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Technological change, energy, environment and growth in Japan

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Abstract

A considerable amount of research has shown that that carbon tax combined with research subsidy may be regarded as an optimal policy in view of diffusing low carbon technologies for the benefit of the society. The paper exploits the macro economic approach of the endogenous growth models with technological change for a comparative assessment of these policy measures on the economic growth in the US and Japan in the medium and the long run. The results of our micro estimates reveal several important differences across the Japanese and US energy firms: lower elasticity of innovation production function in R&D expenditure, lower probability of a radical innovation, and larger advances of dirty technologies in Japan. This may explain our quantitative findings of stronger reliance on carbon tax than on research subsidies in Japan relative to the US.

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

Keywords: endogenous growth, technological change, innovation, carbon tax, energy

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1 Introduction

The 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 Schumpetarian 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 government as a social planner. Not only the models are rich in explaining numerous regularities on company growth (Lentz and Mortensen (2008), Acemoglu et al. (2013)), but they also allow to incorporate various 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)). 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 paper by Acemoglu et al. (2016) incorporates competition by clean and dirty firms along the lines of the Klette and Kortum (2004) model. Another attractive feature of the Acemoglu et al. (2016) approach is its interrelation with microdata. Namely, the elasticity for R&D production function, the quality differences between carbon-emitting and carbon-neutral technologies, and various parameters on firm dynamics are taken from the real world data on companies and their patents.

Estimating the models with the country-level data enables a quantitative evaluation of regulatory policies, which are targeted at correction of market failures pertaining to environmental issues. However, the empirical evidence on the macro level impact of environmental pollution and the actions of the social planner in the models with technological change is often limited to the US economy. It is generally believed that the changeover to carbon-neutral technologies leads to increased applicability of clean technology, e.g. in terms of patent citations (Popp and Newell (2012)). The diffusion of the clean technologies across economic industries enhances social welfare through mitigating pollution and climate change: a reduction in fossil fuel emissions limits temperature increase (Acemoglu et al. (2016); Golosov et al. (2014)). Yet, the effect on the overall economic growth may be ambiguous within different time horizons.

It should be noted that confronting pollution has long been on the agenda in many other developed countries, such as the EU or Japan (Internatinal Energy Agency (2016)). In particular, Japan may be a pioneering country with the long history of environmental taxes, government subsidies and company initiatives on environmentally friendly technologies. Since 2003 Japan has been implementing strategic energy policy, which includes various technological issues of energy efficiency along with concerns for emissions and environment (Ministry of Economy, Trade and Industry (2014)). As a part of the concept for "greening the Japanese tax system" within the forth energy plan, in 2012 the country introduced a carbon tax on consumers (Ministry of Environment (2017)). The tax is targeted at diffusing green technologies at the levels of households and firms. The revenues from the carbon tax along with sources from other energy taxes are used to provide subsidies for development of environmentally-friendly technologies (Ministry of Finance (2010); Ministry of Finance (2015); Wakiyama and Zusman (2016)).

The purpose of this 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 newly extends the common approaches of policy estimates in the macroeconomics of Japanese energy sector, as the exploited methodology of the Acemoglu et al. (2016) model uniquely allows for technological changes within the clean and dirty sectors. Using the large datasets on Japanese manufacturing corporations and the nationwide data on their patents in clean and dirty technologies over the last quarter century, we numerically evaluate the size of the clean and dirty sector. Next, we follow the endogenous growth model by Acemoglu et al. (2016) and empirically estimate the optimal values of carbon tax and research subsidies, along with the impact of these policy instruments on innovation rates and economic output in the carbon-emitting and carbon-neutral sectors. We model carbon cycle following Acemoglu et al. (2016) and Golosov et al. (2014), and contrast the estimates across the US and Japan.

The results of our micro analysis reveal several important differences across the Japanese and US firms: lower elasticity of innovation production function in Japan, lower probability of a radical innovation and larger advances of dirty technologies in terms of labor productivity. This may explain our quantitative findings of stronger reliance on carbon tax than on research subsidies in Japan in comparison to the US.

2 Related literature

The studies in the microeconomic context reveal a behavioral response of firms and consumers to both market mechanisms and regulatory actions (De Groot et al. (2001), Tanikawa (2004)). A few analyses show that the choices of environmentally friendly technologies is linked to energy prices and the history of firm's innovative activity (Aghion et al. (2016); Popp and Newell (2012), Popp (2006)). As regards policy instruments, carbon tax combined with research subsidy may be regarded as an optimal policy in view of 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 demonstrate that regulations aimed at decreasing carbon emissions lead to a drop of the gross domestic product and/or its growth rate in many countries (Metz et al. (2007), Table 3.12; Jorgenson and Wilcoxen (1990)). Therefore, redirecting the revenues from carbon taxes toward the development of the carbon-neutral technologies may mitigate the problem of the GDP decrease. For instance, the analysis in Dasgupta and Mäler (2000) examines the optimality of carbon taxes in view of total factor productivity. More generally, the link between clean/dirty technologies and economic output is studied within the endogenous growth models with technological change. The models assume that competitive firms conduct R&D to raise profits through improving the quality of their technology (Klette and Kortum (2004)).

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

The reviews of the literature on the links between economic growth, carbon emissions and governmental policies may be found in Xepapadeas (2005) and Jorgenson et al. (1993). The microeconomic evidence on the impact of policy instruments on innovative activity in the energy sector along with a meta review of the research focused at carbon emissions and technological change in the energy sector is given in Popp et al. (2010).

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

3 The Acemoglu et al. (2016) model

3.1 Theoretical framework

The Acemoglu et al. (2016) model accounts for competition between carbon-emitting and carbon-neutral technology in economic production and R&D. It builds upon the key concepts of the endogenous growth models with technological change: the firm with the best quality owns the market for a product line (Romer (1990); Grossman and Helpman (1990)); firms innovate to maximize profits through 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.

Profit-maximizing firms produce intermediate goods, choosing carbon-emitting or carbon-neutral technology based on the gap in labor productivity (quality) between technologies and the size of carbon tax. Firms make decision on R&D, and the decision is influenced by the R&D subsidy. The intermediate goods (e.g. energy) are used to produce the final good. Carbon emissions lead to economic damage: namely, cause a decrease in the 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 exhaustible resource, which is used for carbon-emitting technology. The carbon emissions, which occur during the production process, increase in atmospheric carbon concentration. A rise on CO2 brings a negative effect both on social welfare and the amount of the final good.

Below we provide a formal description of the carbon cycle, according to the Acemoglu et al. (2016) and Golosov et al. (2014) models, as well as the link on carbon emissions and production, and the analytical description for 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 the 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.

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

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

Social welfare:

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

where $\ln Y_T^{base} = \int_0^1 \ln y_{iT} di$ is output under absence of emissions, ρ is discount rate, $S_T^{perm} = \int_0^T \phi_p K_t dt$ 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 on carbon-neutral technologies and tax on carbon emissions. The model studies an 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 the primary interest are output by firms using carbon-neutral and carbon-emitting technologies; innovative activity by clean and dirty firms; overall growth in 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 model parameters on innovation come from the micro data: firm's products, equivalent to the sic3 or sic4 codes in the US industrial classification; the division of economy into clean and dirty sectors, based on patent classes; the probability of a 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 firm's products. Finally, the model is calibrated with the simulated method of moments: theoretical moments for the four variable 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 to clean technology).

At the second stage, the optimal values of the policy instruments are found within 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 with the 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; a long-term economic growth but a decrease of growth in the short and medium-run run. The deceleration in production is explained by the superiority of the existing dirty technologies, which may be revealed from the micro data on the quality in the carbon-neutral and carbon-emitting sectors.

4 Data on Japan

Several sources of data on Japanese economy are used for our quantification. Firstly, we exploit meteorological data of two types. National carbon emissions per capita come from the World Bank, which accumulates the estimates of the Carbon Dioxide Information Analysis Center, Environmental Sciences Division, Oak Ridge National Laboratory (Tennessee, US). We use the Japan Meteorological Agency data on the atmospheric carbon concentration, which are measured at the three stations: Ryori (120 km from Sendai on the Pacific coast of Honshu island, in the Tohoku area), Minamitorishima (an island 1848 km southeast from 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, so we choose the data from this station for the analysis.

Secondly, we use 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 to a non-anonymous company data from the Japan National Innovation Survey (2015). The survey focuses on innovative firms and contains a crosswalk to patent database.

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

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

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 of 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 carbon cycle draws upon the Archer (2005) approach on the existence of the transitory component of carbon 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 carbon cycle equation using the Japan's data for 1986-2008, so that the final time period were comparable to the US estimates (Figure 1).

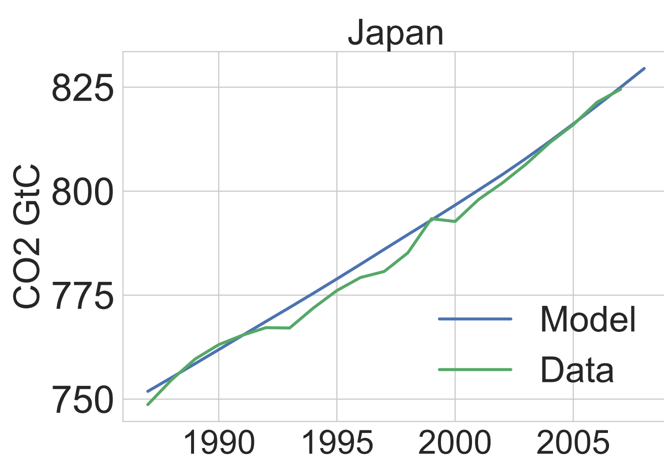

Figure 1: **Estimating carbon cycle in Japan based on meteorological data from Ryori station**

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 similar time period, as reported in Acemoglu et al. (2016) (where it equals 0.0313) and Golosov et al. (2014) (0.0228). The share of transitory component is close to the estimate in Golosov et al. (2014) (0.393), while it departs from the value in Acemoglu et al. (2016). See Table 1 for detailed comparison.

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

Parameter	Definition	U.S. Acemoglu 2016	U.S. 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	0.393	0.4173

5.2 Carbon-neutral and carbon-emitting technology

Our definitions of carbon-neutral technologies combine the approaches of the three sources. First, we use the OECD (2009) methodology on patent classes for environmentally friendly technologies, as descried in *Patent search strategy for the identification of selected "environmental" technologies developed as part of the OECD project on "Environmental Policy and Technological Innovation"*. Second, we supplement the above list of patent classes with the World International Property Organization, WIPO (2017) *International Patent Classification (IPC) Green inventory*. Finally, we add the patent classes for energy sector from the corresponding appendix to Popp and Newell (2012).

The groups of patent classes, exploited in our analysis for the definition of carbon-neutral technologies are summarized in Table 2.

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 additionally considers the manufacture of motor vehicles and manufacture of general purpose machinery, which is based on 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 look at the years following the Revision of the Japan Patent Law. The revision allowed multiple claims and may have influenced the strength of the Japanese patents, especially in their applicability across industrial fields.

Our sample, which is the overlap of the Nikkei NEEDS and the Japan National Innovation Survey, contains 1178-2565 manufacturing firms in 1989-2013. There are 303-589 energy firms a year, according to our definition. The annual share of energy firms is stable at 23-25% of all firms.

Table 2: **Carbon-neutral technologies based on 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 fertilisers derived from waste)	WIPO
Nuclear power generation	WIPO
Administrative, regulatory or design aspects (e.g. carbon-emissions trade)	WIPO

Table 3: **Energy sector based on 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)

Following Acemoglu et al. (2016), we define a clean firm as the 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 across the US and Japanese firms. There is only a negligible number of firms with over a quarter of clean patents in Japan. If we wanted to establish the size of clean sector as 10-11% of producers (to make the Japan's economy comparable to the US), it would require an extremely loose definition of having only a 1% of clean patents. Accordingly, we exploit a reasonable compromise of 5% of clean patents for a firm to be regarded as environmentally friendly. The value may be supported by the micro evidence on the relative weight of the environmentally friendly initiatives in the behavior of Japanese firms. The threshold of 5% gives the share of clean firms as 3% of firms in Japan (1 to 5% in various years).

5.4 Technology gaps

According to the Acemoglu et al. (2016) model, the technological 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

$$gap_{i,t} = n^d_{i,t} - n^c_{i,t}, \tag{7}$$

where $n^d_{i,t}$ and $n^c_{i,t}$ are numbers of innovation steps in the *dirty* and *clean* technology for the product i by time t.

Following the empirical strategy in the Acemoglu et al. (2016), we first compute 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. annual number of patents per product by all firms). The resulting distribution of technology gap from equation (7) is given in Figure 2. As may be revealed from the distribution, dirty technology is one to four steps ahead for most products, and only for a few products the lead of dirty technology is 10 to 120 steps. The shape of the distribution is generally close to that in the US. However, the findings for the US economy in Acemoglu et al. (2016) show that clean technology is advanced up to 10 steps over the dirty for a few products. Yet, we failed to find such a pattern with Japan's data.

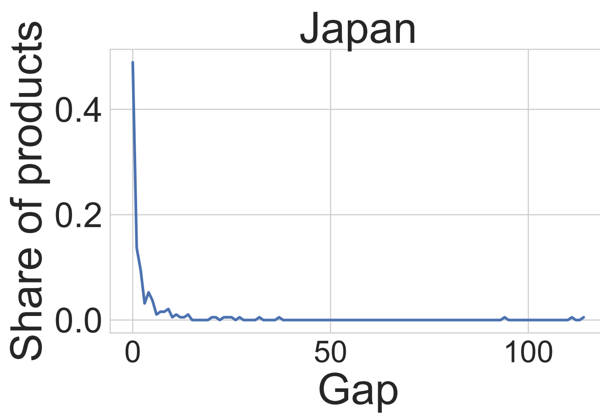

Figure 2: **Technology gap between carbon-emitting and carbon-neutral sectors across products**

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 a radical innovation the Acemoglu et al. (2016) compare the citations for the patents within their three years to the citations within their ten years. Patents are defined as 'major entrants' if their cites in the 3 years exceed the 90-th percentile (i.e. a reasonable threshold value) of the cites 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 a radical innovation. Our use of the patent data for Japan's economy within the same approach produces a slightly lower estimate of 0.024.

Another variable is linked to innovation outcomes. The mean patent flow is defined by Acemoglu et al. (2016) as annual number of citation weighted patents per product. While the US estimate is 43 patents for the energy sector, our calculations give the value of 39 patents for Japan (preliminary analysis for the whole manufacturing sector).

The second group of parameters relate to the R&D production function. The Acemoglu et al. (2016) strategy follows the microeconomic approach to proxy the R&D output by patents and considers the 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 regression equation. The resulting value of the R&D elasticity equals 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 products counts or by domestic sales). Our calculations with the data for Japan's energy sector give the range of elasticity [0.082, 0.563], so the mean estimate is about 0.3. This value is lower than in the US.

The share of the R&D labor in the unskilled labor is 0.055 in the US, as estimated in Acemoglu et al. (2016) according to micro data. We use the estimate of 0.014, which is reported for Japan in the NISTEP survey (Kanda et al. (2016)). It may be noted that the share of the 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 exploited in model calibration through simulated method of moments. The variables relate to microdata 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), while only 0.037 for Japan with our data); growth of domestic sales per worker (4 times higher in Japan than in the US).

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

	U.S.	Japan
Patents		
Probability of a radical innovation	0.04	0.024 (whole economy)
Patents per product (citation weighted)	43	39 (manufacturing)
R&D		
Share of R&D labor in the unskilled 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

Notes: The U.S. data for energy sector in 1975–2004 come from Acemoglu et al. (2016). Japanese estimates for energy sector (if not otherwise mentioned) are based on our data for 1989–2012. Regarding entry rate of firms, the Acemoglu et al. (2016) use the labor share of entrants, while we use the number of firms with the Japanese data.

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

6 Results

Our computations exploit the python codes from Acemoglu et al. (2016). While the Acemoglu et al. (2016) analyzes various ways to parametrize the time profiles for the policy instruments, we focus on two most realistic profiles in terms of policy implementation. Constant policies imply fixed values of research subsidies and carbon tax over the whole period of time, while the three step policies (often analyzed in the Japanese context. e.g. Ministry of Environment (2017)) allow for step-wise changes in the course of adapting policy instruments.

The results of our estimates with the model calibrated with Japanese data may be compared across the three-step policy with the Acemoglu et al. (2016) estimates for the US. The values 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 (our Figure 3, right panel and Figure 10 in Acemoglu et al. (2016)). At the same time, carbon tax is negligible during the first period in the US, yet, it is as high as 0.1 in Japan. Similarly, there is a higher reliance on carbon tax and a lower reliance on research subsidies in Japan relative to the US in the second period.

The combination of carbon tax with research subsidy switches the innovation in Japan from the carbon-emitting to carbon-neutral sector (Figure 4). Moreover, innovation in the carbon-emitting sector vanishes after 50 years of policy implementation. There is a redirection of production from the dirty to clean sector: the output of the dirty sector steadily declines, while the production in the clean sector gradually increases (Figures 5-6). At the same time, the results reveal that the carbon-neutral sector would disappear in the medium-run under the lassez-faire. The optimal policy instruments not only sustain the growth of clean production, but lead to overall economic growth in the long-run (Figure 7). Nonetheless, we should note a considerable time horizon for the decline of the aggregate output before the trend is reversed. The finding may be linked to the Golosov et al. (2014) estimate of 20 years, which are required to reach the laissez-faire level of production in the US under the energy policy implementation. The length of the period is longer in Japan, which may be explained by stronger distortions due to relatively lower advances of the clean technologies.

The environmental effects of policy instruments are similar to those in Acemoglu et al. (2016): the decrease of national carbon emissions and lower contribution of the country to the temperature increase.

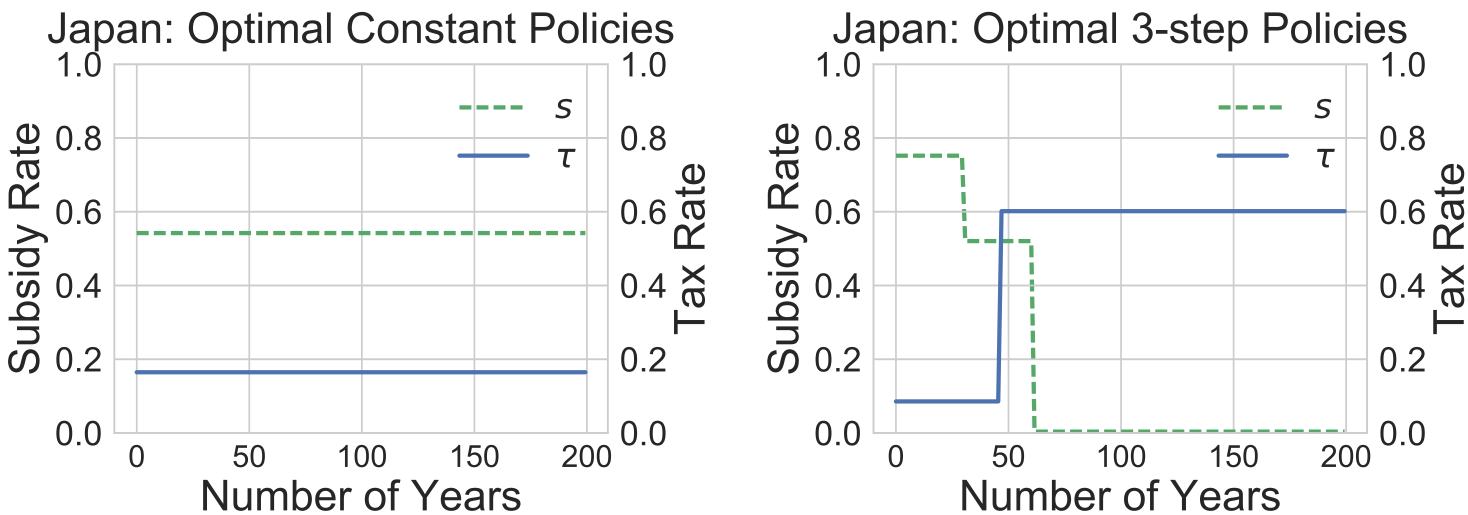

Figure 3: **Tax rate and research subsidy under optimal policies**

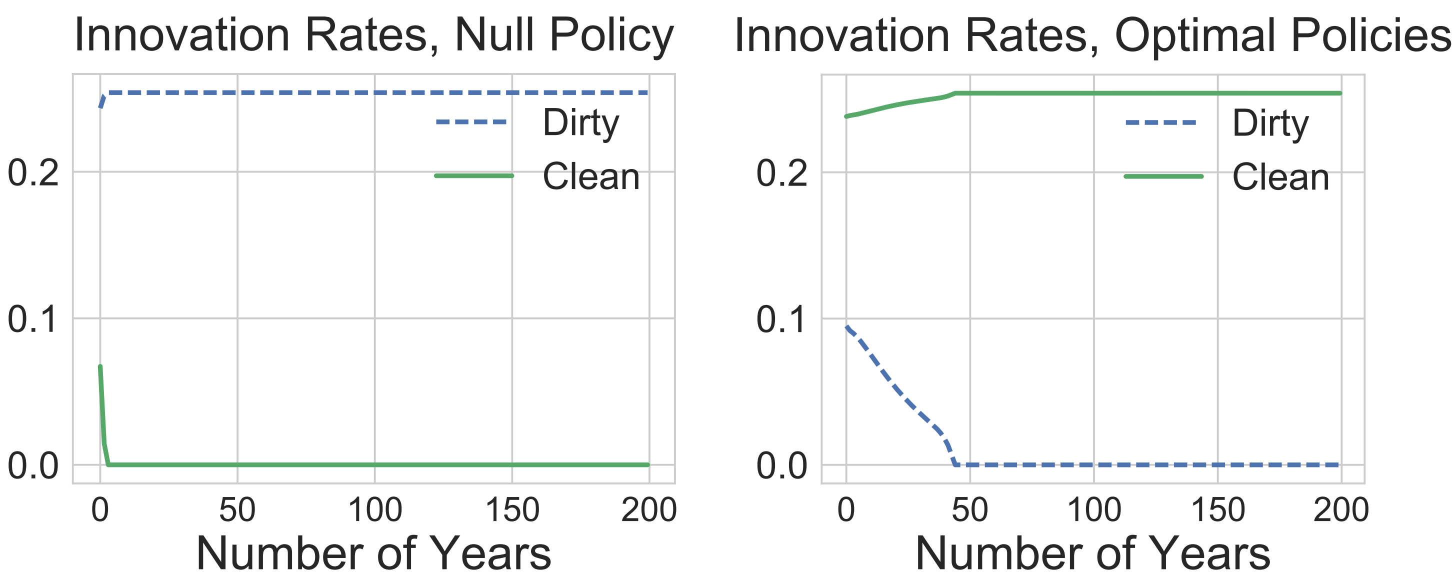

Figure 4: **Innovation rates under laissez-faire and optimal constant policies**

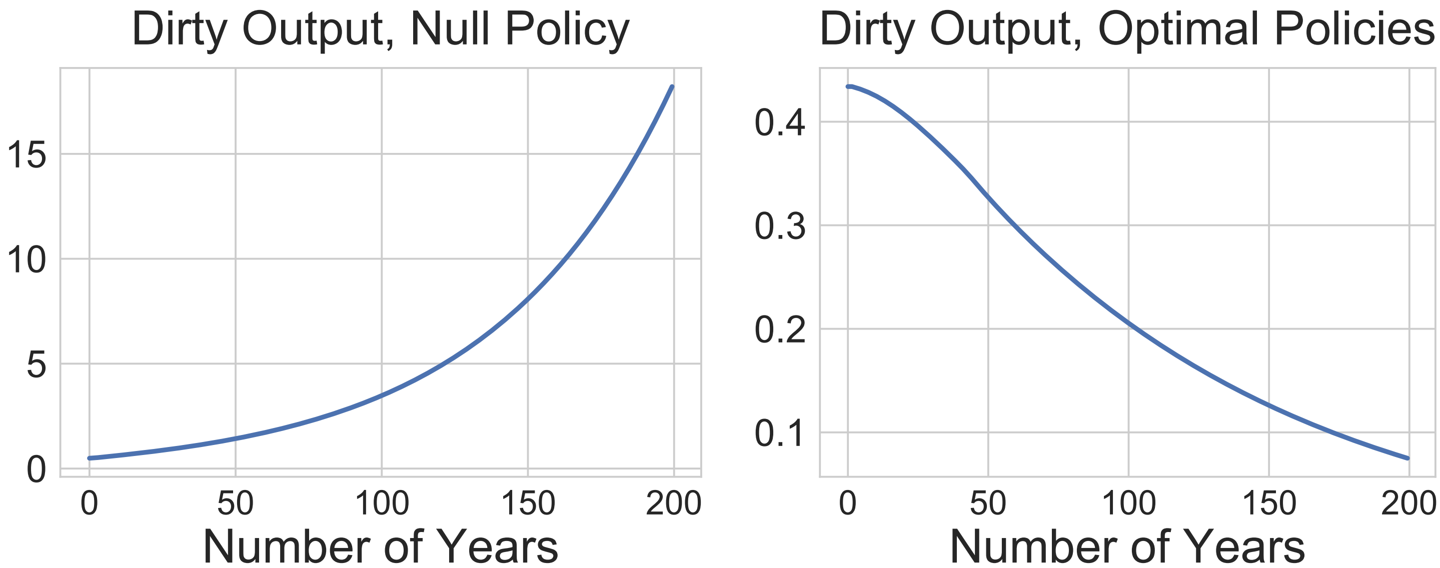

Figure 5: **Output in the carbon-emitting sector under laissez-faire and optimal constant policies**

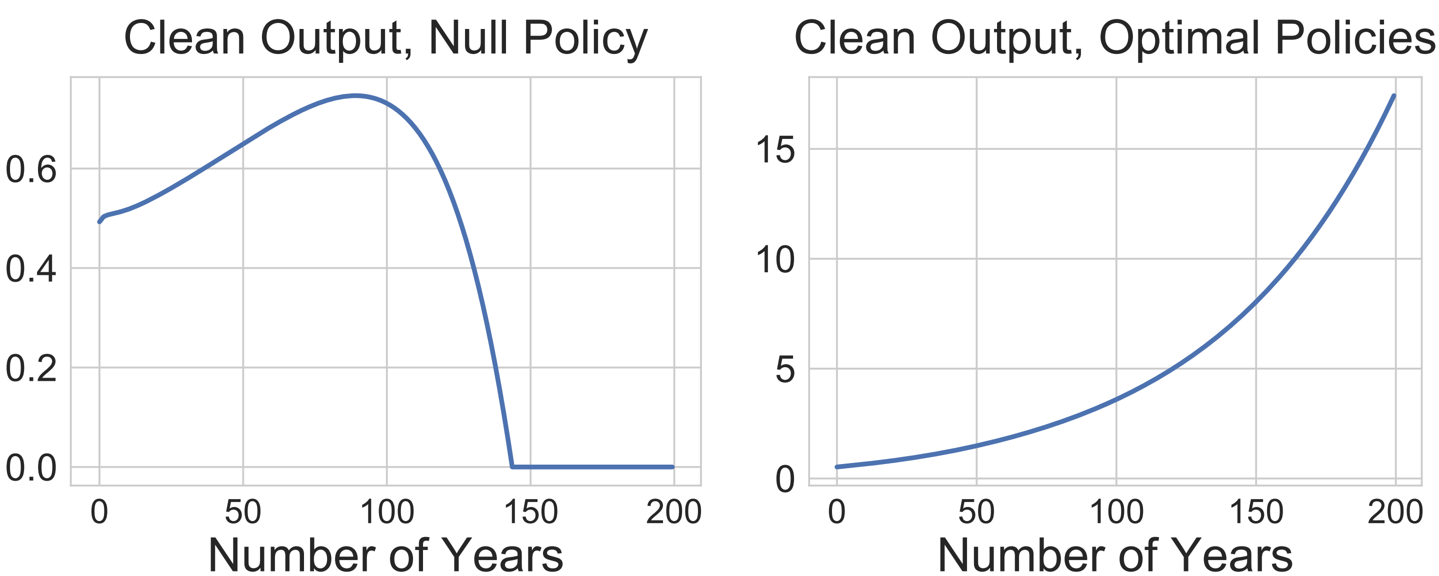

Figure 6: **Output in the carbon-neutral sector under laissez-faire and optimal constant policies**

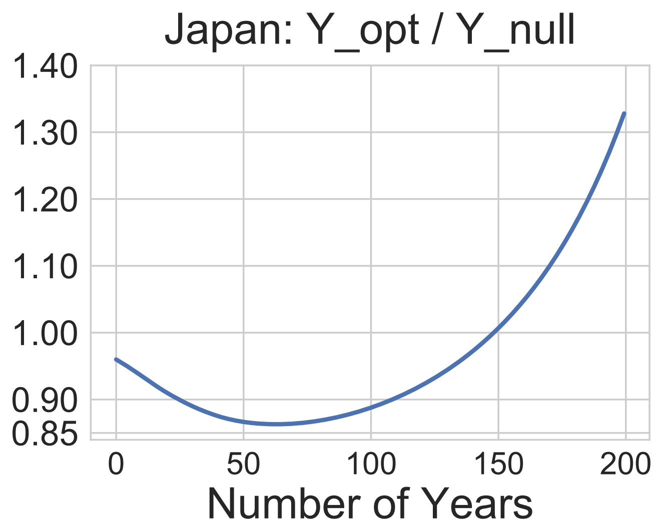

Figure 7: **The ratio of economic output under optimal constant policies to output under the laissez-faire**

7 Discussion and Conclusion

The decrease of the economic output due to the development of carbon-neutral technologies within the regulatory policy implementation may be explained by technology costs. For instance, the empirical microeconomic analyses demonstrate that technology costs negatively affect the individual decision about the adoption of the 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 become another impediment for introducing clean technologies at small firms (Jaffe et al. (2003)). At the same time, financial considerations may be of a secondary importance in comparison with alternative investment choices, capital depreciation and energy prices (see the analysis for the Dutch firms in Nijkamp et al. (2001) and the qualitative study on the incentives of Japanese firms in their voluntary adoption of environmental technologies in Tanikawa (2004)).

It may be noted that the market mechanisms, such as an increase 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). For instance, the research supports the premise about the impact of energy prices on the R&D intensity of a firm, i.e. the R&D per firm's size (Aghion et al. (2016)). However, market forces alone lead to a slow diffusion and diminish the potential for reducing emissions (Popp et al. (2010)). In fact, there is a certain 'habit-formation' in the firm's decision about technological development. For instance, econometric estimates demonstrate that the R&D may be regarded as a function of firm's past history in terms of its clean/dirty innovation (Aghion et al. (2016)).

Accordingly, there is a need for governmental policies, targeted at stimulating the diffusion of the currently existing green technologies. Judging from a macroeconomic perspective, the costs of clean technologies (borne by the government through research subsidies) may be evaluated against economic gains. The gains may be measured in terms of the long-run macro growth or the increase in the social welfare owing to preventing carbon emissions.

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