Unpacking the Green Innovation Slowdown*

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Abstract

Despite escalating climate concerns and intensifying policy support, aggregate green innovation has puzzlingly slowed since 2010 across various OECD countries. Using U.S. patent data, we document that green innovation is concentrated among firms with information and communication technology (ICT) capabilities and that these firms primarily drive the post-2010 stagnation. To rationalize these facts, we develop and estimate a general equilibrium model featuring endogenous technology-class selection, directed innovation, and firm dynamics. In the model, ICT firms possess a comparative advantage in green innovation through lower innovation costs. Our model highlights a fundamental policy trade-off: ICT-targeted green subsidies are more efficient than uniform subsidies when dirty innovation is relatively costly, while the reverse holds when dirty innovation is cheap, due to general-equilibrium crowd-out effects. Quantitatively, we find that the ICT innovation slowdown, modeled as a slower decline in ICT-green innovation costs, is the primary catalyst for the slowdown in green innovation, overshadowing the effects of falling energy prices and shifts in entrant composition. Policy counterfactuals reveal that an ICT-targeted subsidy yields a higher consumption-to-subsidy multiplier than a uniform subsidy, both before and during the green innovation slowdown.

Keywords: Climate change; green innovation; firm heterogeneity; general purpose technology.

JEL classification: D24, E22, O16, O30, O40.

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1 Introduction

Achieving a successful transition away from carbon-intensive technologies requires sustained growth in green innovation to overcome the entrenched dominance of dirty technologies in energy production (Acemoglu et al., 2012, 2016a). A defining feature of the contemporary green technological frontier is that clean technologies are increasingly integrated with information and communication technologies (ICT). This synergy is evident when contrasting traditional environmental innovations with their ICT-integrated counterparts: conventional solar panels versus AI-optimized photovoltaic systems that dynamically adjust to weather patterns and electricity demand; standard wind turbines versus digital twins that simulate performance in thousands of scenarios to maximize energy capture; and basic battery storage versus smart-grid ecosystems that employ machine learning to balance intermittent renewable supply with complex consumption patterns. A prominent example is Next Kraftwerke, a German clean-tech company and electricity trader that operates one of Europe's largest virtual power plants (VPPs). Rather than physically owning centralized power stations, the company relies on digital networking to aggregate distributed energy resources into a unified, dispatchable network. Its VPP acts as a shock absorber for the power grid by rapidly scaling up or down the generation and consumption of controllable units to balance supply and demand. Companies such as Stem Inc., Uplight, and Tesla in the U.S., Enel in Italy, and Statkraft in Norway provide further examples of this ICT-enabled green transition. These examples illustrate that digital capabilities are becoming central to the next wave of green innovation. Consistent with this technological shift, policymakers have increasingly advocated for a "twin transition" that jointly promotes digitalization and decarbonization (e.g., Centre, 2022; Srinivasan, 2024).

Despite this technological promise and expanding policy support, recent evidence documents a puzzling aggregate slowdown in green innovation since the early 2010s across various OECD countries (Acemoglu et al., 2023; Aghion et al., 2024; Popp et al., 2022).[1] Several explanations

[1] See Figures 4.7 and 4.8 of Popp et al. (2022) and Figures 1 and A2 of Aghion et al. (2024) for evidence across OECD countries and China, as well as Figures 1 and 2 of Acemoglu et al. (2023) for evidence in the U.S., Canada, France, and Germany.

have been proposed. The shale gas revolution lowered fossil energy prices and may have reduced incentives to invest in clean technologies. The decline in early-stage financing for green startups may have changed entrant composition and weakened the contribution of new green innovators. The financial crisis may also have constrained firms' ability to finance risky green R&D. Yet there is far from a consensus on the causes of the green innovation slowdown and the relative importance of these forces.

Moreover, the firm-level dynamics behind the aggregate slowdown remain insufficiently understood. If modern green innovation increasingly relies on ICT capabilities, then the slowdown need not be uniform across firms. Instead, ICT-intensive green innovators may have played a disproportionately large role in both the earlier rise and the subsequent stagnation of green patenting. Understanding whether this is the case is crucial not only for diagnosing the slowdown, but also for designing effective climate innovation policy.

This policy question is especially relevant because emerging policy designs increasingly distinguish between ICT-capable and traditional green innovators, albeit often without a rigorous economic rationale. The European Green Deal explicitly advocates for a "twin transition," and Horizon Europe has created targeted calls that require applicants to integrate AI or ICT into clean energy projects. Similarly, the European Innovation Council Accelerator evaluates "Green Deal" proposals using scoring criteria that reward the use of advanced digital technologies, creating de facto preferential access for ICT-green firms.[2][3] In the U.S., ARPA-E's DIFFERENTIATE program exclusively funds AI-driven grid optimization projects, while the Department of Energy's Grid Modernization Initiative prioritizes proposals that combine machine learning with grid-scale storage.[4][5] China's 14th Five-Year Plan for Green Development similarly emphasizes the green and low-carbon development of data centers through coordination with wind, photovoltaic, and

[2]This program issued a budget of €0.497 billion for green innovation subsidies in 2021. For comparison, a 2024 European Commission generative AI flagship initiative, GenAI4EU, has a similar budget of €0.5 billion.

[3]The European Green Deal can be found at the online report by European Commission: Towards a green, digital and resilient economy: our European Growth Model, as well as the European Commission funding application system: Green Deal innovations for the Economic Recovery.

[4]See the U.S. government for the introduction of the program: ARPA-E's DIFFERENTIATE program, AI works on three aspects in green energy tech innovation: conceptual design, detailed design and inverse design.

[5]The U.S. Grid Modernization Initiative can be found at U.S. Department of Energy: Department of Energy's GMI.

national data-hub infrastructure.[6] These policies reflect the growing belief that digital capabilities can accelerate decarbonization. However, they do not by themselves answer a central economic question: when should scarce green innovation subsidies be targeted toward ICT-capable firms, and when should they be distributed more broadly across green innovators?

In this paper, we show that firm-level heterogeneity in ICT capabilities is central to both understanding the green innovation slowdown and designing green innovation policy. Using U.S. patent data from 1999 to 2017, we document that ICT-green firms account for a rapidly growing share of green innovation: their share of all green patents rises from 16 percent in 1999 to 55 percent in 2017. More importantly, the aggregate stagnation in green innovation after 2010 is overwhelmingly driven by a sharp deceleration among ICT-green firms. This pattern suggests that the slowdown is not simply a sector-wide decline in clean technological opportunities. Rather, it reflects changes in the behavior and incentives of a specific group of firms that had become increasingly important at the green technological frontier.

Motivated by these empirical patterns, we build a general equilibrium model of directed technical change with heterogeneous firms that endogenously choose technology classes and innovation intensities. Firms differ along an ICT dimension. ICT firms have a comparative advantage in green innovation because they face lower green innovation costs, capturing their ability to integrate digital capabilities with environmental applications. Firms choose whether to operate with dirty or green technologies, decide how much to innovate in the chosen technology class, and may enter or exit the market. The model generates endogenous technology switching, directed innovation, and aggregate feedback through labor allocation, entry and exit, production prices, and energy prices. This framework allows us to quantify the sources of the green innovation slowdown and compare the welfare implications of alternative subsidy designs.

The model focuses on three forces that may account for the slowdown in green innovation. The first is a slowdown in ICT innovation efficiency, motivated by previous literature on the broader deceleration of ICT-driven productivity growth since mid-2000s (e.g., Gordon and Sayed (2020);

[6] See the website of Chinese government: White paper by China's State Council Information Office: Carbon Peaking and Carbon Neutrality China's Plans and Solutions.

Kelly et al. (2021)). We model this force as a deceleration in the decline of green innovation costs for ICT firms. This mechanism directly weakens the green innovation advantage of ICT firms. Because ICT firms account for a large and rising share of green patents, a deterioration in their green innovation incentives can have large aggregate effects. The second force is the decline in fossil energy prices, which raises the relative profitability of dirty production and dirty innovation. In the model, lower energy prices reduce the cost of dirty production, weaken firms' incentives to switch to green technologies, and increase the opportunity cost of allocating resources toward green innovation. The third force is a shift in entrant composition, which captures the possibility that the pool of new firms after 2010 became less favorable to green innovation. Since entrants draw initial productivities and may subsequently transition into green production, a decline in the green potential of entrants can slow the replenishment of the green innovation base. These three forces operate through distinct but interacting channels. ICT-green innovation costs affect the intensive innovation margin of incumbent ICT firms; fossil energy prices affect the relative profitability of dirty versus green technologies; and entrant composition affects the extensive margin of firm entry, technology switching, and future innovation capacity. Embedding all three forces in general equilibrium is important because each affects not only the firms directly exposed to the shock, but also aggregate prices, labor allocation between production and research, entry, and the relative returns to dirty and green innovation. By considering these forces together, the model allows us to evaluate the ICT channel without abstracting from other explanations emphasized in prior work.

Our theoretical analysis reveals a nuanced policy trade-off. When the opportunity cost of dirty innovation is high, ICT-targeted green subsidies yield a significantly higher consumption-to-subsidy multiplier than uniform subsidies. In this case, directing subsidies toward ICT firms is efficient because these firms have a comparative advantage in green innovation and can generate more green technological progress per unit of subsidy. Conversely, when dirty innovation is cheap, heavily subsidizing ICT firms can reduce aggregate production and consumption by reallocating too many resources away from dirty innovation and production. In that case, a uniform subsidy can be more efficient. This trade-off reflects two opposing forces: the higher productivity of ICT firms in producing green innovation and the general-equilibrium opportunity cost of moving resources

away from dirty technologies that may remain productive in the short run.

We estimate the model using the simulated method of moments and find that the ICT-green innovation slowdown is the primary catalyst for the aggregate slowdown in the green transition. Specifically, a slower decline in ICT-green innovation costs explains more of the post-2010 stagnation than falling energy prices or changes in entrant composition within our estimated model and sample period. We then compare a universal green innovation subsidy with a subsidy targeted only to ICT firms, calibrating both to match the observed ratio of green subsidies to R&D. We find that, both before and during the green innovation slowdown, targeting ICT firms yields a higher consumption-to-subsidy multiplier than a universal subsidy.

These quantitative results suggest that the digital component of green innovation is not merely a descriptive feature of recent clean technologies; it is a quantitatively important determinant of the aggregate green innovation path and of the relative efficiency of alternative policy instruments. Importantly, our results should not be interpreted as implying that other mechanisms emphasized in previous literature are unimportant. Rather, we identify an economically meaningful ICT-green innovation channel that complements existing explanations of the slowdown.

Related Literature. This paper contributes to three strands of literature. First, we provide new empirical facts and extend the models of directed technical change and climate innovation (e.g., Acemoglu et al., 2012, 2016a, 2023; Aghion et al., 2024, 2025; Caggese et al., 2024; Cavenaile, 2019; Fried, 2018) by incorporating firm heterogeneity along the ICT dimension. Our framework links micro-level firm heterogeneity in innovation capabilities to aggregate green innovation dynamics through general equilibrium channels. We also provide a quantitative explanation for the green innovation slowdown since the early 2010s, while explicitly recognizing that existing work has identified other important forces behind the slowdown and that our contribution is to isolate a complementary firm-level ICT mechanism. Existing literature (see, e.g., Gordon and Sayed (2020); Kelly et al. (2021)) has documented a slowdown in ICT innovation and productivity growth since around 2005; we are the first to show that this slowdown can be intrinsically linked to the slowdown in green innovation.

Second, we bridge the literature on ICT as a general purpose technology with the literature on environmental innovation (e.g., Acemoglu et al., 2016b; Andres et al., 2022; Fouquet, 2017; Napolitano et al., 2020). This literature emphasizes that general purpose technologies such as ICT and AI diffuse across sectors and reshape innovation networks, with clean technologies often acting as downstream recipients of ICT spillovers. Andres et al. (2022), for example, argue that dirty and green technologies differ in their absorptive capacities and in their intrinsic connections to ICT and AI. We extend this insight by showing that a deceleration in the green productivity of ICT capabilities can itself become a source of aggregate green innovation slowdown. We provide new empirical evidence that ICT-capable firms have become central to green patenting, and we develop a quantitative framework that formalizes how ICT capabilities generate heterogeneous innovation costs and opportunity costs across firms.

Third, our work speaks to the design of climate policies under firm heterogeneity. A large literature compares carbon taxes, broad green subsidies, and regulatory tools (e.g., Acemoglu et al., 2016a; De Haas and Popov, 2023; Hambel et al., 2024; Hsu et al., 2023; Schuldt and Lessmann, 2023), often without distinguishing among firms by innovation capability. More recent work (e.g., Aghion et al., 2024; Dörr, 2022) highlights the importance of firm-level financial constraints and advocates for targeting subsidies to small, financially constrained green innovators. Our analysis complements this literature by asking a different policy question: how should a given green innovation subsidy budget be allocated between ICT-intensive firms and the broader population of green innovators? In doing so, we provide a quantitative framework that connects the policy debate on the twin digital and green transitions to the design of firm-specific green innovation subsidies.

Roadmap. The rest of this paper proceeds as follows. Section 2 presents our empirical decomposition of green innovation trends. Section 3 develops the theoretical model and analyzes the mechanism of the model. Section 4 estimates the model and evaluates policy counterfactuals. Section 5 concludes.

2 Data and Empirical Facts

This section documents the firm-level heterogeneity underlying the aggregate slowdown in green innovation. We first describe the patent and firm-level data and then decompose changes in green patenting along three dimensions: technological capability (ICT-green versus non-ICT-green firms), innovation persistence (frequent versus infrequent innovators), and firm size.

2.1 Data and Variables

2.1.1 Data Description

Our patent data come from the USPTO (obtained via ORBIS Intellectual Property) and cover patent applications from 1999 to 2017. We assign patents to years using their application dates. Each patent is assigned a unique IPC (International Patent Classification) code, which indicates the technology class to which it belongs.

Firm-level financial and employment variables are drawn from ORBIS Historical. Patents in ORBIS Intellectual Property are linked to firms through Bureau van Dijk (BvD) identifiers, which allows us to merge patent records with firm-level balance-sheet and employment information. We restrict the analysis to U.S. firms and their associated patent applications.

We restrict our analysis to a subset of industries heavily involved in green and digital innovation, defined by their IPC codes: transportation, electricity, mechanical engineering (excluding weapons and blasting), and information and communication technology. These industries closely map into the dirty-versus-green technological dichotomy central to our theoretical framework.

We define green patents using the World Intellectual Property Organization (WIPO) IPC Green Inventory, which identifies patent classes related to environmentally sound technologies. The inventory covers alternative energy production, transportation, energy conservation, waste management, agriculture and forestry, and administrative, regulatory, or design aspects of environmental technologies.

We define ICT patents using the IPC codes listed in Appendix A.1; these codes include the core

ICT category as well as related technologies in information processing and system control.

2.1.2 Firm Classification

First, we divide green firms into two time-invariant categories over the sample period: $h \in H = \{I, N\}$, where I denotes an ICT-green firm and N denotes a non-ICT-green firm. In the baseline classification, an ICT-green firm is a firm for which ICT-green patents account for more than 5 percent of its total green patents over the full sample period. Firms that own green patents but do not meet this threshold are classified as non-ICT-green firms. Appendix A.4.2 shows that the main patterns are robust to alternative thresholds and to year-by-year classifications.

Second, within each ICT category, we classify firms by innovation persistence. Frequent innovators, denoted by S, are firms that patent in both the current and previous years. Entering innovators, denoted by E, appear in the current year but not in the previous year, whereas exiting innovators, denoted by X, patent in the current year but not in the subsequent year. The difference between entrants and exiters captures the dynamic contribution of infrequent innovators.

Third, we classify firms by size, $G = \{s, l\}$, using employment. A firm is classified as large (l) if its employment is above the median throughout the sample period and as small (s) otherwise.

2.2 Decomposing Green Patent Change

To quantify the contribution of different firm groups to the aggregate green innovation trend, we employ a dynamic decomposition framework following Melitz and Polanec (2015). The number of new green patents in a year can be written as:

$$\Phi_t = \sum_{g \in G_t} \sum_{h \in H_t} \sum_{\phi_t} \phi_t^{S,g,h} + \sum_{g \in G_t} \sum_{h \in H_t} \sum_{\phi_t} \phi_t^{X,g,h}, \tag{2.1}$$

where ϕ_t denotes the number of green patents filed by a firm in year t. The first term aggregates green patents filed by continuing innovators, while the second term aggregates green patents filed by firms that exit patenting in the following year. Both terms are further split by ICT status H

and firm-size group G. Equivalently, aggregate green patenting can be written using current-year entrants:

$$\Phi_t = \sum_{g \in G_t} \sum_{h \in H_t} \sum_{\phi_t} \phi_t^{S,g,h} + \sum_{g \in G_t} \sum_{h \in H_t} \sum_{\phi_t} \phi_t^{E,g,h}, \tag{2.2}$$

where the first term again captures continuing innovators, while the second term captures firms that enter patenting in year t. Let $\Phi_t^{S,g,h} = \sum_{\phi_t} \phi_t^{S,g,h}$ denote total green patents filed by continuing innovators in group (g, h) in year t, and define $\Phi_t^{X,g,h}$ and $\Phi_t^{E,g,h}$ analogously for exiting and entering innovators. Taking the difference between the entrant-based expression in year t and the exiter-based expression in year $t-1$ gives:

$$\Delta\Phi_t = \sum_{g \in G_t} \sum_{h \in H_t} (\Phi_t^{S,g,h} - \Phi_{t-1}^{S,g,h}) + \sum_{g \in G_t} \sum_{h \in H_t} (\Phi_t^{E,g,h} - \Phi_{t-1}^{X,g,h}). \tag{2.3}$$

The first term captures the change in green patenting by continuing firms within a fixed group, and the second term captures net entry into green patenting. This decomposition separates the intensive margin of incumbent innovation from the extensive margin generated by entry and exit.

2.3 Facts

Based on this decomposition, we establish four stylized facts. The first two motivate the model's focus on ICT capabilities and incumbent innovation, while the latter two provide additional evidence on firm experience and firms' exposure to dirty technologies.

Fact 1. ICT-green firms increasingly dominate green innovation, and the green innovation slowdown is concentrated among these firms. Figure 2.1 demonstrates that the aggregate growth in green patents prior to 2010 was predominantly driven by ICT-green firms. While all firm types experienced a stagnation and subsequent decline in green patenting around 2010, the aggregate slowdown is overwhelmingly attributable to the sharp reversal in the trend of ICT-green firms.[7] Additionally, although the share of ICT-green patents as well as the number of it is increasing over

[7] In Figure A.1, we show that the share of ICT-related green patents among all patents is increasing rapidly up to 2010 and become stagnated.

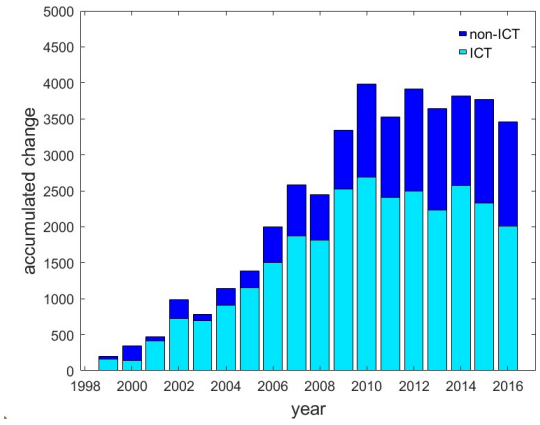


Figure 2.1: Accumulated change of green patents by firm type

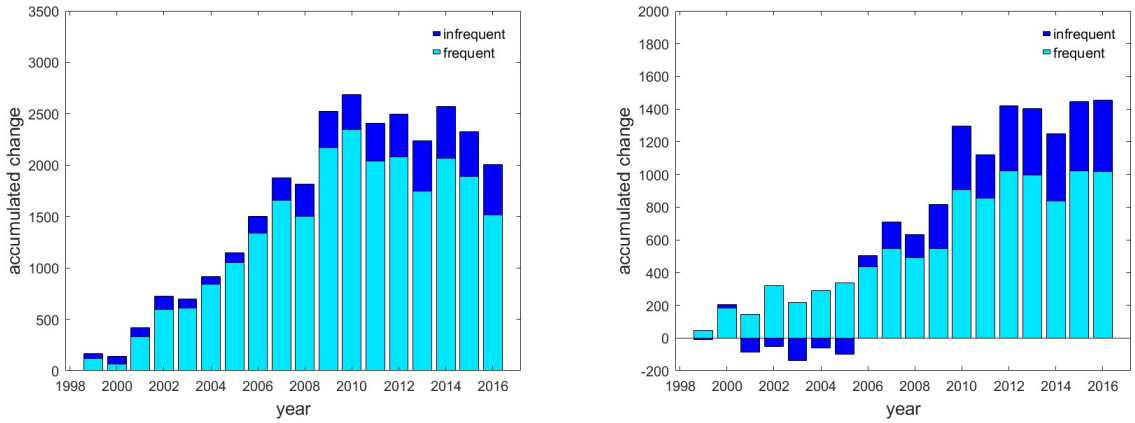
Note: An ICT-green firm is defined as a firm for which ICT-green patents account for more than 5% of all green patents over the full sample period.

time and exhibits growth slowdown since 2010, as shown by Figure A.1, the fraction of ICT-green firms among all green firms remains stable, as documented in Appendix **??**.

These facts refine the aggregate evidence documented in Popp et al. (2022): the slowdown is not evenly distributed across the firm population, but is concentrated among firms that combine green and ICT-related innovation.

Fact 2. Most green innovation is done by frequent and large ICT-green firms. The innovation slowdown is also driven by these firms. Applying the dynamic decomposition, we separate frequent innovators from firms that enter or exit patenting. Figure 2.2 shows that the aggregate pattern is driven mainly by the frequent innovators rather than by the net contribution of entering and exiting firms. Figure 2.3 further shows that, within ICT-green firms, the post-2010 stagnation is concentrated among large firms.

The patent-level trends are consistent with the broader literature. Figure 2.4 shows that the share of green patents declines after 2010, while the number of green patents stagnates. Appendix A.3 shows the corresponding pattern for ICT-green patents: both their number and share increased during the 2000s and then flattened around 2010.



(a) ICT green firms (b) non-ICT green firms

Figure 2.2: Accumulated green patents change by innovator type

Note: Frequent innovators are firms with consecutive green-patenting records. Infrequent innovators are firms that enter or exit green patenting.

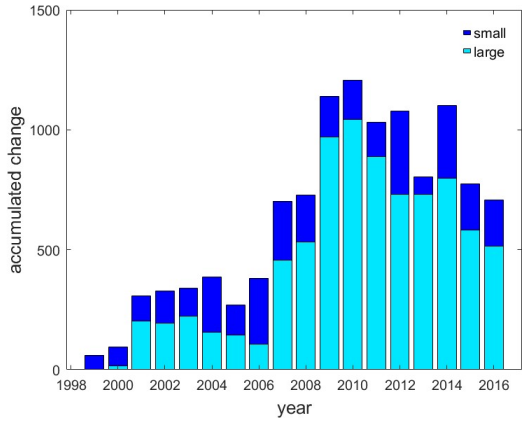


Figure 2.3: Accumulated green patents change by firm size: ICT firms

Note: FNote: Firm size is measured by whether employment is above or below the sample median. This figure uses the patent–ORBIS matched sample.

Fact 3. Experienced green innovators account for most of the change in green patenting. We next decompose the accumulated change in green patents by firms' experience in green innovation. Experience is measured as the number of years since a firm's first granted green patent. We classify firms with at least four years of green-patenting experience as experienced innovators and firms with fewer than four years as inexperienced innovators; four years is the median experience among

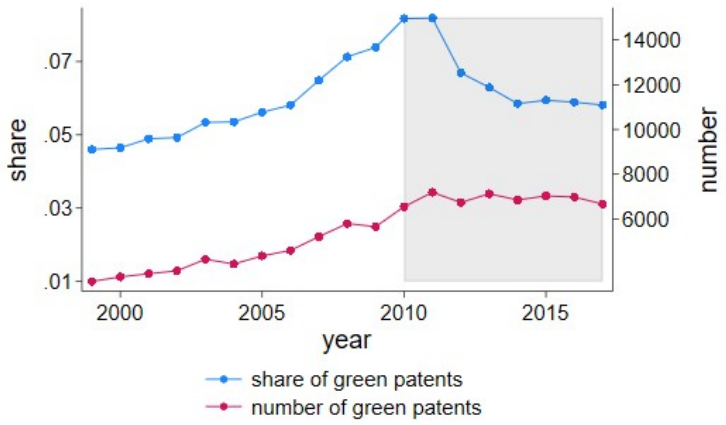


Figure 2.4: Green innovation trends

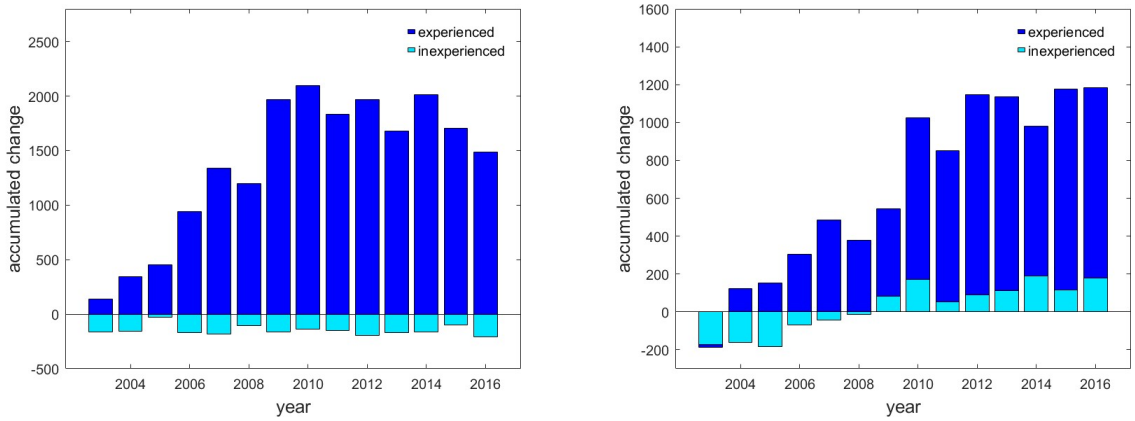
Note: Green patents are defined using the IPC Green Inventory. Patents are dated by application year and restricted to granted patents owned by firms with BvD identifiers.

firms with a green-patenting record.

Figure 2.5 shows that the change in green patenting is driven primarily by experienced firms. This conclusion is strengthened when green patents are weighted by backward citations, indicating that both the quantity and the citation-weighted quality of green innovation are concentrated among experienced innovators. This evidence is consistent with the quantitative results below, where entrants play only a limited role in explaining the slowdown.

Fact 4. Firms differ substantially in their exposure to dirty technologies. We finally compare firms according to their ratio of dirty to green patents. The upper panels of Figure 2.6 compare firms with no dirty patents to firms with a positive dirty-patent ratio, capturing an extensive-margin difference in dirty exposure. The lower panels restrict attention to firms with positive dirty-patent ratios and compare firms above and below the median dirty-to-green ratio, capturing intensive-margin heterogeneity.

On the extensive margin, firms with positive dirty-patent ratios contribute slightly more, partly because many firms with zero dirty patents are small. The intensive-margin comparison is clearer: among firms with positive dirty-patent ratios, those with lower dirty exposure dominate green patenting and account for most of the slowdown, both in patent counts and in citation-weighted

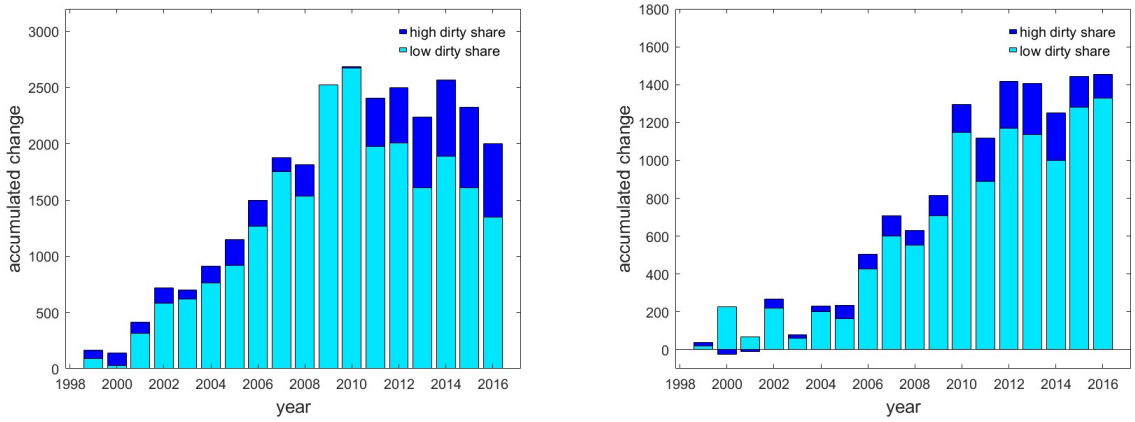


(a) ICT firms (b) non-ICT firms

Note: Experienced green firms are those with at least four years since their first green patent; inexperienced firms have fewer than four years of green-patenting experience.

Figure 2.5: Firm experience of green patenting

measures.



(a) ICT firms (b) non-ICT firms

Note: The panels compare firms with above versus below dirty-to-green patent ratio of one, which is the median level among firms with positive dirty-patent ratios.

Figure 2.6: Firms' heterogeneous degree of green innovation

2.4 Robustness

Technology-specific green innovation decomposition. Motivated by Popp et al. (2022), we re-estimate the decomposition separately by green technology field to examine whether the baseline facts are driven by a particular technology class.

We divide green patents into bio-fuel, hydro and thermal; wind and solar; transportation; waste management; and energy storage. Wind and solar, transportation, and energy storage account for most of the growth in green innovation and exhibit patterns similar to the full sample. Appendix A.4.1 reports the results.

Alternative definitions of ICT-green firms. In Appendix A.4.2, we test the robustness of the ICT-green firm definition using firms' year-by-year status. We also raise the threshold to 10 percent and use an absolute ICT-green patent threshold, applying each definition either over the full sample period or year by year. Appendix A.4.2 shows that the main decomposition is robust across these definitions.

Alternative thresholds for firm categorizations In Appendix A.4.3, we use two years of green-patenting experience as an alternative cutoff. This threshold corresponds to the 25th percentile of the experience distribution and confirms that the baseline findings are not driven by the median-experience split.

3 The Model

Time is discrete and indexed by $t \in \{0, 1, 2, \dots\}$. As illustrated in Figure 3.1, the economy contains two technological trajectories, dirty and green, denoted by $m \in \{d, g\}$. At the beginning of each period, potential entrants decide whether to enter. Conditional on entry, a firm draws an ICT or non-ICT type according to an exogenous probability distribution.[8] Incumbent firms then choose a technology class, make production decisions, choose directed innovation intensity within that

[8] In the extension in Section B.4, firms can endogenously choose their type.

class, and decide whether to continue or exit. Innovation, entry, and technology-transition costs are paid in labor. The details are specified below.

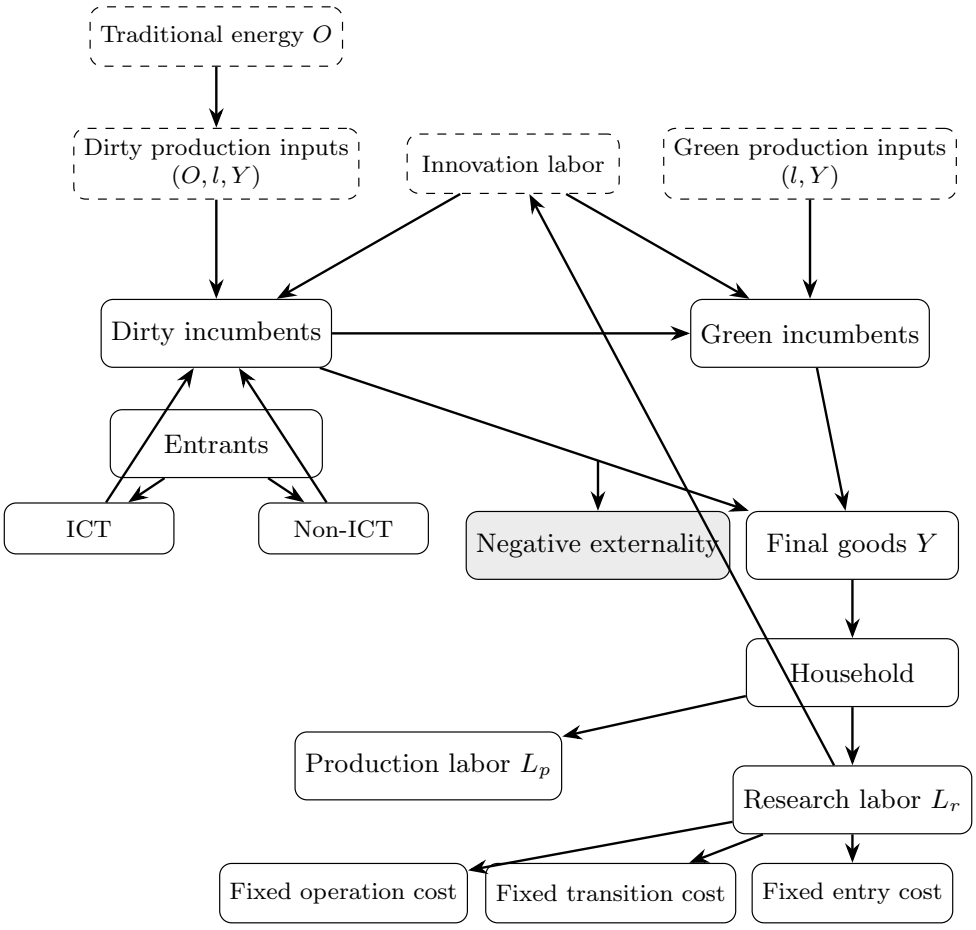


Figure 3.1: Model Setup

3.1 Model Setup

Household and environmental externality A representative household maximizes her expected lifetime utility:

$$\begin{aligned} &\max \sum_{t=0}^{\infty} \beta^t u(C_t, E_t) \\ &\text{s.t.} \quad W_t + P_t C_t \leq W_{t-1}(1 + r_t) + w_t L, \end{aligned} \tag{3.1}$$

where

$$u(C_t, E_t) = C_t - \Xi E_t, \tag{3.2}$$

C_t is aggregate consumption, E_t is aggregate dirty output (defined formally in equation (3.38)), and Ξ parameterizes the marginal disutility of environmental externalities caused by dirty production.[9] β denotes the discount factor. P_t is the price of the final goods. W_t is the wealth of households in period t (value of firms in period t), and r_t is the rate of return on owning firms. The household supplies labor L inelastically in each period in a competitive labor market. Solving the household's utility maximization problem in stationary equilibrium yields the standard Euler equation:

$$\beta = \frac{1}{1+r}. \tag{3.3}$$

Final goods technology A perfectly competitive final-goods sector produces aggregate output Y_t according to the CES technology:

$$Y_t = \left[\int_a y_{d,t}(a)^{\frac{\sigma-1}{\sigma}} \, d\mu_{d,t}(a) + \int_a y_{g,t}(a)^{\frac{\sigma-1}{\sigma}} \, d\mu_{g,t}(a) \right]^{\frac{\sigma}{\sigma-1}}, \tag{3.4}$$

where $y_{d,t}(a)$ and $y_{g,t}(a)$ denote the outputs of dirty and green intermediate firms with technology-specific productivity a. The parameter $\sigma > 1$ is the elasticity of substitution across intermediate varieties, and $\mu_{d,t}(a)$ and $\mu_{g,t}(a)$ are the endogenous productivity measures for dirty and green firms.

Final-goods producers purchase dirty and green intermediate varieties at prices $p_{d,t}(a)$ and $p_{g,t}(a)$ and sell the final good at price P_t. Profit maximization by the representative final-goods producer yields the intermediate-goods demand function:

$$y_{m,t}(a) = \left(\frac{p_{m,t}(a)}{P_t} \right)^{-\sigma} Y_t, \; m \in \{d, g\} \tag{3.5}$$

[9] Relatedly, Andreoni and Levinson (2001) uses the linear functional form to estimate the environmental Kuznets curve; Balleer and Endrikat (2023) use a log-utility function: $\log C - \Xi \log E$.

where the price of final goods is defined as: $P_t = \left[\int_a p_{d,t}(a)^{1-\sigma} d\mu_{d,t}(a) + \int_a p_{g,t}(a)^{1-\sigma} d\mu_{g,t}(a)\right]^{\frac{1}{1-\sigma}}$.

Intermediate firm operation Firms with an inherited status-quo technology class $m \in \{d, g\}$ solve the following problem (entrants are born as dirty firms, while incumbents inherit their technology class from the previous period):

$$V_t^S(\mathbf{a}, m) = \max_{1_E(\mathbf{a},m)} \left[\max_{x(\mathbf{a},m)\in\{m,-m\}} U_t^S(\mathbf{a}, m; x(\mathbf{a}, m)), 0 \right], \tag{3.6}$$

where $x = -m$ denotes a transition to the alternative technology class, while $x = m$ denotes remaining in the current class. The vector $\mathbf{a} = (a_d, a_g)$ contains the firm's dirty and green productivities. Although only the productivity of the chosen technology is used in current production, productivity in the alternative technology affects the firm's option value and therefore its forward-looking decisions. Exit yields an outside option of zero. The superscript $S \in \{u, n\}$ denotes the firm's time-invariant type: ICT (u) or non-ICT (n). Let 1_E be an indicator equal to one if the firm exits and zero otherwise.

Intermediate firm production Intermediate firms operate in a monopolistically competitive market. They can adopt either dirty or green technologies, with productivities specific to each class. Because firms' production decisions are made conditional on their productivity levels, the time subscript t can be omitted.

Dirty firms utilize labor, intermediate final goods, and fossil fuels (e.g., oil) to produce a dirty variety. The effective price of fossil fuels, inclusive of a proportional carbon tax τ, is given by:

$$P^* = P_o(1 + \tau), \tag{3.7}$$

which can also be interpreted as the price of dirty energy. Green firms use labor and final goods, but not fossil fuels, to produce a green variety.

A dirty firm produces according to

$$y_d(a) = \exp(a)^{\frac{1}{\sigma-1}} [Y^D(a)^\eta \cdot (O(a))^{1-\eta}]^{1-\alpha} \cdot (l(a))^\alpha, \tag{3.8}$$

where $\alpha \in (0,1)$ is the labor share, $\eta \in (0,1)$ parameterizes the relative intensity of final goods versus fossil fuels in the intermediate bundle, and $\exp(a)^{\frac{1}{\sigma-1}}$ is the firm's scaled idiosyncratic productivity. By embedding final goods Y^D as an intermediate input, we introduce a critical economy-wide general equilibrium feedback: higher aggregate productivity lowers intermediate input costs for all firms. Consistent with the framework in Aghion et al. (2025), we assume that green technologies are relatively more intensive in final goods, intrinsically biasing the economy toward clean production as aggregate productivity grows.[10]

The corresponding production function for a green firm is:

$$y_g(a) = \exp(a)^{\frac{1}{\sigma-1}} \cdot Y^D(a)^{1-\alpha} \cdot (l(a))^\alpha \tag{3.9}$$

Given demand from final goods producers, a dirty firm solves the following per-period profit-maximization problem:

$$\begin{aligned} \max_{p_d(a), l_d(a), O(a), Y_d^D(a)} \; & p_d(a) y_d(a) - w l_d(a) - P Y_d^D(a) - P_o(1+\tau) O(a) \\ \text{s.t.} \quad & y_d(a) = \left(\frac{p_d(a)}{P} \right)^{-\sigma} Y, \end{aligned} \tag{3.10}$$

A green firm solves the analogous problem:

$$\begin{aligned} \max_{p_g(a), l_g(a), Y_g^D(a)} \; & p_g(a) y_g(a) - w l_g(a) - P Y_g^D(a) \\ \text{s.t.} \quad & y_g(a) = \left(\frac{p_g(a)}{P} \right)^{-\sigma} Y. \end{aligned} \tag{3.11}$$

[10] Specifically, Aghion et al. (2025) model clean technologies as relying heavily on intermediate goods from upstream supply chains, whereas dirty technologies rely solely on labor. In our framework, this corresponds to green technologies having a higher cost share for the intermediate final good $(1-\alpha)$ compared to dirty technologies $(\eta(1-\alpha))$. As general productivity A grows, the relative price of the intermediate final good falls, which disproportionately reduces the production cost of green firms and accelerates the green transition.

The first-order conditions yield optimal prices, input demands, and output, shown in Appendix B.1. The optimal production profit of a dirty firm can be written as

$$\pi_d(a) = C_d \Pi \exp(a) (w^\alpha P^{\eta(1-\alpha)} P_o^{(1-\eta)(1-\alpha)})^{1-\sigma}, \tag{3.12}$$

where $C_d = \left(\frac{1+\tau}{(1-\eta)(1-\alpha)}\right)^{(1-\sigma)(1-\alpha)(1-\eta)} \cdot \left(\frac{1}{\alpha}\right)^{(1-\sigma)\alpha} \cdot \left(\frac{1}{(1-\alpha)\eta}\right)^{(1-\sigma)(1-\alpha)\eta}$. The optimal production profit of a green firm can be written as

$$\pi_g(a) = C_g \Pi \exp(a) (w^\alpha P^{1-\alpha})^{1-\sigma}, \tag{3.13}$$

where $C_g = \left(\frac{1}{\alpha}\right)^{(1-\sigma)\alpha} \cdot \left(\frac{1}{1-\alpha}\right)^{(1-\sigma)(1-\alpha)}$. $\Pi \equiv \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \frac{1}{\sigma} P^\sigma Y$ is the defined common market size index among firms. For convenience, we define $\Pi_d \equiv C_d \Pi (w^\alpha P^{\eta(1-\alpha)} P_o^{(1-\eta)(1-\alpha)})^{1-\sigma}$ and $\Pi_g \equiv C_g \Pi (w^\alpha P^{1-\alpha})^{1-\sigma}$, so $\pi_d(a) = \Pi_d \exp(a)$ and $\pi_g(a) = \Pi_g \exp(a)$.

Intermediate firm innovation Conditional on staying in the market and the technology class chosen, incumbents make innovation investments to maximize their value:

$$\begin{aligned} U_t^S(\mathbf{a}, m; x(\mathbf{a}, m)) = \max_{e \in [0,1]} \; & \pi_x(a_x) - n_f - \mathbf{1}\{x \neq m\} \cdot c - \Phi_x^S(e) \\ & + \frac{\gamma}{1+r_t} \left[e \cdot V_{t+1}(a_x \exp(J), a_{-x}, x) + (1-e) V_{t+1}(a_x \exp(-J), a_{-x}, x) \right], \end{aligned} \tag{3.14}$$

where $U_t^S(\mathbf{a}, m; x(\mathbf{a}, m))$ represents the firm's value after the technology class choice but prior to the realization of innovation outcomes. γ represents the exogenous exit rate of the firm. n_f represents the fixed operation cost. $\mathbf{1}\{x \neq m\} \cdot c$ represents the transition cost to switch the technology class. A successful innovation upgrades the firm's productivity by a factor of $\exp(J)$, whereas failure results in relative obsolescence, degrading productivity by $\exp(-J)$. The productivity depreciation exists because innovation investments are irreversible; in the event of failure, the firm cannot easily revert back to the old technology and might have lower production efficiency (see, e.g., Sui (2022); Utterback (1996)).

Following Atkeson and Burstein (2010), we parameterize the innovation cost functions such

that ICT (u) and non-ICT (n) firms face differentiated green innovation costs:

$$\Phi_g^u(e,a) = h_g^u \exp(a) \exp(\xi_g^u e), \tag{3.15}$$

and

$$\Phi_g^n(e,a) = h_g^n \exp(a) \exp(\xi_g^n e), \tag{3.16}$$

while they have homogeneous dirty innovation cost

$$\Phi_d(e,a) = h_d \exp(a) \exp(\xi_d e). \tag{3.17}$$

Each innovation cost function is governed by a scale parameter h and a curvature parameter ξ. Costs are proportional to $\exp(a)$, so more productive (and hence larger) firms face higher absolute innovation costs. Costs are convex in innovation probability e, capturing that firms have to pay higher innovation cost if they want to have higher innovation probability. Therefore, the innovation probability e captures firms' innovation incentive.

Entrants Potential entrants make an entry decision governed by a standard free-entry condition, driving the ex ante expected value of entry to be equal to the entry cost n_e. We assume that all new entrants initially adopt the dirty technology:

$$n_e = \frac{1}{1+r_t} \int [\theta V_t^u(\mathbf{a}, d) + (1-\theta) V_t^n(\mathbf{a}, d)] dG_t^e(\mathbf{a}), \tag{3.18}$$

where θ is the probability that an entrant draws the ICT type u. Entrants draw initial productivities from an exogenous joint distribution $G_t^e(a) = G_e(\bar{a}_d, a_g)$. Initial dirty productivity is degenerate at $\bar{a}_d$, while initial green productivity is drawn from a distribution whose density decreases as green productivity increases.

Although firms enter as dirty producers, they can later pay a transition cost to switch to green technology. Green technology is absorbing: after becoming green, a firm cannot return to dirty production, although it may still exit. This assumption captures the irreversibility of many green

capital investments, consistent with Lanteri (2018). This asumption is also consistent with our empirical evidence that most green firms are incumbent firms.

Distribution evolution Given the joint distributions from the previous period $\Psi(a_m, a_{-m}, m)$ and $\Psi(a_m, a_{-m}, -m)$, the distribution $\tilde{\Psi}(a_m, a_{-m}, m)$ after the technology class choice evolves as follows:

$$\tilde{\Psi}(a_m, a_{-m}, m) = \mathbf{1}\{x = m\}\Psi(a_m, a_{-m}, -m) + \mathbf{1}\{x = m\}\Psi(a_m, a_{-m}, m), \tag{3.19}$$

and after innovation, the updated distribution $\Psi'(a_m, a_{-m}, m)$ is:

$$\begin{aligned}\Psi'(a_m, a_{-m}, m) =& G_e(a'_m, a'_{-m}) + (1-\gamma)e_m(\frac{a_m}{J}, a_{-m})\tilde{\Psi}(\frac{a_m}{J}, a_{-m}, m) \\ &+ (1-\gamma)(1 - e_m(a_m J, a_{-m}))\tilde{\Psi}(a_m J, a_{-m}, m).\end{aligned} \tag{3.20}$$

The updated joint distributions $\Psi'(a_m, a_{-m}, m)$ uniquely determine the stationary marginal distributions over productivity for dirty and green firms, $\mu_d(a_d)$ and $\mu_g(a_g)$. Specifically, these marginal productivity measures are obtained by integrating the updated joint distribution over both dirty and green productivities and summing across firm types:

$$\mu_d(a_d) = \sum_{S\in\{u,n\}} \int \Psi'^S(a_d, a_g, d)da_g, \tag{3.21}$$

$$\mu_g(a_g) = \sum_{S\in\{u,n\}} \int \Psi'^S(a_d, a_g, g)da_d. \tag{3.22}$$

These distributions then form the basis for aggregating intermediate varieties into final production.

Aggregate productivity Define the aggregate productivity of green (g) and dirty (d) technology of ICT (u) and non-ICT firms (n) as

$$\begin{aligned} A_d^n &= \int \exp(a)d\mu_d^n(a), \quad A_d^u = \int \exp(a)d\mu_d^u(a), \\ A_g^n &= \int \exp(a)d\mu_g(a), \quad A_g^u = \int \exp(a)d\mu_g^u(a). \end{aligned} \tag{3.23}$$

where $A_d^n, A_d^u, A_g^n, A_g^u$ represents the aggregate productivity of non-ICT dirty firms, ICT dirty firms, non-ICT green firms and ICT green firms, respectively. The aggregate productivity of each technology class is to sum up that of the ICT and non-ICT firms together such that

$$A_d = A_d^n + A_d^u, \quad A_g = A_g^n + A_g^u. \tag{3.24}$$

The aggregate productivity for the economy is

$$A = [(P^{\eta(1-\alpha)} P_o^{(1-\eta)(1-\alpha)})^{1-\sigma} C_d A_d + P^{(1-\alpha)(1-\sigma)} C_g A_g]^{\frac{1}{\sigma-1}}, \tag{3.25}$$

a weighted average of dirty and green productivity, where the weights are the variable costs of using dirty and green technologies. It satisfies the linear aggregate production function

$$Y = \frac{1}{\alpha}(\frac{\sigma}{\sigma-1})^{\sigma-1} A L_p. \tag{3.26}$$

For future convenience, we normalize the distribution of firms by entrants' mass, denoted as

$$\tilde{\mu}_d = \frac{\mu_d}{M^e}, \quad \tilde{\mu}_g = \frac{\mu_g}{M^e}. \tag{3.27}$$

The aggregated productivity computed according to the normalized distribution is denoted as $\tilde{A}_d, \tilde{A}_g, \tilde{A}$.

3.2 The Equilibrium

Equilibrium definition The stationary competitive equilibrium is a collection of forward looking decision rules $\{e_d^S, e_g^S, x^S, 1_E^S\}^{S\in\{u,n\}}$, production decisions $\{p_d, l_d, Y_d^D, O; p_g, l_g, Y_g^D\}^{S\in\{u,n\}}$, value functions $\{V_t^S, V_t^{0,S}\}^{S\in\{u,n\}}$, the stationary distributions over productivity $\{\mu_d^S(\mathbf{a}), \mu_g^S(\mathbf{a})\}^{S\in\{u,n\}}$ and aggregates $\{\Pi, P, Y, M_e, C, Y^D, L_p, L_r\}$, such that given oil price P_o,

1. Representative households maximize their life-time utility such that equation (3.3) is satisfied;

2. Firms maximize production profit per period according to equations (3.10) and (3.11);

3. Firms maximize the value function in each decision stage according to equations (3.6) and (3.14);

4. The free entry condition holds, i.e., equation (3.18) holds.

5. The distribution μ_d, μ_g over productivity is stationary;

6. The labor market clears, i.e., equation (3.34) holds;

7. The output market clears, i.e., equation (3.33) holds;

The equilibrium ratio of production labor and research labor in the economy is

$$\chi \equiv \frac{L_p}{L_r} = \frac{\Pi\alpha(\sigma-1)A^{\sigma-1}}{L_r}, \tag{3.28}$$

where

$$L_r = \int \Phi_d(e_d)d\mu(a_d) + \int \Phi_g(e_g)d\mu_g(a_g) + \int c \cdot \mathbf{1}\{x(a,d) = g\}d\mu_d(a) + n_f \cdot M_I + n_e M_e \tag{3.29}$$

includes all costs other than production costs. n_f is the fixed per-period operation cost, n_e is the entry cost, and $\int c \cdot \mathbf{1}\{x(a,d) = g\}d\mu_d(a)$ captures the total transition costs paid by dirty incumbents making the green switch. M_e, M_I are the masses of entrants and incumbents, respectively.

Computing equilibrium aggregates The aggregate variables are $\{\Pi, P, Y, M_e, C, Y^D, L_p, L_r\}$. The aggregate variables are jointly pinned down by the following system of equations:

By definition:

$$\Pi \equiv \left(\frac{\sigma}{\sigma-1}\right)^{1-\sigma} \frac{1}{\sigma} P^\sigma Y. \tag{3.30}$$

Free entry condition (FEC):

$$n_e = \frac{1}{1+r_t} \int [\theta V_t^u(\mathbf{a}, d) + (1-\theta)V_t^n(\mathbf{a}, d)]dG_t^e(\mathbf{a}) \tag{3.31}$$

The price of final goods:

$$P = \frac{\sigma P^{\eta(1-\alpha)}}{(\sigma-1)w^{-\alpha}} \left[\left(\frac{1}{P_o^{-(1-\eta)(1-\alpha)}} \right)^{1-\sigma} C_d A_d + \left(\frac{1}{P^{-(1-\eta)(1-\alpha)}} \right)^{1-\sigma} C_g A_g \right]^{\frac{1}{1-\sigma}}. \tag{3.32}$$

The aggregate consumption:

$$C = Y - Y^D. \tag{3.33}$$

The labor market clearing condition:

$$L_p + L_r = L. \tag{3.34}$$

The ratio of production and research labor:

$$\chi = \frac{L_p}{L_r} = \frac{\Pi\alpha(\sigma-1)A^{\sigma-1}}{L_r}. \tag{3.35}$$

The measure of entrants M_e:

$$M_e = \frac{L_p}{\alpha\Pi(\sigma-1)\tilde{A}^{\sigma-1}}. \tag{3.36}$$

The amount of final goods used as intermediate input:

$$Y^D = \frac{(1-\alpha)\Pi}{P(\sigma-1)} \left[\frac{\eta C_d A_d}{P^{(\sigma-1)(1-\alpha)\eta} P_o^{(\sigma-1)(1-\alpha)(1-\eta)}} + \frac{C_g A_g}{P^{(\sigma-1)(1-\alpha)}} \right]. \tag{3.37}$$

Finally, aggregate dirty output, which enters the environmental externality, is

$$E = (\sigma-1)\Pi_d (A_d^n + A_d^u)^{\frac{\sigma}{\sigma-1}}. \tag{3.38}$$

3.3 Model Mechanism

This section characterizes the model mechanisms in three steps. First, we describe firms' optimal technology and innovation decisions. Second, we decompose the aggregate equilibrium conditions to identify the main general-equilibrium channels. Third, we vary innovation costs, energy prices, input shares, and entrant distributions to show how these mechanisms map into steady-state outcomes.

3.3.1 Decision Rules and General Equilibrium Effects

Incumbent innovation incentive and technology class choice Prior to realizing innovation outcomes, incumbent firms select their optimal technology class. Given our assumption that only dirty firms can undergo a technological transition, their optimal decision takes the form of a threshold rule, illustrated in Figure 3.2. For dirty firms with low latent green productivity, there exists a dirty productivity cutoff below which the firm optimally exits the market. In this region, transitioning to green production is strictly dominated by the outside option of exit. When a dirty firm's green productivity is sufficiently high, there exists a threshold dirty productivity below which the firm optimally switches to green technology (illustrated by the colored regions). The cutoff is non-decreasing in green productivity. Comparing the left and right panels reveals that dirty ICT firms exhibit a higher transition threshold. Facing lower green innovation costs, ICT firms anticipate higher continuation values upon switching, making them more likely to undergo the green transition than non-ICT firms with identical current productivities. This systematic difference highlights the extensive margin advantage of ICT firms in navigating the green transition.

Next, we examine the optimal directed innovation policies of ICT and non-ICT incumbents. The optimal stopping problem governing technology class selection generates an important option-value effect: dirty ICT firms operating near the transition cutoff invest systematically less in dirty innovation. Because they face lower barriers to green innovation, they possess a higher continuation value from transitioning post-failure, dampening their current incentive to improve the dirty technology. This mechanism is visible in the left panel of Figure 3.3. The green innovation

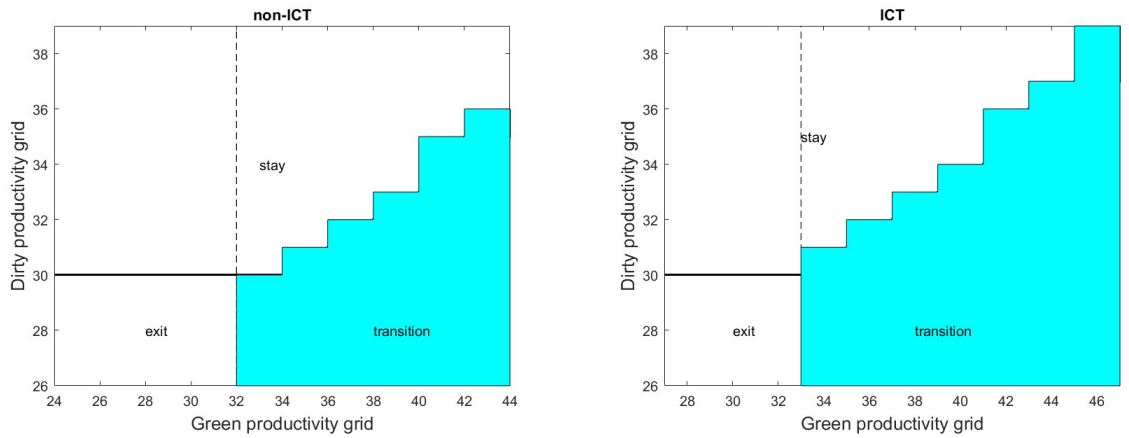


Figure 3.2: Technology class selection and exit of dirty firms

decision rules are shown in the right panel of Figure 3.3. When green productivity is low enough, the firm exits the market and has no incentive to devote positive innovation. As ICT firms have a lower green innovation cost compared to non-ICT firms (which will be implied from data in the next section), the green innovation intensity is markedly higher.

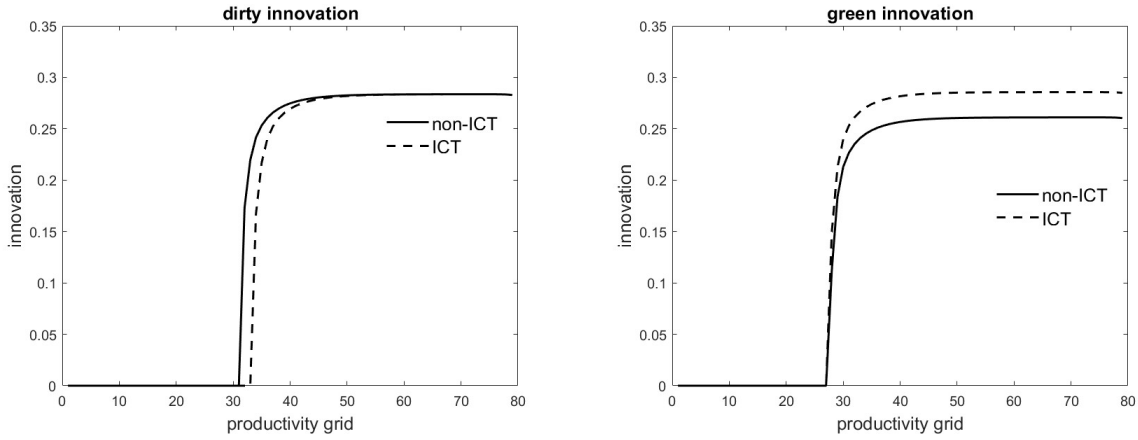


Figure 3.3: Optimal innovation incentive

First order decomposition of incumbent production profits To disentangle the model's transmission mechanisms, we must trace how micro-level decisions aggregate into general equilibrium price effects. The variable profits of intermediate producers act as the sufficient statistics governing firm entry, exit, technology switching, and directed innovation. We therefore analyze the determinants of these profitability metrics via a first-order decomposition.

Recall that the variable production profit for dirty firms is

$$\Pi_d = \Pi C_d (P^{\eta(1-\alpha)} P_o^{(1-\eta)(1-\alpha)})^{1-\sigma}, \tag{3.39}$$

and the variable production profit of green firms is

$$\Pi_g = \Pi C_g P^{(1-\alpha)(1-\sigma)}. \tag{3.40}$$

In a first step, we need to understand what determines the common part of variable profit, Π. The aggregated production labor implies that $L_p = \alpha \frac{\sigma-1}{\sigma} PY$, combined with the definition of Π, gives:

$$\Pi = (L - L_r) \frac{1}{\alpha(\sigma-1)} \frac{1}{(P\frac{\sigma-1}{\sigma})^{1-\sigma}}. \tag{3.41}$$

Equation (3.42) formally highlights that aggregate profitability is governed strictly by the endogenous reallocation of labor between production and research ($L - L_r$), compounded by shifts in the aggregate price level (P).

$$\Delta \log \Pi = \Delta \log(L - L_r) + (\sigma - 1)\Delta \log P. \tag{3.42}$$

We can further decompose the aggregate productivity A:

$$\begin{aligned} \Delta \log A = & \underbrace{\frac{1}{(\sigma-1)(1-\omega_d)} [\Delta \log M_e + \sum_{S\in\{u,n\}} \iota_d^S \Delta \log \tilde{A}_d^S + \sum_{S\in\{u,n\}} (\iota^S - \iota_d^S) \Delta \log \tilde{A}_g^S]}_{\text{Innovation and extensive margin entry}} \\ & \underbrace{- \frac{(1-\eta)(1-\alpha)}{1-\omega_d} \Delta \log P_o}_{\text{Direct resource price effect}}, \end{aligned} \tag{3.43}$$

where $\iota_d^S = \frac{C_d A_d^S (P^{\eta(1-\alpha)} P_o^{(1-\eta)(1-\alpha)})^{1-\sigma}}{P^{1-\sigma}}$ represents the ratio of the aggregate ICT (or non-ICT) dirty profits, and $\omega_d = \iota_d \eta(1-\alpha) + (1-\iota_d)(1-\alpha)$ is a weighed average of the dirty price share and the green price share, and that $\iota_d = \iota_d^u + \iota_d^n$, $\iota^S = \iota_d^S + \iota_g^S$. This decomposition cleanly splits the price

adjustment into an endogenous supply-side response (entry and directed aggregate productivity) and an exogenous input cost shock (fossil fuel prices). Note that the final goods price P is the inverse of A, hence $\Delta \log P = -\Delta \log A$.

We further decompose the variable profits of using the dirty technology:

$$\begin{aligned}\Delta \log(\Pi_d) =& \underbrace{\Delta \log(L - L_r)}_{\text{labor reallocation}} - \Lambda_d [\underbrace{\Delta \log M_e}_{\text{entry}} + \underbrace{\sum_{S \in \{u,n\}} (\iota^S - \iota_d^S) \Delta \log \tilde{A}_g^S + \sum_{S \in \{u,n\}} \iota_d^S \Delta \log \tilde{A}_d^S}_{\text{technology sorting}}] \\ &+ \underbrace{(\sigma - 1)(1 - \eta)(1 - \alpha)(\Lambda_d - 1) \Delta \log P_o}_{\text{resource price effect}}\end{aligned} \tag{3.44}$$

where $\Lambda_d = \frac{1-(1-\alpha)\eta}{1-\omega_d}$. Analogously, we have the decomposition for variable profits of using green technology:

$$\begin{aligned}\Delta \log(\Pi_g) =& \Delta \log(L - L_r) - \Lambda_g [\Delta \log M_e + \sum_{S \in \{u,n\}} \iota_d^S \Delta \log \tilde{A}_d^S + \sum_{S \in \{u,n\}} (\iota^S - \iota_d^S) \Delta \log \tilde{A}_g^S] \\ &+ (\sigma - 1)(1 - \eta)(1 - \alpha) \Lambda_g \Delta \log P_o\end{aligned} \tag{3.45}$$

where $\Lambda_g = \frac{\alpha}{1-\omega_d}$. The relative variable profit across technologies can be shown as the following:

$$\begin{aligned}\Delta \log(\Pi_d) - \Delta \log(\Pi_g) =& (\Lambda_g - \Lambda_d) [\Delta \log M_e + \sum_{S \in \{u,n\}} \iota_d^S \Delta \log \tilde{A}_d^S + \sum_{S \in \{u,n\}} (\iota^S - \iota_d^S) \Delta \log \tilde{A}_g^S] \\ &+ (\sigma - 1)(1 - \eta)(1 - \alpha)(\Lambda_d - \Lambda_g - 1) \Delta \log P_o.\end{aligned} \tag{3.46}$$

Thus, to a first-order approximation, aggregate labor reallocation affects dirty and green variable profits symmetrically and therefore drops out of relative profitability. The dirty-to-green profitability gap is instead governed by differential productivity dynamics, entry, and fossil-energy prices. Appendix B.3 provides analytical results linking energy prices to firm decisions and aggregate outcomes. A larger entrant mass reduces the relative profitability of dirty production, implying that stronger entry pressure favors green technology. Higher aggregate productivity also tilts the

economy toward green production because green technologies are more intensive in final-goods inputs. Finally, a higher fossil-energy price lowers dirty profits directly and encourages firms to switch toward green technology.

We next derive the response of real consumption and welfare. From equation (3.33), the change in real consumption is:

$$\begin{aligned}\Delta \log C = &\underbrace{\frac{Y}{C}(\Delta \log \Pi - \sigma \Delta \log P)}_{\text{aggregate output}} - \frac{Y^D}{C}(1-\sigma)(1-\alpha)\,[\underbrace{\sum_{S\in\{u,n\}} \tilde{\iota}_d^S(\eta \Delta \log P + (1-\eta)\Delta \log P_o)}_{\text{change of inputs: dirty firms}} \\ &+ \underbrace{\sum_{S\in\{u,n\}} (\tilde{\iota}^S - \tilde{\iota}_d^S)\Delta \log P}_{\text{change of inputs: green firms}}] - \frac{Y^D}{C}(\Delta \log \Pi - \Delta \log P) \\ &\underbrace{- \frac{Y^D}{C}[\sum_{S\in\{u,n\}} \tilde{\iota}_d^S \Delta \log \tilde{A}_d^S + \sum_{S\in\{u,n\}} (\tilde{\iota}^S - \tilde{\iota}_d)\Delta \log \tilde{A}_g + \Delta \log M_e]}_{\text{change of inputs due to firm distribution}},\end{aligned} \tag{3.47}$$

where $\tilde{\iota}_d^S = \frac{\eta C_d A_d^S (P^{\eta(1-\alpha)} P_o^{(1-\eta)(1-\alpha)})^{1-\sigma}}{P^{1-\sigma}}$. The first term represents the change of aggregate output, which derives from market size change and aggregate productivity change. It includes the effect generated from productivity distribution change, resource price and labor reallocation, as shown in equation (3.42) and (3.43). Moreover, the aggregate price or the productivity distribution can affect the amount of inputs. Aggregate price affects the market size for final goods producer and thus its demand for final goods as inputs. The price also change the relative cost of inputs, making the firms remake the production decisions. The net effect of the aggregate price is shown as the second term in equation (3.47). Finally, the dirty and green productivity, entrants' contributions directly determines the distribution of firms, and thus determines the aggregate demand for these inputs. The difference part of output and input in terms of final goods is the change of real consumption.

It is then convenient to derive the change of externality and welfare according to equation (3.38).

The change of welfare W is:

$$\Delta \log W = \frac{C}{W}\Delta \log C - \frac{\Xi E}{W}[\Delta \log \Pi_d + \frac{\sigma}{\sigma - 1}(\Delta \log \tilde{A_d} + \Delta \log M_e)] \tag{3.48}$$

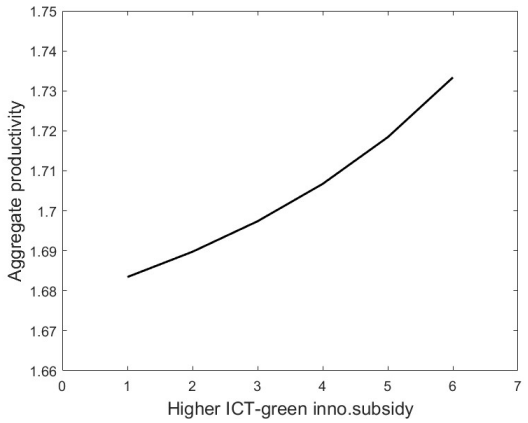
where $\Delta \log \Pi_d$ is the change in dirty variable profits. Dirty productivity therefore affects welfare through three channels: real consumption in (3.47); dirty variable profits, which shape firms' technology and innovation choices in (3.44); and aggregate dirty output, which directly determines pollution in the last term of (3.48).

3.3.2 Difference between ICT firms and non-ICT firms

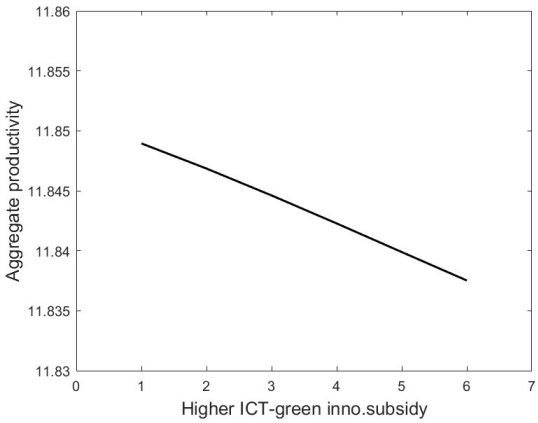
Role of the different innovation cost of ICT and non-ICT firms We now isolate the model's core mechanisms by analyzing comparative statics with respect to green innovation costs. A reduction in green innovation costs triggers a cascade of general equilibrium adjustments: it alters the opportunity cost of directed innovation, shifts input prices via changes in the aggregate price index, and induces aggregate labor reallocation. Importantly, these cost shocks operate through both a direct partial-equilibrium channel on firm-level R&D and an indirect general-equilibrium channel operating through aggregate prices and market size.

The first mechanism operates through a composition effect: a lower cost of green innovation for ICT firms induces marginal, lower-productivity dirty firms to transition to green technologies, which potentially dampens the mechanical increase in aggregate productivity. In addition, this could affect the mass of entrants by changing the expected value at the time of entry, which also contributes to aggregate productivity. Secondly, labor reallocates between production and research, which affects market size and output as well. Third, the overall effect on aggregate productivity determines the direction of the change of the aggregate price, which changes the relative profit of using dirty and green technology and further affects green innovation and the transition of firms.

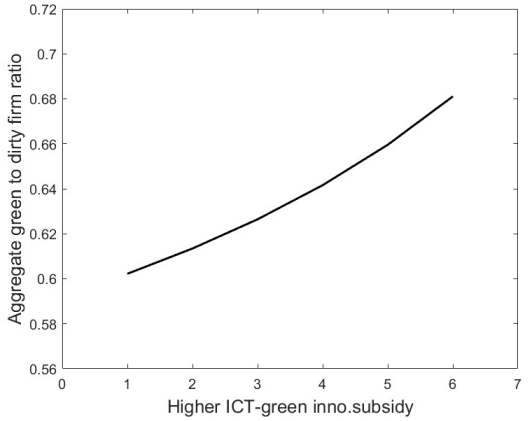
The lower panels of Figure 3.4 show that reducing ICT-green innovation costs promotes the green transition. The key distinction between the left and right panels is the opportunity cost of choosing green technology: the left panels correspond to a lower opportunity cost of green



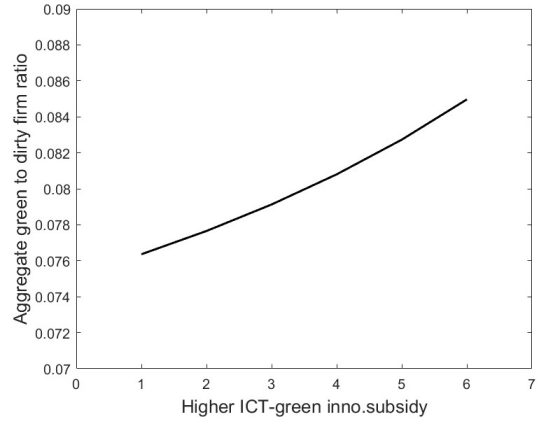
(a) high dirty innovation cost: A



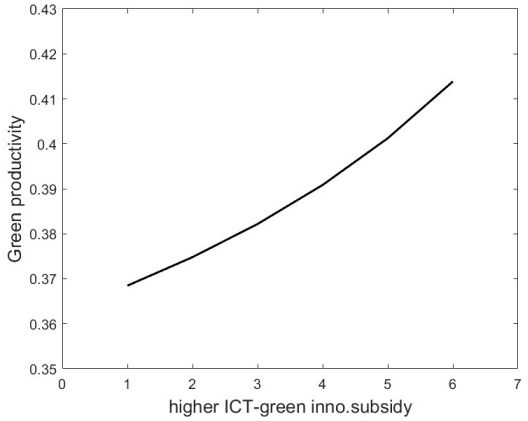
(b) low dirty innovation cost: A



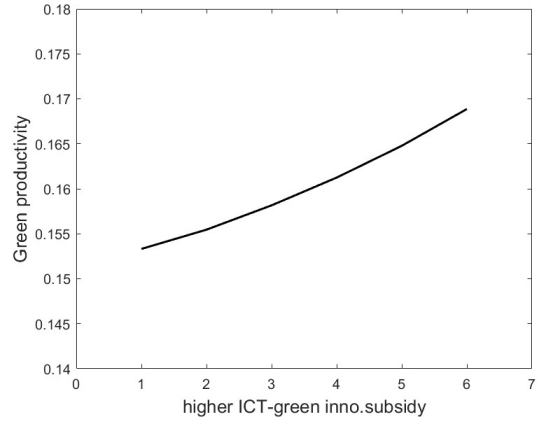
(c) high dirty innovation cost: green firm share



(d) low dirty innovation cost: green firm share



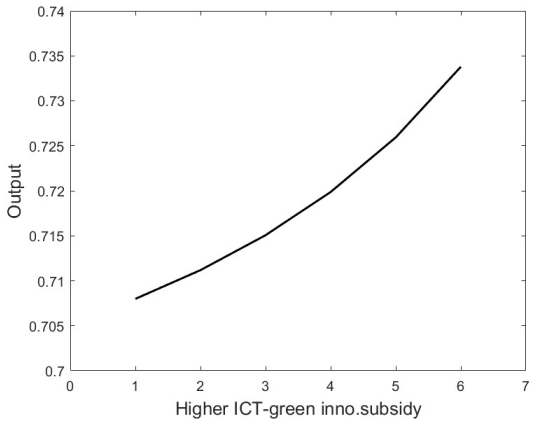
(e) high dirty innovation cost: green productivity



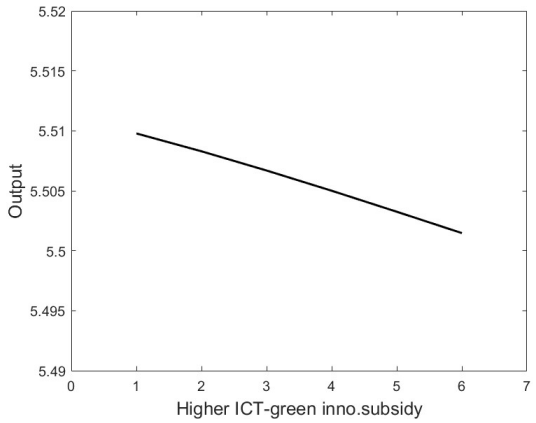
(f) low dirty innovation cost: green productivity

Figure 3.4: General equilibrium effects of innovation cost reduction

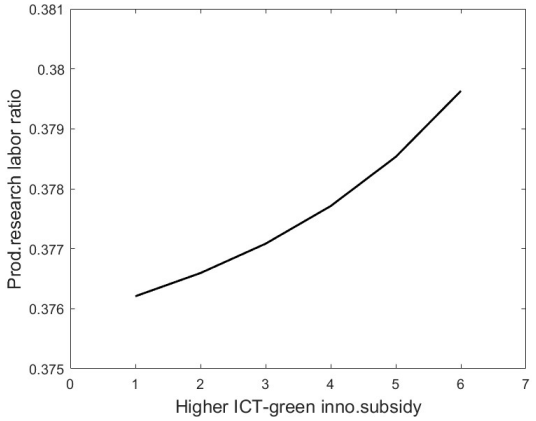
Note: Each grid of X-axis is to increase the green innovation subsidy such that innovation cost faced by firms are half.



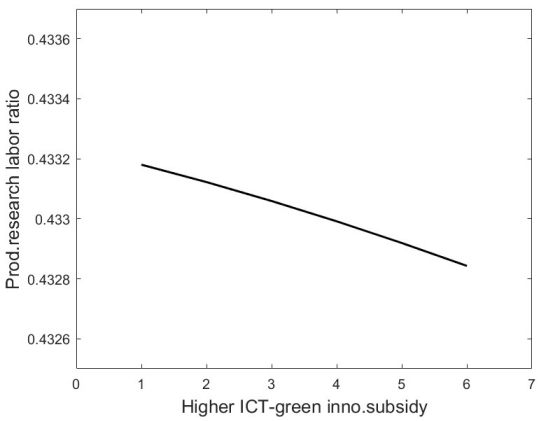
(a) high dirty innovation cost: Y



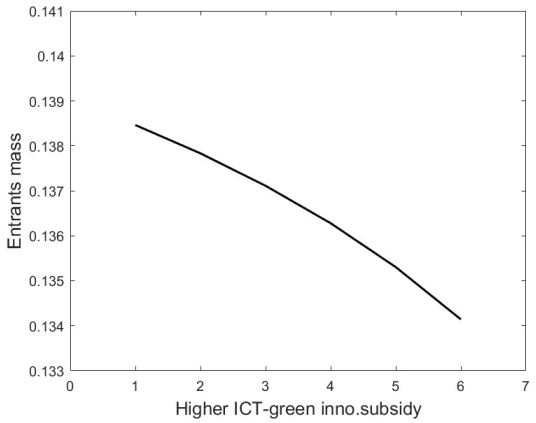
(b) low dirty innovation cost: Y



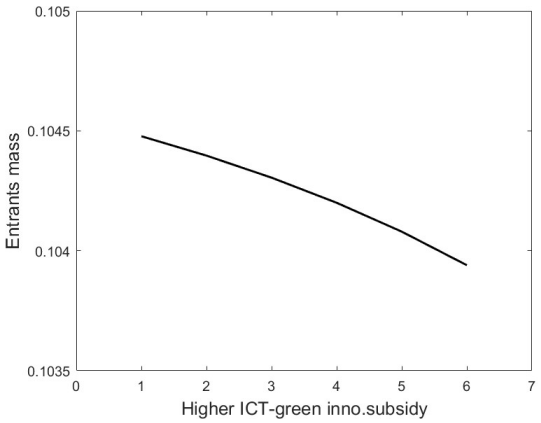
(c) high dirty innovation cost: χ



(d) low dirty innovation cost: χ



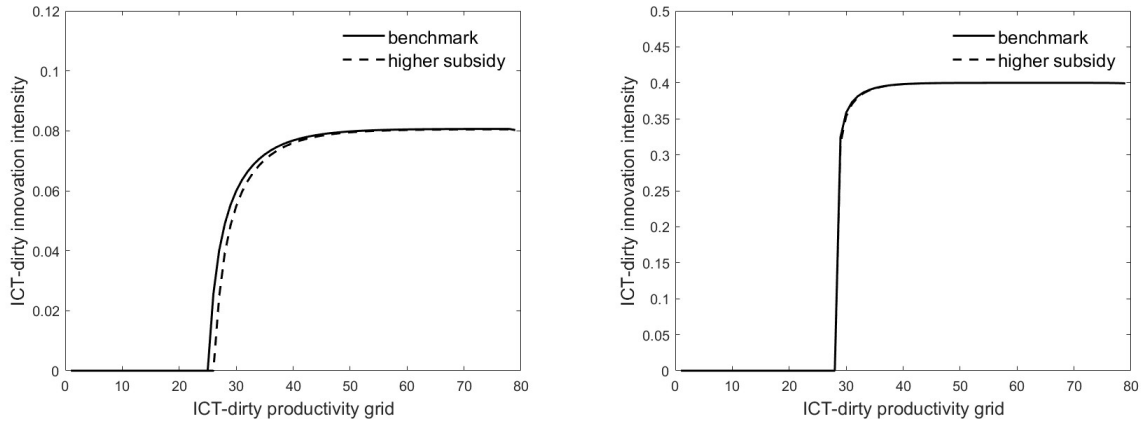
(e) high dirty innovation cost: M_e



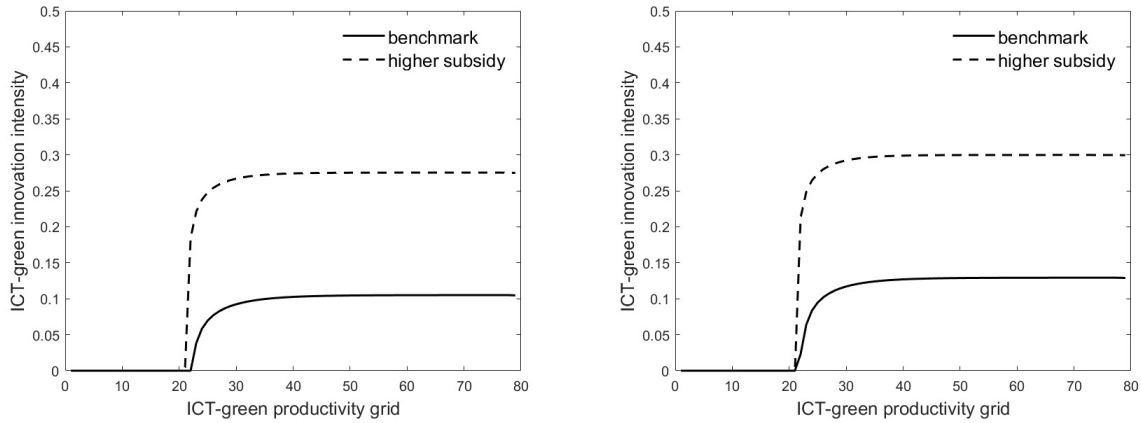
(f) low dirty innovation cost: M_e

Figure 3.5: General equilibrium effects of innovation cost reduction

Note: Each grid of X-axis is to increase the green innovation subsidy such that innovation cost faced by firms are half.



(a) high dirty innovation cost: e_d^u (b) low dirty innovation cost: e_d^u



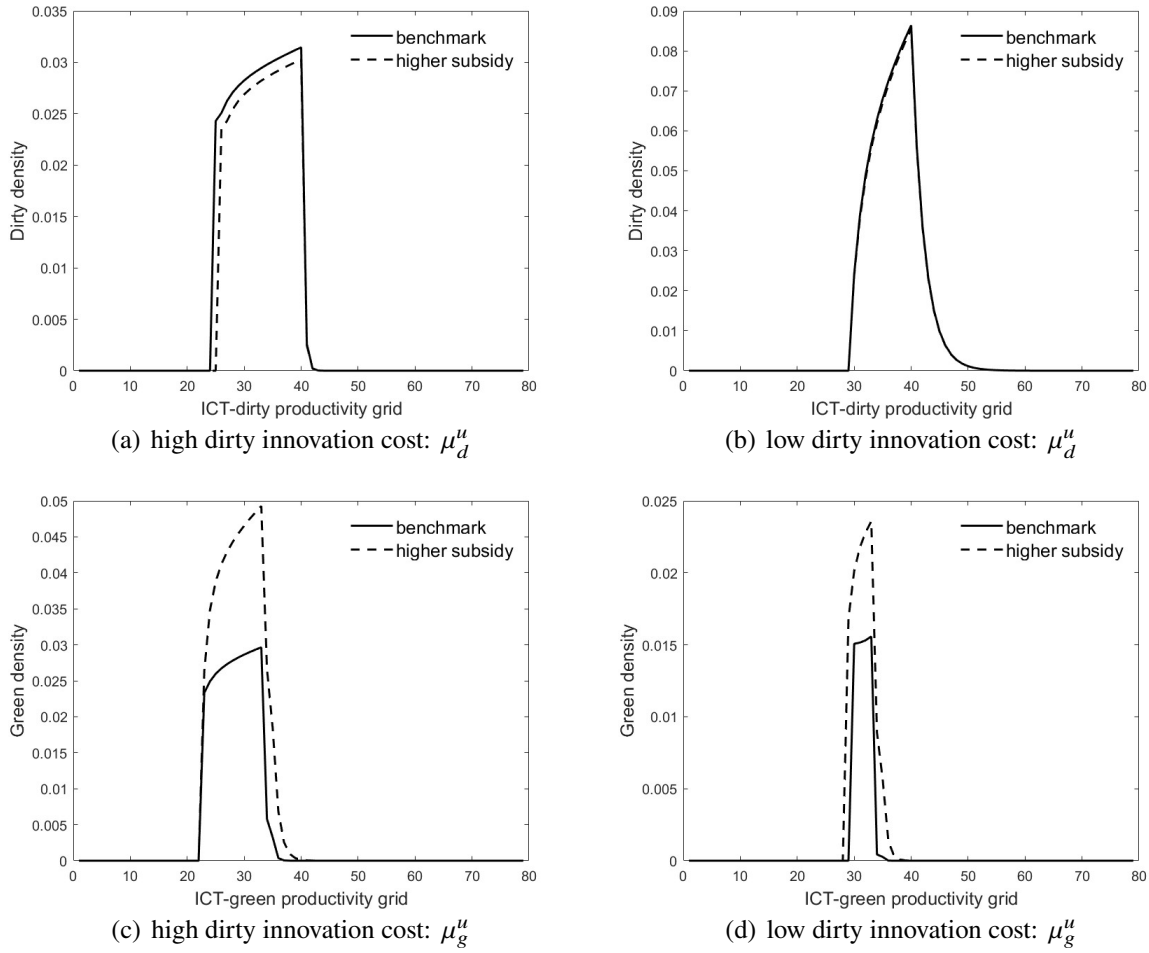
(c) high dirty innovation cost: e_g^u (d) low dirty innovation cost: e_g^u

Figure 3.6: General equilibrium effects of innovation cost reduction

Note: Each grid of X-axis is to increase the green innovation subsidy such that innovation cost faced by firms are half.

innovation relative to dirty innovation. Figure 3.6 shows that, in both cases, ICT firms increase green innovation and reduce dirty innovation. Figure 3.7 shows the corresponding distributional shift: ICT-green productivity moves upward, while ICT-dirty productivity shifts downward. The aggregate productivity response, however, differs across cases. When the opportunity cost of green innovation is low, aggregate productivity rises with the ICT-green subsidy. When the opportunity cost is high, aggregate productivity falls. Therefore, the relative cost of dirty and green innovation governs whether targeted green innovation subsidies raise aggregate productivity or mainly reallocate resources away from productive dirty technologies.

Figure 3.5 shows that labor reallocation moves with aggregate productivity, reflecting both



(a) high dirty innovation cost: μ_d^u (b) low dirty innovation cost: μ_d^u

(c) high dirty innovation cost: μ_g^u (d) low dirty innovation cost: μ_g^u

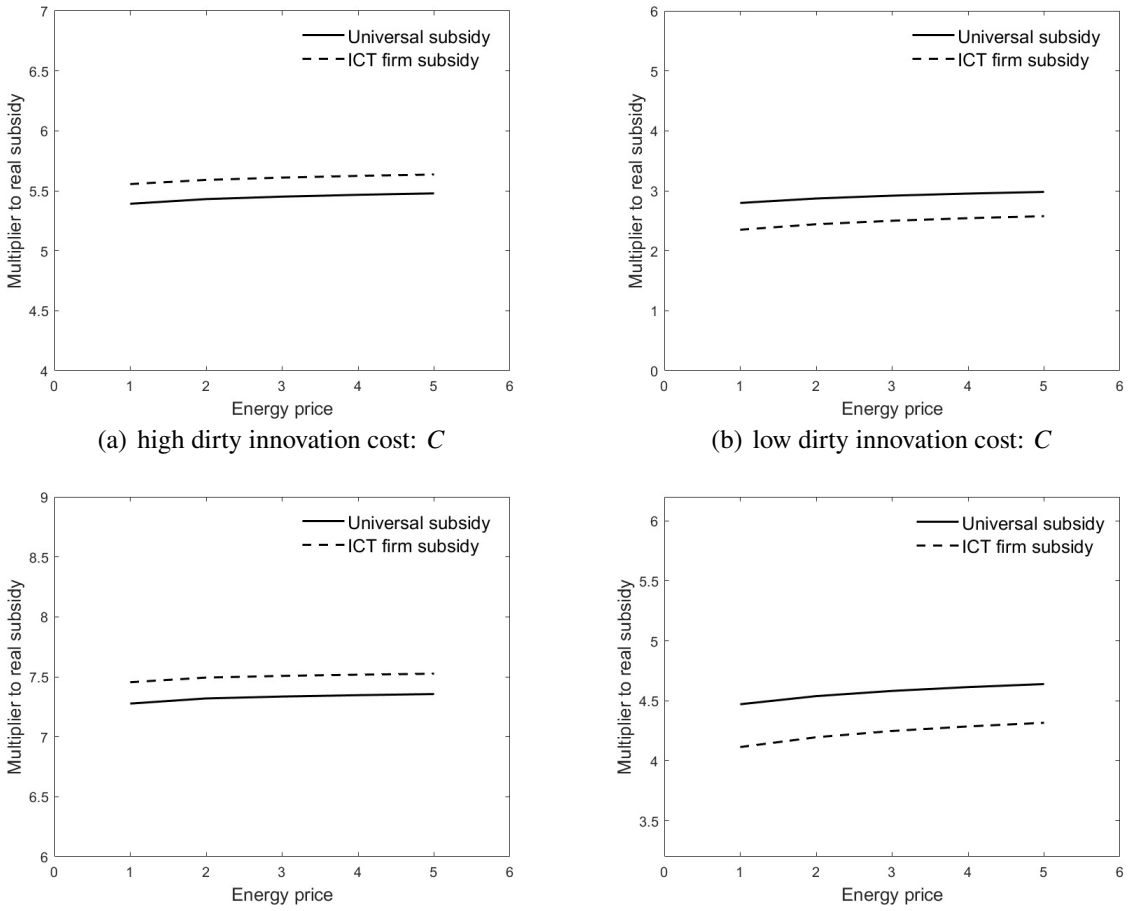
Figure 3.7: General equilibrium effects of innovation cost reduction

Note: Each grid of X-axis is to increase the green innovation subsidy such that innovation cost faced by firms are half.

reallocation between production and research and reallocation across technology classes. Entry also adjusts because entrants' expected value depends on market size, innovation returns, and labor allocation. In these simulations, the entrant mass falls as green innovation costs decline. Equation (3.45) clarifies why these general-equilibrium responses matter: productivity redistribution, labor reallocation, and entry all feed back into green variable profits, thereby amplifying or dampening the direct effect of innovation-cost reductions.

Green Innovation Subsidy: Universal or ICT Only To ground our policy counterfactuals empirically, we anchor our calibrations to historical U.S. clean energy R&D data. According to

the U.S. Energy Information Administration, public R&D dedicated to clean energy in 2016 was approximately $347 million, amounting to roughly 0.056% of total aggregate R&D expenditure. We use this 0.056% ratio as the baseline budget constraint for our subsidy experiments.



(a) high dirty innovation cost: C (b) low dirty innovation cost: C

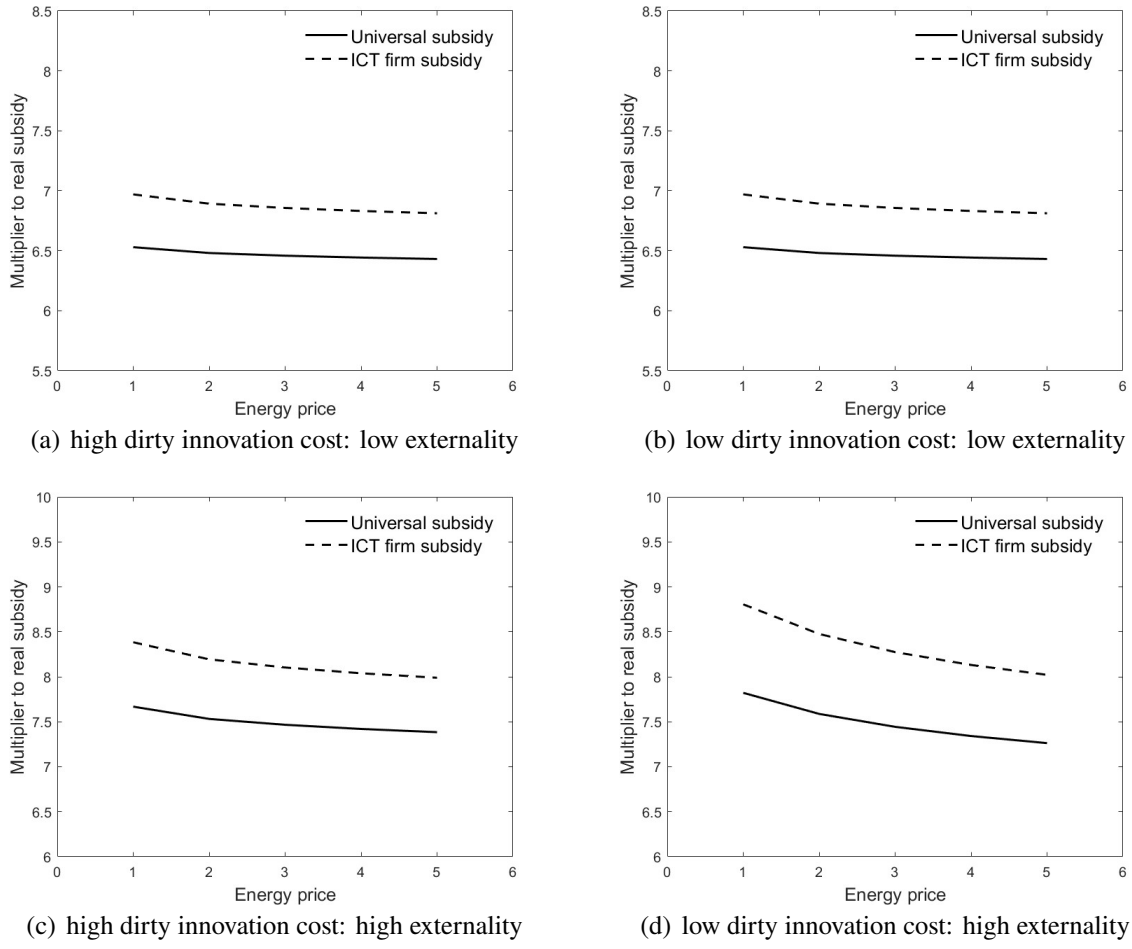
(c) high dirty innovation cost: A (d) low dirty innovation cost: A

Figure 3.8: Consumption and productivity change under subsidies

Note: The multiplier computed in the Y-axis is: $\frac{C^i - C^0}{S^i/P}$, which is the ratio of consumption increment to real subsidies. The subsidy amount of each policy is to target green subsidy to R&D ratio in the data, which is 0.056%.

First of all, we allocate the green innovation subsidy proportional to firm size which does not distinguish ICT or non-ICT firms. Then we concentrate all green subsidies on ICT firms. Both types of subsidies target data of 0.056% of total R&D spending in the economy.

As the energy price potentially affects aggregate productivity and the green transition, we compare the efficiency of policy under changes in the energy price. The standards we select is



(a) high dirty innovation cost: low externality

(b) low dirty innovation cost: low externality

(c) high dirty innovation cost: high externality

(d) low dirty innovation cost: high externality

Figure 3.9: Welfare change under subsidies: higher vs low externality

Note: The multiplier computed in the Y-axis is: $\frac{W^i - W^0}{S^i/P}$, which is the ratio of welfare increment to real subsidies. The subsidy amount of each policy is to target green subsidy to R&D ratio in the data, which is 0.056%.

to compare the policy efficiency to the case without any subsidy. The efficiency of policy i is measured by a multiplier:

$$\text{efficiency}_i = \frac{W^i - W^0}{S^i/P},$$

where W^i is welfare under policy i, as described in 3.1:

$$W = C - \Xi E.$$

W^0 is welfare under no policies. S^i/P is the amount of subsidy in terms of real goods.

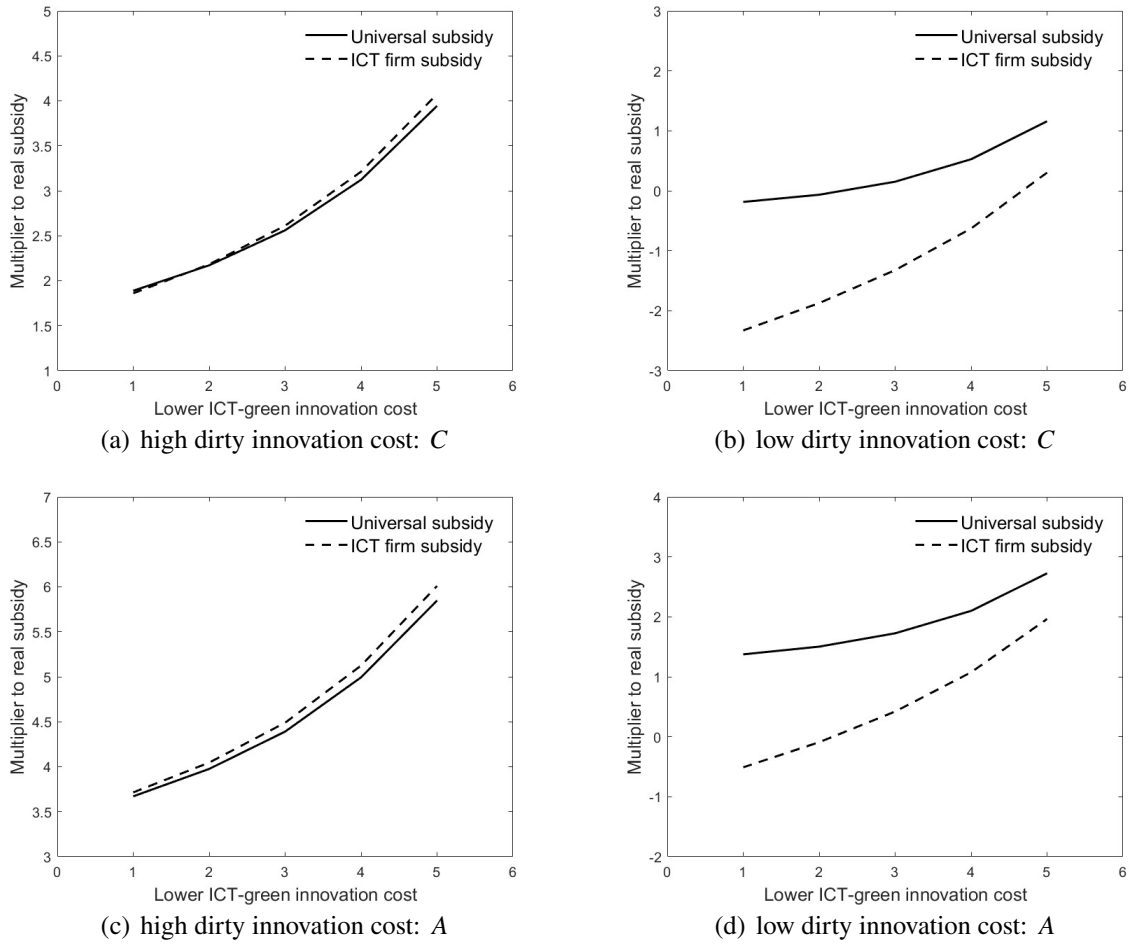
Policy under energy price change The consumption result is shown in the left panel of Figure 3.14. The Y-axis is the relative change compared to the benchmark without any subsidies. When the cost of dirty to green innovation is high, both subsidies increase consumption as in the left panel, and subsidizing green ICT firms are more efficient. Strikingly, when the opportunity cost is low (right panel), the universal subsidy generates a positive consumption response, whereas the highly concentrated ICT subsidy actually crowds out consumption by overallocating resources to a narrow subset of firms. The pattern is rather stable along the change of the energy price. The result is consistent with the above analysis that it is more efficient to concentrate subsidies on firms with a comparative advantage in green innovation when the resulting loss in dirty-technology productivity is low.

We also compute the welfare multiplier rather than the consumption multiplier in Figure 3.15. As in the first panel, in which case the cost of dirty to green innovation is relatively high, when the price of energy increases, the welfare increment generated by the ICT green subsidy decreases significantly. This implies that although the energy price and the green subsidy complement the green transition, the marginal effect of the ICT green subsidy is low when the energy price is already high. In addition, a higher price of energy drives down aggregate productivity, which also mitigates the effect of subsidy. When the cost of dirty to green innovation is relatively low, the decreasing effect is much weaker. This is because a lower relatively lower cost of dirty innovation weakens the effect of energy price on the green transition. The bottom panels are used to set a higher value of the externality parameter. In both cases, the welfare increase is higher compared with the low externality case and the subsidized ICT green innovation is significantly improved. But in case the cost of dirty to green innovation is relatively high, the sensitivity of the efficiency of the policy to the energy price is also increased.

Policy under ICT green innovation cost change

Policy under ICT entrants productivity change

Policy under green innovation cost change



(a) high dirty innovation cost: C (b) low dirty innovation cost: C

(c) high dirty innovation cost: A (d) low dirty innovation cost: A

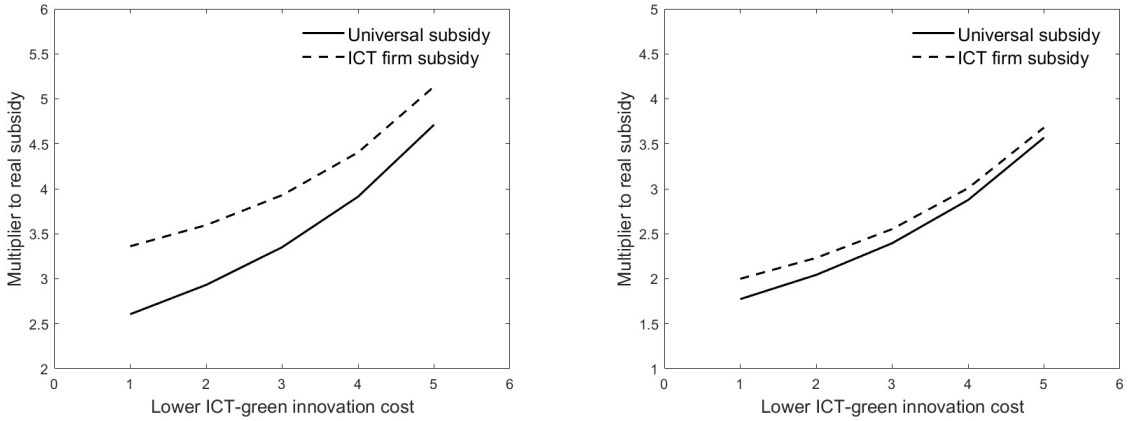
Figure 3.10: Consumption and productivity change under subsidies

Note: The multiplier computed in the Y-axis is: $\frac{C^i - C^0}{S^i/P}$, which is the ratio of consumption increment to real subsidies. The subsidy amount of each policy is to target green subsidy to R&D ratio in the data, which is 0.056%.

3.3.3 Unpacking Green Innovation Slowdown

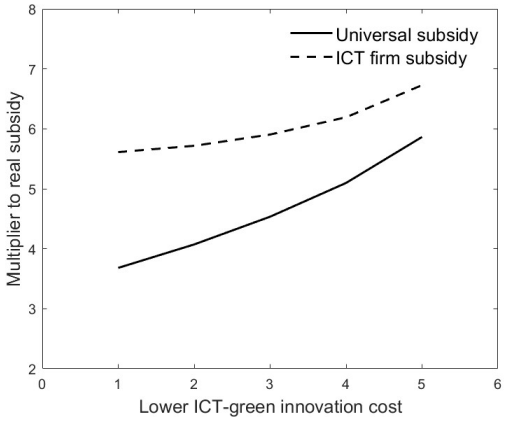
Our theoretical framework provides a structural mechanism to unpack the post-2010 slowdown in aggregate green innovation by synthesizing three distinct but interacting macroeconomic forces.

First, the primary driver is the deceleration in the decline of ICT-green innovation costs. As the "low-hanging fruit" of integrating digital capabilities with clean technologies are exhausted, the marginal cost of further ICT-driven green innovation stabilizes. This directly reduces the optimal green innovation intensity of ICT incumbents, dampening the intensive margin of green patenting and lowering their continuation value for transitioning to green production. Given the empirical

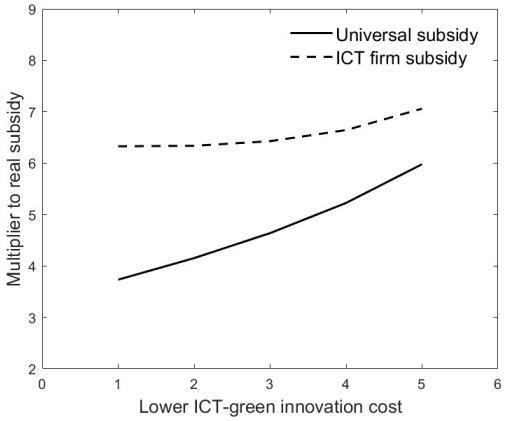


(a) high dirty innovation cost: low externality

(b) low dirty innovation cost: low externality



(c) high dirty innovation cost: high externality



(d) low dirty innovation cost: high externality

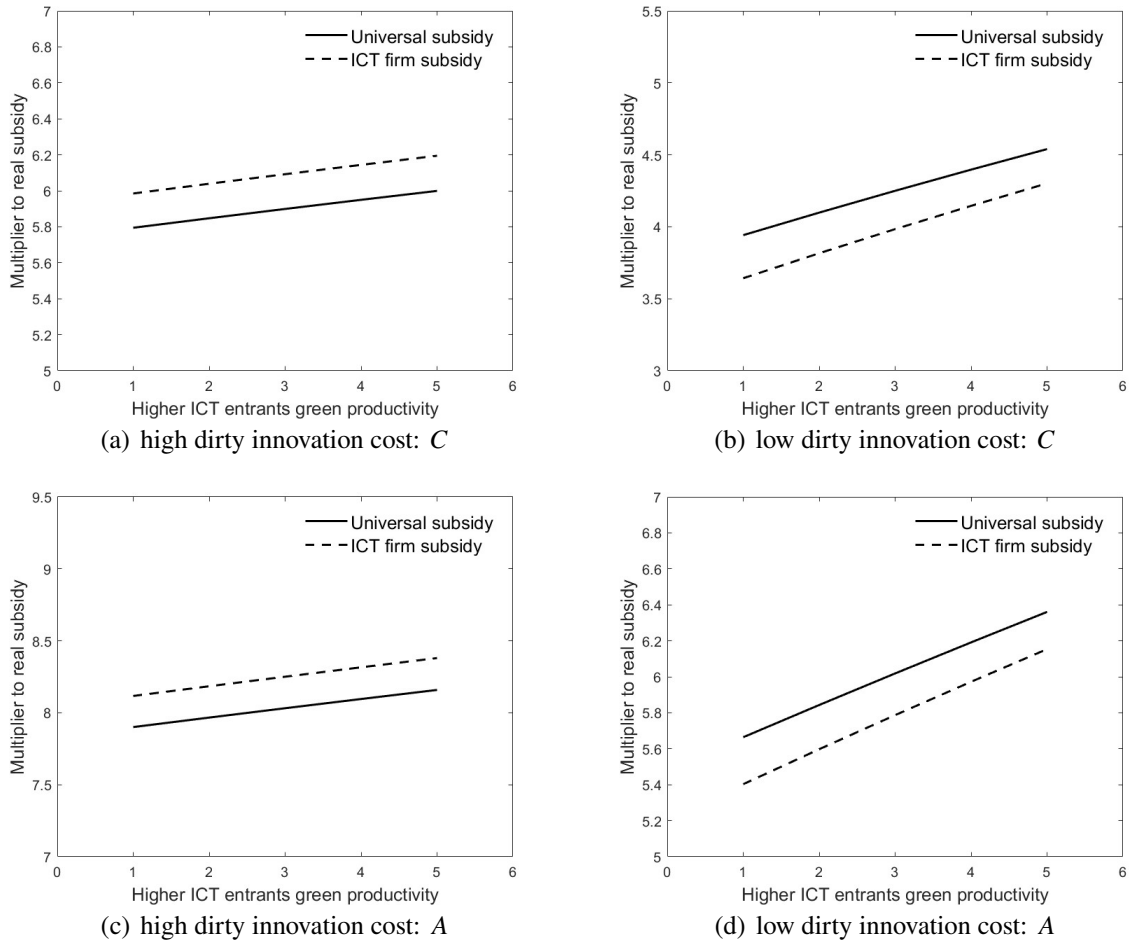
Figure 3.11: Welfare change under subsidies: higher vs low externality

Note: The multiplier computed in the Y-axis is: $\frac{W^i - W^0}{S^i/P}$, which is the ratio of welfare increment to real subsidies. The subsidy amount of each policy is to target green subsidy to R&D ratio in the data, which is 0.056%.

dominance of ICT firms in green innovation, this partial-equilibrium deterioration translates into a significant macroeconomic stagnation.

Second, a reduction in fossil energy prices—such as the drop caused by the shale gas revolution—mechanically increases the relative profitability of operating a dirty technology. In general equilibrium, this exogenous input price shock raises the opportunity cost of the green transition, thereby increasing the productivity threshold required for dirty firms to switch. This slows the extensive margin of clean technology adoption and reallocates aggregate research labor back toward dirty innovation.

Finally, a deterioration in the green productivity distribution of new entrants weakens the



(a) high dirty innovation cost: C (b) low dirty innovation cost: C

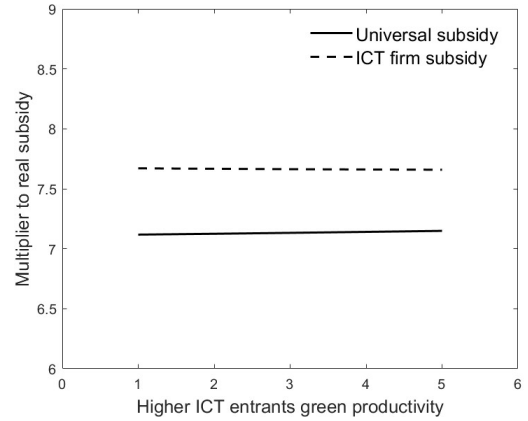
(c) high dirty innovation cost: A (d) low dirty innovation cost: A

Figure 3.12: Consumption and productivity change under subsidies

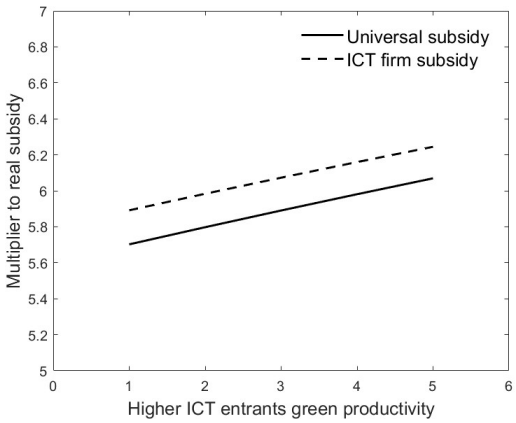
Note: The multiplier computed in the Y-axis is: $\frac{C^i - C^0}{S^i/P}$, which is the ratio of consumption increment to real subsidies. The subsidy amount of each policy is to target green subsidy to R&D ratio in the data, which is 0.056%.

economy's future innovation capacity. Because all entrants are born dirty but hold the option to transition, a worse green productivity draw at entry implies that fewer new firms will eventually cross the endogenous transition threshold over their lifecycle. Over time, this failure to replenish the green innovation base with high-potential young firms compounds the stagnation. Together, these three forces generate a mutually reinforcing feedback loop that rationalizes the post-2010 empirical slowdown in the green transition.

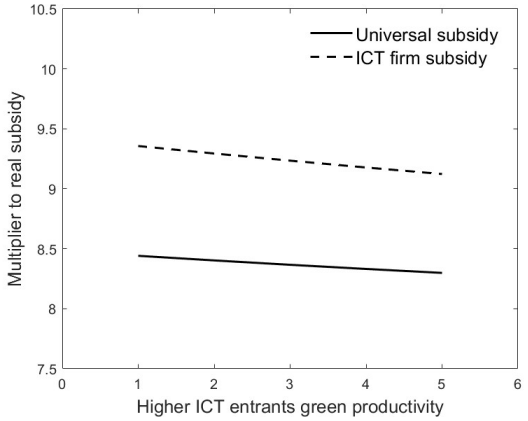
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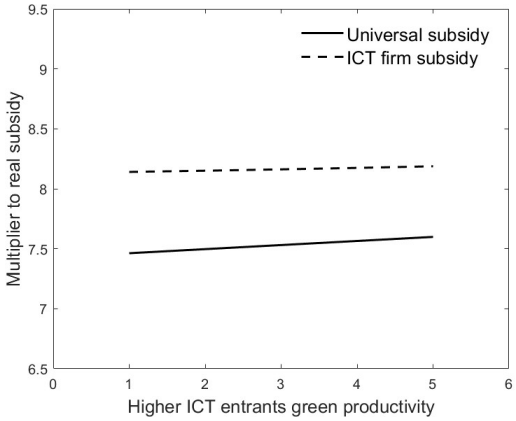
(a) high dirty innovation cost: low externality



(b) low dirty innovation cost: low externality



(c) high dirty innovation cost: high externality



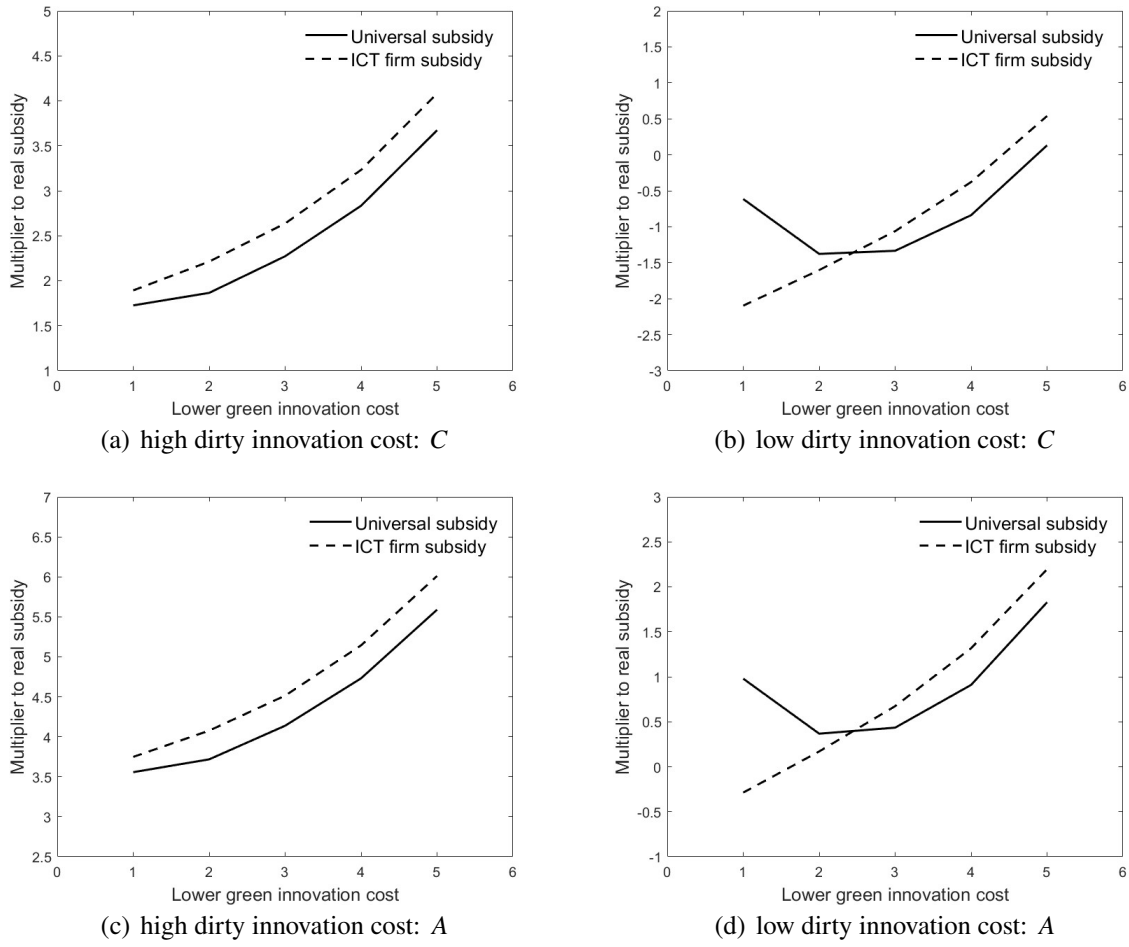
(d) low dirty innovation cost: high externality

Figure 3.13: Welfare change under subsidies: higher vs low externality

Note: The multiplier computed in the Y-axis is: $\frac{W^i - W^0}{S^i/P}$, which is the ratio of welfare increment to real subsidies. The subsidy amount of each policy is to target green subsidy to R&D ratio in the data, which is 0.056%.

3.3.4 Role of Other Mechanisms

Role of the share of final goods as intermediate inputs In this section, we study the interplay between the final goods input share of dirty technology (where the corresponding share for green technology is 1 minus the labor share) and the reduction in green innovation costs. This interplay is essential because changes in innovation costs precipitate adjustments in aggregate prices and productivity, which sequentially alter input prices for firms, thereby generating a feedback loop. Crucially, the direction of this effect depends on the real wage, $\frac{w}{P}$. If $\frac{w}{P} < 1$, labor is relatively cheaper than the final goods input. Holding the energy price constant, a higher final goods input



(a) high dirty innovation cost: C (b) low dirty innovation cost: C

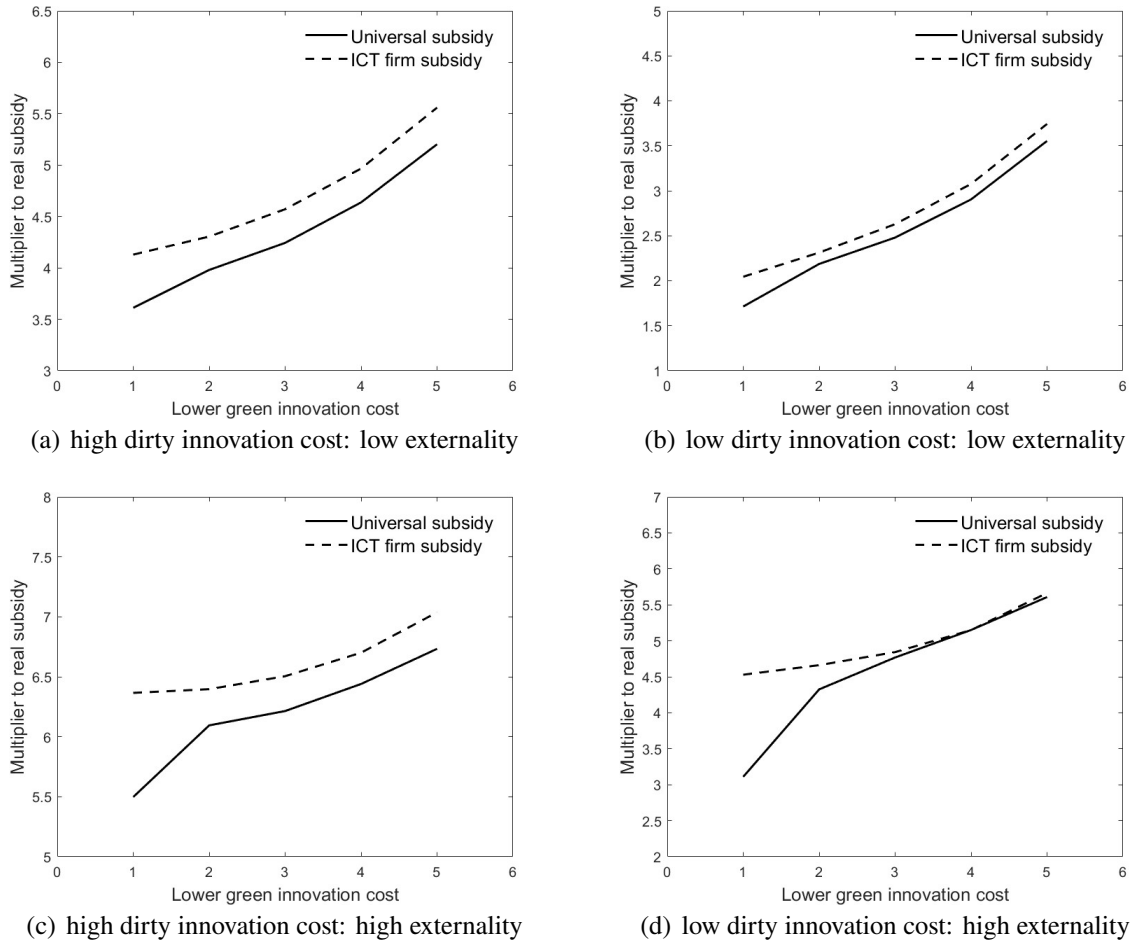
(c) high dirty innovation cost: A (d) low dirty innovation cost: A

Figure 3.14: Consumption and productivity change under subsidies

Note: The multiplier computed in the Y-axis is: $\frac{C^i - C^0}{S^i/P}$, which is the ratio of consumption increment to real subsidies. The subsidy amount of each policy is to target green subsidy to R&D ratio in the data, which is 0.056%.

share for dirty technology lowers the opportunity cost of production for green technology, thus implicitly subsidizing the green transition. Conversely, if $\frac{w}{P} > 1$, a higher final goods input share for dirty technology raises the opportunity cost of green production.

In Figure 3.16, the case falls into $\frac{w}{P} > 1$ that the final goods are cheaper than labor. As shown in the upper two panels in Figure 3.16, a lower share or a lower innovation cost implies a higher distribution of green productivity. The lower share also implies a higher degree of increment when reducing the cost of green innovation. This is because as in the middle panels, aggregate productivity is increasing and price is decreasing. The lower input share of dirty final goods implies that dirty technology benefits less from the decrease in input price, leading to a faster green



(a) high dirty innovation cost: low externality

(b) low dirty innovation cost: low externality

(c) high dirty innovation cost: high externality

(d) low dirty innovation cost: high externality

Figure 3.15: Welfare change under subsidies: higher vs low externality

Note: The multiplier computed in the Y-axis is: $\frac{W^i - W^0}{S^i/P}$, which is the ratio of welfare increment to real subsidies. The subsidy amount of each policy is to target green subsidy to R&D ratio in the data, which is 0.056%.

transition. As in the lower panels, a lower share implies a higher reallocation of labor to production as the innovation cost changes. It also implies a higher entrant mass due to lower productivity and a lower market size in this case.

Role of entrant productivity distribution In this section, we analyze how the change in entrant distributions affects the equilibrium outcomes. In a benchmark case, we assume that the ICT and non-ICT entrants have the same distribution that the probability mass declines with potential green productivity as they enter as dirty firms. We move the probability mass of low green productivity ICT firms to high green productivity ICT firms such that the distribution becomes first order

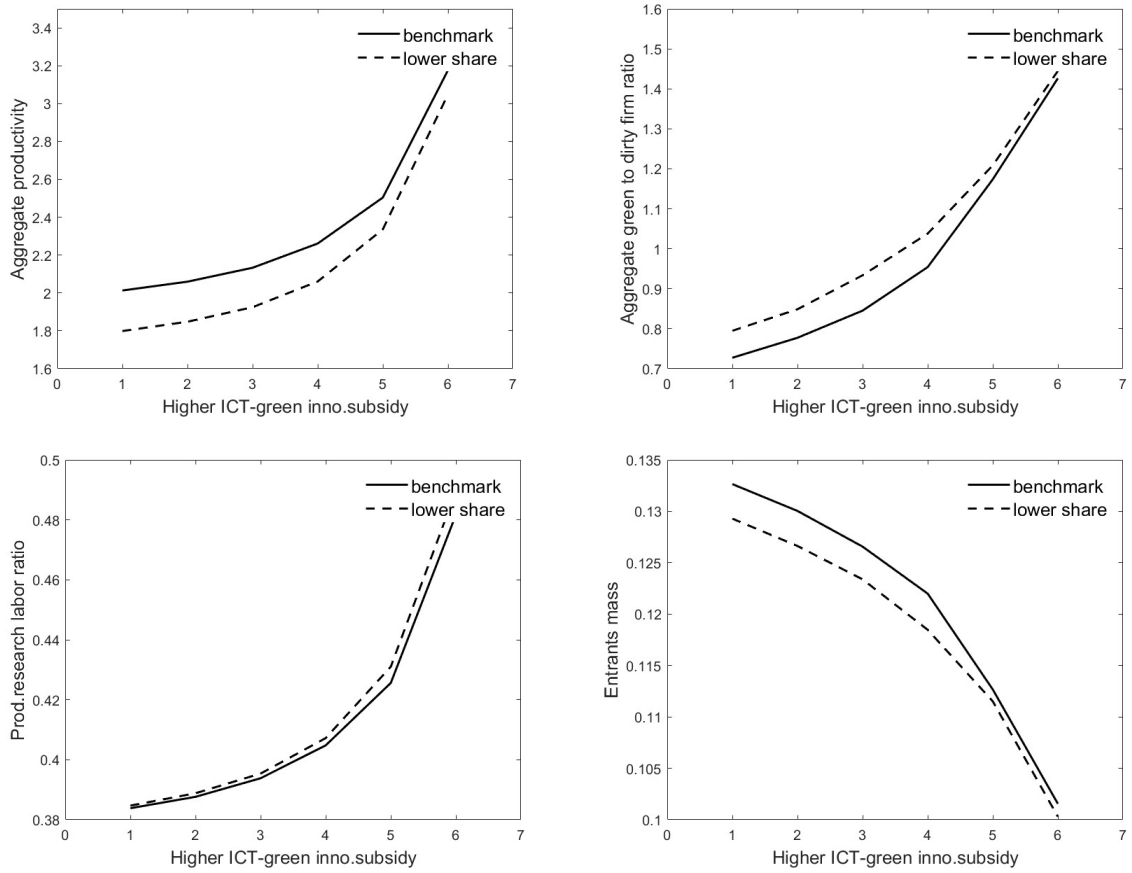


Figure 3.16: General equilibrium effects of final goods input share: high dirty innovation cost

stochastically dominates the previous one.

From the upper four panels of Figure 3.18, the productivity distribution of green ICT firms shifts rightward, implying a more green transition. The overall effect on aggregate productivity is also positive. However, when the opportunity cost of green technology is high, the positive effect generated by higher entrants' green productivity is weakened much as we can see that all the slopes are lower than the benchmark. The reason is that a higher loss of dirty productivity mitigates the positive effect originating from entrants' improvement.

Role of the energy price change In this part, we further explore how energy prices interact with the above change in green innovation costs. The first feature is that increasing the energy price reduces aggregate productivity. Although it encourages the green transition of firms, it causes a loss of dirty productivity by increasing its production cost as in the first panel of Figure 3.19, which

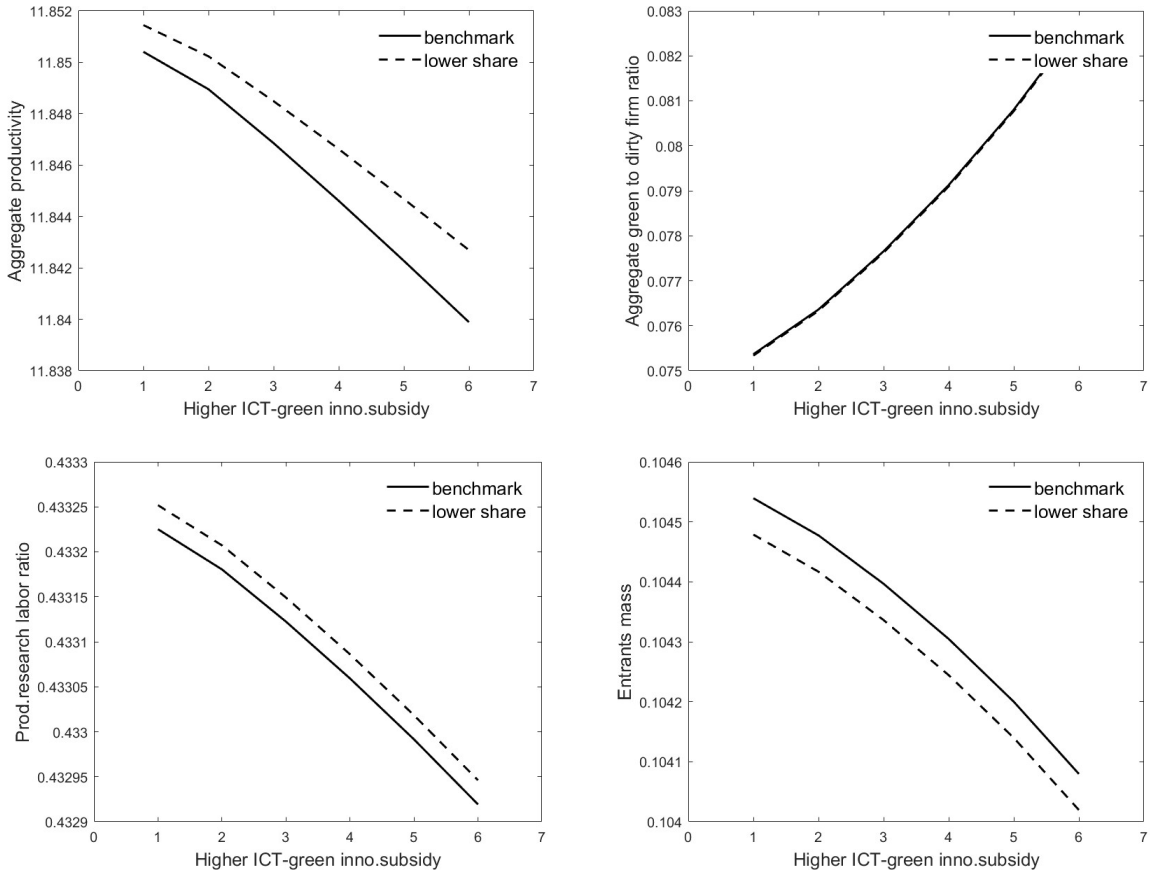


Figure 3.17: General equilibrium effects of final goods input share: low dirty innovation cost

shows that the overall effect on aggregate productivity is decreasing. Furthermore, it shows that when the opportunity cost of green innovation is higher, the energy price has a stronger effect on the decreasing productivity but a weaker effect on the green transition. The results demonstrate that a higher green innovation subsidy and a higher energy price complement the green transition.

The bottom panels of Figure 3.19 show the pattern of labor reallocation and the mass of the entrants, respectively. Higher energy price change implies higher labor reallocation towards production and lower entrants' mass but in opposite direction with lower green opportunity cost.

4 Quantitative Analysis

To quantitatively evaluate drivers of green innovation slowdown and the efficacy of targeted climate policies, we parameterize the model using a combination of external calibration and Simulated

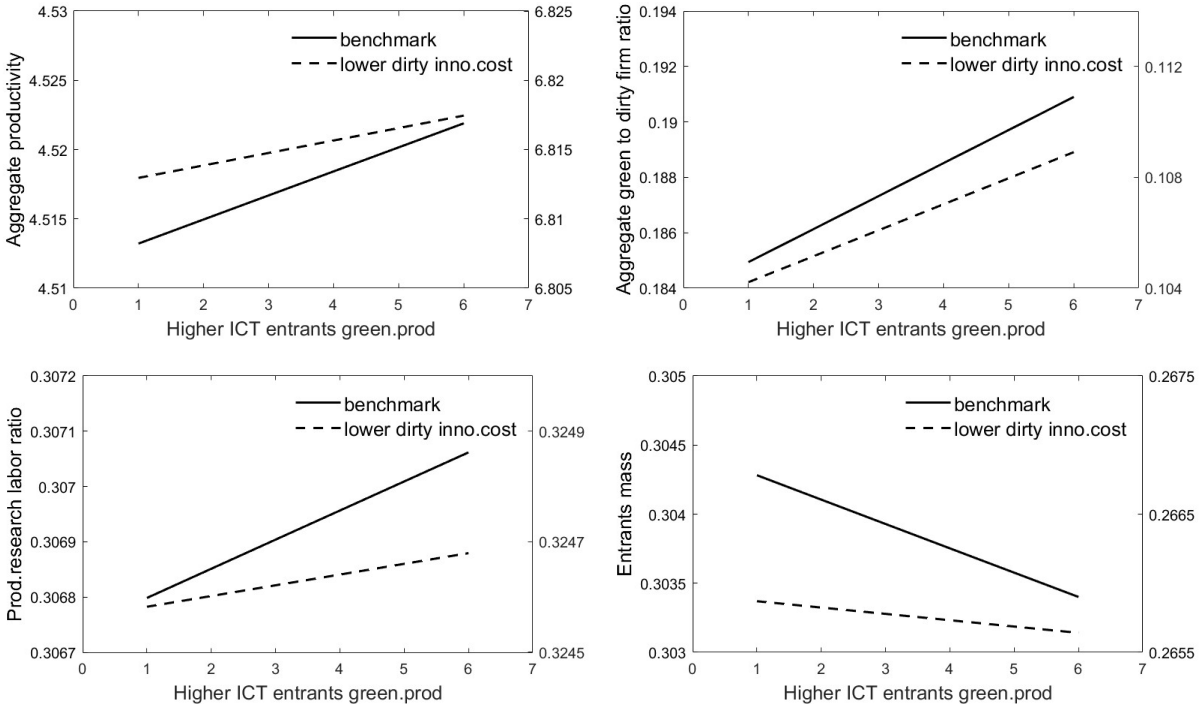


Figure 3.18: General equilibrium effects of ICT entrants green productivity change

Note: Each grid of X-axis is to reshape the ICT entrants green productivity distribution which first order stochastic dominates the previous one.

Method of Moments (SMM) estimation. The model features 18 parameters. We assign 10 parameters externally based on standard macroeconomic literature and directly observable data: $\{h_d, \xi_d, \xi_g^n, \xi_g^u, \alpha, \eta, \gamma, \sigma, \beta, \theta\}$. The remaining 8 parameters, $\{h_g^n, h_g^u, k^u, c, P_o, n_e, n_f, J\}$, are estimated internally to match key micro-level moments derived from the matched firm-patent dataset described in Section 2. We fix the curvature parameters of the innovation cost functions, focusing on the identification of scale parameters h_g^n and h_g^u to capture the differential R&D efficiency across firm types.

Next, we implement a green innovation subsidy schedule for all firms proportional to their firm size. We then compute another green subsidy policy which targets on ICT firms only. The result implies that the ICT targeted green subsidy policy always dominate the universal green subsidy policy, though the degree of dominance depends on energy price, ICT entrant's distribution and ICT-green innovation cost.

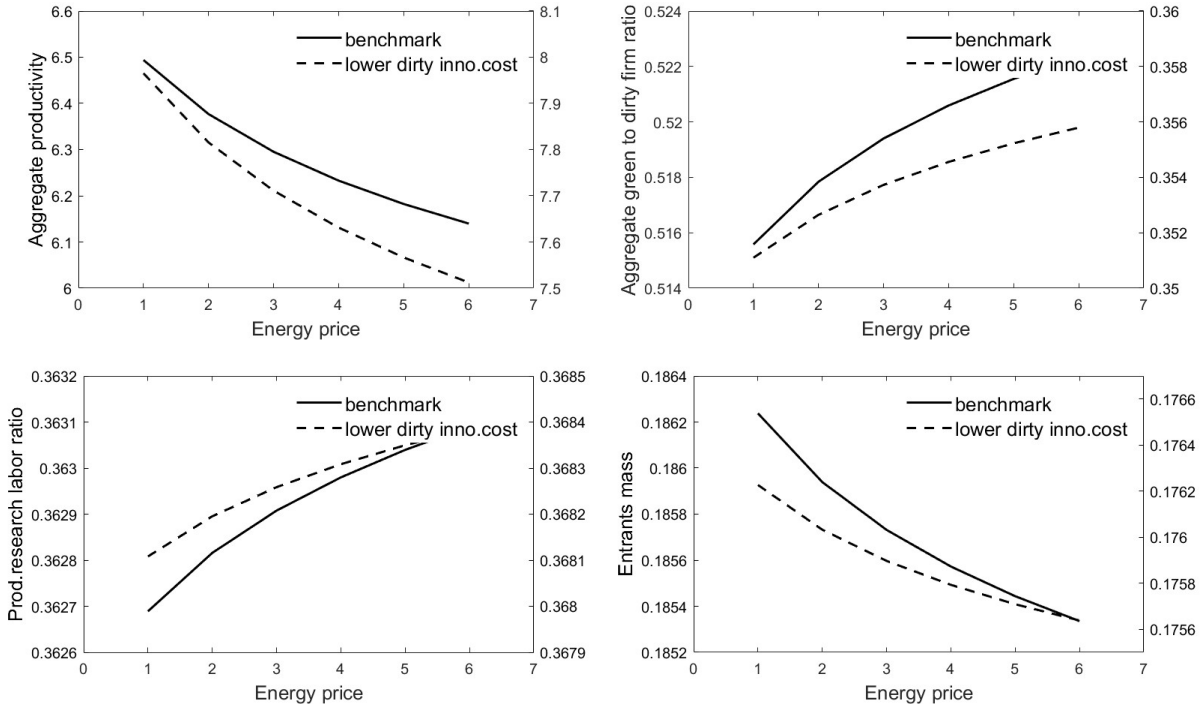


Figure 3.19: General equilibrium effects when energy price change

4.1 Parameterization

In this section, we estimate the parameters listed in Table 4.1 using simulated methods of moments (SMM). There are 16 parameters, 8 of them are externally estimated and 8 of them are internally estimated.

4.1.1 External Estimation

The labor share of income is to target recent data of firms in U.S., the value is estimated to be around 0.6 by Smith et al. (2022). The share of oil input when using dirty technology is $(1-\alpha)(1-\eta)$, the value of which is 0.04 implied by Acemoglu et al. (2016a). Therefore, given the labor share, the value of η is 0.9. Our model assumes an exogenous exit rate γ, we adopt the value used in Atkeson and Burstein (2010), to match the average exit rate of large firms in the United States. The discount factor β is computed by the inverse of the annual interest rate. The elasticity of substitution σ among the output varieties is a common estimator in the literature. Upon entry, firms are randomly assigned to be an ICT firm with probability θ, and we use the ratio of ICT innovators to total

Table 4.1: Model parameterization

Parameter	Notation	Value	Targeted Moments	Model	Data
External					
labor.share	α	0.65	Smith et al. (2022)		
final.goods.share	η	0.9	Acemoglu et al. (2016a)		
exit.prob	γ	0.0055	Atkeson and Burstein (2010)		
discount factor	β	0.95	interest.rate		
elas.of.subs	σ	1.5	common estimates		
share.ICT.firm	θ	0.515	share.ICT.firm		
dirty.cost	h_d	3.24	Assigned.value		
dirty.curvature	ξ_d	30	Assigned.value		
green.curvature	ξ_g^n	30	Assigned.value		
ICT.green.curvature	ξ_g^u	30	Assigned.value		
Internal					
non-ICT green cost	h_g^n	2.08	non-ICT.green.to.dirty.sales.ratio	0.73	0.72
ICT green cost	h_g^u	1.23	ICT.non-ICT.green.sales.ratio	1.72	1.72
ICT entrant distribution	k^u	0.728	green.firm.ratio	0.58	0.58
transition cost	c	0.05	non-ICT.green.dirty.firm.ratio	0.40	0.39
energy price	P_o	0.02	ratio.sd.log-sales.non-ICT.green/dirty	1.15	1.15
innovation step size	J	0.485	std.firm.log-sales	1.14	1.16
entry costs	n_e	2.118	entrant.ratio	0.02	0.02
operation costs	n_f	0.136	firm.exit.rate	0.09	0.10

Notes: Balleer and Endrikat (2023) summarize that the parameter value of Ξ could vary from 0.03 to 1.87 according to literature's estimation of how much people are willing to pay for reduce on unit of pollution. We consider different values of the parameter, which delivers different policy implications.

innovators in the patent data as its value. We set the dirty innovation cost scale and curvature parameter h_d, ξ_d, the curvatures of green innovation and non-ICT green innovation cost ξ_g, ξ_g^u as given.

4.1.2 Internal Estimation

To ensure identification, we partition the internally estimated parameters into two blocks based on their primary sensitivity to specific data moments. The first group contains 5 parameters $h_g^n, h_g^u, k^u, c, P_o$. The second group contains 3 parameters n_e, n_f, J .

The first group includes the scalars of the cost of green innovation of ICT and non-ICT firms h_g^u, h_g^n. The other three parameters are the transition cost c, the shape of the ICT entrants distribution

k^u, and the energy price P_o. We jointly discipline these parameters from the following moments: 1. non-ICT green to dirty firms' sales ratio; 2. ICT green to non-ICT green firms' sales ratio; 3. green firm ratio; 4. non-ICT green to dirty firm ratio; 5. ratio of log-sales standard deviation of non-ICT green firms to dirty firms.

The second group includes three parameters. The innovation step size J is estimated to match the standard deviation of firm log-sales. n_e affects the entry mass from free entry decisions, and we match it to real entrants' rate[11]. n_f affects firms that hit the margin of exit or maintain operations and we use the firm exit rate to match this moment.

We then jointly minimize the loss function within each group as follows:

$$\min \sum_{k=1}^{N} \frac{|model_k - data_k|}{(|model_k| + |data_k|)^{\frac{1}{2}}} \tag{4.1}$$

The data we target is the data in 2006. This year serves as a benchmark during of our main interested sample period from 2006 to 2014, that witness a first emerging but then stagnation of green and ICT-green related indicators of green innovation. The estimated parameter values and matched moments are listed in Table 4.1.

4.2 Model Validation

To validate the model and unpack the drivers of the post-2010 green innovation slowdown, we estimate the model to back out the implied time paths of three key exogenous forcing variables: the energy price (P_o), the green productivity distribution of ICT entrants (k^u), and the ICT green innovation cost (h_g^u). We map these unobserved forcing variables to three dynamically evolving empirical moments: the aggregate share of green firms, the ICT to non-ICT green firms' sales ratio, and the overall green to dirty firms' sales ratio.

Motivated by the previous literature, we focus on these three parameters. Acemoglu et al. (2023) trace part of the green slowdown to the shale gas revolution: the large and persistent decline

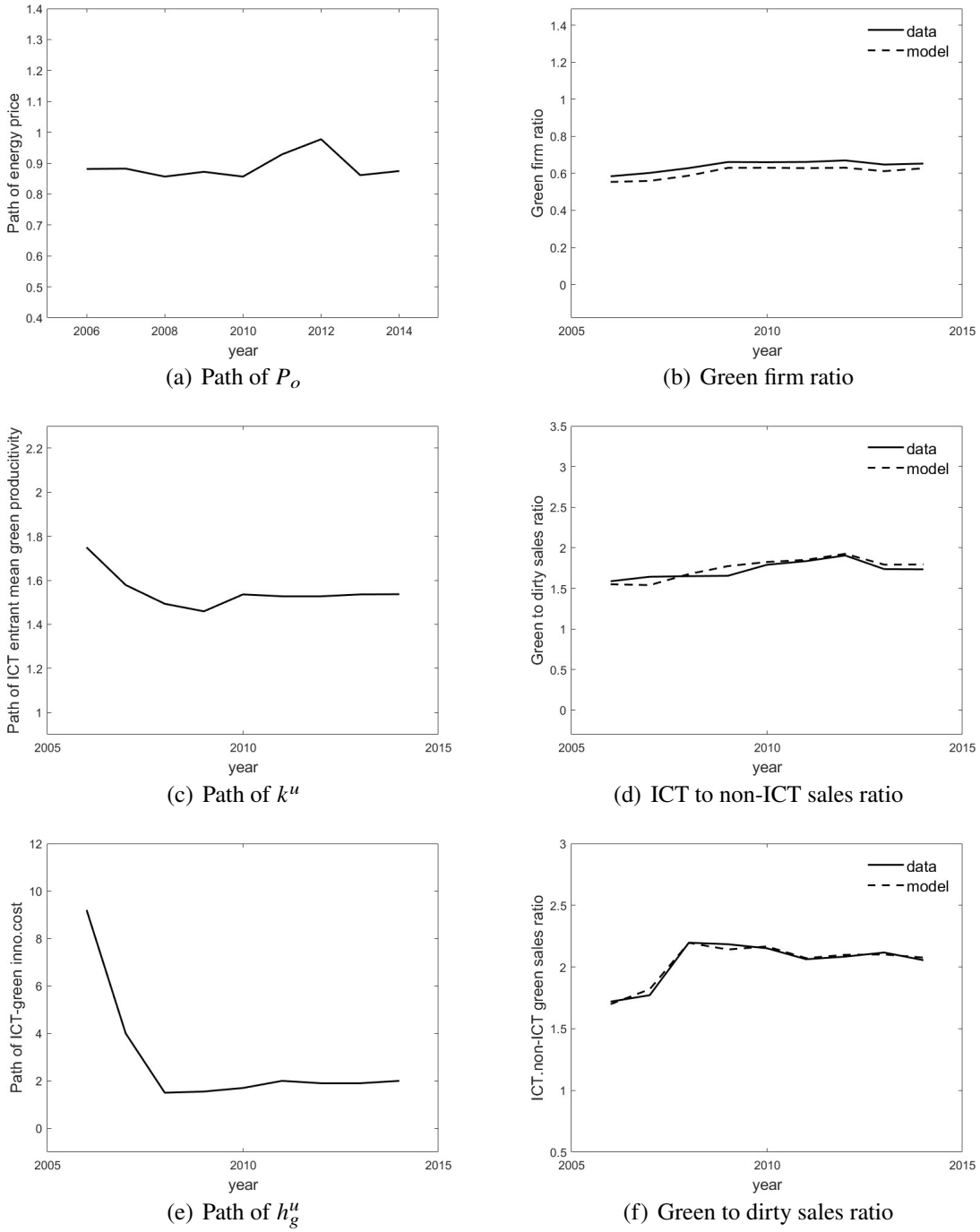
[11] Clementi and Palazzo (2016) calibrate their model with a targeted firm entry rate of 0.062 and firm inaction rate 0.081. Decker et al. (2016) estimates U.S. firm entry rate drop to around 0.02 and firm exit rate around 0.05 around 2010.

in the cost of fossil energy - lowered the relative profitability of green technologies and discouraged innovation in clean alternatives. This motivates us to model changing energy prices. Atkeson and Kehoe (2007) and Aghion et al. (2009) explain the growth of the productivity of specific technologies of incumbents with the productivity of the entrants. Hockerts and Wüstenhagen (2010) emphasizes the impact of green entrants on incumbents' green transition and sustainability goal of the economy. Though our paper abstracts from the strategic interactions, we simply nest the impact into entrants' green productivity and influence through adjustments of aggregate variables. Acemoglu et al. (2016a) and Aghion et al. (2024) model that the competition between green and dirty technologies depends on the creative destruction rate between them, which is based on the relative cost of innovation. Our paper also emphasizes the importance of this mechanism. Specifically, we are interested in varying the cost of ICT-green innovation in this paper to study the green transition.

4.2.1 Green Innovation Slowdown: Model VS Data

The model-implied evolution of the energy price, displayed in the top-left panel of Figure 4.1, exhibits a steady increase until 2011, followed by a sharp decline. This trajectory generates an initial surge in the incentive for clean technology adoption, which subsequently dissipates. Though joint targeted, a closely related moment is the share of green firms among all firms in the economy. The time series is shown as in the first right panel of Figure 4.1: the quickly emerging of the share of green firms since 2006 up to 2009 or 2010, and then witnesses a stagnation and drop until 2014. The energy price change can preliminarily explain the change in the sorting of firms to dirty and green technology, but unable to tell the differences between ICT and non-ICT firms.

The data implies the path of green productivity distribution of ICT entrants, the mean of the distribution is shown in the second left panel of Figure 4.1. The pattern shows that ICT entrants productivity decreases first and then increases until the stagnation since 2010. The explanation is that entrants distribution is more powerful to generate change in extensive margin green transition rather than incremental green innovation that are reflected from sales ratio. Hence, it first implies lower entrant distribution in face of a widening gap between green firm ratio and green sales



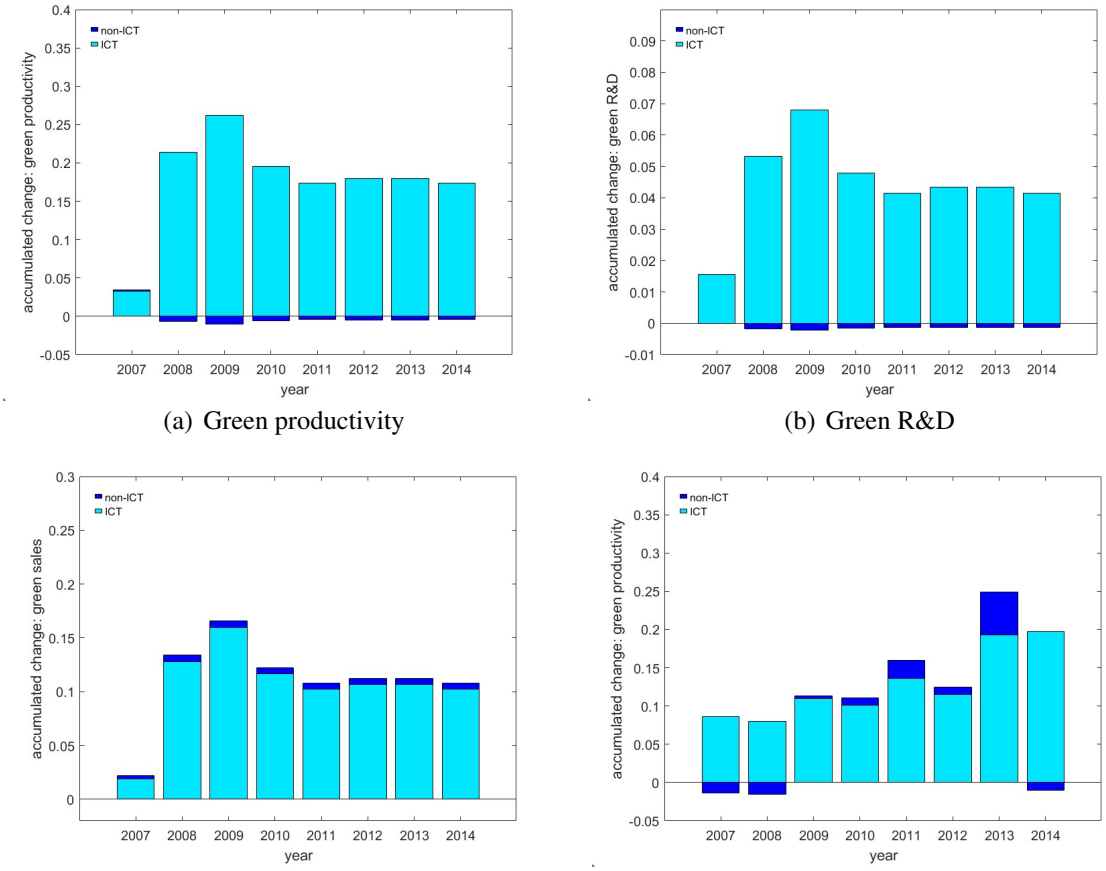
(a) Path of P_o (b) Green firm ratio

(c) Path of k^u (d) ICT to non-ICT sales ratio

(e) Path of h_g^u (f) Green to dirty sales ratio

Figure 4.1: Trends of parameter implied from data

ratio. But then the pattern reverses which implies a higher and stagnated entrants productivity distribution. The moments are shown in the second right panel of Figure 4.1, as the sales share increases gradually but slows down around 2010 and drops. The emergence of it lags behind the green firm ratio change.



(a) Green productivity (b) Green R&D

(c) Green sales (d) Green sales(data)

Figure 4.2: Accumulated change of aggregate variables

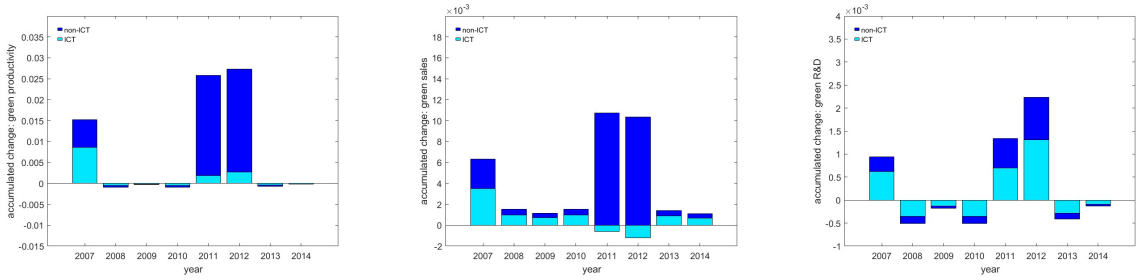
The structurally estimated path of the ICT-green innovation cost scalar h_g^u reveals dramatic non-linearities, as depicted in the bottom-left panel of Figure 4.1. The cost of ICT-enabled green innovation plummets between 2006 and 2009, driving rapid clean technology accumulation. Crucially, this cost decline abruptly halts in 2010, partially reversing before entering a sustained period of stagnation. This parameter trajectory tightly matches the empirical ICT-to-non-ICT green sales ratio, which similarly plateaus around 2010. This exercise underscores that the exhaustion of low-hanging fruit in ICT-green innovation is the primary determinant of the broader green innovation slowdown.

Lastly, we jointly vary the three parameters to compute the accumulated changes of aggregate variables that 2006 serves as the benchmark year, as shown in Figure 4.2. The first panel is the accumulated change of aggregate green productivity, the second panel shows the change of

aggregate green sales and the third shows the aggregate successful green R&D. Our model implies a stagnation of green productivity and innovation around 2010 which are mainly driven by ICT firms.

4.3 Disentangling Drivers of Green Innovation Slowdown

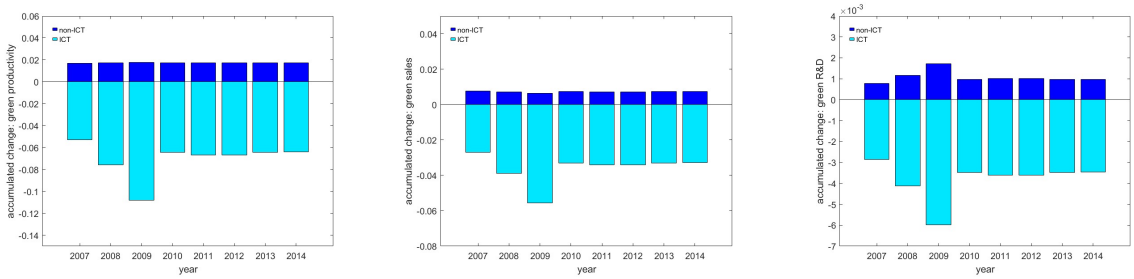
Change of Energy Prices Prior work, including Popp et al. (2022), Acemoglu et al. (2023), and Aghion et al. (2024), emphasizes energy prices as an important determinant of the opportunity cost of green innovation, especially after the shale gas expansion lowered fossil-energy prices. Our model incorporates this channel together with the ICT entrant distribution and ICT-green innovation costs. Figure 4.3 shows that energy prices mainly affect aggregate green productivity and non-ICT green sales. For green R&D, the response is more evenly distributed across ICT and non-ICT firms. For example, in 2011, the energy-price channel accounts for roughly 25 percentage of the ICT-green productivity change generated by jointly varying all three parameters.



(a) green productivity (b) green sales (c) green R&D

Figure 4.3: Vary energy price

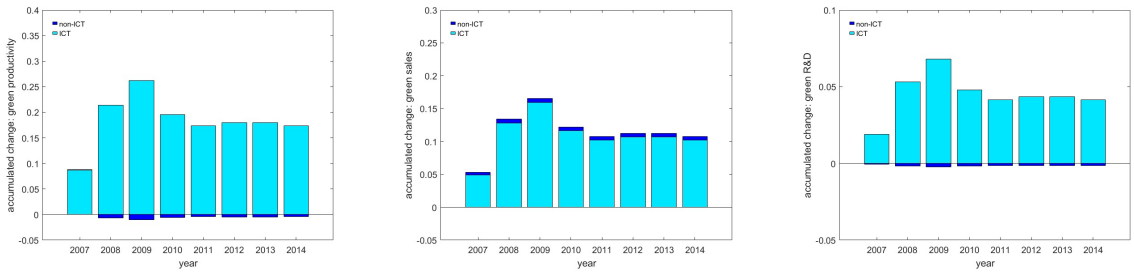
Change of ICT Entrants Productivity Distribution We next vary only the green-productivity distribution of ICT entrants. Figure 4.4 shows that the losses in green productivity, green sales, and green R&D associated with weaker ICT entrant quality peak around 2009 and then stabilize. This pattern suggests that the intensive transition margin, captured by green sales, initially grows faster than the extensive transition margin, captured by the green-firm share; during the stagnation period, the gap between the two margins becomes more stable.



(a) green productivity (b) green sales (c) green R&D

Figure 4.4: Vary ICT entrants productivity distribution

Change of ICT Green Innovation Cost Finally, we vary only the ICT-green innovation cost. Figure 4.5 generates the empirical pattern most directly: aggregate green productivity, green sales, and green R&D rise before 2010 and then stagnate. This channel is therefore the main driver of the moments in the quantitative exercise. It indicates that the slowdown in green sales and green innovation is driven primarily by ICT firms and, within that group, by the deceleration in ICT-green innovation cost reductions.



(a) green productivity (b) green sales (c) green R&D

Figure 4.5: Vary ICT-green innovation cost

4.4 Analysis of Subsidy Policies

We now use the estimated model to compare two subsidy regimes: a universal green innovation subsidy and an ICT-targeted green innovation subsidy. We compute welfare multipliers for 2006, representing the green innovation boom, and for 2010, representing the onset of the slowdown. The 2010 counterfactuals update the relevant parameter paths for energy prices, the ICT entrant distribution, and ICT-green innovation costs. Table 4.2 reports the results.

Table 4.2: Policy analysis: welfare multiplier of innovation subsidies

Exogenous ICT choice	year	$\Xi = 0$	$\Xi = 10$	$\Xi = 50$
Benchmark				
Policy1	2006	3.59	3.40	2.64
Policy2	2006	13.35	12.20	7.61
Energy price				
Policy1	2010	3.45	3.42	3.30
Policy2	2010	12.75	12.52	11.59
Entrant distribution				
Policy1	2010	3.41	3.26	2.62
Policy2	2010	15.40	14.00	8.39
Innovation cost				
Policy1	2010	3.49	3.34	2.71
Policy2	2010	17.14	15.97	11.29

Notes: The multiplier computed in the table is: $\frac{W^i - W^0}{S^i/P}$, which is the ratio of welfare increment to real subsidies. The subsidy amount of each policy is to target green subsidy to R&D ratio in the data, which is 0.056%.

The counterfactuals deliver three main conclusions. First, the ICT-targeted subsidy substantially outperforms the universal subsidy in both the 2006 boom environment and the 2010 slowdown environment. Because ICT firms have a comparative advantage in green innovation, targeting scarce fiscal resources toward these firms generates more welfare per unit of subsidy.

Second, this ranking is robust to different values of the environmental externality parameter Ξ. The absolute multipliers decline as the externality becomes more severe, but the ICT-targeted subsidy remains the more effective instrument.

Third, lower ICT-green innovation costs and higher ICT entrant green productivity complement ICT-targeted subsidies: the targeted multiplier rises relative to the benchmark year. These forces reduce the effectiveness of the universal subsidy because they widen the innovation advantage of ICT firms. The energy-price effect is more ambiguous. Higher energy prices weaken both policies when the environmental externality is low because they reduce aggregate productivity, but they

strengthen the policies when the externality is high because they induce additional switching toward green technology and reduce pollution.

4.5 Model Extensions

Appendix B.4 studies several model extensions to assess the robustness of the policy implications.

5 Conclusion

This paper investigates the puzzling deceleration in green innovation since the early 2010s. Leveraging rich U.S. patent and firm-level data, we develop an empirical decomposition framework revealing that the green transition is overwhelmingly driven by firms possessing distinct ICT capabilities. Crucially, we demonstrate that the aggregate macroeconomic stagnation in green patenting is mostly attributable to a sharp slowdown among these ICT-green firms. This motivates a general equilibrium model in which heterogeneous firms face different green innovation costs and make endogenous decisions about technology class choice, innovation, entry, and exit. Estimating the model, we find that the slowdown in ICT-green innovation cost reductions is the main force behind the stagnation in the green innovation transition. Falling energy prices and weaker ICT entrant green productivity also reduce incentives for green innovation, but their quantitative effects are smaller. Because ICT-green firms face distinct innovation costs and respond differently to market conditions, their behavior is central to the aggregate green transition. Policy counterfactuals show that an ICT-targeted green innovation subsidy outperforms a universal green innovation subsidy both before and after the slowdown.

Our emphasis on ICT capabilities is particularly salient given the current proliferation of artificial intelligence and the concomitant surge in energy demand from hyperscale digital infrastructure. As AI and complementary digital technologies increasingly permeate the innovation frontier, tech-intensive firms will act simultaneously as the primary engines of clean technological change and as major consumers of global energy output. Our findings provide a rigorous economic rationale for the "twin transition" agenda: to be effective and efficient, modern climate policy must explic-

itly account for the profound heterogeneity in innovation capabilities, recognizing that the road to decarbonization is increasingly digital.

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Online Appendix for "Unpacking the Green Innovation Slowdown" by Yeju Chen and Xiaomei Sui

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A Empirical Appendix

A.1 List of Green-Innovation-Related Technologies and Corresponding IPC Codes

We divide the industries according to patent codes to the second sub-level of category. We focus on patents that are relevant to dirty and green technology dichotomy. The categorization is as follows:

- Transportation: $B60 - B68$;
- Electricity: H;
- Mechanical Engineering except weapons and blasting: F except $F41, F42, F99$;
- Petroleum , Gas or Coke: $C10$;
- Hydraulic engineering: $E02$;
- Earth of rock drilling, Mining: $E21$;
- Inorganic chemistry: $C01$;
- Treatment of water, Waste water, or sludge: $C02$;
- Physical or chemical process of apparatus in general: $B01$

The list of green patents are drawn from green patent inventory from WIPO (World Intellectual Property Organization) official website: IPC green inventory.

The full list of ICT relevant patent is categorized according to Table 2 of Inaba and Squicciarini (2017). The IPC-based taxonomy of ICT technologies is called J-tag which is in collaboration with an expert from the Japan Patent Office. The category mainly falls in the following technology classes but with addition and exclusion based on expert discussions:

- Testing and Measuring: $G01$;
- Optical device: $G02$;

Table A.1: Summary statistics: green patents of ICT firms

ICT	application year	mean	sd	N	min	max
	1999	1.99	5.14	779	0	52
	2000	2.03	5.71	844	0	80
	2001	1.82	5.82	929	0	82
	2002	2.04	7.98	965	0	164
	2003	2.34	9.03	970	0	150
	2004	2.41	9.12	933	0	162
	2005	2.51	10.99	981	0	191
	2006	2.73	11.67	989	0	187
	2007	3.02	14.61	1011	0	253
	2008	3.37	20.23	1017	0	456
	2009	3.17	17.93	1062	0	314
	2010	3.71	23.53	1098	0	429
	2011	3.79	23.04	1117	0	475
	2012	3.47	19.07	1141	0	385
	2013	3.50	17.60	1156	0	346
	2014	3.12	15.09	1214	0	305
	2015	3.58	17.26	1150	0	345
	2016	3.58	16.12	1083	0	319
	2017	3.21	14.21	1106	0	306

- Computing, Calculating and Counting: $G06$;
- Signaling: $G08$;
- Information Storage: $G11$;
- Electric Elements: $H01$;
- Electronic Circuitry: $H03$;
- Electric Communication Technique: $H04$.

We also characterize the dirty patents, following the definition by Andres et al. (2022), which are related to combusting engine or fossil fuel production technique.

Table A.2: Summary statistics: green patents of non-ICT firm

non-ICT	application year	mean	sd	N	min	max
	1999	1.09	3.70	1525	0	69
	2000	1.04	3.36	1630	0	66
	2001	1.09	4.00	1707	0	72
	2002	1.03	4.42	1675	0	131
	2003	1.13	4.26	1701	0	102
	2004	1.01	4.04	1726	0	98
	2005	1.08	4.22	1751	0	85
	2006	1.08	3.95	1752	0	76
	2007	1.19	3.99	1824	0	73
	2008	1.25	4.95	1899	0	114
	2009	1.21	4.11	1902	0	78
	2010	1.21	3.91	2042	0	76
	2011	1.41	4.81	2097	0	111
	2012	1.29	4.47	2152	0	94
	2013	1.35	4.94	2283	0	105
	2014	1.32	5.52	2317	0	148
	2015	1.28	3.87	2269	0	65
	2016	1.35	4.71	2305	0	87
	2017	1.35	4.62	2300	0	99

A.2 Summary Statistics

We first present the summary statistics of green patents that are applied and granted by ICT and non-ICT firms respectively in each year. The results for ICT-green firms are shown in Table A.1. The results for non-ICT-green firms are shown in Table A.2. The results show that the ICT firms dominate in average application and granted number of green patents while the non-ICT firms dominate in number of green firms since they admit a wider range of industry. The ICT firms also have higher standard deviation of applied green patents. The results also imply that the mean green patents by both ICT and non-ICT firms peaked around 2010, but the pattern is more obvious for ICT firms.

Next, we provide information presented in Table A.3. The first column is the share of ICT-green firms to all green firms. The second column is the share of green patents applied and granted by these ICT-green firms. The last column is the share of ICT-green patents to all green patents in each year.

Table A.3: Summary statistics: other information

year	number of ICT firms	green patents by ICT firms	ICT-green patent
1999	0.34	0.48	0.23
2000	0.34	0.50	0.26
2001	0.35	0.48	0.26
2002	0.37	0.53	0.30
2003	0.36	0.54	0.33
2004	0.35	0.56	0.31
2005	0.36	0.57	0.32
2006	0.36	0.59	0.34
2007	0.36	0.58	0.32
2008	0.35	0.59	0.26
2009	0.36	0.59	0.26
2010	0.35	0.62	0.24
2011	0.35	0.59	0.25
2012	0.35	0.59	0.24
2013	0.34	0.57	0.22
2014	0.34	0.55	0.23
2015	0.34	0.59	0.21
2016	0.32	0.56	0.19
2017	0.32	0.53	0.22

The results reveal that ICT related firms account for a significant fraction in green firms. The fraction of green patents attributed to ICT-green firms emerge from around 50% to the peak of 62% in 2010 and then declines. In patent level, the similar pattern is shown while the peak is earlier which is around 2006.

A.3 Additional Empirical Facts

Trends of ICT-green patents Figure A.1 provides additional trends of the ICT-green patents. We find that the share of ICT-green patents to total green patents drop dramatically from 2006 until 2010 and keep declining after then. The number of ICT-green patents slowdown and drops from 2011.

Firm experience of green patenting We present the share of firms with three groups of experience of green innovation in Figure A.2. We find that the firms with experience less than 4 year

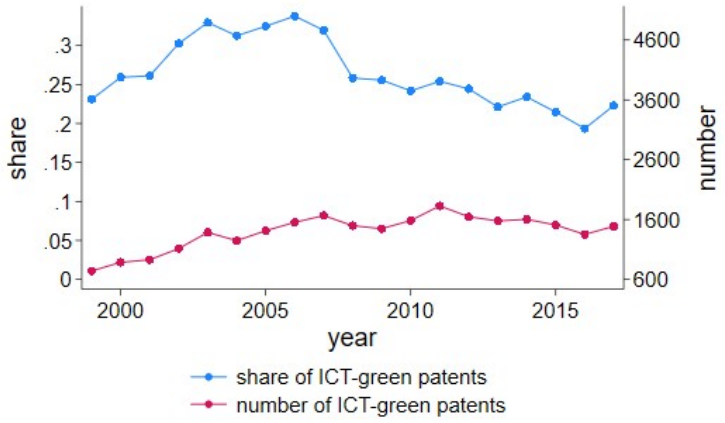


Figure A.1: ICT green innovation trends

Note: The ICT green patent is defined as patents fallen both into the IPC green inventory and the ICT patent category.

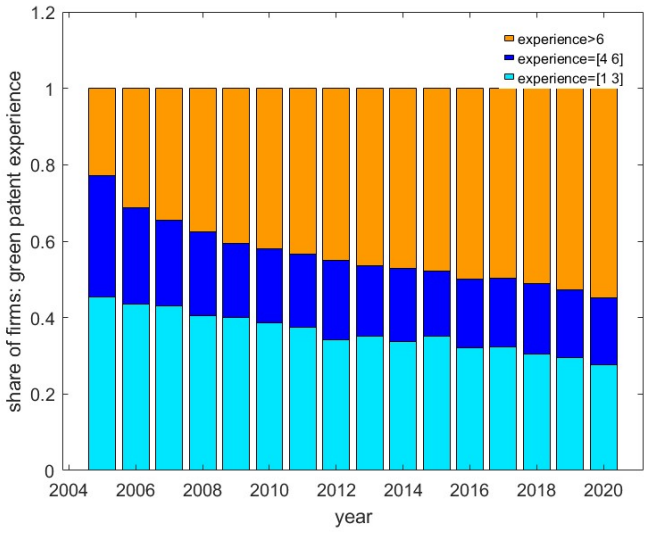
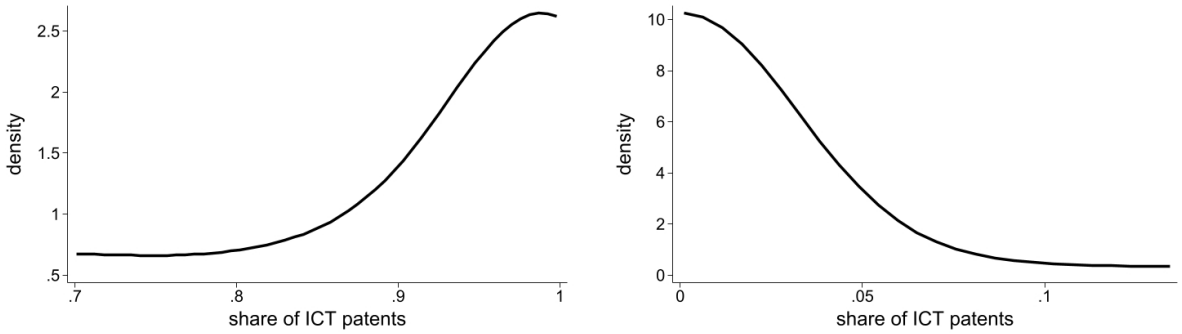


Figure A.2: Share of firms: experience of green patenting

Note: The graph shows the share of firms active in green patenting in a year which have experience of green patenting with experience of 1 to 3 years (green patenting entrants counted as 1 year experience), 4 to 6 years and above 6 years.

drops over time, indicating that entrants are playing a weaker role in green innovation. While the firms with experience more than 6 year increases gradually.

Share of ICT patents of ICT and non-ICT green firms In this part, we compare the degree of ICT applied in firms according to our cutoff definition of ICT-green firm being that higher than 5% of ICT-green patent throughout the sample makes the firm an ICT-green firm. The result is shown in Figure A.3. The left panel shows that most ICT-green firms have ICT patent share concentrated over than 70%, while the right panel shows that the non-ICT green firms have ICT patent share concentrated less than 5%. This justify our definition which emphasizes that ICT-green firms are deeply connected to ICT in technological sense.



(a) ICT-green firms (b) non-ICT green firms

Figure A.3: Density of firm share of ICT patents

Note: The share is the ratio of ICT patents to all patents of the firm throughout the sample. The density applies Gaussian kernel.

Share of green firms that cite ICT patents In this part, we study firm-level citations of ICT patents. The result is shown in Figure A.4. The blue line shows the share of green firms that have positive ICT citations overtime. The red line shows the share of green firms that have positive ICT citations where the ICT patents are granted by the firm itself overtime. The result shows that both of the measure grows overtime more than doubled.

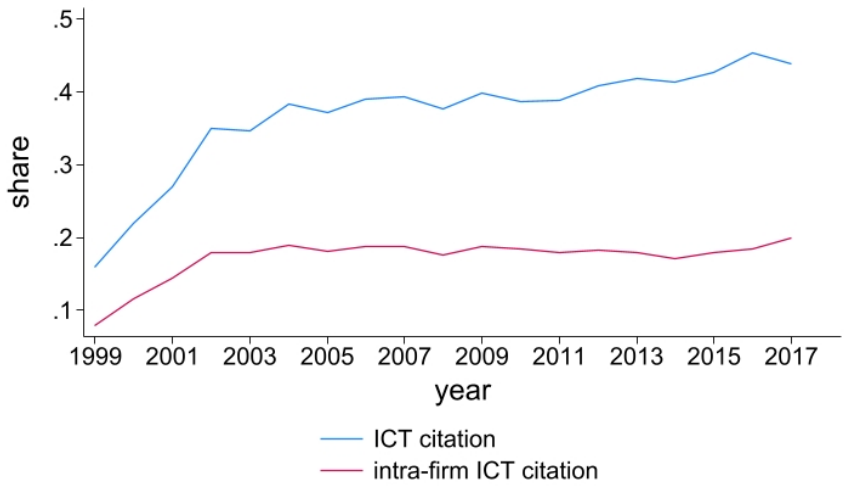


Figure A.4: Share of green firms that have ICT citations

Note: The blue line shows the share of green firms have positive ICT citations overtime. The red line shows the share of green firms have positive ICT citations that the ICT patent belongs to the firm itself overtime.

A.4 Robustness Check

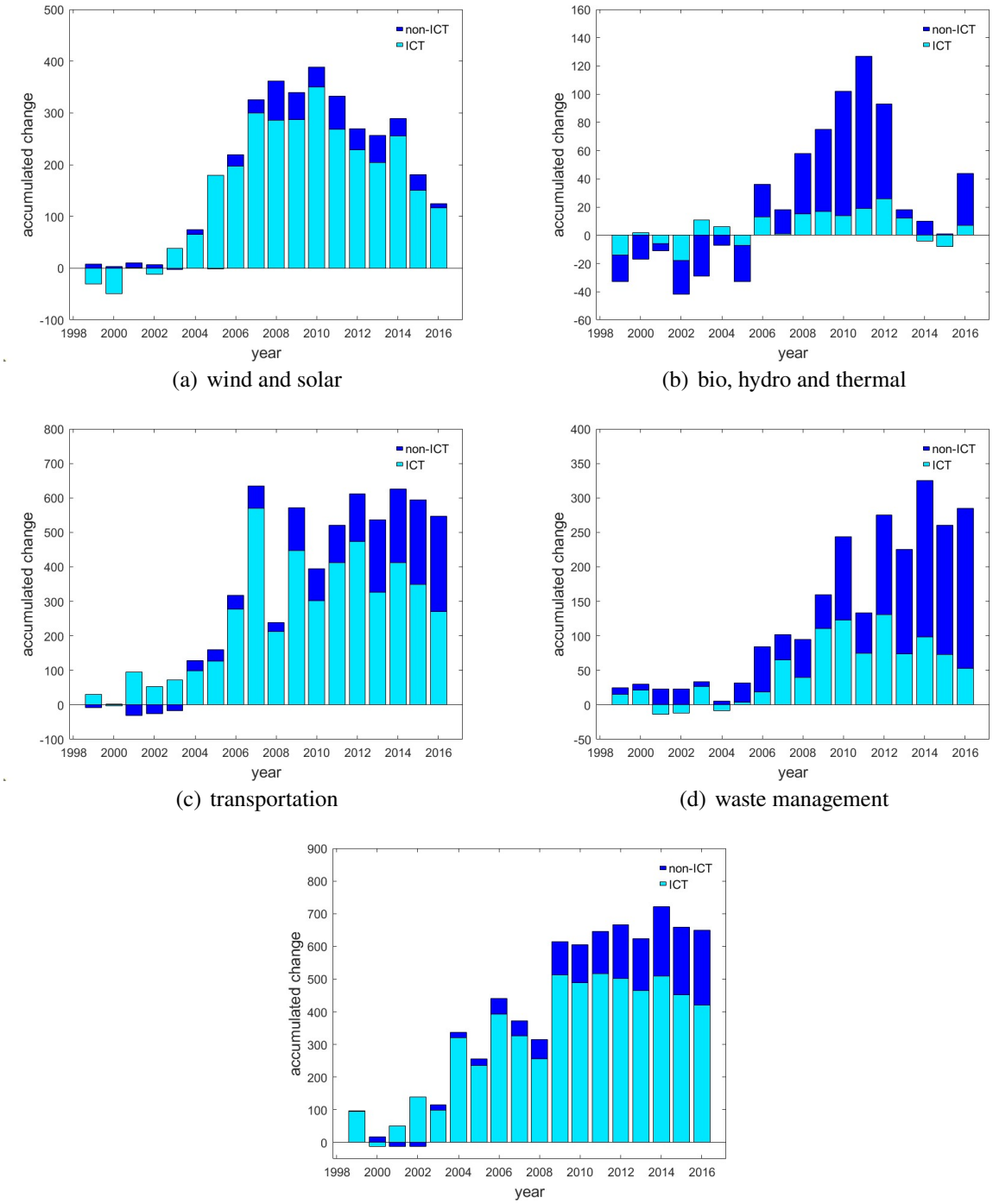
A.4.1 Decomposition of Green Patents in Different Technology Fields

This section decomposes green patents by technology field. We divide energy-production technologies into wind and solar and into bio-fuel, hydro, and thermal technologies. Wind and solar technologies are typically intermittent and therefore require coordination between supply and demand, making them especially complementary with ICT and AI tools. The remaining categories are energy storage, transportation, and waste management. Figure A.5 shows that, in most fields, an increasing share of green innovation is conducted by ICT firms.

A.4.2 Alternative Definitions of ICT Firm

In this section, we show our empirical findings are robust to alternative measures of ICT-green firms. The first exercise is to change the threshold to

A.4.3 Robustness Check: Firm Experience and Dirty to Green Patent Share



(a) wind and solar

(b) bio, hydro and thermal

(c) transportation

(d) waste management

(e) energy storage

Figure A.5: Accumulated green patents change by fields

Note: The fields are defined according to IPC codes. The ICT firms are to adopt the definition in the baseline that firm owns over 5% of ICT green patents throughout the sample.

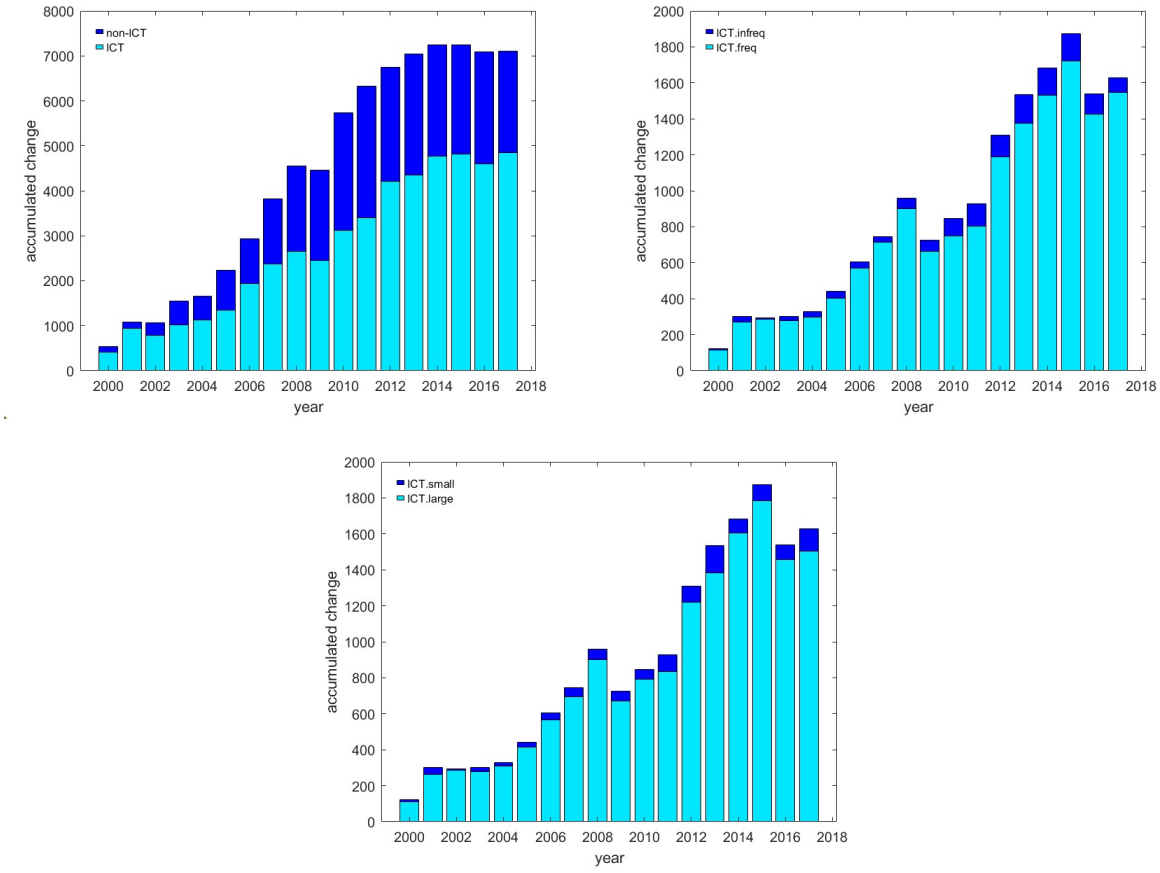
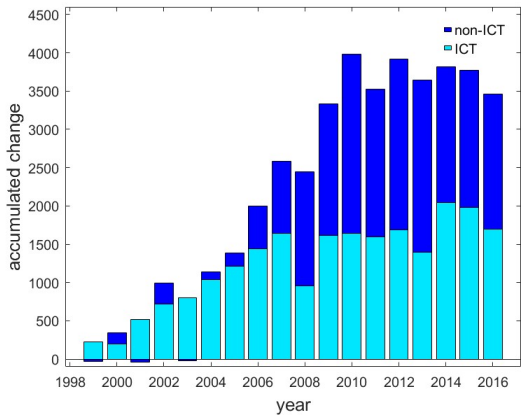
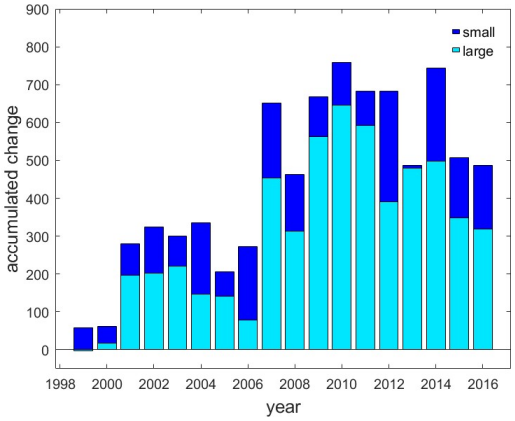


Figure A.6: Accumulated green patents: alternative definition of ICT patent

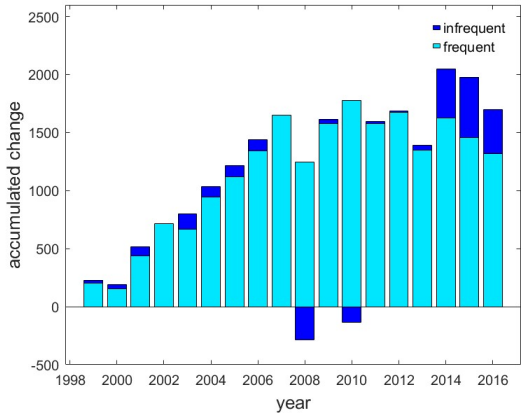
Note: The above figure uses a wider range of definition of ICT patent.



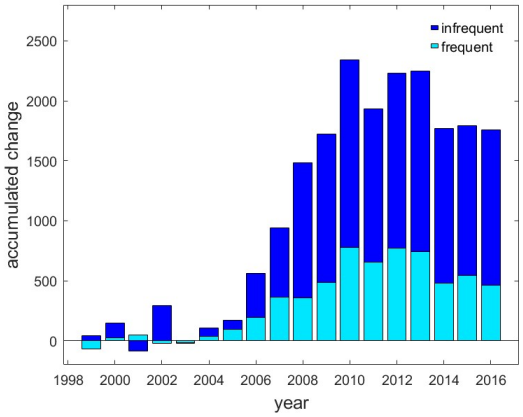
(a) ICT and non-ICT firms



(b) Large and small ICT firms



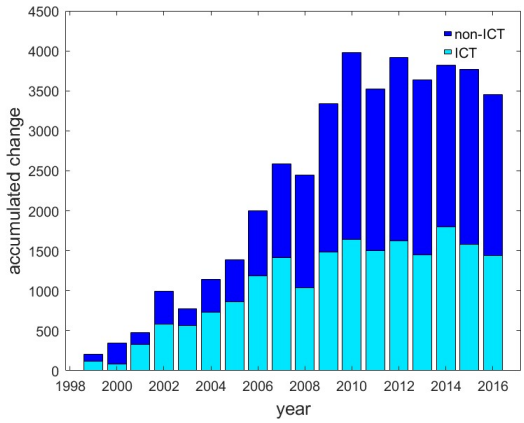
(c) ICT frequent and infrequent innovators



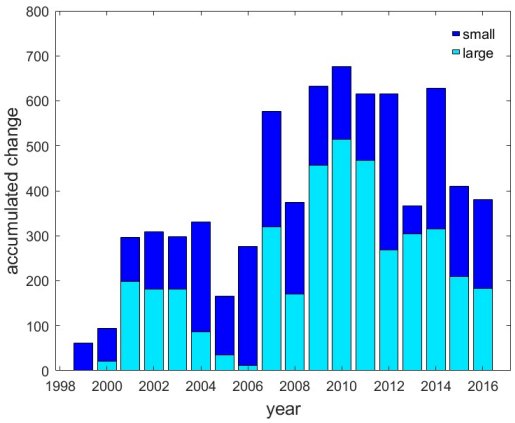
(d) non-ICT frequent and infrequent innovators

Figure A.7: Alternative measure of ICT-green firm: 5% threshold and year by year

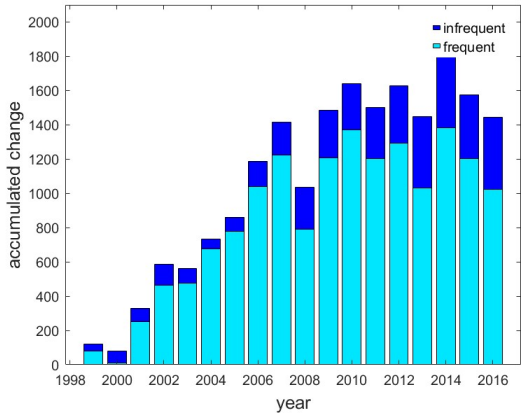
Note: In this robustness check, we define an ICT-green firm as that had a share of ICT-green patent over 5% of all green patents year by year.



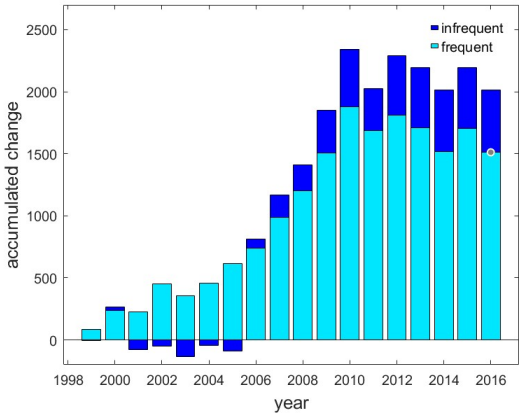
(a) ICT and non-ICT firms



(b) Large and small ICT firms

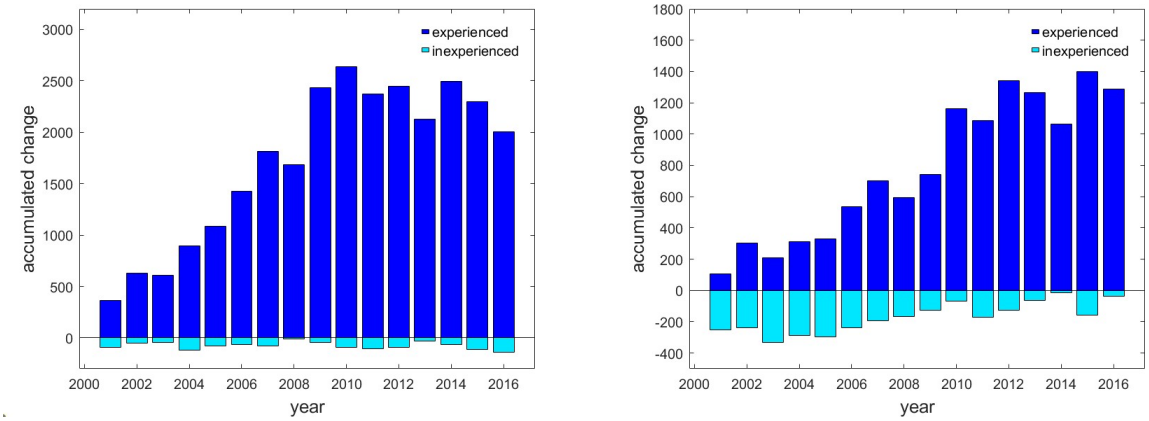


(c) ICT frequent and infrequent innovators



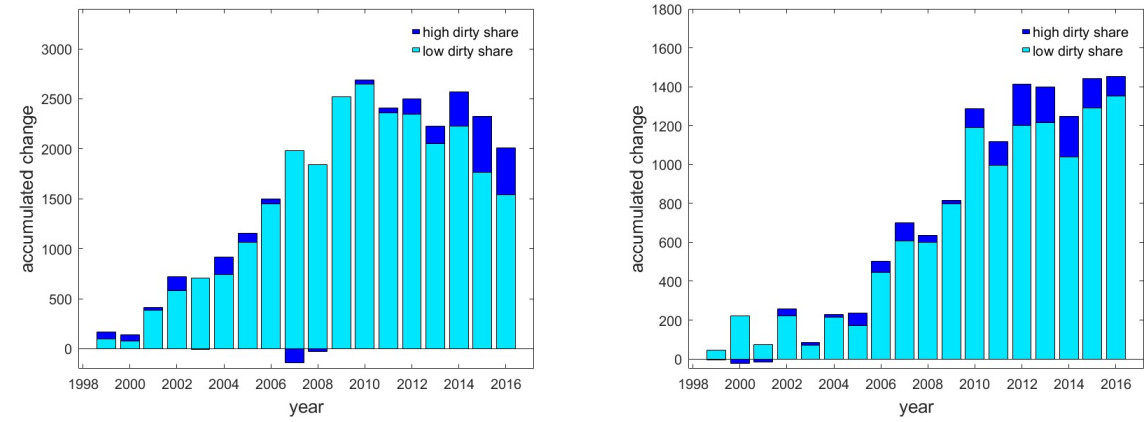
(d) non-ICT frequent and infrequent innovators

Figure A.8: Alternative measure of ICT-green firm: 10% threshold throughout sample



Note: The panels compare experienced firms with at least three years since their first green patent with inexperienced firms have fewer than three years of green-patenting experience.

Figure A.9: Robustness check: Firm experience of green patenting



Note: The panels compare firms with above versus below dirty-to-green patent ratio of 1.5, which is the 75% percentile level among firms with positive dirty-patent ratios.

Figure A.10: Robustness check: Firms' degree of green patenting

B Model Appendix

B.1 Decision Rules of Intermediate Firms

From the FOCs of optimal production decisions, we know the proportions of inputs by dirty firms:

$$\frac{O(a)}{l(a)} = \frac{(1-\eta)(1-\alpha)}{\alpha}\frac{w}{P_o(1+\tau)} \tag{B.1}$$

and:

$$\frac{Y^D(a)}{l(a)} = \frac{(1-\alpha)\eta}{\alpha}\frac{w}{P} \tag{B.2}$$

Analogously, the firm that uses the green technology have input share:

$$\frac{Y(a)}{l(a)} = \frac{1-\alpha}{\alpha}\frac{w}{P}. \tag{B.3}$$

The profit maximization problem of dirty firms yield the expression of prices and inputs, the expression of final goods demand is:

$$Y_d^{D*}(a) = \frac{P^\sigma Y(\frac{\sigma}{\sigma-1})^{-\sigma}\exp(a)\alpha^{\alpha(\sigma-1)}(1-\alpha)^{1+(1-\alpha)(\sigma-1)}\eta^{1+\eta(1-\alpha)(\sigma-1)}(1-\eta)^{(1-\eta)(1-\alpha)(\sigma-1)}}{w^{\alpha(\sigma-1)}(P_o(1+\tau))^{(1-\eta)(1-\alpha)(\sigma-1)}P^{1+(\sigma-1)\eta(1-\alpha)}} \tag{B.4}$$

The expression of labor demand by dirty firms is:

$$l_d^*(a) = \frac{P^\sigma Y(\frac{\sigma}{\sigma-1})^{-\sigma}\exp(a)\alpha^{1+\alpha(\sigma-1)}(1-\alpha)^{(1-\alpha)(\sigma-1)}\eta^{\eta(1-\alpha)(\sigma-1)}(1-\eta)^{(1-\eta)(1-\alpha)(\sigma-1)}}{w^{1+\alpha(\sigma-1)}(P_o(1+\tau))^{(1-\eta)(1-\alpha)(\sigma-1)}P^{(\sigma-1)\eta(1-\alpha)}} \tag{B.5}$$

The expression of fossil fuel demand by dirty firms is:

$$O^*(a) = \frac{P^\sigma Y(\frac{\sigma}{\sigma-1})^{-\sigma}\exp(a)\alpha^{\alpha(\sigma-1)}(1-\alpha)^{1+(1-\alpha)(\sigma-1)}\eta^{\eta(1-\alpha)(\sigma-1)}(1-\eta)^{1+(1-\eta)(1-\alpha)(\sigma-1)}}{w^{\alpha(\sigma-1)}(P_o(1+\tau))^{1+(1-\eta)(1-\alpha)(\sigma-1)}P^{(\sigma-1)\eta(1-\alpha)}} \tag{B.6}$$

The expression of total output selected by dirty firms is:

$$y_d^*(a) = \frac{P^\sigma Y(\frac{\sigma}{\sigma-1})^{-\sigma}(\exp(a))^{\frac{\sigma}{\sigma-1}}\alpha^{\alpha\sigma}(1-\alpha)^{(1-\alpha)\sigma}(1-\eta)^{(1-\eta)(1-\alpha)\sigma}\eta^{\eta(1-\alpha)\sigma}}{w^{\alpha\sigma}(P_o(1+\tau))^{(1-\eta)(1-\alpha)\sigma}P^{\sigma\eta(1-\alpha)}} \tag{B.7}$$

The expression of output price by dirty firms is:

$$p_d^*(a) = \frac{\frac{\sigma}{\sigma-1}(\exp(a))^{-\frac{1}{\sigma-1}}\alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}(1-\eta)^{(\eta-1)(1-\alpha)}\eta^{-\eta(1-\alpha)}}{w^{-\alpha}(P_o(1+\tau))^{-(1-\eta)(1-\alpha)}P^{-\eta(1-\alpha)}} \tag{B.8}$$

Similarly, we solve the profit maximization problem of green firms. The expression of final goods demand is:

$$Y_g^{D*}(a) = \frac{P^\sigma Y(\frac{\sigma}{\sigma-1})^{-\sigma}\exp(a)\alpha^{\alpha(\sigma-1)}(1-\alpha)^{1+(1-\alpha)(\sigma-1)}}{w^{\alpha(\sigma-1)}P^{1+(\sigma-1)(1-\alpha)}} \tag{B.9}$$

The expression of labor demand by green firms is:

$$l_g^*(a) = \frac{P^\sigma Y(\frac{\sigma}{\sigma-1})^{-\sigma}\exp(a)\alpha^{1+\alpha(\sigma-1)}(1-\alpha)^{(1-\alpha)(\sigma-1)}}{w^{1+\alpha(\sigma-1)}P^{(\sigma-1)(1-\alpha)}} \tag{B.10}$$

The expression of total output selected by green firms is:

$$y_g^*(a) = \frac{P^\sigma Y(\frac{\sigma}{\sigma-1})^{-\sigma}(\exp(a))^{\frac{\sigma}{\sigma-1}}\alpha^{\alpha\sigma}(1-\alpha)^{(1-\alpha)\sigma}}{w^{\alpha\sigma}P^{\sigma(1-\alpha)}} \tag{B.11}$$

The expression of output price by green firms is:

$$p_g^*(a) = \frac{\frac{\sigma}{\sigma-1}(\exp(a))^{-\frac{1}{\sigma-1}}\alpha^{-\alpha}(1-\alpha)^{-(1-\alpha)}}{w^{-\alpha}P^{-(1-\alpha)}} \tag{B.12}$$

B.2 Deriving Aggregate Variables

Final goods price and aggregate productivity According to definition in the model part, the aggregate final price is:

$$\begin{aligned} P &= [\int_{\omega\in\Omega_j} p(\omega)^{1-\sigma}d\omega]^{\frac{1}{1-\sigma}} \\ &= [\int_{a\in A_d} p_d(a)^{1-\sigma}d\mu(a) + \int_{a\in A_g} p_g(a)^{1-\sigma}d\mu(a)]^{\frac{1}{1-\sigma}} \\ &= \frac{\sigma}{(\sigma-1)w^{-\alpha}}[(P^{\eta(1-\alpha)}P_o^{(1-\eta)(1-\alpha)})^{1-\sigma}C_dA_d + P^{(1-\alpha)(1-\sigma)}C_gA_g]^{\frac{1}{1-\sigma}} \end{aligned} \tag{B.13}$$

where we denote for convenience that:

$$C_d(\tau) = (\frac{1+\tau}{(1-\eta)(1-\alpha)})^{(1-\sigma)(1-\alpha)(1-\eta)} \cdot (\frac{w}{\alpha})^{(1-\sigma)\alpha} \cdot (\frac{1}{(1-\alpha)\eta})^{(1-\sigma)(1-\alpha)\eta} \tag{B.14}$$

and:

$$C_g = (\frac{w}{\alpha})^{(1-\sigma)\alpha} \cdot (\frac{1}{1-\alpha})^{(1-\sigma)(1-\alpha)} \tag{B.15}$$

The aggregate productivity is defined as:

$$A = [(P^{\eta(1-\alpha)} P_o^{(1-\eta)(1-\alpha)})^{1-\sigma} C_d A_d + P^{(1-\alpha)(1-\sigma)} C_g A_g]^{\frac{1}{\sigma-1}} \tag{B.16}$$

The productivity index $\tilde{A}$ without considering entrants' mass is $A = M_e^{\frac{1}{\sigma-1}} \tilde{A}$.

Justification of aggregate productivity The aggregate production labor is:

$$L_p = \alpha(\frac{\sigma}{\sigma-1})^{-\sigma} P^{\sigma} Y [C_d A_d (P^{\eta(1-\alpha)} P_o^{(1-\eta)(1-\alpha)})^{1-\sigma} + C_g A_g P^{(1-\alpha)(1-\sigma)}] \tag{B.17}$$

Plug into the expression of P, we have:

$$L_p = \alpha(\frac{\sigma}{\sigma-1})^{-\sigma} PY \tag{B.18}$$

With the definition such that $P = \frac{\sigma}{\sigma-1} A^{-1}$. Rearrange we get a linear production function of aggregate output Y on production labor L_p:

$$Y = \frac{1}{\alpha}(\frac{\sigma}{\sigma-1})^{\sigma-1} A L_p \tag{B.19}$$

Hence we justify that our definition of aggregate productivity corresponds to a aggregate production function F such that $Y = AF(L^p)$, where F is linear in L_p.

Market size By definition, the common part of aggregate variable profit of dirty and green technology, which captures a market size effect, is given bt:

$$\Pi =: (\frac{\sigma}{\sigma-1})^{1-\sigma}\frac{1}{\sigma}P^{\sigma}Y \tag{B.20}$$

Production labor demand The aggregate dirty profit is:

$$\begin{aligned}\tilde{\Pi}_d &= \int P^{\sigma}Y(\frac{\sigma}{\sigma-1})^{1-\sigma}\frac{1}{\sigma}\exp(a_d)\cdot(\frac{p_o(1+\tau)}{(1-\eta)(1-\alpha)})^{(1-\sigma)(1-\alpha)(1-\eta)} \\ &\cdot(\frac{w}{\alpha})^{(1-\sigma)\alpha}\cdot(\frac{P}{(1-\alpha)\eta})^{(1-\sigma)(1-\alpha)\eta}d\mu(a) \\ &= C_d P^{\sigma}Y A_d(\frac{\sigma}{\sigma-1})^{1-\sigma}\frac{1}{\sigma}P^{(1-\sigma)(1-\alpha)\eta}p_o^{(1-\sigma)(1-\alpha)(1-\eta)}\end{aligned} \tag{B.21}$$

Note that $wL_p^d = \tilde{\Pi}_d(\sigma-1)\alpha$. And the aggregate green profit is:

$$\tilde{\Pi}_g = C_g P^{\sigma}Y A_g\cdot(\frac{\sigma}{\sigma-1})^{1-\sigma}\frac{1}{\sigma}P^{(1-\sigma)(1-\alpha)} \tag{B.22}$$

Note that $wL_p^g = \tilde{\Pi}_g(\sigma-1)\alpha$. We normalize the wage rate to be unity.

Research labor and production labor The ratio of the production labor to research labor in the downstream is:

$$\chi = \frac{L_p}{L_r} = \frac{\Pi(\sigma-1)\alpha[C_d A_d(P^{\eta(1-\alpha)}P_o^{(1-\eta)(1-\alpha)})^{1-\sigma} + C_g A_g P^{(1-\alpha)(1-\sigma)}]}{\int\Phi_d(a_d)e_d^2(a,m)d\mu(a) + \int\Phi_g(a_g)e_g^2(a,m)d\mu(a) + c\cdot M_c + n_f\cdot(M_d+M_g) + n_e M_e} \tag{B.23}$$

The labor market clearing condition is:

$$L_p + L_r = L \tag{B.24}$$

which implies $L_r = \frac{L}{1+\chi}, L_p = \frac{\chi L}{1+\chi}$.

Entrant mass By labor market clearing condition:

$$Y = \frac{L - L_r}{P^{\sigma}(\frac{\sigma}{\sigma-1})^{-\sigma} w^{\alpha(1-\sigma)-1} \cdot \alpha[C_d A_d (P^{\eta(1-\alpha)} P_o^{(1-\eta)(1-\alpha)})^{1-\sigma} + C_g A_g P^{(1-\alpha)(1-\sigma)}]} \tag{B.25}$$

Plug the expression of Y in market size expression, we have:

$$M_e = \frac{L - L_r}{\alpha\Pi(\sigma-1)[C_d \tilde{A}_d (P^{\eta(1-\alpha)} P_o^{(1-\eta)(1-\alpha)})^{1-\sigma} + C_g \tilde{A}_g P^{(1-\alpha)(1-\sigma)}]} \tag{B.26}$$

By definition of $\tilde{A}$, it can be expressed as:

$$M_e = \frac{L_p}{\alpha\Pi(\sigma-1)\tilde{A}^{\sigma-1}} \tag{B.27}$$

Final goods input and consumption The input amount is:

$$\begin{aligned} Y^D &= \int_{a\in A_d} Y_d^D(a)d\mu(a) + \int_{a\in A_g} Y_g^D(a)d\mu(a) \\ &= \frac{(1-\alpha)\Pi}{P(\sigma-1)}[\frac{\eta C_d A_d}{P^{(\sigma-1)(1-\alpha)\eta} p_o^{(\sigma-1)(1-\alpha)(1-\eta)}} + \frac{C_g A_g}{P^{(\sigma-1)(1-\alpha)}}] \end{aligned} \tag{B.28}$$

and the consumption is:

$$C = Y - Y^D \tag{B.29}$$

The aggregate dirty output E is:

$$\begin{aligned} E &= C_d P^{\sigma} Y P^{\eta(1-\alpha)(1-\sigma)} P_o^{(1-\eta)(1-\alpha)(1-\sigma)} (A_d^n + A_d^u))^{\frac{\sigma}{\sigma-1}} (\frac{\sigma}{\sigma-1})^{-\sigma} \\ &= (\sigma-1)\Pi_d (A_d^n + A_d^u)^{\frac{\sigma}{\sigma-1}} \end{aligned} \tag{B.30}$$

B.3 Analytical Results

Exogenous sorting to green transition We need to separate the general equilibrium effect through the aggregate price adjustment, from the effect from firm decision changes. To understand how the resource price works on firm decisions, we consider a case where firms using dirty technology

are randomly sorted to green technology with an exogenous probability v. Hence, firms only make decisions on entry and innovation within technology class and without considering transition.

Proposition B.1 *When no labor is used ($\alpha \to 0$) and under exogenous sorting to green technology, when the resource input price changes, firm variable profits and all decisions have no change.*

Proof Assume that the resource input price changes from P_o to $\tilde{P}_o$. Because sorting is exogenous, dirty firms have the following value function in original technology class selection stage:

$$V_t^S(a,m) = vU_t^S(a,d;g) + (1-v)U_t^S(a,d;d) \tag{B.31}$$

Before it, the firms decide whether to continue the operation:

$$V_t^{0,S}(a,m) = max\ [0, V_t^S(a,m)] \tag{B.32}$$

Firstly, we argue that $\tilde{P} = P\frac{\tilde{P}_o}{P_o}$ is a solution to the fixed point of P. By the fixed point equation:

$$\tilde{P}^{1-\sigma} = [\frac{\sigma}{(\sigma-1)w^{-\alpha}}]^{1-\sigma}[\tilde{P_o}^{(1-\eta)(1-\sigma)}\tilde{P}^{\eta(1-\sigma)}C_dA_d + \tilde{P}^{1-\sigma}C_gA_g] \tag{B.33}$$

Obviously, it is the solution of the original problem given all other aggregate variables unchanged. Let $\tilde{\Pi} = \Pi(\frac{\tilde{p_o}}{p_o})^{(1-\eta)(1-\sigma)}$. This ensures that the variable profits of dirty technology is unchanged. By the solution of $\tilde{P}$, the variable profit of green technology also remains unchanged. By uniqueness of the solution, $\tilde{\Pi}$ is the new solution to the new dynamic problem. Hence, firms decisions are unchanged in the process. Q.E.D □

The input of labor leads to some general equilibrium effect on aggregate price, which makes the across technology adjustment not completely shut down even in the case of exogenous sorting. However, once we ignore this effect, we find that the endogenized process of technology class selection breaks down the invariance clearly. For whichever value of $\tilde{\Pi}$ chosen in the new optimization problem, dirty firms are separated into two groups according to their own selection: transition or non transition. This would generate a kink point of the value function of dirty firms, which makes

the variable profit of either group change. Once this happens, the relative variable profit across technology also changes. Hence, variable profit dispersions make firms sorted more or less to green technology which changes the aggregates through directed innovation decisions further.

B.4 Model Extensions

B.4.1 Endogenous Choice of Being ICT Entrants

In this section, we endogenize the decision of being an ICT firm or a normal firm upon entry. Entrants still draw from a distribution of productivity $G_e(\bar{a_d}, a_g)$, but can choose the investment of being an ICT firm. Let e denote the investment rate. The entrants problem becomes:

$$V_t^E(a_d, a_g) = \max_e \; e \cdot V_t^u(\mathbf{a}) + (1-e)V_t^n(\mathbf{a}) - \Phi^E(a_d, e), \tag{B.34}$$

where the investment cost function takes the same format as the innovation costs:

$$\Phi^E(a_d, e) = h^E \exp(a_d) \exp(\xi^E e), \tag{B.35}$$

Note that since they have the same dirty productivity upon entry, we assume that the investment cost is proportional to the exponential of green productivity upon entry. We have the following entrant investment rates versus green productivity as in Figure B.1.

As green productivity increases, the marginal benefit of being an ICT firm increases faster than investment cost, causing more firms to choose ICT. When the cost of green innovation of ICT decreases, it provides firms with a higher incentive to be an ICT firm as well.

The distribution of ICT-green entrants is therefore $G_e(\cdot, a_g) \cdot e(a_g)$ and the free entry condition becomes:

$$n_e = \frac{1}{1+r_t} \int [e(a_g)V^u(a,d)dG_e(a) + (1-e(a_g))V^n(a,d)dG_e(a)]. \tag{B.36}$$

This extension allows us to have richer general equilibrium effects and implications. The reduc-

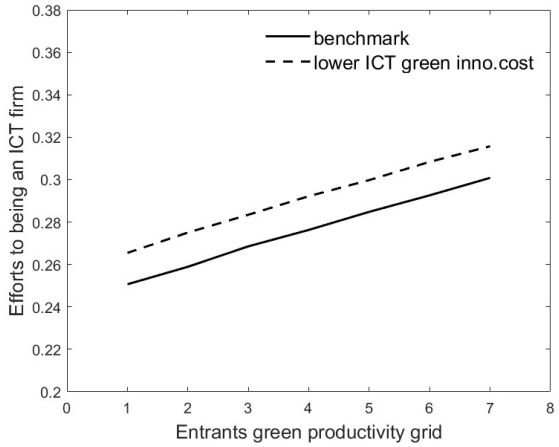
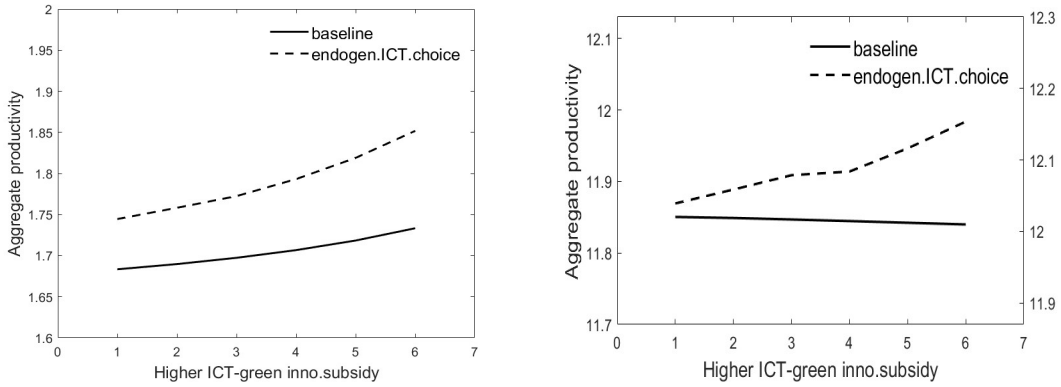


Figure B.1: Entrants effort of being an ICT firm given dirty productivity

tion in ICT-green innovation cost not only incentivizes ICT entrants to innovate more intensively in this direction but also attracts a larger fraction of firms into ICT. The higher fraction of ICT firms will then amplify the effects of innovation cost reduction.



(a) high dirty innovation cost: A (b) low dirty innovation cost: A

Figure B.2: ICT-green innovation cost reduction: endogenize ICT choice

Note: Each grid of X-axis is to increase the green innovation subsidy such that innovation cost faced by firms are half.

We repeat the mechanism exercise by gradually increasing the ICT-green innovation subsidy. Figure B.2 reports the results. When dirty innovation is relatively costly, the opportunity cost of the green transition is low, so aggregate productivity rises with the ICT-green subsidy. Allowing entrants to choose ICT status raises both the level and the slope of the productivity response, reflecting positive selection into ICT at entry. When dirty innovation is relatively cheap, the

exogenous-type model predicts a decline in productivity because the opportunity cost of the green transition is high. With endogenous ICT choice, however, a larger share of entrants choose the ICT type; because ICT firms are more productive innovators, this selection margin partly offsets the productivity decline.

C Quantitative Appendix

C.1 Computation Algorithm

1. Guess the initial value of the aggregate price $P^{(i)}$.

2. With the guessed price:

   (a) Guess the initial value of market size $\Pi^{(i,j)}$.

   (b) Given the guessed values, compute the variable profit for dirty and green technology. Through the dynamic programming of downstream firms, solve out the corresponding innovation decision rules e_d, e_g, the technology class choice rule m', the value functions V_d, V_g and the distribution conditional on technology class $\tilde{\mu}_d(a), \tilde{\mu}_g(a)$.

   (c) Compute the equilibrium Π^* through free entry condition. Repeat step $2.(a) \sim 2.(c)$ until $\Pi^{(i,j)} = \Pi^*$.

   (d) With the solved Π^*, compute equilibrium decision rules, value functions and the distributions. Compute the equilibrium price P, aggregate productivity A_g, A_d. Compute out the implied aggregate price P^* through the definition.

3. Repeat step $1 \sim 2$ until $P^* = P^{(i)}$.

4. Compute the equilibrium decision rules, distributions and aggregate variables based on the converged value of P^* and Π^*.