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Technological Change, Energy, Environment and Economic Growth in Japan

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Technological Change, Energy, Environment and Economic Growth in Japan

Abstract

A considerable amount of research has shown that a carbon tax combined with research subsidies may be regarded as optimal policy for encouraging the spread of low-carbon technologies for the benefit of society. The 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 reveal several important differences between Japanese and US energy firms: lower elasticity of the innovation production function in R&D expenditure, lower probability of radical innovation, and predominance of dirty technologies in Japan. This may explain our quantitative findings of stronger reliance on carbon tax in Japan as opposed to research subsidies in the US.

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

Keywords: Endogenous growth; technological change; innovation; carbon tax; energy

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1 Introduction

Endogenous growth models with technological change assume that competitive firms conduct R&D to raise profits through improving their technology (Klette and Kortum, 2004). Stemming from the Schumpeterian concept of creative destruction and the Arrow and Debreu (1954) general equilibrium framework, the models account for the actions of the main economic agents on 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 (Lentz and Mortensen, 2008; Acemoglu et al., 2013), but they also make it possible to incorporate various economic externalities.

A few recent models focus on environmental impact of technological change: for instance, the economic and social effect of pollution in terms of carbon emissions (Popp et al., 2010; Jaffe et al., 2003). In particular, the approach by Golosov et al. (2014) offers an extension of the Romer (1986) endogenous growth model, where producers have carbon-emitting or carbon-neutral technologies and innovate to change their technologies. A related framework in the paper by Acemoglu et al. (2016) incorporates competition by clean and dirty firms along the lines of the Klette and Kortum (2004) model. An attractive feature of the Acemoglu et al. (2016) approach is its interrelation with microdata: 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.

Estimating the models with company-level data for a given country enables a quantitative evaluation of regulatory policies, targeted at correction of market failures pertaining to environmental issues. However, empirical evidence on the macro-level impact of environmental pollution and the actions of the social planner in models with technological change is generally limited to the US economy (Acemoglu et al., 2016; Golosov et al., 2014; Dasgupta and Mäler, 2000). It is generally believed that the changeover to carbon-neutral technologies in one industry leads to increased application of clean technology in other industries. This can be determined, for instance, on the basis of patent citations, see Popp and Newell (2012). The diffusion of clean technologies across industries enhances social welfare by mitigating pollution and climate change (reduction of fossil fuel emissions limits temperature increase, see (Acemoglu et al., 2016; Golosov et al., 2014). But the effect on overall economic growth may vary depending on time horizons.

Confronting pollution has long been on the agenda in many developed countries, notably in the EU and Japan (International Energy Agency, 2016). In particular, Japan might be viewed as a pioneering country, since it has a long history of environmental taxes, government subsidies and company initiatives for environmentally friendly technologies. 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, the country introduced a carbon tax on consumers as a part of the concept for "greening the Japanese tax system" within the forth 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 technologies (Ministry of Finance, 2010, 2015; Wakiyama and Zusman, 2016).

The purpose of the present paper is to provide a quantitative estimate of the effects of carbon emissions and regulatory energy policy on economic growth in Japan. Our empirical analysis goes beyond 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 optimal values of carbon tax and research subsidies, and the impact of these policy instruments on innovation rates and economic output in the carbon-emitting and carbon-neutral sectors. We model the carbon cycle following Acemoglu et al. (2016) and Golosov et al. (2014), and compare the estimates for the US and Japan.

The results of our micro analysis reveal several important differences between Japanese and US firms: lower elasticity of innovation production function in Japan, lower probability of radical innovation and higher labor productivity of production with dirty technology in comparison with clean production. This may explain our quantitative finding of stronger reliance on carbon tax than on research subsidies in Japan in comparison with the US.

2 Related literature

Studies in the microeconomic context show a behavioral response of firms and consumers to both market mechanisms and regulatory actions in the field of energy economics (De Groot et al., 2001; Tanikawa, 2004). A few analyses suggest that the choice of environmentally friendly technologies are linked to energy prices and a history of firm's innovative activity (Aghion et al., 2016; Popp and Newell, 2012; Popp, 2006). As for policy instruments, carbon tax combined with research subsidies may be regarded as an optimal policy for minimizing carbon emissions and/or maximizing social welfare (Fischer and Newell, 2008; Popp, 2006;

Gerlagh and Van der Zwaan, 2006).

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 and Wilcoxen, 1990). Using revenues obtained from carbon taxes for the development of carbon-neutral technologies may mitigate the problem of GDP decrease. Accordingly, the link between clean/dirty technologies and economic output is studied within endogenous growth models with technological change. The models assume that competitive firms conduct R&D to raise profits by improving the quality of their technology (Klette and Kortum, 2004).

The firms choose whether to develop carbon-emitting or carbon-neutral technologies, and the decision is based the current quality gap between technologies, the size of carbon taxes and the size of research subsidies (Acemoglu et al., 2016). The results of a few analyses show that the optimal regulatory policies foster production in the carbon-neutral sector and lead to overall economic growth in the medium (Golosov et al., 2014) or long term (Acemoglu et al., 2016).

Recent applications to the US economy, reported in the literature, include research that focuses on the choice of optimal carbon taxes and research subsidies to foster development of clean technologies and positively affect output and economic growth (Acemoglu et al., 2016; Golosov et al., 2014). The analysis in Dasgupta and Mäler (2000) examines the optimality of carbon taxes in view of total factor productivity.

Reviews of the literature on links between economic growth, carbon emissions and government policies can be found in Xepapadeas (2005) and Jorgenson et al. (1993). Microeconomic evidence on the impact of policy instruments on innovation in the energy sector as well as meta-review of research focused at carbon emissions and technological change in the energy sector are given in Popp et al. (2010).

Some approaches for studying the effect of carbon taxes in Japan through computable equilibrium models with aggregate-level regression analysis are mentioned in Ministry of the Environment (2017).

3 The Acemoglu et al. model

3.1 Theoretical framework

The model proposed by Acemoglu et al. (2016) accounts for competition between carbon-emitting and carbon-neutral technology in economic production and R&D. It builds on the key concepts of endogenous growth models with technological change: the firm offering the best quality owns the market for the relevant product line (Romer, 1990; Grossman and Helpman, 1990); firms innovate to maximize profits by adding new products/improving the quality of existing products (Klette and Kortum, 2004; Lentz and Mortensen, 2008). The key environmental actions of the agents in the Acemoglu et al. (2016) model may be summarized as follows.

Firstly, profit-maximizing firms produce intermediate goods, choosing between carbon-emitting or carbon-neutral technology based on the gap in labor productivity (quality) between the technologies and the size of carbon tax. Firms make a decision on R&D, and the decision is influenced by the R&D subsidy. Secondly, the producer of the aggregate final good uses intermediate goods (e.g. energy) as inputs. Carbon-emissions cause economic damage, decreasing productivity of the final good. Finally, the government collects carbon taxes, imposes taxes on consumers to balance its budget and provides R&D subsidies.

The Acemoglu et al. (2016) model looks at a stock of an exhaustible resource, which is used for carbon-emitting technology. The carbon emissions occur during the production process and cause an increase in the atmospheric carbon concentration. The rise in CO2 has a negative effect on both social welfare and the amount of the final good.

Below we provide a formal description of the carbon cycle, according to the models of Acemoglu et al. (2016) and Golosov et al. (2014), as well as the link between carbon emissions and production, and the analytical description of social welfare from Acemoglu et al. (2016).[1]

Atmospheric carbon concentration S_t if $t = T$ is the date when emission began:

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

where carbon emission K_t is proportionate to output of the dirty sector Y_t^d:

$$K_t = \kappa Y_t^d, \tag{2}$$

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

$$d_l = (1 - \phi_p)(1 - \phi_0 e^{-\phi l}), \tag{3}$$

ϕ_p is the fraction of emissions permanently remaining in the atmosphere;
ϕ is the rate of decay of carbon concentration over time.

[1]The explicit formula for social welfare is reconstructed according to the code, which supplements the Acemoglu et al. (2016) paper.

Carbon emission and production:

$$\ln Y_t = -\gamma(S_t - \bar{S}) + \int_0^1 \ln y_{i,t} di, \tag{4}$$

where Y_t is aggregate output in the economy, $\bar{S}$ is pre-industrial level of carbon concentration, $y_{i,t}$ is the quantity of intermediate good, $\gamma = 5.3 \cdot 10^{-5} GtC^{-1}$.

Social welfare:

$$W = \underbrace{\int_0^T \ln Y_t e^{-\rho t} dt + e^{-\rho T}\Big[\ln Y_T^{base} +}_{\text{Production less Distortions}} \underbrace{\frac{g_T}{\rho}}_{\text{Growth Potential}} \underbrace{-\frac{\gamma}{\rho}\Big(S_T^{perm} + S_T^{trans}\frac{\rho}{\rho+\phi} - \bar{S}\Big)\Big]}_{\text{Emission Damage}}, \tag{5}$$

where $\ln Y_T^{base} = \int_0^1 \ln y_{iT} di$ is the output under absence of emissions, ρ is the discount rate (equal to 0.1), $S_T^{perm} = \int_0^T \phi_p K_t dt$ is carbon permanently remaining in the atmosphere, S_T^{trans} is the transitory part of carbon in the atmosphere: $\dot{S}_t^{trans} = -\phi S_t^{trans} + \phi_0 K_t$.

3.2 Research question, empirical strategy and key findings

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 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 *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 overall growth of the economy. The model assumes that all innovations are patented.

The empirical strategy at the first stage involves fitting the carbon cycle with the national data on carbon emissions. The fitted values of carbon concentration are then used in the endogenous growth model. A number of the model's parameters on innovation come from the micro data: the firm's products, equivalent to the sic3 or sic4 codes in the US industrial classification; division of the economy into clean and dirty sectors, based on patent classes; the probability of radical innovation and the technology gap between clean and dirty sectors, according to patent citations; the elasticity of innovation production function, where innovation is either R&D expenditure or patent counts per product of the firm. Finally, the model is calibrated with the simulated method of moments: theoretical moments for the four variables must be close to the empirical counterparts (share of skilled labor, entry and exit rates of firms, sales growth per worker), and the remaining variables are estimated from the model (e.g., number of researchers in old and new firms, relative productivity of dirty compared with clean technology).

At the second stage, the optimal values of the policy instruments are estimated using the calibrated model. The objective function for the social planner is welfare which is the sum of production and quality increase less distortions and 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 in 1975–2004 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 carbon-neutral sector; and long-term economic growth, but 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.

4 Data

We use several blocks of data on the Japanese economy for our quantification. Firstly, we use 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 of 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 stations. However, the history of observations is the longest at the Ryori station, which explains our choice of data from this station in the analysis.

Secondly, we exploit several databases on Japan's companies. The Nikkei NEEDS contain the financial and administrative data for 6,500 companies. Most of the companies are large corporations, and they account for 50-80 percent of production in corresponding Japanese industries. The Nikkei NEEDS data are manually matched[2] to a non-anonymous company data from the Japan National Innovation Survey (2015). The survey focuses on innovative

[2]See details on matching algorithms in Besstremyannaya et al. (2018).

firms and contains a crosswalk to patent database.

Thirdly, the patent statistics are calculated using the Institute of Intellectual Property Patent Database (2015). This is a recently created NBER-like database (Goto and Motohashi, 2007), which contains Japan's domestic patent applications submitted since 1964.

Finally, we use aggregate data on R&D labor from the Japanese Science and Technology Indicators 2016 by the National Institute of Science and Technology Policy, Tokyo.

5 Quantification for Japan

5.1 Carbon cycle

We fit the Acemoglu et al. (2016) and Golosov et al. (2014) exponential (geometric) equation for the carbon cycle (6), using the 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).

Atmospheric carbon concentration

$$\underbrace{S_t}_{\text{Carbon concentration}} = \int_0^{t-T} (1 - d_l) \underbrace{K_{t-l}}_{\text{Carbon emissions}} dt, \tag{6}$$

where $t = T$ is the start of emissions, $1 - d_l$ is the amount of carbon emitted l years ago and left in the atmosphere, and:

$$d_l = (1 - \phi_p)(1 - \phi_0 e^{-\phi l})$$

The description of the carbon cycle draws on the approach used by Archer (2005) on the existence of a transitory carbon component in the atmosphere. So the parameters of interest are the rate of decay of carbon concentration ϕ and the share of the transitory component of carbon at period zero ϕ_0.

We fit the equation using Japan's data for 1986–2008, so that the final time period was comparable to the US estimates (Figure 1).

We find that $\widehat{\phi} = 0.0202$ and $\widehat{\phi_0} = 0.4173$. The values of the rate of decay are close to 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.

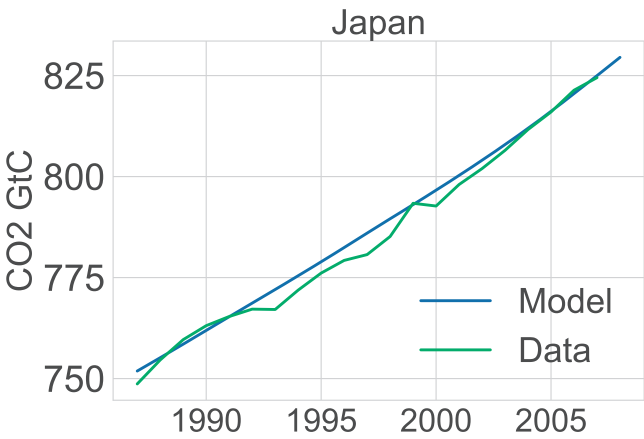

Figure 1: **Estimating the carbon cycle in Japan based on meteorological data of Ryori station**

Table 1: **Contrasting parameters of the carbon cycle in Japan and the US**

Parameter	Definition	US Acemoglu 2016	US Golosov 2014	Japan
ϕ_p	share of emissions permanently remaining: Intergovernmental Panel on Climate Change (World Meteorological Organization and the UN)	0.2	0.2	0.2
ϕ	rate of decay of carbon concentration	0.0313	0.0228	0.0202
ϕ_0	$(1-\phi_p)\phi_0$ share of transitory component in period 0	0.7661	0.3930	0.4173

5.2 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 the above 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 energy sector from the corresponding appendix to Popp and Newell (2012).

The groups of patent classes used in our analysis for the definition of carbon-neutral technologies can be summarized as follows (Table 2).

Table 2: **Carbon-neutral technologies, according to the International Patent Classification**

Clean/green technologies	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; soil improvement: organic fertilizers derived from waste)	WIPO
Nuclear power generation	WIPO
Administrative, regulatory or design aspects (e.g. carbon-emissions trade)	WIPO

5.3 Energy sector

We use the UN International Industrial Classification codes to define energy sector firms following 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 codes is given in Table 3.

We focus on the time period after 1989 in order to include the years after the 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 and the Japan National Innovation Survey, contains 1178–2565 manufacturing firms in 1989–2013. 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.

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 with the US data), we choose a lower value of 5% for our sample. Indeed, 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 over a quarter of clean patents. If we wanted to establish the size of the clean sector as 10–11% of producers (to make the Japan's economy comparable to the US), it would require an extremely loose definition, by which just 1% of clean patents would

Table 3: **Energy sector, according to the UN International Industrial Classification**

Industry name/code	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)

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% implies that the share of clean firms in Japan is on average 3% of all firms (varying from 1 to 5% in different years).

5.4 Technology gaps

According to the model of Acemoglu et al. (2016), technology change is reflected in labor productivity. Next, the gap between dirty and clean technologies for each product is defined as the difference in the number of innovation steps. Formally, this is given by

$$gap_{i,t} = n_{i,t}^{d} - n_{i,t}^{c}, \tag{7}$$

where $n_{i,t}^{d}$ and $n_{i,t}^{c}$ are innovation steps of *dirty* and *clean* technology for product i by time t.

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 sic3 level. Then this innovation flow of patents of clean and dirty technologies is normalized by the mean patent flow (i.e., the annual number of patents per product by all firms). The resulting distribution of the technology gap from equation (7) is given on Figure 2. 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 for a few products in the US according to Acemoglu et al. (2016), but we found no similar pattern for Japan.

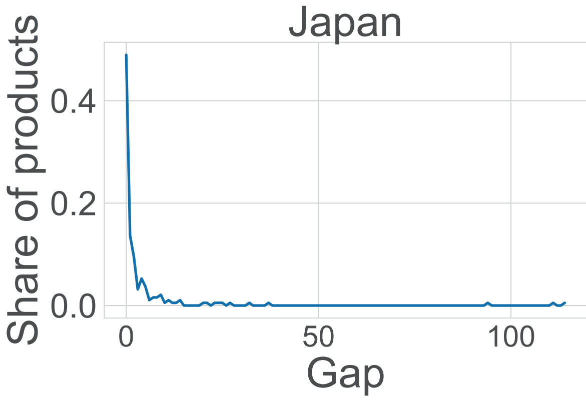

Figure 2: **Technology gap between carbon-emitting and carbon-neutral sectors across products**

5.5 Parameters for Japan's economy and the energy sector

The parameters, related to technological change in the energy sector, are listed in Table (4) and 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) compare citations for patents within three years after patenting to citations within ten years. Patents are defined as 'major entrants' if their citations in the 3 years exceed the 90-th percentile (i.e. a reasonable threshold value) of the citations for patents as old as 10 years. The share of major entrants, which equals 0.076 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 slightly lower estimate of 0.024.

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 is 43 patents for the energy sector, our calculations give a value of 39 patents for Japan (preliminary analysis for the whole manufacturing sector).

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 (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 [0.082, 0.563], so the mean estimate is 0.3. This value is lower than in the US.

The share of R&D labor in the unskilled labor is 0.055 in the US, as estimated in Acemoglu et al. (2016) using micro data. We use the estimate of 0.014, which is reported for Japan in the survey by Kanda et al. (2016). It may be noted that the share of R&D labor turns out to be several times lower in Japan then in the US.

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: entry rate and exit rate of firms (comparable across energy sectors in the US and Japan); mean R&D expenditure per domestic sales (0.066 in Acemoglu et al. (2013), but only 0.037 for Japan on our data); and growth of domestic sales per worker (4 times higher in Japan than in the US).

Table 4: **Contrasting parameters for the energy sector in Japan and the US**

	U.S.	Japan
Patents		
Probability of radical innovation	0.04	0.024[a]
Patents per product (citation weighted)	43	39[b]
R&D		
Share of R&D labor	0.055	0.014
Elasticity of innovation output in R&D expenses	0.5	0.3
Production (moments for calibration)		
Entry rate of firms	0.013	0.008
Exit rate of firms	0.018	0.013
Growth of domestic sales per worker	0.012	0.048
Share of R&D expenditure in sales	0.066	0.037

[a]whole economy
[b]manufacturing

Notes: The U.S. 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 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 US-Japan differences in the gaps between dirty and clean technologies, lower elasticity of innovation output in R&D expenses, and lower probability of radical innovation in Japan may imply reliance on carbon tax rather than on research subsidies in the context of the Acemoglu et al. (2016) and Golosov et al. (2014) models.

6 Results

Our computations use Python codes from Acemoglu et al. (2016).[3] While Acemoglu et al. (2016) analyze various ways to parametrize the time profiles for policy instruments, we focus on the two policy instruments, which are most realistic to implement. Constant policies imply fixed values of research subsidies and carbon tax over the whole period of time, while three-step policies (often analyzed in the Japanese context) allow for step-wise changes in the course of adapting policy instruments (Ministry of the Environment, 2017).

The results with the model calibrated with Japanese data can be compared with the US estimates by Acemoglu et al. (2016) for the three step policy. The value of research subsidy is close to 0.8 in the US during the first period of time, while it is below 0.8 in Japan.[4]. However, carbon tax is negligible during the first period in the US, while it is as high as 0.1 in Japan. Similarly, there is higher reliance on carbon tax 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 (Figure 4). 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 (Figures 5–6). The results reveal that the carbon-neutral sector would disappear in the medium-run under the *laissez-faire*. However, the optimal policy instruments not only sustain the growth of clean production, but lead to overall economic growth in the long term (Figure 7). 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. The length of the period is longer in Japan, which may be explained by more distortions due to 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 limited contribution by the country to temperature increases.

[3]The codes are available as a 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, we load our data into load_data.py. Then, we enter parameters for Japan's carbon cycle, energy sector and R&D into infinite_weave.py. This way we can use estimation_weave.py to calibrate the remaining parameters for Japanese economy. Next, we compare impact of different policy measures, using generate_policy.py. Our optimization technique is based on the Nelder–Mead algorithm.

[4]See Figure 3, right panel and Figure 10 in Acemoglu et al. (2016).

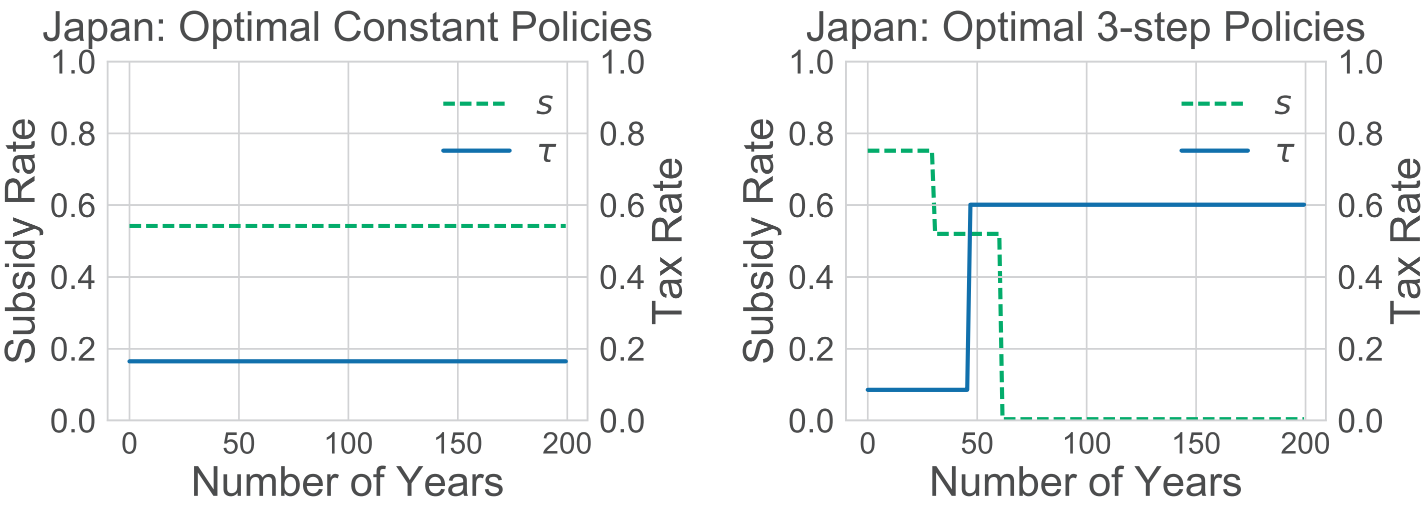

Figure 3: **Tax rate and research subsidies under optimal policies**

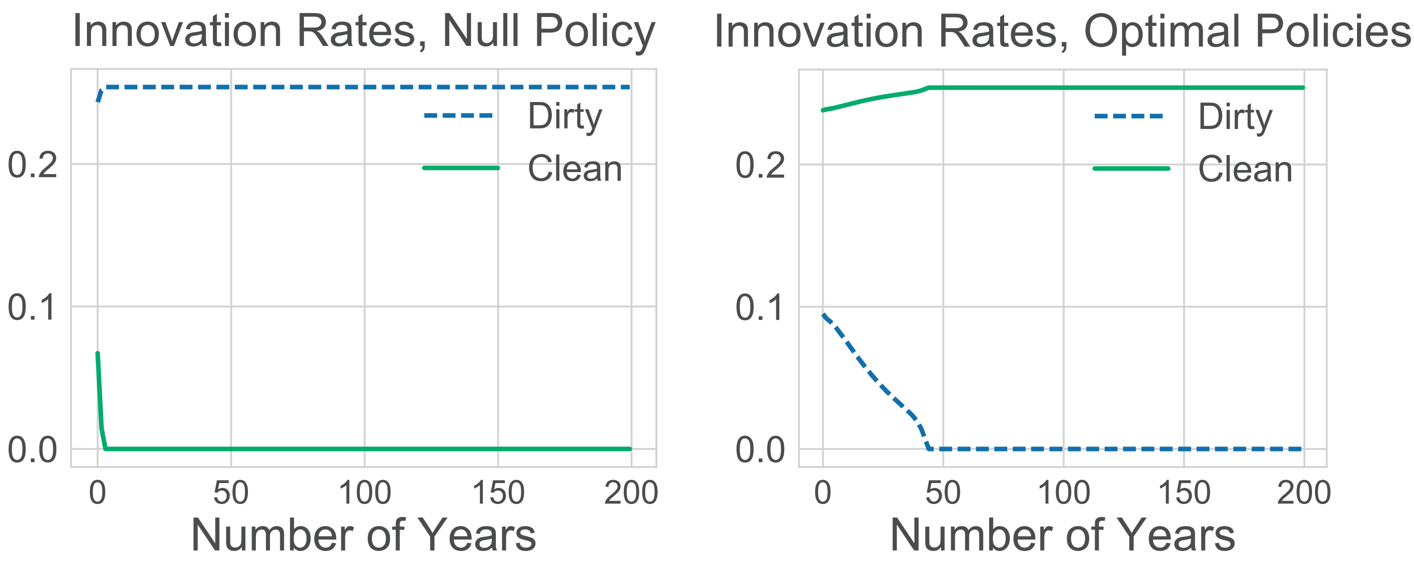

Figure 4: **Innovation rates under the *laissez-faire* and optimal constant policies**

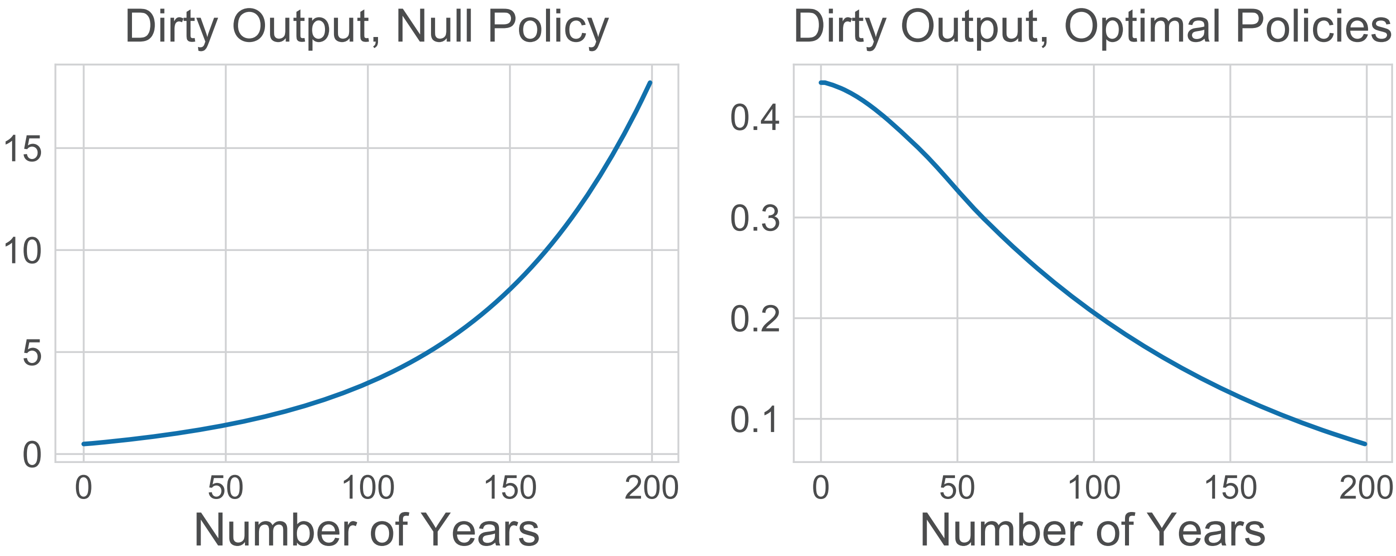

Figure 5: **Output in carbon-emitting sector under the *laissez-faire* and optimal constant policies**

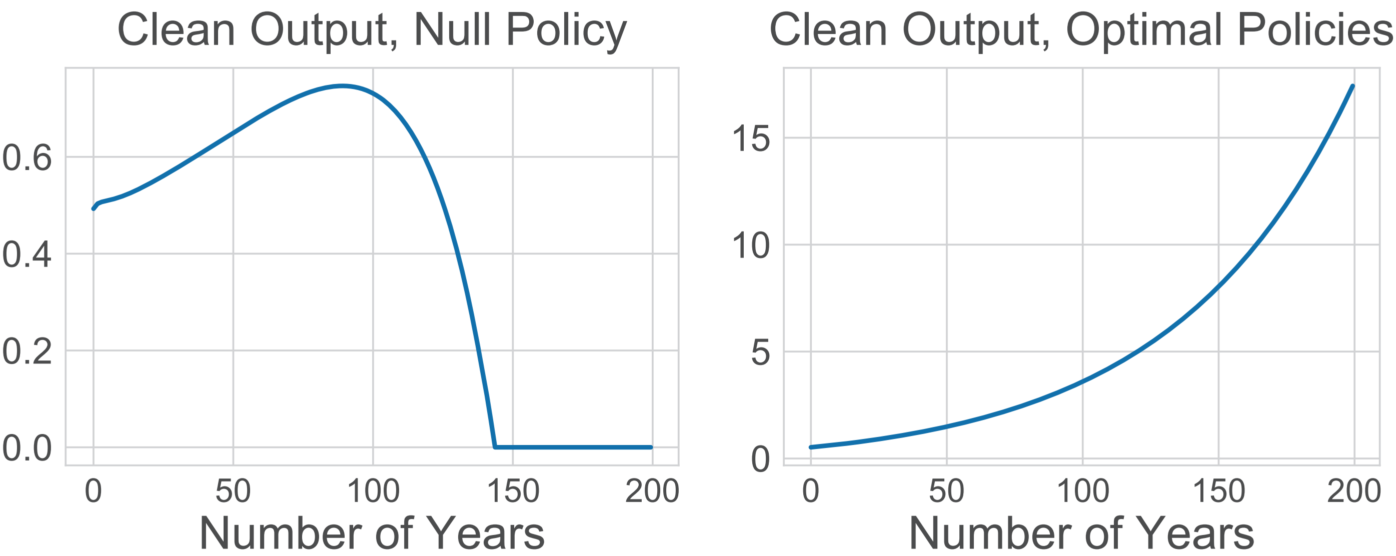

Figure 6: **Output in carbon-neutral sector under the *laissez-faire* and optimal constant policies**

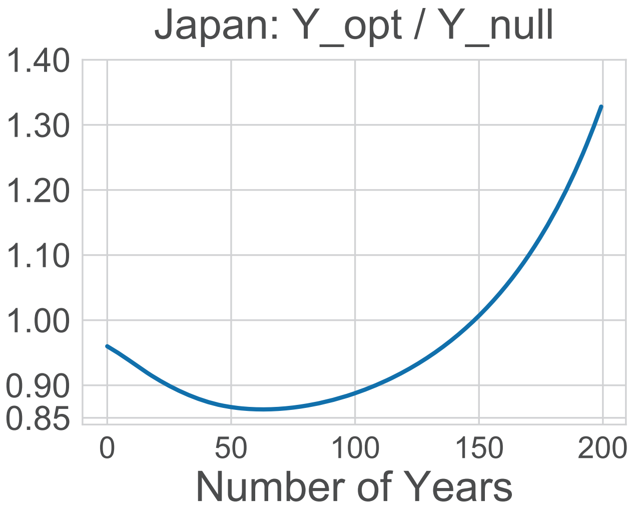

Figure 7: **Ratio of economic output under optimal constant policies to output under the** *laissez-faire*

7 Discussion and Conclusion

Decline of economic output associated with the development of carbon-neutral technologies 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 and Metcalf, 1995; Jaffe and Stavins, 1995).

Inadequate access to financing may be an impediment to introducing clean technologies at small firms (Jaffe et al., 2003). But financial impediments may be of secondary importance in comparison with alternative investment choices, capital depreciation and energy price.[5] The incentives of Japanese firms in their voluntary adoption of environmental technologies are analyzed in similar qualitative research by Tanikawa (2004).

It may be noted that market mechanisms, such as increase of energy prices, can also be viewed as an economic incentive for firms and households to employ carbon-neutral technologies (Jaffe et al., 2003; Sanstad et al., 1995). For instance, research supports the premise regarding impact of energy prices on R&D intensity of a firm, namely, R&D relative to the firm's size, as is shown in Aghion et al. (2016).

However, market forces alone cause only slow propagation of carbon-neutral technologies and diminish the potential for reducing emissions (Popp et al., 2010). In fact, there is a certain 'habit-formation' in decision by firm regarding technology development. For instance,

[5]See the socio-economic analysis for the Dutch firms in Nijkamp et al. (2001).

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).

Accordingly, there is a need for governmental policies that stimulate the diffusion of currently existing green technologies. 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 increase of social welfare thanks to the prevention of carbon emissions.

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