УДК 338.1, 338.2, 332.1

DOI: 10.17323/1813-8691-2025-29-1-72-102

The Impact of Carbon Tax and Research Subsidies on Economic Growth in Japan[1]

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A considerable amount of work has shown that a carbon tax combined with research subsidies may be regarded as effective policy for encouraging the spread of low-carbon technologies for the benefit of society. This paper exploits the macroeconomic approach of endogenous growth models with technological change in order to make a comparative assessment of the impact of such policy measures on economic growth in the US and Japan in the medium and long term. Our estimates

[1] The article was prepared with the support of the Basic Research Program of HSE University, Moscow, Russia. We are indebted to the Editor, an anonymous referee, Petros Sofronis, Dmitry Veselov, Konstantin Styrin, Pavel Krivenko, and participants of the 2019 EEA – ESEM Congress and of public seminars at Stanford University's US-Asia Technology Management Center (July 2023 and March 2024), at HSE University's International Laboratory for Macroeconomic Analysis (April-May 2019) and at the International Institute for Carbon-Neutral Energy Research (Kyushu University, Japan, May 2017) for helpful comments. Path dependence as one of the key features of the [Acemoglu et al., 2016] model, the need to touch upon the contribution of several countries to carbon emissions, measured at any meteorological station, and potential technology adoption across countries were kindly noted by the anonymous referee.

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The article was received: 11.06.2024/The article is accepted for publication: 06.02.2025.

with the micro and macro data reveal similarities among Japanese and US energy firms as regards the elasticity of the innovation production function in R&D expenditure and the probability of radical innovation. However, according to energy patent statistics, clean innovation is not as wide-spread in Japan as it is in the US. This may explain our quantitative findings of the need for a stronger reliance on a carbon tax in Japan as opposed to the US.

Key words: endogenous growth; technological change; innovation; carbon tax; energy.

JEL Classification: O11, O13, O47, Q43, Q49.

For citation: Besstremyannaya G., Dasher R., Golovan S. The Impact of Carbon Tax and Research Subsidies on Economic Growth in Japan. *HSE Economic Journal.* 2025; 29(1): 72–102.

1. Introduction

Confronting pollution and mitigating climate change has long been on the agenda in many developed countries, notably in the Nordic part of the EU and Japan [Gokhale, 2021; Fujii, Managi, 2016; International Energy Agency, 2016]. In particular, Japan might be viewed as a country with a long history of public and private environmental initiatives in support of eco-innovation which led to the decrease of carbon emissions from 1990 to 2022 [Green House Inventory Office, 2024]. Since 2003, Japan has been implementing a strategic energy policy, which addresses various technology issues related to energy efficiency as well as concerns about emissions and the environment [Ministry of Economy, Trade and Industry, 2014]. In 2012, Japan was among the first Asian countries to introduce a carbon tax on consumers as a part of the concept of "greening the Japanese tax system" within the fourth energy plan [Ministry of the Environment, 2017]. The tax is intended to encourage the use of green technologies by households and firms. Revenues from the carbon tax and other energy taxes are used to provide subsidies to develop environmentally-friendly (clean) technologies [Ministry of Finance, 2010, 2015; Wakiyama & Zusman, 2016]. However, Japan continues to contribute a third of the world's carbon emissions, and the size of the carbon tax is considerably lower than in other developed countries or than the IMF recommended value [Gokhale, 2021].

The use of a carbon tax as the sole policy instrument causes only the slow propagation of carbon-neutral technologies [Popp et al., 2010]. Accordingly, there is a need for other governmental policies (most commonly, in the form of research subsidies) that help offset the cost of firm's R&D targeted at eco-innovation. Since the 1990s, several generations of R&D-based endogenous growth models have been applied for the analyses of the impact of the carbon tax and research subsidies in Japan. Firstly, these are models with carbon-emitting (dirty) technology in the energy sector [Goto & Sawa, 1993; Goto, 1995; Mizunoya & Higano, 2000]. Variations of the approach include models with many industries [Lee et al., 2012; Takeda & Arimura, 2021; Matsumura et al., 2024] or with monetary policy [Hamaguchi, 2024]. The models do not explicitly include both carbon-neutral (clean) and carbon-emitting (dirty) sectors but may use the concept of energy efficiency (e.g. as in [Goto, 1995]) which should lead to a decrease in energy use and hence a fall in carbon emissions. Secondly, there are general equilibrium models with clean and dirty sectors [Lee at al., 2022; Silva Herran & Fujimori, 2021] but there exists no competition between clean and dirty technologies. Finally, there are approaches to studying the effect of carbon taxes in Japan through computable equilibrium models with aggregate-level regression analysis [Ministry of the Environment, 2017].

To the best of our knowledge, the richer, more realistic and more modern model of monopolistic competition [Klett, Kortum, 2004] as well as the concept of competing carbon-emitting and carbon-neutral technologies [Acemoglu et al., 2012; Aghion et al., 2016] have not yet been applied to the analysis of Japanese environmental policy. The purpose of this paper is to provide a quantitative estimate of the effects of carbon emissions and research subsidies on economic growth in Japan within such a framework.

We employ the Acemoglu et al.'s (2016) model which is unique in the class of the Klette & Kortum (2004) endogenous growth models with clean and dirty sectors in four aspects: 1) the potential use of clean or dirty technology for each product of a firm, 2) technological change in the clean and dirty sectors, where innovation may be radical (breakthrough) or incremental, 3) habit formation (path dependence) in the firm's choice of clean or dirty technology, and 4) richness in the use of microdata, including firm's financials, the R&D production function and patent data. Specifically, the elasticity of the R&D production function, quality differences between carbon-emitting and carbon-neutral technologies, and various parameters on firm dynamics are taken from real world data on companies and their patents.

The empirical analysis goes beyond the traditional assessment of macroeconomic policy in the Japanese energy sector, as the methodology of the [Acemoglu et al., 2016] model, which we use, uniquely allows for technological changes within the clean and dirty sectors. We exploit large datasets on Japanese manufacturing corporations and national data on their patents in clean and dirty technologies over the last quarter century to numerically evaluate the size of the clean and dirty sectors. Next, we follow the endogenous growth model by [Acemoglu et al., 2016] and empirically estimate the scenario with a combination of a carbon tax and research subsidies as regards the impact of these policy instruments on innovation rates and economic output in the carbon-emitting and carbon-neutral sectors. The results of our micro analysis with firm-level and patent-level data reveal many similarities between Japanese and US innovative energy firms as regards the elasticity of output with respect to R&D inputs, the probability of radical innovation and the number of patents per firm product in the energy sector, the share of R&D expenditure in firm sales, and the share of R&D labor in total labor. However, there exists an important difference between innovative firms in the two countries: in Japan there is a higher labor productivity with dirty technology in comparison with clean technology (the difference in productivity is called the technology gap in [Acemoglu et al., 2016]). This may explain our quantitative finding of a stronger reliance on the carbon tax in Japan in comparison with the US and the relatively longer period of a temporary fall in overall economic output due to the introduction of policy measures in Japan.

The paper builds on several streams of literature dealing with clean and dirty technologies in Japan[2]. Microeconomic analyses have studied the impact of the carbon tax (and research

[2] Concerning the microeconomic literature in the international context, evidence on the impact of policy instruments on innovation in the energy sector as well as a meta-review of research focused on carbon emissions and technological change in the energy sector are given in [Popp et al., 2010]. A few analyses suggest that the choice of environmentally friendly technologies are linked to energy prices and a history of a firm's innovative activity [Aghion et al., 2016; Popp, 2006; Popp & Newell, 2012]. As for policy instru-

subsidies) on production and emissions in Japan, and on energy use and investment in energy efficiency [Nakata & Lamont, 2001; Wakiyama & Zusman, 2016; Aden & Dirir, 2023]. Another focus of the microeconomic research is the impact of green innovation and R&D expenditure on firm growth [Kimura, 2023; Iino et al., 2021; Adebayo & Kirikkaleli, 2021; Hosono et al., 2022; Suzuki & Takemura, 2016]. Consumer willingness to pay for green products and the search for the optimal mix of clean/dirty energy, especially after the 2011 Great East Japan Earthquake are also on the agenda of microeconomic research in Japan [Komiyama & Fujii, 2017; Nomura &Akai, 2004]. Studies in the microeconomic context show a behavioral response of firms and consumers to market mechanisms and regulatory actions in the field of energy economics [De Groot et al., 2001; Tanikawa, 2004].

Concerning the preceding macroeconomic literature, here we list the streams of earlier studies along the lines of the reviews in Aghion et al. (2016) and Acemoglu et al. (2016), and add applications of such approaches to research on Japan. Firstly, there are models with the carbon cycle and the cost of carbon emissions [Nordhause, 2008; Golosov et al., 2014], as well as models with technological change in the energy sector [Smulders & de Nooji, 2003; Hassler et al., 2012] that enable researchers to assess the impact of a carbon tax on economic growth. There are similar models applied to the Japanese economy [Matsumura et al., 2024; Hamaguchi, 2024; Goto & Salva, 1993]. The second stream of research are models with clean and dirty sectors and technological change in each sector [Acemoglu et al., 2012; Gans, 2012; Golosov et al., 2014]. Analyses of the Japanese economy under such an approach may be found in Lee et al. (2022) and Silva Herran & Fujimori (2021). Thirdly, there are models allowing for competition between clean and dirty technologies [Acemoglu et al., 2012; Aghion et al., 2016].

Overall, the findings of macroeconomic analyses show that regulations aimed at reducing carbon emissions lead to a decline of gross domestic product and/or its growth rate in many countries [Metz et al., 2007, Table 3.12; Jorgenson & Wilcoxen, 1990]. Using revenues obtained from carbon taxes for the development of carbon-neutral technologies may mitigate the problem of a GDP decrease. Reviews of the literature on links between economic growth, carbon emissions and government policies can be found in [Xepapadeas, 2005; Jorgenson et al., 1993].

The remainder of the paper is organized as follows. Section 2 outlines the model of Acemoglu et al. (2016) which is employed in the empirical part of the paper. Data on Japan is descrybed in Section 3. Section 4 proceeds with the quantification of the model parameters for Japan. The results of the policy analysis for the Japanese economy as well as the robustness of estimates and the limitations of the approach are given in Section 5. The final section contains a discussion of the results and overall conclusions of the analysis.

The paper is essentially a replication of Acemoglu et al.'s (2016) article for Japan. As regards the replication of the analysis with the endogenous growth model based on US data for Japan, we believe that although not focused on the clean or dirty sectors, the work closest to ours is Kodama & Li (2019), who employ Aghion et al.'s (2019) model with heterogeneous innovation.

ments, a carbon tax combined with research subsidies may be regarded as an optimal policy for minimizing carbon emissions and/or maximizing social welfare [Fischer & Newell, 2008; Gerlagh & Van der Zwaan, 2006; Popp, 2006].

2. The Acemoglu et al.'s (2016) model

2.1. Key insights into the theoretical framework

Overview of the model and research question. The [Acemoglu et al., 2016] model belongs to the literature on competing clean and dirty sectors in the economy [Acemoglu et al., 2012; Gans, 2012] but the novelty of the model is the consideration of clean and dirty technology for each product as well as the path dependence of clean or dirty innovation. The model builds on the key concepts of endogenous growth models with technological change: the firm offering the best quality owns the market for the relevant intermediate good (product) [Grossman & Helpman, 1990; Romer, 1990]; firms innovate to maximize profits by adding new products or improving the quality of existing products [Klette & Kortum, 2004; Lentz & Mortensen, 2008]. Following the seminal work by [Akcigit & Kerr, 2010], the innovation in the model is heterogeneous: it may be radical (breakthrough) or incremental. The model assumes that all innovations are patented and the economy is closed.

The [Acemoglu et al., 2016] model is used as a tool to find the optimal values for a combination of two policy instruments: subsidies for research into carbon-neutral technologies and a tax on carbon emissions. The model studies the evolution of a non-steady state equilibrium, focusing on the time profiles of economic variables across optimal policies and the *laissez-faire* (null) policy. The variables of primary interest are output by firms using carbon-neutral and carbon-emitting technologies, innovative activity by clean and dirty firms, and the overall growth of the economy. The key features of the [Acemoglu et al., 2016] model is summarized in the following.

Market competition between firms with clean and dirty technologies. The model employs the [Klette & Kortum, 2004] framework of the monopolistic competition of firms who produce a continuum of intermediate goods in the economy. There are dirty (carbon-emitting) and clean (carbon-neutral) technologies for each good and a quality ladder as regards the labor productivity of clean and dirty technologies. Only firms with the most advanced technology within the clean and dirty sector may produce each good. There are incumbent firms who aim at sustaining their monopoly position in the market for each intermediate good and new entrants whose purpose is to enter the market through quality competition. There is a free entry condition to the market. Entrants and incumbents have a number of goods and technologies and are engaged in monopolistic competition.

Profit-maximizing firms invest in R&D expecting a resulting innovation that will boost the quality (labor productivity) of the technology used in manufacturing the good. There is also a quality gap (difference in labor productivity) between the two technologies for each good. The "active" technology (i.e. clean or dirty) used in the market for each good is chosen based on the marginal cost which depends on taxes and the price of exhaustible resources (employed within the dirty technology). A firm's decision on R&D is influenced by the R&D subsidy from the government.

Heterogeneous innovation. Similarly to the approach of [Akcigit & Kerr, 2010], there are two types of innovation in the model. Incremental innovation leads to minor advances in the current leading-edge technology. So incremental clean innovation improves the current best clean technology and incremental dirty innovation enhances the best dirty technology. Radical (breakthrough) innovation causes an advance over the leading-edge technology, regardless of whether it is clean or dirty.

The path dependence of innovation. A key feature of the model is the path dependence of the firm's choice of each technology – namely, the fact the type of firm's innovative activity (i.e. clean or dirty) depends on the firm's past innovative activity, and that clean innovation, if sustained for a while, is self-reinforcing[3]. There is a stock of knowledge within each technology (clean or dirty) which a firm can employ for further quality improvements. It is conjectured for simplicity "that each firm specializes in either clean or dirty technologies" [Acemoglu et al., 2016, p. 63].

Although this plausible supposition about firm behavior has been already put forward in the microeconomics literature [Popp, 2006; Popp & Newell, 2012], to the best of our knowledge, the work by [Acemoglu et al., 2016] may be regarded as the first macroeconomic model with a path dependency of clean/dirty innovation[4]. The introduction of the carbon cycle in the model stems from the literature with the general equilibrium framework and most closely resembles the approach in [Golosov et al., 2014].

R&D decision of firms. The application of the [Klette & Kortum, 2004] framework means that R&D expenditure leads to a Poisson flow rate of new innovation. A subsidy for clean or dirty technology enhances a firm's investment in the corresponding type of R&D. The R&D decision of firms is path dependent.

Final good. The producer of the aggregate (final) good uses intermediate goods as inputs. The producer of the final good is a profit maximizer, so the choice of a clean or dirty intermediate good is conducted according to their relative quality (labor productivity) and the size of the carbon tax on the dirty intermediate good.

Policy instruments and their impact. The government collects carbon taxes, imposes taxes on consumers to balance its budget and provides R&D subsidies to clean/dirty technologies. The policy instruments are the carbon tax and research subsidies. The research subsidy enhances R&D investment into technology. The carbon tax affects the choice of technology used by firms that produce intermediate goods as well as impacting the choice of clean or dirty intermediate goods by the final good producer. There is also the welfare damage of carbon emissions as they increase the amount of carbon in the atmosphere.

The welfare effect of dirty technology. The use of dirty technologies leads to carbon emissions that impact production and social welfare. Specifically, carbon-emissions cause economic damage, decreasing the productivity of the final good.

2.2. Formal description of the model

This section borrows from pp. 57–71 of Acemoglu et al. (2016) to provide a list of the key equations of the model which point to the key parameters used in the empirical estimation.

Consumption. The utility function of a representative household is $U_0 = \int_0^{\infty} e^{-\rho t} \ln C_t dt$, where C_t is consumption at time t and $\rho > 0$ is the social discount rate. The household works in all the firms in the economy, as well as owning them, so the budget constraint becomes

[3] We are grateful to the anonymous referee for highlighting path dependency as one of major features of the model [Acemoglu et al., 2016].

[4] Path dependency is a key element of another seminal macroeconomic model which also appeared in 2016 [Aghion et al., 2016].

$w_t^u + w_t^s L^s + \Pi_t - T_t \geq C_t$, where Π_t is net profit, w_t^u and w_t^s are the wage rates for unskilled (with measure one) and skilled (with measure L^s) labor respectively (skilled labor does R&D), and T_t is transfers.

Intermediate goods. Each intermediate good $y_{i,t}$ can be produced with either dirty or clean technology, denoted by $j \in \{c, d\}$. (Below the terms "dirty/clean technology" and "dirty/clean sector" are often used interchangeably.) The production function of firm f for clean technology is

$$y_{i,t}^c(f) = q_{i,t}^c(f) l_{i,t}^c(f), \tag{1}$$

where $l_{i,t}^c(f)$ is labor and $q_{i,t}^c(f)$ is labor productivity.

The production function for dirty technology uses not only labor but also an exhaustible resource $e_{i,t}$:

$$y_{i,t}^d(f) = q_{i,t}^d(f) l_{i,t}^d(f)^{1-\nu} e_{i,t}(f)^{\nu} \tag{2}$$

where $e_{i,t} = \zeta l_{i,t}^e$, $\nu \in (0,1)$, $\zeta > 0$ and the stock of the exhaustible resource is given by

$$\dot{R}_t = -\int_0^1 e_{i,t} di. \tag{3}$$

The solution of the cost minimization problem by producers within the dirty sector yields

$$e_{i,t} = \left(\frac{\nu}{1-\nu} \frac{w_t^u}{p_{e,t}} \right) l_{i,t}^d. \tag{4}$$

Denote $\tilde{P}_{e,t}$ as the normalized price of the exhaustible resource:

$$\tilde{P}_{e,t} \equiv (1-\nu)^{\nu-1} \left(\frac{p_{e,t}}{w_t^u \nu} \right)^{\nu}. \tag{5}$$

Carbon cycle. The atmospheric carbon concentration S_l is due to carbon emissions accumulating in the atmosphere. It negatively affects the aggregate production Y_t as follows:

$$lnY_t = -\gamma\left(S_t - \overline{S}\right) + \int_0^1 lny_{i,t} di, \tag{6}$$

where $\overline{S}$ is the preindustrial level of the atmospheric carbon concentration, γ is a parameter with positive values reflecting the negative impact, and $y_{i,t}$ is the amount of intermediate good i. The amount of atmospheric carbon concentration S_t, if $t = T$ is the date when emission began is expressed as:

(7) $$S_t = \int_0^{t-T} (1 - d_l) K_{t-l} dl,$$

where carbon emission K_t is proportionate to the total output of dirty sectors $Y_t^d = \int_0^1 y_{i,t}^d di$:

(8) $$K_t = \kappa Y_t^d$$

and $(1 - d_l)$ is the share of a unit of carbon, emitted l years ago and left in the atmosphere, and:

(9) $$d_l = (1 - \varphi_P)(1 - \varphi_0 e^{-\varphi l}),$$

with φ_P denoting the fraction of emission permanently remaining in the atmosphere; $(1 - \varphi_P)$ being the fraction of the transitory component in the first period; φ indicating the rate of decay of the carbon concentration.

Heterogeneous innovation. R&D expenditure targeted at the clean or dirty sectors may lead to successful innovation. The aggregate innovation rate by entrants and incumbents is denoted as z_t^j. The innovation can be of two types: an incremental innovation (which occurs with probability $1 - \alpha$) and a breakthrough innovation (with probability α).

An incremental innovation implies an improvement of one step in the quality ladder and this is modelled as a proportional improvement of quality by $\lambda > 1$. An incremental innovation during Δt causes the creation of a new technology $q_{i,t+\Delta t}^c = \lambda q_{i,t}^c$, but a breakthrough innovation in sector j that is behind sector $-j$ leads to a new technology with $q_{i,t+\Delta t}^j = \lambda q_{i,t}^{-j}$, meaning that it builds on the more advanced technology level of sector $-j$. An incremental innovation in the clean sector implies that labor productivity is $q_{i,t}^c = \lambda^{n_{i,t}^c}$, where a positive integer $n_{i,t}^c$ denotes the number of steps that this technology has taken since time $t = 0$. A similar equation holds for the dirty sector, $q_{i,t}^d = \lambda^{n_{i,t}^d}$.

The relative productivity of the dirty to clean technology is given as $\frac{q_{i,t}^d}{q_{i,t}^c} = \lambda^{n_{i,t}}$, where $n_{i,t} \equiv n_{i,t}^d - n_{i,t}^c$ is the technology gap between the dirty and clean sectors for intermediate good i at time t.

The price-adjusted policy gap m_t is derived as

(10) $$m_t \equiv \frac{1}{\ln\lambda}\left[\ln\left(\frac{1+\tau_t^d}{1+\tau_t^c}\tilde{P}_{e,t}\right)\right],$$

where $\tilde{P}_{e,t}$ is the price for exhaustible resource and τ_t^j are taxes.

Price and quantity of intermediate goods. Using the final good as a numeraire, the demand for the intermediate good can be expressed as:

$$y_{i,t} = \frac{Y_t}{p_{i,t}}. \tag{11}$$

Let $\tilde{q}^d_{i,t}$ and $\tilde{q}^c_{i,t}$ be defined as the qualities in the dirty (clean) sector, which are adjusted by taxes and the price of the exhaustible resource in the case of the dirty (clean) sector as follows:

$$\tilde{q}^d_{i,t} \equiv \frac{q^d_{i,t}}{\left(1+\tau^d_t\right)\tilde{P}_{e,t}} \text{ and } \tilde{q}^c_{i,t} \equiv \frac{q^c_{i,t}}{1+\tau^c_t}. \tag{12}$$

The profit maximization problem of the producers of intermediate goods in the dirty (clean) sector yields:

$$p^j_{i,t} = min\left\{\frac{\lambda w^u_t}{\tilde{q}^j_{i,t}}, \frac{w^u_t}{\tilde{q}^{-j}_{i,t}}\right\} \text{ and } y^j_{i,t} = max\left\{\frac{\tilde{q}^j_{i,t}}{\lambda w^u_t}, \frac{\tilde{q}^{-j}_{i,t}}{w^u_t}\right\} \cdot Y_t. \tag{13}$$

Denote $\bar{Q}_t \equiv \exp\left(\int \ln \tilde{q}_{it} di\right)$ as the quality index of tax-adjusted labor productivities, and $\Lambda_t \equiv \prod_n \lambda\left(n - m_t\right)^{-\mu_{n,t}}$ as an inverse function of equilibrium markups.

Plugging the optimal values of the intermediate goods in the production function of the final good yields:

$$w^u_t = \bar{Q}_t \Lambda_t. \tag{14}$$

R&D production function. Denote u^j_f as the number of intermediate goods in which firm f has the leading method of production in sector j; u^j_f is also considered as the stock of knowledge which may be used for subsequent innovations. Assume that each firm specializes in either clean or dirty technologies. The Poisson flow rate of new innovations is

$$X^j_f = \theta\left(H^j_f\right)^{\eta}\left(u^j_f\right)^{1-\eta}, \tag{15}$$

where u^j_f is the knowledge stock, H^j_f denotes researchers (labor in the R&D sector), η is the R&D elasticity with respect to researchers, and $\theta > 0$. Define $x^j \equiv X^j / u^j$ as innovation per intermediate good. So the flow rate of innovation is $X^j = u^j x^j$.

The demand for researchers is

$$h^j\left(x^j\right) = \left(\frac{x^j}{\theta}\right)^{1/\eta}. \tag{16}$$

An innovation of incumbents requires $F_{I,i}$ researchers per intermediate good and entrants have to engage $F_E > F_I$ researchers. The mass of entrants who conduct R&D is denoted E_i^j.

Policy instrument. The policy instrument is a proportional subsidy from the government to R&D in the clean or dirty sector: the subsidy rate is $s_t^j \in [0,1]$ and the government budget becomes

(17) $$(1+\chi)S_t = T_t.$$

Here parameter χ measures the wastage of the subsidy in the course of R&D research, and hence the difference D_t (distortions) between output and consumption becomes

(18) $$D_t = \chi S_t.$$

Value function. The value of a given firm is given as

(19) $$\begin{aligned} rV^j_{\vec{n}^j} - \dot{V}^j_{\vec{n}^j} = \sum_{i=1}^{u} \Bigg\{ & \pi^j_{n_i} + z^j\left(V^j_{\vec{n}^j_{-i}} - V^j_{\vec{n}^j}\right) + \\ & + z^{-j}\left[1-\alpha+\mathbb{I}_{(n_i^j \le 0)}\alpha\right]\left(V^j_{\vec{n}^j_{-i}\cup\{n_i^j-1\}} - V^j_{\vec{n}^j_i}\right) + \\ & + \mathbb{I}_{\left(n_i^j > 0\right)} z^{-j}\alpha\left(V^j_{\vec{n}^j_i\cup\{-1\}} - V^j_{\vec{n}^j_i}\right)\Bigg\} + \\ & + \int \max_{x^j \ge 0}\Bigg\{u^j x^j\left(\mathbb{E}_n V^j_{\vec{n}^j\cup\left\{n^j_{u+1}\right\}} - V^j_{\vec{n}^j}\right) - \\ & - \left(1-s^j\right)u^j w^s\left[\left(x^j\right)^{1/n}\theta^{-1/\eta} + \mathbb{I}_{\left(x^j>0\right)}F_I\right]\Bigg\} dF_I, \end{aligned}$$

where $\vec{n}^j \equiv \left[n_1^j,\dots,n_u^j\right]$ is the vector of intermediate goods for which this firm holds the leading-edge technology of type j, n_i^j is the technology gap between technologies j and $-j$ for the same intermediate good, and $\vec{n}^j_{-i}$ is $\vec{n}^j$ without its *i*-th element n_i^j.

Here $\pi^j_{n_i}$ denotes the profits generated from u^j intermediate goods.

The technology gap declines by one step to $n_i^j = n_i^j - 1$ owing to an incremental innovation (with probability $1-\alpha$) or if technology j was already behind $\left(n_i^j \le 0\right)$. The firm falls behind by one step to $n_i^j = -1$ in the case of a breakthrough innovation (probability α) and when technology j was leading $\left(n_i^j > 0\right)$.

The form of the value function implies that innovation is path dependent. Indeed, when the use of clean technology is profitable for certain intermediates, then the average profit for producers who use clean technology is $\Gamma_t^c \equiv \sum_{n<m}\mu_{n,t}\pi_t\left(m_t - n\right)$, where $\mu_{n,t}$ denotes the share of intermediate goods for which the clean technology is exactly n steps behind the dirty one at time t. The sequence $\left\{\Gamma_t^c\right\}_{l=0}^{\infty}$ affects incentives through the expected per product value of innovation which (owing to the form of the value function, as is shown in Lemma 1 of [Acemoglu et al., 2016]) is proportionate to $\mu_{n,t}$. After clean innovation has been sustained for a certain period of time, the share of intermediates with markup larger than or equal to the quality gap ($n \leq m$) goes up, and this increases the probability of a successful clean innovation for a profitable intermediate good.

Free entry, labor market clearing conditions and production. The free-entry condition for technology j is expressed as;

(20) $$\max_{x_{E,t}^j \geq 0}\left\{x_{E,t}^j \bar{v}_t^{-j} Y_t - \left(1 - s_t^j\right) w_t^s \left[h\left(x_{E,t}^j\right) + F_E\right]\right\} \leq 0,$$

and it becomes an equality when $E_t^j > 0$.

The labor market-clearing condition for skilled workers includes demand from incumbent and entrant firms as follows:

(21) $$L^s = \sum_j \left\{\mathbb{I}_{\left(x_{E,t}^j > 0\right)}\left[h\left(x_{E,t}^j\right) + F_E\right] E_t^j + \int_0^1 \mathbb{I}_{\left(x_{i,t}^j > 0\right)}\left[h\left(x_{I,t}^j\right) + F_{I,i,t}\right] di\right\},$$

where the expression for $x_{E,t}^j$ and $x_{I,t}^j$ as functions of the normalized skilled wage $\tilde{w}_t^s$ is:

(22) $$x_t^j = I_{\left(x_{i,t}^j > 0\right)}\left[\frac{\eta\theta^{1/n}\bar{v}_t^j}{\left(1 - s_t^j\right)\tilde{w}_t^s}\right]^{\eta/(1-\eta)}$$

The labor market-clearing condition for unskilled workers is:

(23) $$1 = \frac{Y_t}{w_t^u} \cdot \left\{\sum_{n \leq m_t} \frac{\mu_{n,t}}{\left(1 + \tau_t^c\right)\lambda\left(m_t - n\right)} + \right.$$
$$\left. + \left[\nu + \left(1 - \nu\right)\left(\frac{1/\zeta}{\tilde{P}_{e,t}}\right)\right] \sum_{n > m_t} \frac{\mu_{n,t}}{\left(1 + \tau_t^d\right)\lambda\left(n - m_t\right)}\right\}.$$

From this condition it follows that the aggregate output may be expressed as the function of tax-adjusted labor productivities as follows:

(24) $$Y_t = \bar{Q}_t \Lambda_t \Omega_t^{-1} exp\left[-\gamma\left(S_t - \bar{S}\right)\right],$$

where

$$\Omega_t \equiv \sum_{n \le m_t} \frac{\mu_{n,t}}{\left(1+\tau_t^c\right)\lambda\left(m_t - n\right)} + \left[\nu + (1-\nu)\left(\frac{1/\zeta}{\tilde{P}_{e,t}}\right)\right] \sum_{n > m_t} \frac{\mu_{n,t}}{\left(1+\tau_t^d\right)\lambda\left(n - m_t\right)}.$$

Then production in the dirty sector is:

$$Y_t^d = \frac{Y_t}{\left(1+\tau_t^d\right) w_t^u \tilde{P}_{e,t}} \left[\frac{1}{2} Q_{m,t}^d + \frac{1}{\lambda(n-m)} \sum_{n > m_t} Q_{n,t}^d\right], \quad (25)$$

where the quality index $Q_{n,t}^d \equiv \int_{i \in \mu_n} q_{i,t}^d di$.

The solution of the intertemporal maximization problem of the consumer leads to the Euler equation:

$$g_{C,t} = r_t - \rho. \quad (26)$$

Owing to the Hoteling rule, the price of the exhaustible resource satisfies the equation:

$$\frac{p_{e,t}}{w_t^u} = \left(\frac{p_{e,0}}{w_0^u} - \zeta\right) \int_0^t e^{r_s - g_{w,s}} ds + \zeta. \quad (27)$$

The technology gaps evolve according to the following system of equations:

$$\dot{\mu}_{n>1,t} = z_t^d \mu_{n-1,t} + (1-\alpha) z_t^c \mu_{n+1,t} - z_t \mu_{n,t}, \quad (28)$$

when $n > 1$ and when $n \le 1$:

$$\begin{aligned} \dot{\mu}_{1,t} &= z_t^d \mu_{0,t} + (1-\alpha) z_t^c \mu_{2,t} + \alpha z_t^d \sum_{n<0} \mu_{n,t} - z_t \mu_{1,t}, \\ \dot{\mu}_{-1,t} &= z_t^c \mu_{0,t} + (1-\alpha) z_t^d \mu_{-2,t} + \alpha z_t^c \sum_{n>0} \mu_{n,t} - z_t \mu_{-1,t}, \\ \dot{\mu}_{n<-1,t} &= z_t^c \mu_{n+1,t} + (1-\alpha) z_t^d \mu_{n-1,t} - z_t \mu_{n,t}. \end{aligned} \quad (29)$$

Here z_t^j denotes the aggregate innovation rate by entrant and incumbent firms (see subsections "Heterogeneous innovation" and "The R&D production function" above).

Dynamic equilibrium path. For any given time path of taxes and subsidies $\left[\tau_t^j, s_{I,t}^j, s_{E,t}^j\right]_{t=0}^{\infty}$, a dynamic equilibrium path is the time path of the following variables:

$$\left[y_{i,t}^j, p_{i,t}^j, x_{I,t}^j, x_{E,t}^j, Y_t, w_t^s, w_t^u, e_{i,t}, p_{e,t}, R_t, E_t^j, \left\{\mu_{n,t}\right\}_{n=-\infty}^{\infty}, \left\{Q_{n,t}^d\right\}_{n=-\infty}^{\infty}, r_t, S_t\right]_{t=0}^{\infty}$$

where $y_{i,t}^j$ and $p_{i,t}^j$ maximize profits in (13); $x_{I,t}^j$ and $x_{E,t}^j$ come from (22); w_t^u is given by (14); aggregate output Y_t is determined by (24); w^s comes from the free-entry condition (20) under positive entry and from skilled labor market clearing (21) under the absence of positive entry; E_t^j is set by the skilled labor market clearing (21) under positive entry; $\left\{\mu_{n,t}\right\}_{n=-\infty}^{\infty}$ follow (28) and (29); $Q_{n,t}^d$ satisfies (20) and (22); the interest rate comes from the Euler equation (26); the quantity and price of exhaustible resource are given by (4) and (27); R_t is set by (3); and S_t is expressed by (7)–(9) with Y_t^d coming from (25).

2.3. Empirical strategy

The [Acemoglu et al., 2016] model is used as a theoretical tool to find the optimal values for a combination of two policy instruments: subsidies for research into carbon-neutral technologies and a tax on carbon emissions. The model studies the evolution of a non-steady state equilibrium, focusing on the time profiles of economic variables across optimal policies (policies with optimal values of carbon tax rate and research subsidies) and the laissez-faire (null) policy. The variables of primary interest are output by firms using carbon-neutral and carbon-emitting technologies, innovative activity by clean and dirty firms, and the overall growth of the economy. The model assumes that all innovations are patented.

The model has 18 parameters $\left\{\rho,\overline{S},\gamma,\varphi,\varphi_0,\varphi_P,\kappa,\nu,\chi,L^s,\alpha,\eta,\theta,\lambda,F_l,F_E,R_0,\zeta\right\}$, and the distribution of $\left\{\mu_{0,t}\right\}_{n=-\infty}^{\infty}$ that needs to be estimated. The values of the initial level of carbon concentration $\overline{S}$ and the parameter for emission damage to production γ (both come from equation (6)), of the three parameters of the carbon cycle $\left\{\varphi,\varphi_0,\varphi_P\right\}$ of Equation (9) – can be set as exogenous and are not involved in calibrating the other parameters of the model.

The estimation of the model is conducted in several steps. Firstly, there are exogenously set parameters: the value of the social discount rate ρ, the parameter κ in (8) – the share of the dirty output that leads to carbon emissions, the parameter ν in (1) – the elasticity of the dirty output in its production function, and the parameter χ in (18) – the distortionary effects of the R&D subsidies.

These values are set as follows: $\rho = 0.01$, $\nu = 0.04$, $\overline{S} = 581GtC$, and $\gamma = 5.3\cdot 10^{-5}GtC^{-1}$ – in accordance with Golosov et al. (2014); φ_P comes from the Intergovernmental Panel on Climate Change [2007] and equals 20 percent; the parameter κ is set to match the World data on carbon emissions and the amount of dirty output in the US in (8), $\left\{\varphi,\varphi_0\right\}$ are estimated based on the US data for carbon emissions and the data on carbon concentrations from the Hawaii-based Mauna Loa observatory, χ is set at 10 percent.

Secondly, the values of L^s, α, and η are computed from microdata on enterprises, their financials, and R&D activity. Thirdly, the distribution of technology gaps $\left\{\mu_{0,t}\right\}_{n=-\infty}^{\infty}$ is determined with the use of the data on patents pertaining to clean or dirty technologies. Fourthly, six parameters are estimated via the method of moments. These are: θ in (15) – the elasticity of the

R&D production function with respect to researches, λ of subsection "Heterogeneous innovation" – a proportional improvement of quality due to incremental innovation, F_l in subsection "The R&D production function" and in the value function specified in (19) – the number of researches per intermediate good in incumbent firms, R_0 in (3) – the stock of the exhaustible resource, and ζ in (2) – the labor productivity of the extraction of the exhaustible resource. Specifically, theoretical moments for the four variables must be close to their empirical counterparts. The four moments to match the model and the data for the energy sector are: per worker growth rates of the sector (based on (24)–(25)), entry/exit rates of firms (can be computed from (19)), the share of the R&D expenditure in output (where R&D expenditure is used as a proxy for R&D labor in (8)). R_0 and ζ are then estimated to correspond to the national data for the level and the rate of the growth of emissions. The remaining variables are estimated from the model (e.g., the number of researchers in old and new firms).

Finally, the optimal values of the policy instruments are estimated using the calibrated model. The objective function for the social planner is welfare[5] at time T which is the sum of the production and quality increase less distortions and emission damage, where emission damage combines the amounts of emissions permanently remaining in the atmosphere S_T^{perm} and transitory S_T^{trans} and Y_T^{base} implies baseline economic production:

$$W = \underbrace{\int_0^T \ln Y_t e^{-\rho t} dt + e^{-\rho T} \Bigg[\ln Y_T^{\text{base}}}_{\text{Production less Distortions}} + \underbrace{\frac{g_T}{\rho}}_{\text{Growth Potential}} \underbrace{- \frac{\gamma}{\rho} \left(S_T^{\text{perm}} + S_T^{\text{trans}} \frac{\rho}{\rho + \phi} - \overline{S} \right) \Bigg]}_{\text{Emission Damage}}.$$

The time profiles of the main economic and climate variables are then contrasted between the *laissez-faire* and the optimal policies. The findings using data for the US energy sector and energy patents from 1975 to 2004 reveal that a non-trivial combination of the two policy measures is optimal for maximizing social welfare and has the following economic effects: an increase in innovation and quality (labor productivity) in the carbon-neutral sector; a redirection of production to the carbon-neutral sector; and long-term economic growth, but a decrease of growth in the short term. The decrease of growth in the short (and possibly medium) term is explained by the superiority of the existing dirty technologies, which can be seen from the micro data on quality in the carbon-neutral and carbon-emitting sectors.

As shown in Section VI of Acemoglu et al. (2016) on the robustness of the results of the research with respect to the exogenously set values of the aforementioned parameters, the qualitative and, to a large extent, quantitative conclusions about the optimal policy mix of the carbon tax and research subsidies are robust to the choice of the exogenously set parameters as follows: the social discount rate may be changed from 1 percent as in Golosov et al. (2014) to lower values such as 0.1 percent or 0.5 percent as in Stern (2007); instead of setting ν equal 4 percent as in

[5] The explicit formula is inferred from lines 770-784 of the code of infinite_weave.py which supplements the [Acemoglu et al., 2016] paper.

Golosov et al. (2014), it can be assigned lower values of 0 or 2 percent; the parameter γ can be increased two- or five-fold compared to the value in Golosov et al. (2014); χ can be either lowered to 0 (no distortions) or increased to 20 percent. The conclusions are also robust to the values of parameters α (0.3 or 0.5) and η (0.35 or 0.65).

3. Data on Japan

We use several blocks of data on the Japanese economy for our quantification. Firstly, we take meteorological data from two sources. National carbon emissions per capita come from the World Bank, which collects estimates from the Carbon Dioxide Information Analysis Center, Environmental Sciences Division, Oak Ridge National Laboratory (Tennessee, US). We use data from the Japan Meteorological Agency on atmospheric carbon concentrations, which are measured at three stations: Ryori (120 km from Sendai on the Pacific coast of Honshu island, in the Tohoku area), Minamitorishima (an island 1848 km southeast of Tokyo in the North Pacific Ocean) and Yonagunijima (an island in the East China Sea in the Pacific Ocean, 108 km from Taiwan). The values of carbon concentration demonstrate similar seasonality and are generally close across the three stations. However, the history of observations is the longest at the Ryori station.

Secondly, we exploit several databases on Japanese companies. The Nikkei NEEDS database contains the financial and administrative data for 6,500 companies from the late 1960s to the early 1970s and onwards. Most of the companies are large corporations, and they account for 50–80 percent of production in their industries. The Nikkei NEEDS data are manually matched to non-anonymous company data from the Japan National Innovation Survey [2015] and to Orbis, Bureau van Djik data with NACE/US SIC industrial classifications for firm products (with an overlap for about 80 percent of Nikkei NEEDS firms).

Thirdly, patent statistics are calculated using the Tokyo Institute of Intellectual Property Patent Database [2020]. This is a recently created NBER-like database [Goto & Motohashi, 2007], which contains Japan's domestic patent applications submitted since 1964.

In the robustness section of this paper, we employ data for Japanese firms from Orbis, Bureau van Djik (2009–2019) which is linked by Bureau van Djik to the European Patent Office database on firm-level patent statistics (available till 2019).

Finally, we use aggregate data on R&D labor in various sectors of the Japanese economy from the Japan Statistical Agency (2023).

4. Quantification for Japan

4.1. Carbon cycle

We fit the exponential (geometric) equation for the carbon cycle [Acemoglu et al., 2016; Golosov et al., 2014], as described in (7)–(9), which draws on the approach used by [Archer, 2005] on the existence of a transitory carbon component in the atmosphere. We use carbon concentration data from the Ryori meteorological station, the World Bank data on carbon emissions by Japan, and the value of the share of emissions, permanently remaining in the atmosphere, from the Intergovernmental Panel on Climate Change [2007]. We fit equation (7) using Japan's data for 1986–2008, so that the final time period was comparable to the US estimates and find that

$\hat{\phi} = 0.0202$ and $\hat{\phi}_0 = 0.4173$. The values of the rate of decay are close to the parameter estimates for the US economy during a similar time period: 0.0313 as reported in [Acemoglu et al., 2016] and 0.0228 in [Golosov et al., 2014]. The share of the transitory component is close to the estimate in [Golosov et al., 2014], but differs from the value in [Acemoglu et al., 2016]. See Table 1 for a detailed comparison. We discuss the approach in the robustness section of this paper.

Table 1.

Contrasting parameters of the carbon cycle in Japan and the US

Parameter	Definition	US		Japan
		Acemoglu et al., 2016	Golosov et al., 2014	
ϕ_p	share of emissions permanently remaining in atmosphere	0.2	0.2	0.2
ϕ	rate of decay of carbon concentration	0.0313	0.0228	0.0202
ϕ_0	$\left(1-\phi_p\right)\phi_0$ share of transitory component in period 0	0.7661	0.3930	0.4173

4.2. Carbon-neutral and carbon-emitting technology

Our definitions of carbon-neutral technologies combine the approaches of the three sources. Firstly, we exploit the [OECD, 2009] methodology on use of patent classes for environmentally friendly technologies, as described in the patent search strategy for the identification of selected "environmental" technologies, developed as part of the OECD project on "Environmental Policy and Technological Innovation". Secondly, we supplement this list of patent classes using the International Patent Classification (IPC) Green inventory of the World International Property Organization [WIPO, 2017]. Finally, we add the patent classes for the energy sector from the corresponding appendix to [Popp & Newell, 2012]. The groups of patent classes used in our analysis for the definition of carbon-neutral technologies are summarized in Table 2.

Table 2.

Carbon-neutral technologies, according to the International Patent Classification

Clean/green technology classes	Source
Air, water and waste related technologies	OECD/WIPO/Popp and Newell (2012)
Alternative energy production	WIPO/Popp and Newell (2012)
Transportation	WIPO
Energy conservation	WIPO
Agriculture/forestry (e.g. alternative irrigation techniques)	WIPO
Nuclear power generation	WIPO
Administrative, regulatory or design aspects (e.g. carbon-emissions trade)	WIPO

4.3. Energy sector

We use the UN International Industrial Classification codes to define energy sector firms according to the approach of the United Nations Industrial Development Organization [Upadhyaya, 2010]. Our analysis also considers the manufacture of motor vehicles and of general-purpose machinery, following [Acemoglu et al., 2016]. The full list of energy sector NACE Revision 2 codes is given in Table 3.

Following [Acemoglu et al., 2016] we examine energy patents in estimating the probability of breakthrough innovation. For this purpose, the paper uses patent classes in the International Patent Classification[6] which correspond to groups of energy goods and services in Table 3. These codes are: B21-B23 (metal working, metallurgy), B60-B64 (vehicles and motor vehicles), C08 (organic macromolecule), C21-C30 (metallurgy, electrolytic processes, crystal growth), F21-F28 (lighting, heating), G21 (nuclear physics and nuclear engineering), H01-H05 (electricity).

Our empirical analysis focuses on the time period after 1989, in order to include the years after the 1988 revision of the Japan Patent Law. The revision allowed multiple claims and may have influenced the strength of Japanese patents, especially in their applicability across industrial fields.

Our sample, which is an overlap between the Nikkei NEEDS, the Japan National Innovation Survey and Orbis database contains 1178–2565 manufacturing firms from 1989 to 2013. There are 303–589 energy firms each year, according to our definition. The share of energy firms is stable at 23–25% of all firms.

Table 3.

Energy sector, according to the UN International Industrial Classification

Industry name	NACE	Source
Mining of coal and lignite; extraction of peat	05	UNIDO [Upadhyaya, 2010]
Extraction of crude petroleum and natural gas	06	UNIDO [Upadhyaya, 2010]
Mining of uranium and thorium ores	07	UNIDO [Upadhyaya, 2010]
Manufacture of coke, refined petroleum products and nuclear fuel	19	UNIDO [Upadhyaya, 2010]
Electricity, gas, steam and air conditioning supply	35	UNIDO [Upadhyaya, 2010]
Manufacture of motor vehicles	29	[Acemoglu et al., 2016]
Manufacture of general purpose machinery	28	[Acemoglu et al., 2016]

4.4. Technology gaps

Following [Acemoglu et al., 2016], we define a clean firm as a firm, whose share of clean patents in all its patents exceeds a certain threshold. However, instead of using the [Acemoglu et al., 2016] threshold of 25% (which gives 11% of clean firms from the US data), we choose a lower value of 5% for our sample. The empirical distribution for the share of clean patents differs between American and Japanese firms. In Japan there is only a negligible number of firms with

[6] https://www.wipo.int/classifications/ipc/en/

over a quarter of clean patents. If we wanted to establish the size of the clean sector as 10–11% of producers (to make Japan's economy comparable to the US), it would require an extremely loose definition, by which just 1% of clean patents would suffice to make a company clean. As a compromise, we choose a threshold of 5% of clean patents for a firm to be regarded as environmentally friendly. The value is supported by micro evidence on the relative weight of environmentally friendly initiatives in the behavior of Japanese firms, which are attentive to their social responsibility regarding the environment [Tanikawa, 2004]. The threshold of 5% means that the share of clean firms in Japan is on average 3% of all firms (varying from 1 to 5% in different years).

According to the model of [Acemoglu et al., 2016], the technology gap between dirty and clean technologies for each product is defined as the difference in the number of innovation steps (see subsection "Heterogenous innovation"). Formally, this is given by $n_{i,t} \equiv n_{i,t}^{d} - n_{i,t}^{c}$, where $n_{i,t}^{d}$ and $n_{i,t}^{c}$ are innovation steps of *dirty* and *clean* technology for product *i* at time *t*, respectively. The technology gap is employed in the value function (19) and in the derivation of the dynamic equilibrium in the model.

Following the empirical strategy in [Acemoglu et al., 2016], we compute the cumulative number of patents for clean and dirty Japanese incumbent firms at the US SIC3 level (and for robustness check at the US SIC4 level). Then this innovation flow of patents for clean and dirty technologies is normalized by the mean patent flow (i.e., the annual number of energy patents per product by all firms). The resulting distribution of the technology gap is given on Figure 1. As shown by the distribution, dirty technology is one to four steps ahead for most products, although dirty technology leads 10 to 120 steps for few products. The shape of the distribution is generally close to that in the US. However, clean technology is up to 10 steps ahead of dirty technology for a few products in the US according to [Acemoglu et al., 2016], but we found no similar pattern for Japan.

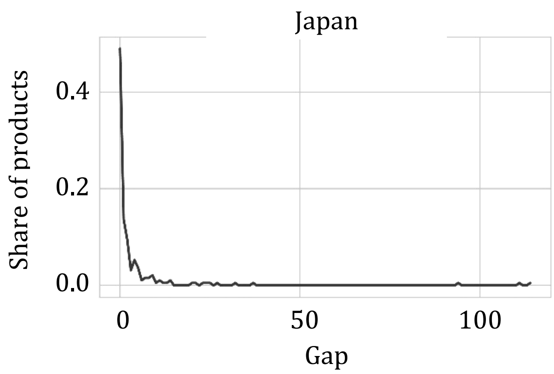

Fig. 1. Technology gap between carbon-emitting and carbon-neutral sectors across products

4.5. Parameters for the Japanese energy sector

To replicate the analysis in [Acemoglu et al., 2016] in estimating moment targets and other parameters related to technological change in the energy sector, this paper considers energy firms with high R&D expenditure (we set the threshold of 1 mln. yen, which is a reasonable country-level analogue to the value of 1 mln. USD used for the US despite being much lower).

The resulting parameters for the energy sector that are listed in Table 4 may be divided into several groups. One group is linked to quality changes through innovation. As innovations are quantified through patents, the quality evaluations are based on patent citations. To compute the probability of radical innovation [Acemoglu et al., 2016] compares citations for energy patents within three years after patenting to citations within 10 years. Patents are defined as 'major entrants' if their citations in the three years exceed the 90th percentile (i.e. a reasonable threshold value) of the citations for patents as old as 10 years. The share of major entrants, which equals 0.04 for the US energy sector, is regarded as an empirical estimate of the probability of radical innovation. Our use of the patent data for Japan's economy with a similar approach produces a comparable estimate of 0.038.

Another variable on innovation outcomes is mean patent flow, which is defined in [Acemoglu et al., 2016] as the annual number of citation-weighted patents per product. While the US estimate for the energy sector is 43 patents, our calculations give a corresponding value of 40 patents for Japan.

The second group of parameters relates to the R&D production function. The [Acemoglu et al., 2016] strategy follows the microeconomic approach to proxy R&D output by patents and takes R&D expenditure as an input. The regression analysis exploits pooled data with firm-level clustered standard errors and adds annual dummies to the right-hand side of the equation. The resulting value for R&D elasticity is 0.5 for the US data: it is the mean estimate across the models in levels and in the first differences and across the two specifications (the normalization of input and output by product counts or by domestic sales). Our calculations with the data for Japan's energy sector give a range of elasticity [0.2, 0.6], so the mean estimate is 0.4. The share of R&D labor in unskilled labor is 0.055 in the US, as estimated in [Acemoglu et al., 2016] using micro data. We infer the value of 0.059 using the data from the Japan Statistical Agency (2023).

The third group of parameters are moment targets – the mean values of the four key variables, which are used in model calibration through a simulated method of moments. The variables relate to microdata on company history and financials, and are comparable across innovative energy firms in the US and Japan: the entry rate and exit rate of firms, mean R&D expenditure per sales, and the growth of sales per worker.

The values of the parameters in Table 4 do not differ appreciably between the innovative energy firms in the US and Japan.

However, the US-Japan differences in the gaps between dirty and clean technologies, which we reported in section 4.4, are likely to result in a higher reliance on carbon tax rather than on research subsidies in the context of the models of [Acemoglu et al., 2016] and [Golosov et al., 2014].

Table 4.

Parameters for the energy sector in Japan and the US

	US	Japan
Patents		
Probability of radical innovation	0.04	0.038
Patents per product (citation weighted)	43	40
R&D		
Share of R&D labor	0.055	0.059
Elasticity of innovation output in R&D expenses	0.5	0.4
Production (moments for calibration)		
Entry rate of firms	0.013	0.017
Exit rate of firms	0.018	0.012
Growth of sales per worker	0.012	0.029
Share of R&D expenditure in sales	0.066	0.056

Note: The US data for the energy sector in 1975–2004 come from [Acemoglu et al., 2016]. Japanese estimates for the energy sector (unless otherwise stated) are based on our data for 1989–2012. Regarding the entry rate of firms, [Acemoglu et al., 2016] use the labor share of entrants, while we use the number of firms with the Japanese data. The table reports the share of R&D labor of all specialties in the sector "Electrical machinery and equipment" using the plant-level data on R&D employment from the Japan Statistical Agency (2023), File 4, columns 1,3,15. (The average share across all industries and plants of all size in Japan is 0.037, and the shares in the other subsectors of the energy sector, as classified in Table 3 in this paper are in the range of 0.02 to 0.2).

5. Results

5.1. Carbon tax, research subsidy, innovation rates, and outputs in the clean and dirty sector

Our computations use Python codes from [Acemoglu et al., 2016][7]. While [Acemoglu et al., 2016] analyze various ways to parametrize the time profiles for policy instruments, we focus

[7] The codes are available as supplementary material to the [Acemoglu et al., 2016] paper on the *Journal of Political Economy* website: https://www.journals.uchicago.edu/doi/suppl/10.1086/684511. Firstly, the data are loaded into load_data.py and the parameters for the carbon cycle, energy sector, and R&D are entered into infinite_weave.py. Then the estimation_weave.py is used to calibrate the remaining six parameters (described in section 2.3 of this paper in the fourth set of estimated parameters), and the calibration starts from the manually entered initial values for the parameters. Our investigation of the algorithm hints at the fact that the model seems to have a knife-edge solution (see [Posch, 2011; Growiec, 2007; Ellison & Fudenberg, 2003]) and no convergence can be achieved under entering the initial values for the six parameters that appreciably differ from the equilibrium ones. So in comparing the impact of different policy measures for the Japanese economy, using the code generate_policy.py, we employ moment targets obtained from the US data. This may be justified by the fact that parameters for the energy sectors of Japan and the US are very similar (Table 4). However, we enter the Japan-specific technology gaps in load_data.py in conducting the estimations with generate_policy.py.

on the two scenarios, which are most realistic to implement and are often analyzed in the Japanese context [Ministry of the Environment, 2017]. Optimal constant policies imply fixed values of research subsidies and carbon taxes over the whole period, while optimal three-step policies allow for step-wise changes in the course of adapting policy instruments.

The results for the Japanese economy as regards carbon taxes and research subsidies are given in Fig. 2 and can be contrasted to those reported by [Acemoglu et al., 2016, Fig. 10] for the US in the case of the three-step policy. The carbon tax is around 0.05 during the first period in the US, while it is twice as much and is close to 0.1 in Japan. The value of research subsidies is close to 0.8 in the US during the first period, while it is below 0.8 in Japan. Similarly, there is higher reliance on carbon taxes and lower reliance on research subsidies in Japan relative to the US in the second period.

The combination of carbon tax with research subsidies switches innovation in Japan from the carbon-emitting to the carbon-neutral sector (Fig. 3). Innovation in the carbon-emitting sector vanishes after 50 years of policy implementation. Similarly, there is a redirection of production from the dirty to the clean sector: the output of the dirty sector steadily declines, while production in the clean sector gradually increases (Fig. 4–5). The results reveal that the carbon-neutral sector would disappear in the medium-run under the laissez-faire, i.e. without the optimal policies.

The optimal policy instruments not only sustain the growth of clean production, but lead to overall economic growth in the long term (Fig. 6). The number of years, during which aggregate output in Japan declines as incentives to use clean technologies are applied, is comparable to the 20 years estimated by [Golosov et al., 2014] for reaching the *laissez-faire* level of production in the US with the application of similar incentives. However, the period is longer in Japan, which may be explained by more distortions due to the relatively slower advance of clean technologies. The environmental effects of policy instruments are similar to those in [Acemoglu et al., 2016]: decrease of national carbon emissions and a limited contribution by the country to temperature increases.

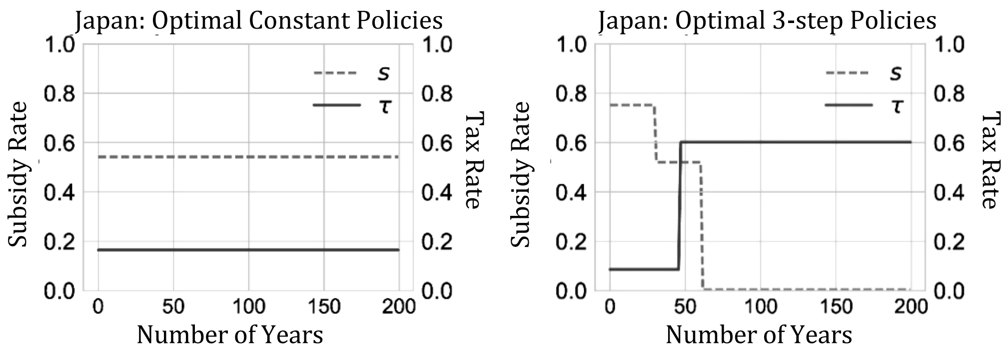

Fig. 2. Tax rate and research subsidies under the optimal policies

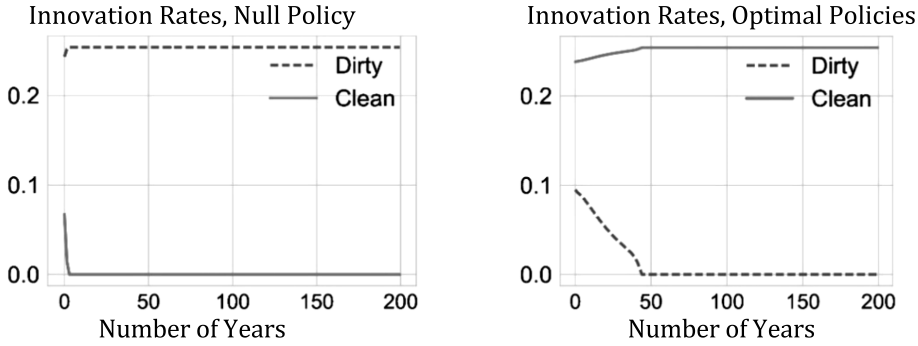

Fig. 3. Innovation rates under the laissez-faire and optimal policies

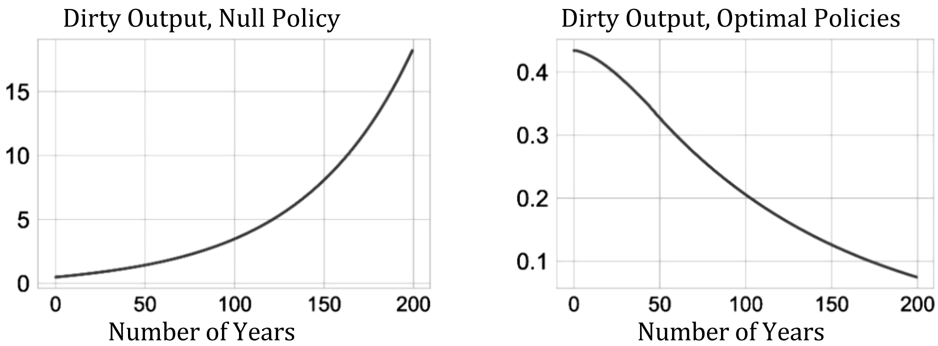

Fig. 4. Output in the carbon-emitting sector under the laissez-faire and optimal policies

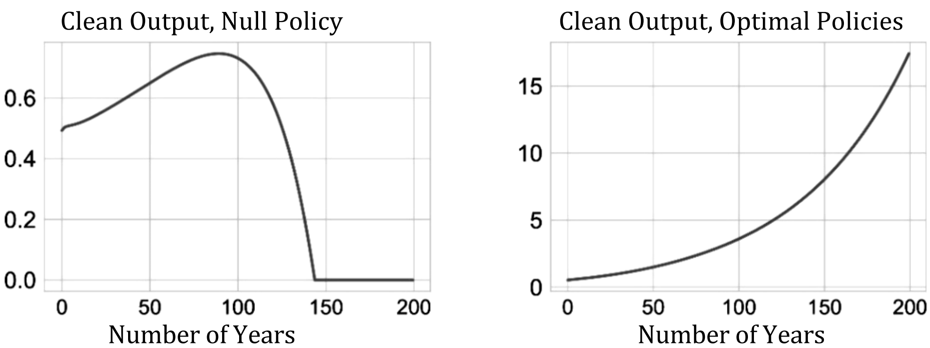

Fig. 5. Output in the carbon-neutral sector under the laissez-faire and optimal policies

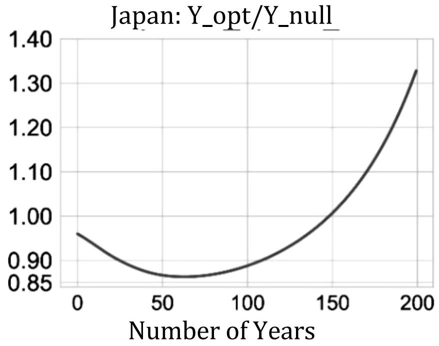

Fig. 6. Ratio of aggregate output in the economy (clean and dirty) under optimal policies to output under the laissez-faire

5.2. Robustness of the estimates and limitations of the analysis

Four types of robustness checks may be justified in evaluating the results of the empirical analysis. Firstly, the question is: how the results within the framework of the [Acemoglu et. al., 2016] model (applied to the data of a given country) are robust to changes in the values of the key parameters. The issue was briefly touched upon at the end of Section 2.3 of this paper and may be expanded here as follows. The results, for instance, as regards the values of the carbon tax rate and research subsidies and the time profiles of production, are generally robust to a range of the social discount rate in the utility function of the representative household (see Fig. 6, 10 and 11 in [Acemoglu et al., 2016]). More specifically, if there is a minor increase in the size of the carbon tax rate due to lowering the social discount rate from 1 to 0.5 percent and there is a noticeable rise of the carbon tax rate when the social discount rate goes down from 1 to 0.1 percent. Arguably, the change of the social discount rate in the opposite direction: from 1 to 2 percent would lead to a negligible fall in the carbon tax rate.

According to Section VI in [Acemoglu et al., 2016], the results are robust to the values of the elasticity of dirty output with respect to exhaustible resources in Equation (2): 0, 2 or 4 percent; to the values of the parameter for the negative impact of the carbon concentration on the overall economic output in the economy in Equation (6); to the share of research subsidies that are lost, i.e. the distortions parameter in Equation (17); to the probability of a breakthrough innovation (0.3, 0.4 or 0.5); and to the elasticity of the R&D production function with respect to labor inputs in Equation (15).

Secondly, an important issue for the robustness check deals with the comparison of the findings for the US and Japan under the change of one of the key exogenous parameters across the two countries. As the national economies of the US and Japan at the end of the 20th century and at the beginning of the 21st century are very similar as regards institutional infrastructure, economic incentives and the principles of political economy, a reasonable candidate for such cross-country differences is social discount rates, which is largely explained by the psychological aspects of consumer behavior. Arguably, the social discount rate in Japan is likely to be lower than in the US, but as is shown in the analysis in Figures 6 and 11 in [Acemoglu et al., 2016], the size of the carbon tax rate does not change during the first 50 years under lowering the social discount rate from 1 to 0.5 percent. Under the lowering of the social discount rate from 1 to 0.1 percent, the carbon tax rate goes up in the first 50 years. So our conclusion about the higher values of the carbon tax rate in Japan in comparison to the US would only be strengthened under the assumption that the social discount rate in Japan is much lower than in the US.

The third question is how the results are robust to alternative ways of computing the technology gap, i.e. the gap between the labor productivity of dirty and clean technologies. Here we follow the approach of [Acemoglu et al., 2016] to consider different ways of computing the technology gap: based on the US SIC3 codes (as reported in Section 4.4 of this paper) or based on SIC4 codes; using the data for energy patents in the whole economy, only in the energy sector or in the manufacturing sector. For this purpose, we employ both Nikkei NEEDS data (which overlap with Japan Innovative Survey) for large innovative Japanese firms from 1989 to 2012 and the data of Orbis, Bureau van Djik for large and medium-sized Japanese firms from 2009 to 2019. In the baseline analysis in this paper, we linked the NIKKEI NEEDS firms to their patents using the Tokyo Institute of Intellectual Property database (2020). Our robustness check employs the European Patent Office data (coming from the Japan Patent Office) and available within the Orbis database with firm – patent level links till 2019.

Our robustness check hints at the key difference between the technology gap in the manufacturing and energy sectors of the US and Japan – generally, there is an absence of products for which the number of innovation steps in clean technology exceeds the number of innovation steps in dirty technology. Exceptions are only a handful of products – 50–100 non-energy sector products in the selected years with a negative technology gap: i.e., the clean technology is ahead of the dirty. However, the value of the lead of clean technology is only 1 step. Yet, the findings for the US economy show that the technology gap is negative for over 9 percent of products, and its absolute values are larger than 1 for 7 percent of products, see Section VI.H in [Acemoglu et al., 2016] and page A-13 in the online supplement to [Acemoglu et al., 2016]. As regards energy sector or energy patents, our robustness checks with the 3-digit or 4-digit code products in 1989–2012 with Nikkei NEEDs firms or for 2009–2019 with Orbis firms (about 1300 patenting firms and overall about 28,000 firms in the energy sector) shows that the technology gap is always positive: there are more innovation steps in the dirty sector than in the clean sector for each product. The fourth issue concerning the robustness of the estimates is the measurement of the parameters for the carbon cycle. In this paper, we used the carbon concentration from the Ryori station owing to it having the longest time series across the three Japanese meteorological stations. In reality, the curves on carbon concentration based on the data from the three stations are very similar in years when the data are available for each station, despite the fact that the geographical proximity to China and other Asian countries varies from 100 to 3,000 kilometers across the three stations. Arguably, carbon emissions from several countries contribute to carbon concentration measured at any of the three Japanese stations. More generally, our empirical exercise fitting the carbon cycle showed that the shape of the data series for Japan (available in Fig. 1 on the working paper version of this paper [Besstremyannaya, Dasher, Golovan, 2019]) does not differ from that for the US in [Acemoglu et al, 2016]. Moreover, the inability to exclude the impact of carbon emissions from several other countries is likely to apply to the measurement of carbon concentration data according to Mauna Loa station in Hawaii[8]. So our estimations, that were targeted at the completeness of using the Japanese data (as regards meteorological figures), may serve as a proof of the robustness of estimating the carbon cycle with data from

[8] The fact was noted by the reviewer to our paper.

different meteorological stations across the world. Moreover, using the estimates of [Acemoglu et al. 2016] or [Golosov et al., 2014] would not change the quantitative or qualitative results of our analysis. In fact, borrowing the US parameters for the carbon cycle is an existing approach in macroeconomic analysis with Japan-based data. For example, model calibration in [Matsumura et al., 2024] employs the carbon cycle parameters from [Golosov et al., 2014].

Finally, we note the remaining limitations of the analysis. The [Acemoglu et al., 2016] model assumes that all innovations are patented. The prevalence of patenting may be considered comparable across the US and Japan [Cohen et al., 2002] and hence the assumption is unlikely to lead to an appreciable overestimation of the technology gap or an underestimation of radical innovation in Japan. However, the model considers a closed economy, so the approach disregards technology adoption across countries[9]. For instance, the spillover effect of clean innovation in the direction from the US to Japan may cause lower values of the lead between dirty and clean technologies in Japan than those estimated with patent data. Concerning the external validity of the analysis, patents may not offer a full representation of clean innovation in developing and emerging countries (e.g. BRICS countries), where clean innovation may appear in the forms of frugal innovation [Besstremyannaya and Dasher, 2024]. Therefore the distribution of the technology gap in emerging countries based on patent data could overestimate the distance between dirty and clean technologies, and lead to the overestimation of the value of the carbon tax in the optimal policies.

Thirdly, the model is of a general equilibrium kind but the calibration of the model deals only with the data for the energy sector and energy patents. This limitation has led to the development of the models in various sectors of the economy which depend on energy to a different extent. However, the existing models, as noted in the Introduction to the present paper, are not as rich in employing microeconomic data or using the principles of quality competition. The fourth limitation of the model concerns the estimate of the elasticity of R&D output with respect to R&D labor or R&D expenses. According to our companion paper on the heterogeneity of the growth of Japanese innovative firms [Besstremyannaya, Dasher & Golovan, 2022], the successful use of R&D expenditure in terms of producing innovation output depends to a large extent on R&D management, which is commonly disregarded in the macroeconomic approach. Moreover, the focus on only patenting firms (and arguably, high-growth firms as such firms are likely to be more successful in innovation) may lead to an overestimation of the elasticity parameter if the analysis is to be expanded to R&D-investing but non-patenting firms.

6. Discussion and Conclusion

Endogenous growth models with technological change assume that competitive firms conduct R&D to raise profits through improving their technology [Klette & Kortum, 2004]. Stemming from the Schumpeterian concept of creative destruction and the [Arrow & Debreu, 1954] general equilibrium framework, the models account for the actions of the main economic agents in the market and the actions of government as a social planner. Not only are the models rich in the explanations they offer of numerous regularities in company growth [Acemoglu et al., 2013; Lentz & Mortensen, 2008], but they also make it possible to incorporate various economic externalities such as carbon emissions. This paper uses the framework of such a model [Acemoglu et al., 2016] and applies the approach for the analysis of the Japanese economy.

[9] The concern was noted by a reviewer of our paper.

The policies considered in this paper are a combination of carbon taxes and research subsidies. The analysis demonstrates that there is a temporary decline of economic output associated with the development of carbon-neutral technologies (both in applications to the US and Japan), and we conjecture that it can be explained by technology costs. For example, empirical microeconomic analyses show that technology costs negatively affect individual decisions to use thermal insulation technologies, and the scope of the effect is several times larger than the effect of energy prices [Hassett & Metcalf, 1995; Jaffe & Stavins, 1995]. Inadequate access to financing may be an impediment to introducing clean technologies at small firms [Jaffe et al., 2003]. However, financial impediments may be of secondary importance in comparison with alternative investment choices, capital depreciation and energy prices[10]. As regards the overall social welfare function, judged from a macroeconomic perspective, the costs of clean technologies (borne by the government through research subsidies) can be offset against economic gains. The gains can be measured in terms of economic growth or an increase of social welfare thanks to the prevention of carbon emissions.

Concerning the comparison of the values of the optimal policy instruments in the US and Japan, this paper finds that the carbon tax rate in Japan should not be below that in the US. Yet, the current value of the carbon tax rate in Japan (as adopted in 2012) was one of the lowest across OECD countries and is several times lower than the US carbon tax rate. Moreover, while the US adopted a policy of increasing its carbon tax rate from 8 to 51 USD per ton of CO2 (which is within the range of international recommendations of 35 to 70 USD), Japan has kept its carbon tax rate constant at the 2012 value of about 2.6 USD [Gokhale, 2021]. Another key finding of the paper is the fact that the length of the period for the decline of aggregate output in Japan owing to introduction of the carbon tax and research subsidies is longer than that in the US. Both findings are driven by the relatively low spread of clean technologies in Japan compared to in the US.

Along with the cross-country analysis, the present paper follows [Acemoglu et al., 2016] to show that the optimal values of both the carbon tax and research subsidies are non-zero for Japan. In fact, market mechanisms, such as the introduction of carbon taxes or theincrease of energy prices, can be viewed as an economic incentive for firms and households to employ carbon-neutral technologies [Jaffe et al., 2003; Sanstad et al., 1995]. However, market forces alone cause only the slow propagation of carbon-neutral technologies and diminish the potential for reducing emissions [Popp et al., 2010][11]. Accordingly, there is a need for research subsidies that stimulate the diffusion of currently existing green technologies.

[10] See the socio-economic analysis for the Dutch firms in [Nijkamp et al., 2001]. The incentives of Japanese firms in their voluntary adoption of environmental technologies are analyzed in similar qualitative research by [Tanikawa, 2004].

[11] In fact, there is a certain "habit-formation" in the decision by a firm regarding technology development. For instance, econometric estimates show that R&D can be viewed as a function of a firm's past history in terms of its clean/dirty innovation [Aghion et al., 2016].

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Влияние налога на выбросы углерода и субсидий на НИОКР на экономический рост в Японии

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Множество исследований свидетельствует о том, что налог на выбросы углерода в сочетании с субсидиями на НИОКР могут рассматриваться как эффективная форма государственной политики для поощрения распространения низкоуглеродных технологий на благо общества. В данной статье используется макроэкономический подход моделей эндогенного роста с технологическими изменениями для проведения оценки влияния таких мер на экономический рост в Японии в среднесрочной и долгосрочной перспективе, и для сравнения наших результатов с существующими выводами о подобных мерах для экономики США. Наши оценки с использованием микро- и макроданных выявляют сходство между японскими и американскими энергетическими компаниями в отношении эластичности функции производства инноваций по расходам на НИОКР и в отношении вероятности радикальных инноваций. Однако, согласно проанализированным нами данным об энергетических патентах в Японии, чистые инновации не так широко распространены в этой стране, как в США. Это может объяснить наши количественные выводы о необходимости более сильной опоры на налог на выбросы углерода в Японии по сравнению с США.

Ключевые слова: эндогенный рост; технологические изменения; инновации; налог на выбросы; энергетика.