	E02B9/08, F03B13/10, F03B13/12, F03G7/05, Y02E10/30
Clean	Renewable Energy Solar	F03G6, F26B3/28, H01L31/04, Y02E10/40, Y02E10/50, Y02E10/60
Clean	Renewable Energy Wind	F03D, H01L27/142, Y02E10/70
Dirty	Hydrofracturing	C10G1, E21B43
Dirty	Traditional Fossil Fuels	C10J, C10L1, C10L3, C10L5, F01K, F02C, F22, F23, F27, F28
Grey	Biomass and waste	C10L5/40, F01K25/14, Y02E20, Y02E50
Grey	Efficiency	B01J8/20, B01J8/24, C10J3, F01K17/06, F01K23, F01K27, F01K3, F01K5, F02B1/12, F02B11, F02B13/02, F02B3/06, F02B49, F02B7, F02C3/20, F02C3/32, F02C3/34, F02C3/36, F02C6/10, F02C7/30, F02G5, F22B31, F22B33/14, F22G, F23B10, F23B30, F23B70, F23B80, F23C1, F23C10, F23C5/24, F23C6, F23D1, F23D17, F23D7, F27B15, Y02E20/10, Y02E20/30, Y02E40

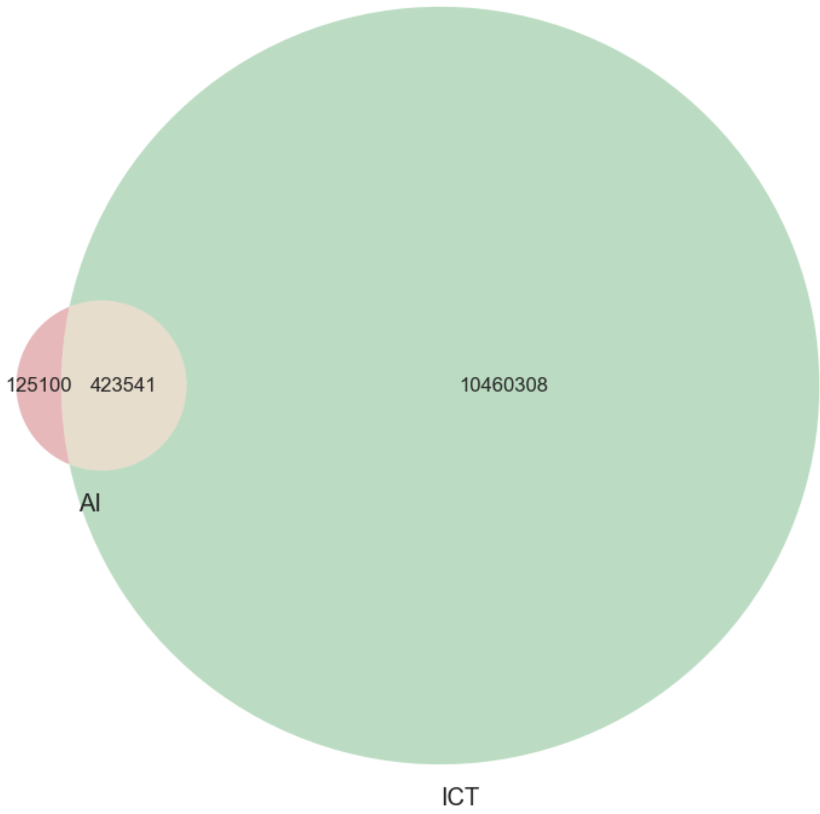
Note: The table lists the technology codes from the Cooperative Patent Classification (CPC) used to identify electricity patents. For maximum coverage we also search for the equivalent codes from the International Patent Classification (IPC). We identify a patent family as belonging to a given category if it has at least one patent with a relevant technology code.

TABLE D.2
Transport Codes

Type	Sub-sector	Codes
Clean	Batteries	Y02T10/70
Clean	Biomass and waste	F02B43/08
Clean	Electric vehicles	B60K1, B60L15, B60L, B60L3, B60L7, B60R16, B60R16/033, B60R16/04, B60S5/06, B60W10, Y02T10/64
Clean	Enabling technologies	Y02T90
Clean	Enabling technologies Systems integration	Y02T90/167, Y02T90/168, Y02T90/169
Clean	Fuel cells, Batteries	H01M
Clean	Hybrid vehicles	B60K6, B60L7/10, B60L7/20, B60W20, Y02T10/62
Clean	Hydrogen vehicles / fuel cells	B60W10/28
Clean/Grey	Mitigation Air	Y02T50
Clean/Grey	Mitigation Maritime	Y02T70
Clean/Grey	Mitigation Rail	Y02T30
Dirty	Internal combustion engine	F02B, F02D, F02F, F02M, F02N, F02P
Grey	Efficiency	F02B1/12, F02B11, F02B13/02, F02B3/06, F02B47/06, F02B49, F02B7, F02D41, F02M23, F02M25, F02M3, F02M39, F02M41, F02M43, F02M45, F02M47, F02M49, F02M51, F02M53, F02M55, F02M57, F02M59, F02M61, F02M63, F02M65, F02M67, F02M69, F02M71, Y02T10/10

Note: The table lists the technology codes from the Cooperative Patent Classification (CPC) used to identify transport patents. For maximum coverage we also search for the equivalent codes from the International Patent Classification (IPC). We identify a patent family as belonging to a given category if it has at least one patent with a relevant technology code.

D.1.5 Overlap Between AI and ICT Patent Families



Note: The venn diagram shows the number of AI patent families which are only categorised as AI, the number of ICT families only categorised as ICT, and the number of families identified by both methodologies. It shows that (1) the pool of ICT families is much larger than that of AI families; (2) the majority of AI families are also categorised as ICT; and (3) the majority of ICT families are not AI. Source: Authors' calculations based on PATSTAT 2021.

FIGURE D.1
AI and ICT Overlap

D.2 Additional Figures and Tables for Family-Level Analysis

D.2.1 Longer Versions of Table 5.3

TABLE D.3
Long Version of Table 5.3

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Clean Family	0.437***	0.530**	0.463**	0.420**	8.243***	7.071**	10.329***	9.951***
	(0.024)	(0.069)	(0.077)	(0.070)	(0.263)	(0.943)	(0.951)	(0.947)
Grey Family	0.264***	0.040	-0.124	-0.151	0.894**	0.432	0.443	0.196
	(0.001)	(0.105)	(0.098)	(0.103)	(0.142)	(0.255)	(0.211)	(0.208)
Nbr Citations Made (1000s)	8.134***	3.081**	0.177	-0.434	103.298***	47.204**	3.524*	-3.953
	(0.497)	(0.610)	(0.302)	(0.235)	(9.297)	(7.022)	(1.124)	(1.487)
Nbr Patents in Family				-0.020				0.124
				(0.010)				(0.062)
Nbr Countries in Family				0.000				-0.573
				(0.011)				(0.279)
Citations Received (3 yrs)				0.026*				0.184**
				(0.008)				(0.035)
Constant	0.121***	0.245**	0.575***	0.624***	1.402***	4.591***	7.691***	9.157**
	(0.010)	(0.042)	(0.033)	(0.030)	(0.107)	(0.461)	(0.443)	(1.172)
Ratio Clean/Dirty	304.35***	212.71**	94.15**	85.39**	501.72***	239.56**	229.29***	220.91***
	(16.63)	(27.86)	(15.77)	(14.24)	(16.00)	(31.96)	(21.11)	(21.02)
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	0.043	0.058	0.060	0.067	0.312	0.441	0.445
Observations	2,550,428	1,495,048	131,564	131,564	2,550,428	1,495,048	131,564	131,564

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

TABLE D.4
Similar to Table 5.3 With More Specifications for AI

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Clean Family	0.470***	0.437***	0.580**	0.408***	0.530**	0.491**	0.490**	0.560***	0.463**	0.420**	0.416**
	(0.000)	(0.024)	(0.067)	(0.026)	(0.069)	(0.068)	(0.067)	(0.000)	(0.077)	(0.070)	(0.071)
Grey Family	0.259***	0.264***	0.050	0.265***	0.040	0.013	0.013	0.241***	-0.124	-0.151	-0.152
	(0.001)	(0.001)	(0.101)	(0.022)	(0.105)	(0.110)	(0.109)	(0.000)	(0.098)	(0.103)	(0.102)
Nbr Citations Made (1000s)	7.928***	8.134***	3.262**	5.492***	3.081**	0.299	0.467	0.545	0.177	-0.434	-0.291
	(0.461)	(0.497)	(0.679)	(0.392)	(0.610)	(0.442)	(0.414)	(0.415)	(0.302)	(0.235)	(0.299)
Nbr Patents in Family						-0.021	-0.027			-0.020	-0.022
						(0.015)	(0.017)			(0.010)	(0.011)
Nbr Countries in Family						0.073	0.076			0.000	0.003
						(0.044)	(0.045)			(0.011)	(0.012)
Citations Received (3 yrs)						0.045**				0.026*	
						(0.010)				(0.008)	
Citations Received (5 yrs)							0.030**				0.017*
							(0.006)				(0.004)
Constant	0.107***	0.121***	0.217**	0.233***	0.245**	0.111	0.113	0.516***	0.575***	0.624***	0.618***
	(0.002)	(0.010)	(0.034)	(0.015)	(0.042)	(0.044)	(0.044)	(0.010)	(0.033)	(0.030)	(0.028)
Ratio Clean/Dirty	327.54***	304.35***	232.66**	163.61***	212.71**	212.71**	212.71**	105.80***	94.15**	85.39***	84.71***
	(0.26)	(4.12)	(27.08)	(10.47)	(27.86)	(27.86)	(27.86)	(0.08)	(15.77)	(8.37)	(8.37)
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	X
Quality Proxies						X	X			X	X
Adjusted R2	0.004	0.006	0.041	0.006	0.043	0.045	0.045	0.002	0.058	0.060	0.060
Observations	2.55e+06	2.55e+06	1.50e+06	1.50e+06	1.50e+06	1.50e+06	1.50e+06	1.15e+05	1.32e+05	1.32e+05	1.32e+05

Linear Regression.
Heteroskedasticity Robust Standard Errors in Parentheses.
Dependent Variable: Percentage of AI Families in Cited Families
Note: To make things more comparable, Column 4 replicates Column 2 but using the same sample of observations as in Column 5.

TABLE D.5
Similar to Table 5.3 With More Specifications for ICT

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Clean Family	8.642***	8.243***	8.119***	10.055***	7.071**	6.770**	6.767**	16.809***	10.329***	9.951***	9.942***
	(0.009)	(0.263)	(0.692)	(0.454)	(0.943)	(0.937)	(0.941)	(0.001)	(0.951)	(0.947)	(0.946)
Grey Family	1.097***	0.894**	0.727*	0.406	0.432	0.190	0.192	0.332***	0.443	0.196	0.199
	(0.020)	(0.142)	(0.179)	(0.200)	(0.255)	(0.449)	(0.449)	(0.000)	(0.211)	(0.208)	(0.202)
Nbr Citations Made (1000s)	109.614***	103.298***	54.146**	80.584**	47.204**	18.434**	19.985**	18.456***	3.524*	-3.953	-2.760
	(10.508)	(9.297)	(7.745)	(10.546)	(7.022)	(2.861)	(2.975)	(1.419)	(1.124)	(1.487)	(1.050)
Nbr Patents in Family						0.250	0.217			0.124	0.111
						(0.215)	(0.205)			(0.062)	(0.058)
Nbr Countries in Family						0.245	0.264			-0.573	-0.562
						(0.120)	(0.126)			(0.279)	(0.275)
Citations Received (3 yrs)						0.330**				0.184**	
						(0.045)				(0.035)	
Citations Received (5 yrs)							0.211**				0.113**
							(0.028)				(0.019)
Constant	1.133***	1.402***	3.954***	2.858***	4.591***	3.252**	3.265**	4.405***	7.691***	9.157**	9.128**
	(0.049)	(0.107)	(0.314)	(0.205)	(0.461)	(0.414)	(0.412)	(0.033)	(0.443)	(1.172)	(1.178)
Ratio Clean/Dirty	525.98***	501.72***	275.06***	340.68***	239.56**	239.56**	239.56**	348.11***	229.29***	220.91***	220.71***
	(0.52)	(1.68)	(23.45)	(15.39)	(31.96)	(31.96)	(31.96)	(0.03)	(21.11)	(4.06)	(4.06)
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	X
Quality Proxies						X	X			X	X
Adjusted R2	0.057	0.067	0.301	0.083	0.312	0.318	0.318	0.103	0.441	0.445	0.445
Observations	2.55e+06	2.55e+06	1.50e+06	1.50e+06	1.50e+06	1.50e+06	1.50e+06	1.15e+05	1.32e+05	1.32e+05	1.32e+05

Linear Regression.
Heteroskedasticity Robust Standard Errors in Parentheses.
Dependent Variable: Percentage of AI Families in Cited Families
Note: To make things more comparable, Column 4 replicates Column 2 but using the same sample of observations as in Column 5.

D.2.2 Separating Transport and Electricity Families

TABLE D.6
Similar to Table 5.3 but Only for Transport Families

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Clean Family	0.502***	0.872**	0.682**	0.625**	3.993***	4.921**	5.409**	5.134**
	(0.050)	(0.111)	(0.141)	(0.132)	(0.194)	(0.608)	(0.753)	(0.699)
Grey Family	0.298***	0.141	-0.115	-0.155	0.663**	-0.198	-1.224	-1.428*
	(0.009)	(0.061)	(0.120)	(0.126)	(0.084)	(0.346)	(0.434)	(0.487)
Nbr Citations Made (1000s)	10.991***	4.180*	0.413*	-0.460	68.676***	38.654**	3.717**	-1.407
	(0.222)	(1.125)	(0.141)	(0.245)	(1.946)	(8.021)	(0.690)	(1.799)
Nbr Patents in Family				-0.022				0.030
				(0.011)				(0.034)
Nbr Countries in Family				-0.020				-0.315
				(0.015)				(0.120)
Citations Received (3 yrs)				0.037*				0.167*
				(0.009)				(0.040)
Constant	0.177**	0.069	0.633**	0.738**	1.373**	2.147**	5.399***	6.067***
	(0.034)	(0.066)	(0.090)	(0.114)	(0.148)	(0.342)	(0.380)	(0.274)
Ratio Clean/Dirty	320.10***	398.99**	87.94**	80.53**	296.07***	258.40**	117.09**	111.14**
	(31.78)	(50.73)	(18.16)	(16.97)	(14.40)	(31.94)	(16.31)	(15.14)
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	0.056	0.072	0.074	0.035	0.174	0.253	0.258
Observations	1,300,651	878,182	83,433	83,433	1,300,651	878,182	83,433	83,433

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

TABLE D.7
Similar to Table 5.3 but Only for Electricity Families

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Clean Family	0.190***	0.187*	0.014	0.003	16.011***	19.803**	33.257**	32.749**
	(0.010)	(0.058)	(0.059)	(0.061)	(0.418)	(2.395)	(3.905)	(3.964)
Grey Family	0.136***	0.066	0.030	0.026	1.546**	2.941**	3.070***	2.974***
	(0.006)	(0.038)	(0.048)	(0.048)	(0.313)	(0.307)	(0.081)	(0.165)
Nbr Citations Made (1000s)	4.332**	0.952	-1.288	-1.421*	150.644*	67.586	-1.612	-15.035
	(0.758)	(0.769)	(0.595)	(0.444)	(45.563)	(41.354)	(10.370)	(10.666)
Nbr Patents in Family				-0.006				0.102
				(0.011)				(0.037)
Nbr Countries in Family				0.002				-0.636
				(0.013)				(0.403)
Citations Received (3 yrs)				0.006				0.194**
				(0.003)				(0.024)
Constant	0.124***	0.295***	0.405***	0.425***	1.264***	5.214**	9.497**	12.015*
	(0.008)	(0.019)	(0.023)	(0.027)	(0.029)	(0.689)	(1.554)	(3.701)
Ratio Clean/Dirty	136.34***	71.53*	3.68	0.89	918.29***	582.47**	751.80**	740.32**
	(7.39)	(22.23)	(15.66)	(16.08)	(23.98)	(70.45)	(88.28)	(89.61)
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	0.003	0.029	0.024	0.024	0.134	0.461	0.708	0.711
Observations	1,249,777	608,033	46,383	46,383	1,249,777	608,033	46,383	46,383

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

D.2.3 Using Count Rather Than Percentage as Outcome Variable

TABLE D.8
Similar to Table 5.3 but Using Count of Citations to AI and ICT

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Clean Family	1.172***	0.903***	0.612***	0.601***	1.393***	0.848***	0.858***	0.844***
	(0.022)	(0.099)	(0.091)	(0.081)	(0.012)	(0.081)	(0.088)	(0.086)
Grey Family	0.647***	0.151**	-0.056	-0.067	0.165***	0.081*	-0.027	-0.042
	(0.002)	(0.064)	(0.052)	(0.055)	(0.003)	(0.045)	(0.023)	(0.026)
Nbr Citations Made (log)	1.261***	1.222***	1.109***	1.116***	1.258***	1.214***	1.117***	1.095***
	(0.010)	(0.048)	(0.093)	(0.084)	(0.022)	(0.022)	(0.024)	(0.022)
Nbr Patents in Family				-0.015***				0.003
				(0.004)				(0.002)
Nbr Countries in Family				-0.039***				-0.033***
				(0.004)				(0.008)
Citations Received (3 yrs)				0.007***				0.002***
				(0.001)				(0.001)
Constant	-6.266***	-5.132***	-4.504***	-4.290***	-3.765***	-2.717***	-2.401***	-2.205***
	(0.049)	(0.163)	(0.400)	(0.358)	(0.069)	(0.072)	(0.092)	(0.087)
Ratio Clean/Dirty	248.32***	176.46**	132.91**	113.18**	308.68***	142.81**	180.33**	159.26**
	(20.82)	(29.65)	(27.91)	(21.00)	(22.49)	(20.75)	(22.65)	(22.72)
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								
Observations	2,550,428	1,157,642	97,052	97,052	2,550,428	1,378,673	125,339	125,339

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

D.2.4 Forward Citations as Outcome Variable

TABLE D.9
Long Version of Table 5.4

	(1) AI	(2) AI	(3) AI	(4) AI	(5) AI	(6) ICT	(7) ICT	(8) ICT
Clean Family	0.508***	0.497***	0.413***	0.394***	0.508***	0.480***	0.413***	0.377***
	(0.024)	(0.022)	(0.042)	(0.041)	(0.024)	(0.040)	(0.042)	(0.042)
Grey Family	0.324***	0.322***	0.265***	0.262***	0.324***	0.342***	0.265***	0.262***
	(0.019)	(0.017)	(0.032)	(0.030)	(0.019)	(0.022)	(0.032)	(0.027)
Nbr Patents in Family	0.013***	0.013***	0.013***	0.012***	0.013***	0.013***	0.013***	0.013***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Nbr Countries in Family	0.017***	0.019***	0.053***	0.053***	0.017***	0.018***	0.053***	0.052***
	(0.003)	(0.003)	(0.006)	(0.006)	(0.003)	(0.003)	(0.006)	(0.005)
Granted	0.217***	0.215***	0.227***	0.229***	0.217***	0.216***	0.227***	0.227***
	(0.039)	(0.039)	(0.035)	(0.035)	(0.039)	(0.038)	(0.035)	(0.035)
Triadic	0.121***	0.129***	0.152***	0.155***	0.121***	0.118***	0.152***	0.149***
	(0.017)	(0.019)	(0.020)	(0.020)	(0.017)	(0.016)	(0.020)	(0.019)
Nbr Citations Made (log)	0.572***	0.553***	0.456***	0.443***	0.572***	0.530***	0.456***	0.431***
	(0.018)	(0.025)	(0.018)	(0.021)	(0.018)	(0.027)	(0.018)	(0.024)
AI Citing		0.240***		0.130***				
		(0.046)		(0.026)				
Clean X Citing AI		0.061***		0.119***				
		(0.014)		(0.022)				
Grey X Citing AI		0.008		0.042				
		(0.017)		(0.028)				
ICT Citing						0.335***		0.156***
						(0.047)		(0.039)
Clean X Citing ICT						-0.111***		0.007
						(0.005)		(0.020)
Grey X Citing ICT						-0.126***		-0.022
						(0.016)		(0.027)
Constant	-1.407***	-1.385***	-0.960***	-0.945***	-1.407***	-1.401***	-0.960***	-0.957***
	(0.088)	(0.093)	(0.090)	(0.095)	(0.088)	(0.090)	(0.090)	(0.091)
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	0.282	0.284	0.338	0.339	0.282	0.285	0.338	0.340
Observations	2.55e+06	2.55e+06	1.47e+06	1.47e+06	2.55e+06	2.55e+06	1.47e+06	1.47e+06

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 D.10
Like Table 5.4, Using Citations Within 5 Years as an Outcome

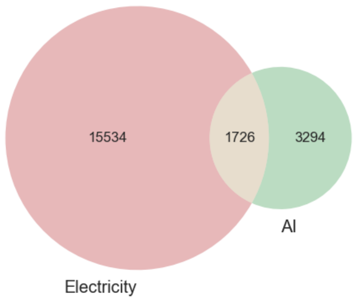
	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Clean Family	0.492***	0.484***	0.395***	0.381***	0.492***	0.468***	0.395***	0.367***
	(0.022)	(0.020)	(0.040)	(0.039)	(0.022)	(0.038)	(0.040)	(0.041)
Grey Family	0.309***	0.308***	0.243***	0.241***	0.309***	0.334***	0.243***	0.247***
	(0.018)	(0.016)	(0.030)	(0.029)	(0.018)	(0.020)	(0.030)	(0.026)
Nbr Patents in Family	0.013***	0.013***	0.014***	0.013***	0.013***	0.013***	0.014***	0.014***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Nbr Countries in Family	0.019***	0.021***	0.051***	0.051***	0.019***	0.020***	0.051***	0.051***
	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)	(0.003)	(0.005)	(0.005)
Granted	0.221***	0.220***	0.242***	0.245***	0.221***	0.221***	0.242***	0.243***
	(0.037)	(0.036)	(0.033)	(0.032)	(0.037)	(0.036)	(0.033)	(0.033)
Triadic	0.144***	0.151***	0.171***	0.173***	0.144***	0.141***	0.171***	0.169***
	(0.021)	(0.022)	(0.020)	(0.020)	(0.021)	(0.019)	(0.020)	(0.020)
Nbr Citations Made (log)	0.584***	0.567***	0.457***	0.446***	0.584***	0.544***	0.457***	0.434***
	(0.021)	(0.027)	(0.018)	(0.021)	(0.021)	(0.030)	(0.018)	(0.024)
AI Citing		0.247***		0.136***				
		(0.050)		(0.027)				
Clean X Citing AI		0.028*		0.078***				
		(0.014)		(0.016)				
Grey X Citing AI		-0.028		0.017				
		(0.017)		(0.019)				
ICT Citing						0.329***		0.157***
						(0.053)		(0.040)
Clean X Citing ICT						-0.115***		-0.007
						(0.005)		(0.018)
Grey X Citing ICT						-0.146***		-0.040
						(0.017)		(0.026)
Constant	-0.985***	-0.967***	-0.520***	-0.508***	-0.985***	-0.984***	-0.520***	-0.521***
	(0.084)	(0.089)	(0.083)	(0.087)	(0.084)	(0.088)	(0.083)	(0.084)
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	0.35133	0.35265	0.39754	0.39836	0.35133	0.35398	0.39754	0.39864
Observations	2.55e+06	2.55e+06	1.48e+06	1.48e+06	2.55e+06	2.55e+06	1.48e+06	1.48e+06

Poisson Pseudo-Likelihood Regression.
Standard Errors in Parentheses. Clustered at the type and firm level.
Dependent Variable: Citations Received Within 5 Years of Priority.

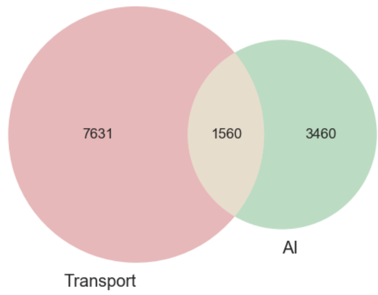
Note: Quality Proxies include the size of the family, the number of countries where the family was filed, the logged number of citations made by the family, whether it is granted, and whether it is triadic.

D.3 Additional Figures and Tables For Firm-Level Analysis

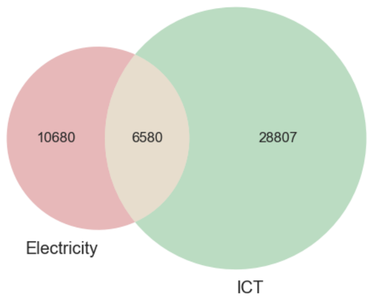
D.3.1 Firms Patenting in Energy and AI/ICT



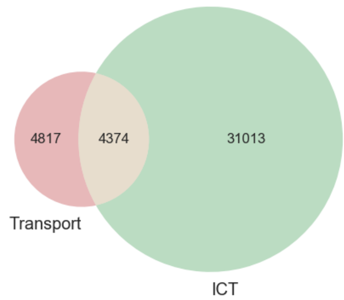
(a) Firms Patenting in Electricity and AI



(b) Firms Patenting in Transport and AI



(c) Firms Patenting in Electricity and ICT



(d) Firms Patenting in Transport and ICT

Note: The figure shows the number of firms which have at least one patent in either electricity/transport, AI/ICT, or both over the study period. Source: Authors' calculations based on PATSTAT 2021 and BvD Orbis.

FIGURE D.2
Firms Patenting in Energy and AI

D.3.2 Additional Regression Tables

D.3.2.1 Comparing Clean and Dirty Portfolios

TABLE D.11
Long Version of Table 5.6

	(1) AI	(2) AI	(3) AI	(4) AI	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Family Count (log)	0.944***	0.974***	0.979***	0.997***	0.888***	0.921***	0.979***	0.970***
	(0.049)	(0.050)	(0.040)	(0.055)	(0.038)	(0.042)	(0.026)	(0.030)
Clean Portfolio	1.471***	-0.020	0.156	-0.599*	0.904***	0.176	0.495***	0.188
	(0.098)	(0.297)	(0.123)	(0.363)	(0.062)	(0.182)	(0.057)	(0.154)
Grey Portfolio	0.873***	-0.121	0.253	-0.516	0.439***	-0.297	0.067	-0.667***
	(0.076)	(0.310)	(0.170)	(0.393)	(0.068)	(0.234)	(0.071)	(0.199)
Total Assets (log)	0.136*	0.146*	-0.083*	-0.074	0.163***	0.154***	0.006	0.013
	(0.080)	(0.079)	(0.048)	(0.048)	(0.055)	(0.053)	(0.034)	(0.033)
Nbr Empoyees (log)	-0.208***	-0.229***	0.069	0.061	-0.097***	-0.114***	0.016	0.017
	(0.057)	(0.058)	(0.065)	(0.065)	(0.031)	(0.032)	(0.043)	(0.043)
Age (log)	-0.521***	-0.525***	-0.416**	-0.428***	-0.460***	-0.466***	-0.284***	-0.258***
	(0.200)	(0.170)	(0.164)	(0.164)	(0.136)	(0.138)	(0.088)	(0.086)
Firm Sectoral Focus		-0.028		-0.101		-0.046		-0.091
		(0.194)		(0.167)		(0.117)		(0.099)
Firm Clean Focus		-0.004		-0.005		-0.001		-0.003*
		(0.004)		(0.003)		(0.002)		(0.002)
Firm Grey Focus		-0.001		0.004		-0.002		-0.006***
		(0.004)		(0.005)		(0.002)		(0.002)
Clean X Firm Sectoral Focus		0.523***		0.179		0.201*		-0.142
		(0.195)		(0.162)		(0.115)		(0.111)
Grey X Firm Sectoral Focus		0.231		-0.045		0.235**		-0.131
		(0.158)		(0.160)		(0.093)		(0.105)
Clean X Firm Clean Focus		0.012***		0.012**		0.006**		0.003
		(0.005)		(0.005)		(0.003)		(0.002)
Grey X Firm Clean Focus		0.011***		0.017***		0.009***		0.009***
		(0.004)		(0.005)		(0.003)		(0.002)
Clean X Firm Grey Focus		0.017***		0.013*		0.010***		0.009***
		(0.004)		(0.007)		(0.002)		(0.002)
Grey X Firm Grey Focus		0.010*		0.003		0.005		0.011***
		(0.006)		(0.006)		(0.004)		(0.003)
Constant	-2.653**	-2.557*	-0.204	-0.361	-2.663**	-2.226*	-0.610	-0.676
	(1.354)	(1.314)	(1.094)	(1.057)	(1.170)	(1.139)	(0.665)	(0.673)
Portfolio Type	Transport	Transport	Electricity	Electricity	Transport	Transport	Electricity	Electricity
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	X	X	X	X
Firm level controls	X	X	X	X	X	X	X	X
Observations	10,733	10,733	10,082	10,082	17,310	17,310	22,476	22,476
R2	0.738	0.740	0.450	0.455	0.835	0.836	0.732	0.733

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.

TABLE D.12
Similar to Table 5.6 With More Specifications for AI in Transport

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	AI	AI	AI	AI	AI	AI	AI	AI
Family Count (log)	1.023***	0.939***	0.944***	0.973***	0.961***	0.974***	0.943***	0.774***
	(0.026)	(0.047)	(0.049)	(0.029)	(0.053)	(0.050)	(0.027)	(0.035)
Clean Portfolio	1.105***	1.433***	1.471***	0.304	-0.013	-0.020	0.796**	0.421
	(0.105)	(0.089)	(0.098)	(0.337)	(0.271)	(0.297)	(0.327)	(0.390)
Grey Portfolio	0.905***	0.837***	0.873***	0.346	-0.135	-0.121	0.482*	0.184
	(0.084)	(0.078)	(0.076)	(0.298)	(0.306)	(0.310)	(0.281)	(0.331)
Total Assets (log)			0.136*			0.146*		0.012
			(0.080)			(0.079)		(0.094)
Nbr Empoyees (log)			-0.208***			-0.229***		0.262**
			(0.057)			(0.058)		(0.115)
Age (log)			-0.521***			-0.525***		-0.114
			(0.200)			(0.170)		(0.075)
Firm Sectoral Focus				-0.218	-0.079	-0.028		
				(0.173)	(0.197)	(0.194)		
Firm Clean Focus				-0.002	-0.006*	-0.004		
				(0.003)	(0.003)	(0.004)		
Firm Grey Focus				0.011***	0.000	-0.001		
				(0.004)	(0.005)	(0.004)		
Clean X Firm Sectoral Focus				1.212***	0.589***	0.523***		
				(0.193)	(0.186)	(0.195)		
Grey X Firm Sectoral Focus				0.669***	0.297*	0.231		
				(0.159)	(0.153)	(0.158)		
Clean X Firm Clean Focus				0.003	0.013***	0.012***		
				(0.004)	(0.004)	(0.005)		
Grey X Firm Clean Focus				0.006	0.011***	0.011***		
				(0.004)	(0.004)	(0.004)		
Clean X Firm Grey Focus				0.008*	0.014***	0.017***		
				(0.004)	(0.004)	(0.004)		
Grey X Firm Grey Focus				-0.004	0.009	0.010*		
				(0.004)	(0.006)	(0.006)		
Firm Sectoral Focus (mean)							-0.251	0.008
							(0.161)	(0.170)
Firm Clean Focus (mean)							0.004	-0.004
							(0.004)	(0.005)
Firm Grey Focus (mean)							0.011**	0.004
							(0.005)	(0.005)
Clean X Firm Sectoral Focus (mean)							1.238***	1.006***
							(0.180)	(0.193)
Grey X Firm Sectoral Focus (mean)							0.699***	0.508***
							(0.151)	(0.167)
Clean X Firm Clean Focus (mean)							-0.006	0.005
							(0.004)	(0.006)
Grey X Firm Clean Focus (mean)							0.001	0.005
							(0.004)	(0.005)
Clean X Firm Grey Focus (mean)							0.005	0.011**
							(0.005)	(0.005)
Grey X Firm Grey Focus (mean)							-0.002	0.009
							(0.004)	(0.005)
Constant	-4.234***	-3.542***	-2.653**	-4.203***	-3.336***	-2.557*	-4.297***	-5.723***
	(0.095)	(0.214)	(1.354)	(0.246)	(0.293)	(1.314)	(0.257)	(1.089)
Portfolio Type	Transport	Transport	Transport	Transport	Transport	Transport	Transport	Transport
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
Observations	30,805	12,902	10,733	30,805	12,902	10,733	30,805	23,447
R2	0.621	0.719	0.738	0.653	0.722	0.740	0.654	0.694

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing AI.
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.

TABLE D.13
Similar to Table 5.6 With More Specifications for AI in Electricity

	(1) AI	(2) AI	(3) AI	(4) AI	(5) AI	(6) AI	(7) AI	(8) AI
Family Count (log)	1.037***	0.968***	0.979***	1.060***	0.964***	0.997***	1.058***	0.890***
	(0.047)	(0.040)	(0.040)	(0.068)	(0.051)	(0.055)	(0.071)	(0.074)
Clean Portfolio	-0.102	0.214*	0.156	-0.441	-0.636**	-0.599*	-0.446	-1.541**
	(0.207)	(0.115)	(0.123)	(0.617)	(0.316)	(0.363)	(0.616)	(0.705)
Grey Portfolio	0.243*	0.203	0.253	0.055	-0.689**	-0.516	-0.026	-0.931**
	(0.141)	(0.146)	(0.170)	(0.403)	(0.334)	(0.393)	(0.387)	(0.443)
Total Assets (log)			-0.083*			-0.074		0.051
			(0.048)			(0.048)		(0.112)
Nbr Empoyees (log)			0.069			0.061		0.276*
			(0.065)			(0.065)		(0.146)
Age (log)			-0.416**			-0.428***		-0.405***
			(0.164)			(0.164)		(0.098)
Firm Sectoral Focus				0.025	-0.063	-0.101		
				(0.225)	(0.156)	(0.167)		
Firm Clean Focus				-0.007	-0.007**	-0.005		
				(0.005)	(0.003)	(0.003)		
Firm Grey Focus				0.008	-0.000	0.004		
				(0.007)	(0.004)	(0.005)		
Clean X Firm Sectoral Focus				-0.580*	0.040	0.179		
				(0.326)	(0.162)	(0.162)		
Grey X Firm Sectoral Focus				0.009	-0.084	-0.045		
				(0.205)	(0.156)	(0.160)		
Clean X Firm Clean Focus				0.006	0.013***	0.012**		
				(0.008)	(0.004)	(0.005)		
Grey X Firm Clean Focus				0.014**	0.019***	0.017***		
				(0.006)	(0.004)	(0.005)		
Clean X Firm Grey Focus				0.015	0.014**	0.013*		
				(0.009)	(0.006)	(0.007)		
Grey X Firm Grey Focus				-0.009	0.007	0.003		
				(0.009)	(0.005)	(0.006)		
Firm Sectoral Focus (mean)							0.081	-0.025
							(0.210)	(0.204)
Firm Clean Focus (mean)							-0.007	-0.015***
							(0.005)	(0.006)
Firm Grey Focus (mean)							0.006	-0.002
							(0.008)	(0.010)
Clean X Firm Sectoral Focus (mean)							-0.620*	-0.562
							(0.346)	(0.372)
Grey X Firm Sectoral Focus (mean)							0.047	-0.239
							(0.199)	(0.214)
Clean X Firm Clean Focus (mean)							0.005	0.024***
							(0.008)	(0.008)
Grey X Firm Clean Focus (mean)							0.014**	0.023***
							(0.006)	(0.006)
Clean X Firm Grey Focus (mean)							0.011	0.022*
							(0.010)	(0.012)
Grey X Firm Grey Focus (mean)							-0.007	0.008
							(0.009)	(0.010)
Constant	-4.090***	-2.898***	-0.204	-4.124***	-2.771***	-0.361	-4.045***	-5.203***
	(0.119)	(0.111)	(1.094)	(0.288)	(0.258)	(1.057)	(0.303)	(1.262)
Portfolio Type	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity
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
Observations	48,082	12,402	10,082	48,082	12,402	10,082	48,082	33,997
R2	0.301	0.433	0.450	0.314	0.437	0.455	0.311	0.374

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing AI.
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.

TABLE D.14
Similar to Table 5.6 With More Specifications for ICT in Transport

	(1) ICT	(2) ICT	(3) ICT	(4) ICT	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Family Count (log)	0.986***	0.891***	0.888***	0.956***	0.921***	0.921***	0.951***	0.850***
	(0.020)	(0.039)	(0.038)	(0.021)	(0.042)	(0.042)	(0.021)	(0.027)
Clean Portfolio	0.816***	0.893***	0.904***	0.560***	0.270*	0.176	0.705***	0.294
	(0.054)	(0.057)	(0.062)	(0.202)	(0.158)	(0.182)	(0.180)	(0.216)
Grey Portfolio	0.449***	0.426***	0.439***	0.043	-0.236	-0.297	0.157	-0.131
	(0.069)	(0.066)	(0.068)	(0.169)	(0.219)	(0.234)	(0.165)	(0.219)
Total Assets (log)			0.163***			0.154***		-0.020
			(0.055)			(0.053)		(0.042)
Nbr Empoyees (log)			-0.097***			-0.114***		0.168***
			(0.031)			(0.032)		(0.049)
Age (log)			-0.460***			-0.466***		0.003
			(0.136)			(0.138)		(0.061)
Firm Sectoral Focus				-0.274***	-0.050	-0.046		
				(0.102)	(0.117)	(0.117)		
Firm Clean Focus				0.004***	-0.001	-0.001		
				(0.001)	(0.002)	(0.002)		
Firm Grey Focus				0.007***	-0.001	-0.002		
				(0.003)	(0.003)	(0.002)		
Clean X Firm Sectoral Focus				0.413***	0.196*	0.201*		
				(0.110)	(0.108)	(0.115)		
Grey X Firm Sectoral Focus				0.515***	0.209**	0.235**		
				(0.082)	(0.086)	(0.093)		
Clean X Firm Clean Focus				-0.001	0.005*	0.006**		
				(0.003)	(0.003)	(0.003)		
Grey X Firm Clean Focus				0.004**	0.008***	0.009***		
				(0.002)	(0.003)	(0.003)		
Clean X Firm Grey Focus				0.004	0.008***	0.010***		
				(0.003)	(0.002)	(0.002)		
Grey X Firm Grey Focus				-0.004	0.005	0.005		
				(0.003)	(0.004)	(0.004)		
Firm Sectoral Focus (mean)							-0.390***	-0.260**
							(0.096)	(0.109)
Firm Clean Focus (mean)							0.007***	0.002
							(0.002)	(0.002)
Firm Grey Focus (mean)							0.008***	0.003
							(0.003)	(0.003)
Clean X Firm Sectoral Focus (mean)							0.506***	0.431***
							(0.103)	(0.114)
Grey X Firm Sectoral Focus (mean)							0.641***	0.524***
							(0.085)	(0.092)
Clean X Firm Clean Focus (mean)							-0.005*	0.004
							(0.002)	(0.003)
Grey X Firm Clean Focus (mean)							0.001	0.005*
							(0.002)	(0.003)
Clean X Firm Grey Focus (mean)							0.002	0.007*
							(0.003)	(0.004)
Grey X Firm Grey Focus (mean)							-0.005	0.003
							(0.003)	(0.005)
Constant	-2.226***	-1.677***	-2.663**	-2.294***	-1.650***	-2.226*	-2.345***	-2.871***
	(0.064)	(0.155)	(1.170)	(0.127)	(0.174)	(1.139)	(0.139)	(0.526)
Portfolio Type	Transport	Transport	Transport	Transport	Transport	Transport	Transport	Transport
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
Observations	30,805	21,231	17,310	30,805	21,231	17,310	30,805	23,447
R2	0.759	0.822	0.835	0.764	0.822	0.836	0.763	0.790

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing 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.

TABLE D.15
Similar to Table 5.6 With More Specifications for ICT in Electricity

	(1) ICT	(2) ICT	(3) ICT	(4) ICT	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Family Count (log)	0.998***	0.998***	0.979***	1.055***	0.991***	0.970***	1.054***	0.927***
	(0.026)	(0.024)	(0.026)	(0.022)	(0.027)	(0.030)	(0.022)	(0.025)
Clean Portfolio	0.732***	0.485***	0.495***	1.103***	0.181	0.188	1.120***	0.463*
	(0.076)	(0.052)	(0.057)	(0.287)	(0.141)	(0.154)	(0.277)	(0.254)
Grey Portfolio	0.011	0.059	0.067	-0.378	-0.558***	-0.667***	-0.402*	-0.999***
	(0.075)	(0.062)	(0.071)	(0.240)	(0.173)	(0.199)	(0.243)	(0.280)
Total Assets (log)			0.006			0.013		-0.011
			(0.034)			(0.033)		(0.026)
Nbr Empoyees (log)			0.016			0.017		0.196***
			(0.043)			(0.043)		(0.037)
Age (log)			-0.284***			-0.258***		-0.112**
			(0.088)			(0.086)		(0.048)
Firm Sectoral Focus				-0.184	-0.099	-0.091		
				(0.137)	(0.090)	(0.099)		
Firm Clean Focus				0.009***	-0.002	-0.003*		
				(0.003)	(0.001)	(0.002)		
Firm Grey Focus				-0.004	-0.005***	-0.006***		
				(0.003)	(0.001)	(0.002)		
Clean X Firm Sectoral Focus				-0.331**	-0.143	-0.142		
				(0.131)	(0.100)	(0.111)		
Grey X Firm Sectoral Focus				-0.051	-0.118	-0.131		
				(0.127)	(0.095)	(0.105)		
Clean X Firm Clean Focus				-0.012***	0.003	0.003		
				(0.004)	(0.002)	(0.002)		
Grey X Firm Clean Focus				0.005	0.008***	0.009***		
				(0.003)	(0.002)	(0.002)		
Clean X Firm Grey Focus				0.002	0.009***	0.009***		
				(0.004)	(0.002)	(0.002)		
Grey X Firm Grey Focus				0.007	0.010***	0.011***		
				(0.004)	(0.002)	(0.003)		
Firm Sectoral Focus (mean)							-0.124	-0.203*
							(0.111)	(0.107)
Firm Clean Focus (mean)							0.010***	0.005*
							(0.003)	(0.003)
Firm Grey Focus (mean)							-0.007	-0.010**
							(0.004)	(0.005)
Clean X Firm Sectoral Focus (mean)							-0.316***	-0.303***
							(0.115)	(0.108)
Grey X Firm Sectoral Focus (mean)							-0.052	-0.182
							(0.113)	(0.114)
Clean X Firm Clean Focus (mean)							-0.013***	-0.001
							(0.004)	(0.003)
Grey X Firm Clean Focus (mean)							0.004	0.011***
							(0.003)	(0.003)
Clean X Firm Grey Focus (mean)							0.001	0.007
							(0.005)	(0.006)
Grey X Firm Grey Focus (mean)							0.008*	0.018***
							(0.005)	(0.006)
Constant	-1.946***	-1.462***	-0.610	-2.347***	-1.315***	-0.676	-2.319***	-2.797***
	(0.078)	(0.081)	(0.665)	(0.172)	(0.138)	(0.673)	(0.181)	(0.324)
Portfolio Type	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity
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
Observations	48,082	28,739	22,476	48,082	28,739	22,476	48,082	34,170
R2	0.601	0.710	0.732	0.616	0.711	0.733	0.616	0.666

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing 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.

D.3.2.2 Examining the Role of AI and ICT Stocks

TABLE D.16
Similar to Table 5.7 Without Energy Stocks and More Specifications for AI

	(1) AI	(2) AI	(3) AI	(4) AI	(5) AI	(6) AI	(7) AI	(8) AI
Family Count (log)	0.780***	0.781***	0.913***	0.916***	0.817***	0.837***	1.001***	1.009***
	(0.028)	(0.029)	(0.044)	(0.046)	(0.083)	(0.090)	(0.040)	(0.040)
Clean Portfolio	1.247***	0.726***	0.970***	1.007***	-0.134	0.079	0.227*	0.126
	(0.129)	(0.126)	(0.132)	(0.146)	(0.222)	(0.181)	(0.121)	(0.138)
Grey Portfolio	0.986***	0.955***	0.762***	0.819***	0.059	0.127	0.069	0.126
	(0.084)	(0.147)	(0.120)	(0.132)	(0.156)	(0.129)	(0.116)	(0.128)
Stock AI (log, t-1)	0.295***	0.179***	-0.065	-0.060	0.241***	0.288***	-0.086	-0.095
	(0.034)	(0.036)	(0.068)	(0.076)	(0.057)	(0.067)	(0.074)	(0.085)
Clean X Stock AI (log, t-1)		0.156***	0.135***	0.129***		-0.094	-0.007	0.005
		(0.040)	(0.040)	(0.042)		(0.070)	(0.044)	(0.045)
Grey X Stock AI (log, t-1)		0.025	0.038	0.029		-0.035	0.038	0.032
		(0.036)	(0.036)	(0.036)		(0.051)	(0.076)	(0.076)
Total Assets (log)				0.160*				-0.065
				(0.088)				(0.047)
Nbr Empoyees (log)				-0.215***				0.037
				(0.056)				(0.079)
Age (log)				-0.633**				-0.342*
				(0.294)				(0.202)
Constant	-4.257***	-3.895***	-3.218***	-2.342*	-3.910***	-4.050***	-2.706***	-0.345
	(0.100)	(0.118)	(0.315)	(1.359)	(0.121)	(0.132)	(0.221)	(1.225)
Portfolio Type	Transport	Transport	Transport	Transport	Electricity	Electricity	Electricity	Electricity
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
Observations	26,810	26,810	11,337	9,610	41,591	41,591	10,957	9,097
R2	0.652	0.655	0.724	0.742	0.326	0.328	0.434	0.448

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing AI.
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.

TABLE D.17
Similar to Table 5.7 Without Energy Stocks and More Specifications for ICT

	(1) ICT	(2) ICT	(3) ICT	(4) ICT	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Family Count (log)	0.880***	0.880***	0.893***	0.890***	0.775***	0.792***	1.038***	1.015***
	(0.022)	(0.023)	(0.042)	(0.043)	(0.032)	(0.034)	(0.023)	(0.025)
Clean Portfolio	0.808***	0.941***	0.941***	0.963***	0.628***	0.913***	0.669***	0.658***
	(0.055)	(0.089)	(0.096)	(0.107)	(0.082)	(0.070)	(0.094)	(0.107)
Grey Portfolio	0.496***	0.514***	0.441***	0.442***	-0.108	-0.047	-0.112	-0.175*
	(0.069)	(0.099)	(0.107)	(0.120)	(0.080)	(0.084)	(0.090)	(0.103)
Stock ICT (log, t-1)	0.102***	0.120***	0.023	0.037	0.169***	0.204***	-0.049	-0.034
	(0.015)	(0.017)	(0.055)	(0.055)	(0.014)	(0.018)	(0.040)	(0.045)
Clean X Stock ICT (log, t-1)		-0.024	-0.005	-0.007		-0.059***	-0.033*	-0.027
		(0.017)	(0.017)	(0.018)		(0.018)	(0.019)	(0.021)
Grey X Stock ICT (log, t-1)		-0.005	0.000	0.001		-0.014	0.031	0.040*
		(0.023)	(0.025)	(0.026)		(0.021)	(0.022)	(0.023)
Total Assets (log)				0.155***				0.008
				(0.052)				(0.032)
Nbr Empoyees (log)				-0.108***				0.031
				(0.033)				(0.046)
Age (log)				-0.571***				-0.218**
				(0.190)				(0.094)
Constant	-2.375***	-2.470***	-1.838***	-2.176*	-2.063***	-2.262***	-1.271***	-0.917
	(0.054)	(0.090)	(0.399)	(1.223)	(0.066)	(0.067)	(0.242)	(0.682)
Portfolio Type	Transport	Transport	Transport	Transport	Electricity	Electricity	Electricity	Electricity
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
Observations	26,810	26,810	18,675	15,604	41,591	41,591	25,213	20,266
R2	0.768	0.768	0.823	0.836	0.625	0.626	0.707	0.725

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing 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.

D.3.2.3 Examining the Role of Energy Stock

TABLE D.18
Similar to Table 5.7 With More Specifications for AI

	(1) AI	(2) AI	(3) AI	(4) AI	(5) AI	(6) AI	(7) AI	(8) AI
Family Count (log)	0.982***	0.982***	0.930***	0.922***	0.971***	1.064***	1.014***	1.017***
	(0.044)	(0.044)	(0.043)	(0.045)	(0.108)	(0.126)	(0.041)	(0.042)
Clean Portfolio	1.026***	0.750***	0.912***	1.014***	-0.202	0.350***	0.142	0.006
	(0.122)	(0.147)	(0.248)	(0.273)	(0.231)	(0.112)	(0.159)	(0.184)
Grey Portfolio	0.846***	0.847***	0.589***	0.645***	0.128	0.134	-0.219	-0.230
	(0.091)	(0.147)	(0.204)	(0.225)	(0.142)	(0.117)	(0.193)	(0.218)
Stock AI (log, t-1)	0.362***	0.273***	0.054	0.020	0.303***	0.333***	-0.029	-0.067
	(0.037)	(0.066)	(0.082)	(0.096)	(0.058)	(0.082)	(0.078)	(0.087)
Stock Energy (log, t-1)	-0.216***	-0.199***	-0.258***	-0.186**	-0.143***	-0.136***	-0.108*	-0.048
	(0.037)	(0.045)	(0.069)	(0.083)	(0.040)	(0.051)	(0.056)	(0.063)
Clean X Stock AI (log, t-1)		0.138*	0.124*	0.137*		-0.030	-0.022	-0.014
		(0.073)	(0.069)	(0.074)		(0.101)	(0.047)	(0.047)
Grey X Stock AI (log, t-1)		-0.061	-0.008	-0.015		-0.060	-0.021	-0.035
		(0.081)	(0.066)	(0.070)		(0.065)	(0.085)	(0.086)
Clean X Energy Stock (log, t-1)		-0.029	0.011	-0.007		-0.112*	0.023	0.033
		(0.046)	(0.059)	(0.065)		(0.068)	(0.037)	(0.042)
Grey X Energy Stock (log, t-1)		0.039	0.046	0.046		0.028	0.086*	0.103*
		(0.051)	(0.051)	(0.057)		(0.042)	(0.047)	(0.053)
Total Assets (log)				0.178**				-0.065
				(0.088)				(0.047)
Nbr Empoyees (log)				-0.201***				0.038
				(0.057)				(0.079)
Age (log)				-0.562*				-0.341*
				(0.308)				(0.203)
Constant	-3.758***	-3.595***	-1.960***	-2.226	-3.774***	-4.075***	-2.339***	-0.210
	(0.106)	(0.127)	(0.493)	(1.394)	(0.136)	(0.114)	(0.316)	(1.203)
Portfolio Type	Transport	Transport	Transport	Transport	Electricity	Electricity	Electricity	Electricity
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
Observations	26,810	26,810	11,337	9,610	41,591	41,591	10,957	9,097
R2	0.658	0.660	0.725	0.742	0.330	0.335	0.435	0.449

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing AI.
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.

TABLE D.19

Similar to Table 5.7 With More Specifications for ICT

	(1) ICT	(2) ICT	(3) ICT	(4) ICT	(5) ICT	(6) ICT	(7) ICT	(8) ICT
Family Count (log)	0.937***	0.939***	0.896***	0.887***	0.977***	1.032***	1.039***	1.016***
	(0.028)	(0.030)	(0.044)	(0.044)	(0.033)	(0.036)	(0.024)	(0.026)
Clean Portfolio	0.735***	0.680***	0.683***	0.697***	0.512***	0.903***	0.489***	0.476***
	(0.056)	(0.075)	(0.112)	(0.126)	(0.081)	(0.064)	(0.092)	(0.102)
Grey Portfolio	0.460***	0.303***	0.067	0.023	-0.000	-0.054	-0.252**	-0.331***
	(0.066)	(0.100)	(0.164)	(0.171)	(0.069)	(0.075)	(0.105)	(0.115)
Stock ICT (log, t-1)	0.121***	0.231***	0.211***	0.197***	0.235***	0.305***	0.081*	0.083*
	(0.017)	(0.022)	(0.066)	(0.060)	(0.014)	(0.019)	(0.042)	(0.049)
Stock Energy (log, t-1)	-0.065***	-0.169***	-0.283***	-0.244***	-0.205***	-0.250***	-0.189***	-0.183***
	(0.023)	(0.026)	(0.047)	(0.049)	(0.019)	(0.023)	(0.039)	(0.045)
Clean X Stock ICT (log, t-1)		-0.121***	-0.068***	-0.072***		-0.099***	-0.092***	-0.084***
		(0.027)	(0.024)	(0.024)		(0.023)	(0.021)	(0.023)
Grey X Stock ICT (log, t-1)		-0.095***	-0.101***	-0.112***		-0.041*	0.001	0.006
		(0.026)	(0.027)	(0.029)		(0.025)	(0.019)	(0.022)
Clean X Energy Stock (log, t-1)		0.109***	0.089***	0.093***		0.017	0.105***	0.101***
		(0.025)	(0.025)	(0.026)		(0.033)	(0.030)	(0.032)
Grey X Energy Stock (log, t-1)		0.100***	0.137***	0.154***		0.057*	0.062***	0.070**
		(0.026)	(0.040)	(0.041)		(0.030)	(0.024)	(0.028)
Total Assets (log)				0.149***				0.010
				(0.052)				(0.032)
Nbr Empoyees (log)				-0.097***				0.036
				(0.034)				(0.046)
Age (log)				-0.505***				-0.170*
				(0.193)				(0.094)
Constant	-2.250***	-2.162***	-1.067***	-1.700	-1.927***	-2.178***	-1.067***	-0.950
	(0.056)	(0.077)	(0.402)	(1.245)	(0.062)	(0.060)	(0.238)	(0.657)
Portfolio Type	Transport	Transport	Transport	Transport	Electricity	Electricity	Electricity	Electricity
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
Observations	26,810	26,810	18,675	15,604	41,591	41,591	25,213	20,266
R2	0.769	0.769	0.824	0.836	0.635	0.639	0.707	0.726

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing 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.

TABLE D.20
Similar to D.18 Controlling for Sectoral/Clean/Grey Focus (Transport)

	(1) AI	(2) AI	(3) AI	(4) AI	(5) AI	(6) AI
Family Count (log)	0.973***	0.974***	0.982***	0.922***	0.841***	0.994***
	(0.029)	(0.050)	(0.044)	(0.045)	(0.048)	(0.046)
Clean Portfolio	0.304	-0.020	0.750***	1.014***	0.689**	0.032
	(0.337)	(0.297)	(0.147)	(0.273)	(0.341)	(0.355)
Grey Portfolio	0.346	-0.121	0.847***	0.645***	0.219	-0.233
	(0.298)	(0.310)	(0.147)	(0.225)	(0.465)	(0.338)
Firm Sectoral Focus	-0.218	-0.028			-0.121	-0.095
	(0.173)	(0.194)			(0.156)	(0.204)
Firm Clean Focus	-0.002	-0.004			-0.005	0.000
	(0.003)	(0.004)			(0.004)	(0.005)
Firm Grey Focus	0.011***	-0.001			0.011***	0.002
	(0.004)	(0.004)			(0.003)	(0.004)
Clean X Firm Sectoral Focus	1.212***	0.523***			1.323***	0.662***
	(0.193)	(0.195)			(0.189)	(0.199)
Grey X Firm Sectoral Focus	0.669***	0.231			0.688***	0.235
	(0.159)	(0.158)			(0.180)	(0.175)
Clean X Firm Clean Focus	0.003	0.012***			-0.001	0.006
	(0.004)	(0.005)			(0.005)	(0.005)
Grey X Firm Clean Focus	0.006	0.011***			0.001	0.011**
	(0.004)	(0.004)			(0.005)	(0.005)
Clean X Firm Grey Focus	0.008*	0.017***			-0.003	0.013***
	(0.004)	(0.004)			(0.005)	(0.004)
Grey X Firm Grey Focus	-0.004	0.010*			-0.007	0.009*
	(0.004)	(0.006)			(0.006)	(0.005)
Total Assets (log)		0.146*		0.178**		0.175**
		(0.079)		(0.088)		(0.084)
Nbr Empoyees (log)		-0.229***		-0.201***		-0.237***
		(0.058)		(0.057)		(0.058)
Age (log)		-0.525***		-0.562*		-0.581**
		(0.170)		(0.308)		(0.268)
Stock AI (log, t-1)			0.273***	0.020	0.326***	0.033
			(0.066)	(0.096)	(0.059)	(0.110)
Clean X Stock AI (log, t-1)			0.138*	0.137*	0.205***	0.143*
			(0.073)	(0.074)	(0.067)	(0.081)
Grey X Stock AI (log, t-1)			-0.061	-0.015	-0.068	-0.057
			(0.081)	(0.070)	(0.090)	(0.081)
Stock Energy (log, t-1)			-0.199***	-0.186**	-0.162***	-0.166*
			(0.045)	(0.083)	(0.054)	(0.090)
Clean X Energy Stock (log, t-1)			-0.029	-0.007	-0.081	-0.040
			(0.046)	(0.065)	(0.049)	(0.067)
Grey X Energy Stock (log, t-1)			0.039	0.046	0.104	0.049
			(0.051)	(0.057)	(0.072)	(0.062)
Constant	-4.203***	-2.557*	-3.595***	-2.226	-3.617***	-2.202*
	(0.246)	(1.314)	(0.127)	(1.394)	(0.200)	(1.287)
Portfolio Type	Transport	Transport	Transport	Transport	Transport	Transport
Portfolio FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Firm FEs		X		X		X
Firm level controls		X		X		X
Observations	30,805	10,733	26,810	9,610	26,810	9,610
R2	0.653	0.740	0.660	0.742	0.696	0.745

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing AI.
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.

TABLE D.21
Similar to D.18 Controlling for Sectoral/Clean/Grey Focus (Electricity)

	(1)	(2)	(3)	(4)	(5)	(6)
	AI	AI	AI	AI	AI	AI
Family Count (log)	1.060***	0.997***	1.064***	1.017***	1.016***	1.091***
	(0.068)	(0.055)	(0.126)	(0.042)	(0.068)	(0.052)
Clean Portfolio	-0.441	-0.599*	0.350***	0.006	0.803	-0.024
	(0.617)	(0.363)	(0.112)	(0.184)	(0.946)	(0.462)
Grey Portfolio	0.055	-0.516	0.134	-0.230	0.911**	-1.207**
	(0.403)	(0.393)	(0.117)	(0.218)	(0.444)	(0.476)
Firm Sectoral Focus	0.025	-0.101			-0.438	-0.077
	(0.225)	(0.167)			(0.284)	(0.178)
Firm Clean Focus	-0.007	-0.005			-0.029***	-0.006
	(0.005)	(0.003)			(0.008)	(0.004)
Firm Grey Focus	0.008	0.004			0.005	0.005
	(0.007)	(0.005)			(0.007)	(0.004)
Clean X Firm Sectoral Focus	-0.580*	0.179			0.089	0.225
	(0.326)	(0.162)			(0.495)	(0.174)
Grey X Firm Sectoral Focus	0.009	-0.045			0.369	-0.237
	(0.205)	(0.160)			(0.287)	(0.150)
Clean X Firm Clean Focus	0.006	0.012**			0.026***	0.009*
	(0.008)	(0.005)			(0.009)	(0.005)
Grey X Firm Clean Focus	0.014**	0.017***			0.029***	0.020***
	(0.006)	(0.005)			(0.008)	(0.006)
Clean X Firm Grey Focus	0.015	0.013*			0.015*	0.011*
	(0.009)	(0.007)			(0.009)	(0.006)
Grey X Firm Grey Focus	-0.009	0.003			-0.009	0.005
	(0.009)	(0.006)			(0.008)	(0.006)
Total Assets (log)		-0.074		-0.065		-0.057
		(0.048)		(0.047)		(0.047)
Nbr Empoyees (log)		0.061		0.038		0.022
		(0.065)		(0.079)		(0.076)
Age (log)		-0.428***		-0.341*		-0.350*
		(0.164)		(0.203)		(0.210)
Stock AI (log, t-1)			0.333***	-0.067	0.582***	-0.020
			(0.082)	(0.087)	(0.104)	(0.096)
Clean X Stock AI (log, t-1)			-0.030	-0.014	-0.285**	-0.073
			(0.101)	(0.047)	(0.122)	(0.060)
Grey X Stock AI (log, t-1)			-0.060	-0.035	-0.317***	-0.123
			(0.065)	(0.086)	(0.084)	(0.087)
Stock Energy (log, t-1)			-0.136***	-0.048	-0.057	-0.054
			(0.051)	(0.063)	(0.072)	(0.065)
Clean X Energy Stock (log, t-1)			-0.112*	0.033	-0.166	-0.011
			(0.068)	(0.042)	(0.122)	(0.051)
Grey X Energy Stock (log, t-1)			0.028	0.103*	-0.056	0.156***
			(0.042)	(0.053)	(0.073)	(0.058)
Constant	-4.124***	-0.361	-4.075***	-0.210	-4.534***	-0.515
	(0.288)	(1.057)	(0.114)	(1.203)	(0.292)	(1.177)
Portfolio Type	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity
Portfolio FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Firm FEs		X		X		X
Firm level controls		X		X		X
Observations	48,082	10,082	41,591	9,097	41,591	9,097
R2	0.314	0.455	0.335	0.449	0.355	0.455

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing AI.
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.

TABLE D.22
Similar to D.18 Controlling for Sectoral/Clean/Grey Focus (Transport)

	(1)	(2)	(3)	(4)	(5)	(6)
	ICT	ICT	ICT	ICT	ICT	ICT
Family Count (log)	0.956***	0.921***	0.860***	0.880***	0.810***	0.937***
	(0.021)	(0.042)	(0.029)	(0.039)	(0.034)	(0.038)
Clean Portfolio	0.560***	0.176	0.895***	0.838***	0.502***	0.339
	(0.202)	(0.182)	(0.080)	(0.151)	(0.188)	(0.216)
Grey Portfolio	0.043	-0.297	0.284***	0.047	-0.322	-0.550**
	(0.169)	(0.234)	(0.097)	(0.180)	(0.263)	(0.248)
Firm Sectoral Focus	-0.274***	-0.046			-0.166*	-0.097
	(0.102)	(0.117)			(0.088)	(0.121)
Firm Clean Focus	0.004***	-0.001			-0.002	-0.002
	(0.001)	(0.002)			(0.003)	(0.002)
Firm Grey Focus	0.007***	-0.002			0.004**	-0.002
	(0.003)	(0.002)			(0.002)	(0.002)
Clean X Firm Sectoral Focus	0.413***	0.201*			0.410***	0.269**
	(0.110)	(0.115)			(0.104)	(0.116)
Grey X Firm Sectoral Focus	0.515***	0.235**			0.473***	0.223**
	(0.082)	(0.093)			(0.084)	(0.095)
Clean X Firm Clean Focus	-0.001	0.006**			0.004	0.005*
	(0.003)	(0.003)			(0.003)	(0.003)
Grey X Firm Clean Focus	0.004**	0.009***			0.006**	0.011***
	(0.002)	(0.003)			(0.003)	(0.003)
Clean X Firm Grey Focus	0.004	0.010***			0.003	0.009***
	(0.003)	(0.002)			(0.003)	(0.002)
Grey X Firm Grey Focus	-0.004	0.005			0.000	0.006*
	(0.003)	(0.004)			(0.003)	(0.004)
Total Assets (log)		0.154***		0.143***		0.134***
		(0.053)		(0.048)		(0.046)
Nbr Empoyees (log)		-0.114***		-0.095***		-0.119***
		(0.032)		(0.034)		(0.035)
Age (log)		-0.466***		-0.503**		-0.511**
		(0.138)		(0.220)		(0.216)
Stock AI (log, t-1)			0.188***	0.076	0.205***	0.101*
			(0.037)	(0.054)	(0.034)	(0.056)
Clean X Stock AI (log, t-1)			0.029	0.064*	0.017	0.039
			(0.039)	(0.038)	(0.035)	(0.034)
Grey X Stock AI (log, t-1)			-0.034	-0.036	-0.056	-0.082*
			(0.046)	(0.041)	(0.048)	(0.044)
Stock Energy (log, t-1)			-0.035	-0.109**	-0.019	-0.102**
			(0.024)	(0.050)	(0.031)	(0.051)
Clean X Energy Stock (log, t-1)			-0.018	-0.021	-0.016	-0.043
			(0.025)	(0.034)	(0.031)	(0.036)
Grey X Energy Stock (log, t-1)			0.047*	0.076**	0.067*	0.061*
			(0.027)	(0.038)	(0.037)	(0.035)
Constant	-2.294***	-2.226*	-2.105***	-1.536	-2.030***	-1.179
	(0.127)	(1.139)	(0.085)	(1.159)	(0.099)	(1.122)
Portfolio Type	Transport	Transport	Transport	Transport	Transport	Transport
Portfolio FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Firm FEs		X		X		X
Firm level controls		X		X		X
Observations	30,805	17,310	26,810	15,604	26,810	15,604
R2	0.764	0.836	0.776	0.836	0.780	0.837

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing 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.

TABLE D.23
Electricity: Similar to D.18 Controlling for Sectoral/Clean/Grey Focus (Electricity)

	(1) ICT	(2) ICT	(3) ICT	(4) ICT	(5) ICT	(6) ICT
Family Count (log)	1.055***	0.970***	1.023***	1.006***	0.941***	1.006***
	(0.022)	(0.030)	(0.039)	(0.025)	(0.034)	(0.028)
Clean Portfolio	1.103***	0.188	1.022***	0.231**	0.930***	0.005
	(0.287)	(0.154)	(0.066)	(0.097)	(0.222)	(0.159)
Grey Portfolio	-0.378	-0.667***	-0.059	-0.340***	-0.195	-1.336***
	(0.240)	(0.199)	(0.069)	(0.112)	(0.304)	(0.233)
Firm Sectoral Focus	-0.184	-0.091			-0.348***	-0.001
	(0.137)	(0.099)			(0.128)	(0.084)
Firm Clean Focus	0.009***	-0.003*			0.001	-0.002
	(0.003)	(0.002)			(0.004)	(0.002)
Firm Grey Focus	-0.004	-0.006***			-0.006	-0.004**
	(0.003)	(0.002)			(0.005)	(0.002)
Clean X Firm Sectoral Focus	-0.331**	-0.142			-0.226*	-0.207**
	(0.131)	(0.111)			(0.129)	(0.092)
Grey X Firm Sectoral Focus	-0.051	-0.131			-0.014	-0.337***
	(0.127)	(0.105)			(0.134)	(0.095)
Clean X Firm Clean Focus	-0.012***	0.003			-0.002	0.002
	(0.004)	(0.002)			(0.004)	(0.002)
Grey X Firm Clean Focus	0.005	0.009***			0.008*	0.009***
	(0.003)	(0.002)			(0.004)	(0.003)
Clean X Firm Grey Focus	0.002	0.009***			0.004	0.007***
	(0.004)	(0.002)			(0.005)	(0.002)
Grey X Firm Grey Focus	0.007	0.011***			0.008	0.012***
	(0.004)	(0.003)			(0.005)	(0.003)
Total Assets (log)		0.013		0.015		0.021
		(0.033)		(0.033)		(0.033)
Nbr Empoyees (log)		0.017		0.036		0.034
		(0.043)		(0.045)		(0.045)
Age (log)		-0.258***		-0.173*		-0.149
		(0.086)		(0.095)		(0.092)
Stock AI (log, t-1)			0.268***	0.083*	0.259***	0.087**
			(0.046)	(0.043)	(0.045)	(0.043)
Clean X Stock AI (log, t-1)			-0.138***	-0.089***	-0.133***	-0.097***
			(0.041)	(0.024)	(0.042)	(0.026)
Grey X Stock AI (log, t-1)			-0.025	0.003	-0.054	-0.013
			(0.047)	(0.032)	(0.048)	(0.038)
Stock Energy (log, t-1)			-0.095***	-0.165***	0.000	-0.166***
			(0.028)	(0.041)	(0.045)	(0.041)
Clean X Energy Stock (log, t-1)			-0.025	0.093***	0.002	0.095***
			(0.032)	(0.027)	(0.052)	(0.028)
Grey X Energy Stock (log, t-1)			0.009	0.072**	-0.034	0.108***
			(0.032)	(0.031)	(0.057)	(0.035)
Constant	-2.347***	-0.676	-2.004***	-0.817	-2.342***	-0.917
	(0.172)	(0.673)	(0.062)	(0.673)	(0.138)	(0.682)
Portfolio Type	Electricity	Electricity	Electricity	Electricity	Electricity	Electricity
Portfolio FEs	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X
Firm FEs		X		X		X
Firm level controls		X		X		X
Observations	48,082	22,476	41,591	20,266	41,591	20,266
R2	0.616	0.733	0.613	0.726	0.624	0.727

Poisson pseudo-maximum likelihood regression. Standard errors in parentheses, Clustered at firm level.
Dependent variable: Count of Families citing 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.