New Technology Indicator for Technological Progress

Wendy Li (Bureau of Economic Analysis, United States)

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Wendy C.Y. Li

U.S. Bureau of Economic Analysis

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Abstract

Economists rely on the total factor productivity (TFP) to measure technological progress. Empirical studies, however, show no straightforward link between TFP and technical changes, and TFP measurement is a point estimate without robustness. As countries start capitalizing R&D, the latest U.S. study shows that the resulting change of the TFP growth may cause more puzzles than reflect the true nature of technological progress.

This paper proposes a new technology indicator, R&D depreciation rate. Based on data for four high-tech industries over five countries, the new indicator shows promising results. The country ranking by the new indicator is consistent with Forbes' global 2000 ranking. In the U.S.-Japan comparison, static TFP level and the new indicator have the same industry comparison results. Moreover, unlike TFP, the time-varying new indicator tells a consistent story with the historic U.S.-Japan industry studies. Lastly, the new indicator is easier to calculate and requires much less data for cross-country comparisons.

JEL classification: O30, O33, C80

Keywords: research and development, technological change, international competitiveness

1. Introduction

Technological progress drives long-term economic growth and improves living standards. In the digital era, technology has affected our lives in many ways, ranging from robotic manufacturing system to medical treatments. Because of the importance of technologies in sustainable economic growth and living standards, we need to have effective indicators to track the dynamics of technological progress and environments in order to derive effective technology policies. That is, policymakers need to have effective indicators to track where the country's current level of technology is, how competitive it is, whether its technology development moves forward, and what drives its technological progress.

Economists often use the total factor productivity (TFP) growth rate to measure technical changes. However, the OECD manual on productivity measurement (OECD, 2001) points out that, in practice, there is no straightforward link between the TFP growth and technical changes, and econometric studies show that R&D expenditures only explain a relative small portion of the overall annual movements in TFP. That is, empirically, not all facets of technological changes are captured by TFP, and the measured TFP may contain other non-technology factors, such as adjustment costs and measurement errors. Moreover, the TFP growth rate is useful for intertemporal comparisons of productivity for a given country or region at different points in time, but it is far less useful for comparing the relative productivity of different countries or regions (Hulten et al, 2001). Because of the problem with applying the TFP growth rate to cross-country comparisons, Jorgenson and Nishimizu (1978) develop the first translog nonparametric estimates of TFP levels for the comparison of two countries. Economists have adopted this approach to conduct cross-country comparisons (Jorgenson et al., 2014). However, the method is still subject to the fact that the TFP level contains items unrelated to technology (OECD, 2001). For cross-country comparisons in terms of the TFP level, more measurement issues, such as currency conversion, will be encountered. As a result, we cannot empirically explain the TFP gap between countries solely as a technological gap. Therefore, TFP levels and the TFP growth rates are not easy to calculate and cannot provide sufficient information for cross-country comparisons on technology.

To better track technological progress, some economists have developed new indicators that use data on patents and journal publications to infer the changes in a country's technology output. But, those data are related to the underlying concepts with substantial measurement errors and distant from the underlying concepts (Hall and Jaffe, 2012). For example, it is well known that patents only cover a portion of innovation, and the distribution of patent values is highly skewed. The same concerns also apply to journal publications. Journal articles can only account for a small portion of a country's innovation outputs and may contribute limitedly to economic outputs. Though, in the pharmaceutical industry, the citations of journal articles have been used to measure a startup's technological capacity. However, it requires enormous resources to successfully develop a new drug. Not all countries can afford the financial and innovation resources required for the development. For instance, in the past decade, China's pharmaceutical industry has been aggressively investing in R&D and the country has increasingly published papers in the related fields. Despite those great improvements in knowledge investments and outputs, China's pharmaceutical industry mainly focuses on the original equipment manufacturing (OEM) and generic drugs production. Hence, using patent counts and growth and/or journal paper counts and citation growth may mistakenly conclude that the innovation capacity of China's pharmaceutical industry is aggressively catching up with or close to those of their counterparts in developed countries. Apparently, a better technology indicator is needed to conduct cross-country comparisons in performance.

Given the fact that we need a better technology indicator, this paper presents a new technology indicator, the industry-specific R&D depreciation rate, for an industry's international technological competitiveness. Business R&D depreciation rates are driven by an industry's pace of technological progress and the degree of market competition (Hall, 1997). Business R&D capital depreciates because its contribution to a firm's profit declines over time. Hence, a firm's R&D depreciation rate can indicate how much a firm can appropriate the return from its investment in R&D. Therefore, within the same industry where all firms face the same technological and competition environment, a firm has a greater technological advantage if its R&D depreciation rate is lower than those of its competitors. This concept has been well identified by the resource-based theory (Dierickx and Cool, 1989), and is evident in the empirical study by Li (2015). Similarly, in a free trade environment, if an industry in country A has a greater technological advantage than the same industry in country B, the industry in country A has a lower R&D depreciation rate than its counterpart in country B. This argument is supported by the results of this study, as shown later in this paper. Therefore, the industry-specific R&D depreciation rate can serve as a technology indicator to provide international performance comparison in technology. In addition, as shown later in the paper, the industry-specific time-varying R&D depreciation pattern can track both the intertemporal industry-level appropriateness of returns on R&D investments within a country and the intertemporal international comparison in technology performance for the same industry between countries. For example, in what industry, are other countries accelerating?

In this paper, I use the methodology developed by Li and Hall (2016) for estimating the depreciation rate of business R&D capital, as well as the data of annual industry gross outputs and R&D investments for four major high-tech industries across five countries. The four high-tech industries are the pharmaceutical, the computers, electronic, and optical products, the motors, and the electrical equipment industries. The five countries include China, Germany, Japan, South Korea, and the United States. The majority of the data cover the decade of the 2000s, but China's data is shorter because it started reporting R&D investments in 2006.[1]

The estimated R&D depreciate rates using these data provide several important results. First, in each industry, the country ranking in technological competitiveness, measured by industry-level R&D depreciation rate, is in general consistent with the country ranking on Forbes' global 2000 list. Second, when I compare the results between the U.S. and Japan for the four industries, the country with a lower industry-level R&D depreciation rate has a higher industry-level TFP. Third, the information derived from the time-varying R&D depreciation rates

[1] The Chinese data are based on the CEIC database which original data source is from China's National Bureau of Statistics. The data for Germany and South Korea are from the OECD website. The data on Japan are from the National Accounts of the Cabinet Office in Japan.

for the motors and the computer, electronic, and optical products industries in Japan and the U.S. is consistent with the historic studies in these two industries over the decade of the 2000s.[2]

This paper is organized as follows. Section 2 provides a brief review of the R&D investment model used in this study, followed by the description of data analysis in Section 3. Section 4 presents time-varying R&D depreciation rates for two major technology industries between the U.S. and Japan, and concluding remarks are given in Section 5.

2. Model

The R&D investment model follows the forward-looking profit model in Li and Hall (2016). The premise of the model is that business R&D capital depreciates because its contribution to a firm's profit declines over time. R&D capital generates privately appropriable returns; thus, it depreciates when its appropriable return declines over time (Hall, 2007). The expected R&D depreciation rate is a necessary and important component of a firm's R&D investment model. A profit-maximizing firm will invest in R&D such that the expected marginal benefit equals the marginal cost. That is, in each period *t*, a firm will choose an R&D investment amount to maximize the net present value of the expected returns to R&D investment:

$$\max_{R_t} E_t[\pi_t] = -R_t + E_t\left[\sum_{j=0}^{\infty} \frac{q_{t+j+d} I(R_t)(1-\delta)^j}{(1+r)^{j+d}}\right] \tag{1}$$

where R_t is the R&D investment amount in period *t*, q_t is the sales in period *t*, $I(R_t)$ is the increase in profit rate due to R&D investment, δ is the R&D depreciation rate, and r is the cost of capital. The parameter d is the gestation lag and is assumed to be an integer which is no less than 0. R&D investment in period *t* will contribute to the profits in later periods but at a geometrically declining rate. We assume that the sales *q* for periods later than *t* grows at a

[2] This dataset only has two industry categories that match those for Japan. I therefore perform time-varying pattern comparison only for these two industries. The time intervals for these two datasets are similar. The U.S. data span between 1997 and 2013, and the Japan data between 2002 and 2012.

constant growth rate, g. That is, $q_{t+j} = q_t (1+g)^j$. This assumption is consistent with the fact that the output of most R&D intensive industries grows fairly smoothly over time.

place "Figure 1: The Concavity of $I(RD)$" here

To resolve the issue that the prices of most R&D assets are generally unobservable, we define *I(R)* as a concave function:

$$I(R) = I_\Omega \left(1 - \exp\left[\frac{-R}{\theta}\right]\right) \tag{2}$$

with $I''(R) < 0$. $I'(\mathrm{R}) = I_\Omega \exp\left(\frac{-R}{\theta}\right) > 0$, and $I'(0) = \mathrm{I}_\Omega = \lim_{R\to\infty} I(R)$. Figure 1 depicts how the function *I* gradually increases asymptotically to I_Ω, with *R*, the current-period R&D investment. The increase in profit rate due to R&D investments, *I'(R)*, has an upper bound at I_Ω when *R* = 0. This functional form has few parameters but nevertheless shows the desired concavity with respect to *R*. In this, our approach is similar to that adopted by Cohen and Klepper (1996), who show that when there are fixed costs to an R&D program and firms have multiple projects, the resulting R&D productivity will be heterogeneous across firms and self-selection will ensure that the observed productivity of R&D will vary negatively with firm size. Our model incorporates the assumption of diminishing marginal returns to R&D investment implied by their assumptions, which is more realistic than the traditional assumption of constant returns to scale (Griliches, 1996). In addition, the model implicitly assumes that innovation is incremental, which is appropriate for industry aggregate R&D, most of which is performed by large established firms. The function *I* includes a parameter θ that defines the investment scale for increases in R&D and acts as a deflator to capture the increasing time trend of R&D investment as a component of investment in many industries. The value of θ can vary from industry to industry, allowing different R&D investment scales for different industries.

Using this function for the profitability of R&D, the R&D investment model becomes the following:

$$E_t[\pi_t] = -R_t + E_t\left[\sum_{j=0}^{\infty}\frac{q_{t+j+d}I(R_t)(1-\delta)^j}{(1+r)^{j+d}}\right]$$
$$= -R_t + I_\Omega\left[1-\exp\left(-\frac{R_t}{\theta_t}\right)\right]\sum_{j=0}^{\infty}\frac{E_t[q_{t+j+d}](1-\delta)^j}{(1+r)^{j+d}} \qquad (3)$$

Note that we have assumed that *d, r,* and δ are known to the firm at time *t*. Because ϑ varies over time, we model the time-dependent feature of θ by $\theta_t \equiv \theta_0(1+G)^t$, where G is the growth rate of ϑ_t. To estimate G, we assume that the growth pattern of industry's R&D investment and its R&D investment scale are similar, and we estimate *G* by fitting the data for R&D investment to the equation, $R_t = R_0(1+G)^t$. This approach is justified by the fact that BEA data on most industry R&D grows somewhat smoothly over time. Using this assumption, Equation (3) becomes:

$$\pi_t = -R_t + I_\Omega\left[1-\exp\left(-\frac{R_t}{\theta_0(1+G)^t}\right)\right]\frac{q_t(1+g)^d}{(1+r)^{d-1}(r+\delta-g+g\delta)} \qquad (4)$$

Note that because of our assumptions of constant growth in sales and R&D, there is no longer any role for uncertainty in this equation, and therefore no error term. Assuming profit maximization, the optimal choice of Rt implies the following first order condition:

$$\frac{\partial\pi_t}{\partial R_t} = -\frac{(1+G)^t}{I_\Omega}\theta_0\exp\left[\frac{R_t}{\theta_0(1+G)^t}\right] + \frac{q_t(1+g)^d}{(1+r)^{d-1}(r+\delta-g+g\delta)} = 0 \qquad (5)$$

For estimation, we add a disturbance to this equation (reflecting the fact that it will not hold identically for all industries in all years) and then estimate ϑ_0 and the depreciation rate δ.

3. Cross-country, cross-industry data analysis

To conduct the estimates for cross-country analysis, I use data from five countries, including China, Germany, Japan, South Korea, and the United States. Each country covers four R&D intensive industries: the motors, the pharmaceutical, the computer, electronic, and optical products, and the electrical equipment industries.[3] The four industries cover all R&D intensive

[3] Due to data constraints, for the electrical equipment industry, I only include the U.S., China, and Japan. Additionally, because the IT hardware industry had a much faster pace of technological progress before the early 2000s, I estimate the U.S. number for the period of 2002 to 2012 to ensure the U.S. data length is the same as Japan's.

industries in Japan and the five countries cover developed countries in the North America, Europe, East Asian, and an Asian developing country, China. The U.S. data are published by the U.S. Bureau of Economic Analysis (BEA), and they have the longest data span from 1987 to 2007. The Chinese data are based on the commercial CEIC database with the original data source from China's National Bureau of Statistics, and they cover the shortest period from 2006 to 2013. Japan's data come from the National Accounts of the Cabinet Office in Japan, covering the period of 2002 to 2012. The data for Germany and South Korea cover the period of 2000 to 2012, and they are available at the OECD data website. Each set of industry data consists of annual industry gross outputs and R&D investments. Because of the data constraints, I chose five countries and four R&D intensive industries for the data analysis.

As a first step in my empirical analysis, I estimate the constant R&D depreciation rate δ_{RD} for the four R&D intensive industries by using the data from those five countries. Figures 2-6 display the time-series data of industry gross output, R&D investment, and R&D intensity for the selected industries in each country. Figure 7 displays the time-series data of industry R&D intensity for each industry across countries.

place "Figure 2: Annual Industry R&D Investment, Gross Output, and R&D Intensity: China" here

place "Figure 3: Annual Industry R&D Investment, Gross Output, and R&D Intensity: Germany" here

place "Figure 4: Annual Industry R&D Investment, Gross Output, and R&D Intensity: Japan" here

place "Figure 5: Annual Industry R&D Investment, Gross Output, and R&D Intensity: South Korea" here

place "Figure 6: Annual Industry R&D Investment, Gross Output, and R&D Intensity: U.S." here

place "Figure 7: Annual R&D Intensity for Each Industry Across Countries" here

In the analysis of U.S. data, the value of I_{Ω} can be inferred from the Bureau of Economic Analysis (BEA) annual return rates of all assets for non-financial corporations. As Jorgenson and Griliches (1967) argue, in equilibrium the rates of return for all assets should be equal to ensure no arbitrage, and so we can use a common rate of return for both tangibles and intangibles, such as R&D assets. For simplicity, I use the average return rates of all assets for non-financial corporations during 1987-2007, 8.9%, for I_Ω. In addition, in equilibrium the rate of returns should be equal to the cost of capital. Therefore, I use the same value for *r*. Japan's correspondent rate, 6%, is provided by Japan's National Accounts. The other three countries do not publish this type of return rates online. Nonetheless, based on the Forbes' global ranking, we expect that the technological gap between Japan and Germany cannot be large and that South Korea does not outperform Japan at the current stage. To aid the analysis, the value of I_Ω of Germany and South Korea is set to be the same as that of Japan. As to China, because IMF reports that China has a low return rate on its investment and that it has an overinvestment issue, the value of I_Ω is set to be 1% (Lee et al., 2012, Geng and N'Diaye, 2012).[4]

The model used for estimation, based on equation (5), is shown below:

$$\varepsilon_t \equiv \frac{\left(1+\hat{G}\right)^t}{I_\Omega} \theta_0 \exp\left[\frac{R_t}{\theta_0\left(1+\hat{G}\right)^t}\right] - \frac{q_t\left(1+\hat{g}\right)^d}{\left(1+r\right)^{d-1}\left(r+\delta-\hat{g}+\hat{g}\delta\right)} \qquad (6)$$

where $\hat{g}$ and $\hat{G}$ are estimated using the entire time period. In order to estimate, we need to make assumptions about I_Ω, *r,* and *d.* The value of I_Ω can be inferred from the BEA annual return rates of all assets for non-financial corporations. As Jorgenson and Griliches (1967) argue, in equilibrium the rates of return for all assets should be equal to ensure no arbitrage, and so we can use a common rate of return for both tangibles and intangibles (such as R&D assets). For simplicity, I_Ω is set to be the average return rates of all assets for non-financial corporations during 1987-2008, which is 8.9 percent. In addition, in equilibrium the rate of return should be equal to the cost of capital. Therefore, we use the same value for *r*.

In this study I use a two-year gestation lag for R&D investments, which is consistent with the finding in Pakes and Schankerman (1984) who examined 49 manufacturing firms across

[4] The dataset for China exhibits characteristics that are clearly different from those for the multi-nation OECD data and the US BEA data. The dataset for Chinese industries covers shorter intervals, and the time series appear to grow steadily without discernible short-term variations seen in the data for other nations.

industries and reported that gestation lags between 1.2 and 2.5 years were appropriate values to use. In addition, in a recent U.S. R&D survey conducted by BEA, Census Bureau and National Science Foundation (NSF) in 2010, the average gestation lag is 1.94 years for all industries.[5] R_t and q_t are taken from the data and also used to compute the average growth rates of output (G) and of R&D (g), so the only unknown parameters in the equation are δ and θ. Given these assumptions, δ and θ are estimated by nonlinear least squares (NLLS), using equation (6). The uncertainty in the estimation of the depreciation rate is based on the bootstrap estimation with 1000 resamples.

The estimated values of constant δ_{RD} and other R&D related statistics for four industries across countries are summarized in Tables 1-4. Tables 5-8 show the cross-country comparison of the industry-specific constant R&D depreciation rates and correspondent country ranking in terms of Forbes' global 2000 ranking. [6] From these four tables, we can see that R&D depreciation rate can serve as a new technology indicator, providing information about a country's international technological competitiveness in each industry that is consistent with the country ranking for each industry in the Forbes' global 2000 ranking.[7]

place "Table 1: R&D Statistics for the Pharmaceutical and Medical Device Industry" here

place "Table 2: R&D Statistics for the Computer, Electronic, and Optical Products Industry" here

place "Table 3: R&D Statistics for the Motors Industry" here

place "Table 4: R&D Statistics for the Electrical Equipment Industry" here

In the following, we discuss the implications of the R&D statistics and the cross-country comparisons by industry.

[5] The NSF 2010 Business R&D and Innovation Survey (BRDIS) received 6,381 responses from 39,968 firms across 38 industries.

[6] http://www.forbes.com/global2000/list/; the Forbes' country ranking is calculated in terms of the number of a country's industry firms on the global ranking.

[7] However, Forbes' global 2000 ranking does not provide a complete ranking for all countries and all industries. In addition, it only covers the largest firms for some industries. Countries without global competitive firms in those covered industries will not be included in the list.

3.1 Pharmaceutical Industry

place "Table 5: The Pharmaceutical Industry" here

In countries where the pharmaceutical industry is strong, such as the U.S., Japan, and Germany, the R&D intensity is highest compared to those for other industries. Table 1 shows that in the U.S., this industry has the highest R&D intensity, absolute R&D investments (shown in Figure 5), higher growth rate of R&D investments, and higher growth rate of industry gross outputs. Although China and South Korea have much higher growth rates in R&D investments than other countries, their technological competitiveness is still far behind as indicated by their R&D depreciation rates. The U.S. is not only ranked as the number one in this industry but its growth rate in R&D investments is also relatively high compared with those for Germany and Japan. Given the fact that the U.S. pharmaceutical industry has a lower R&D depreciation rate and a higher growth rate of R&D investment, it enjoys a higher growth rate of R&D capital than its counterparts in Germany and Japan, which is related to the industry's productivity growth (Eisfeldt and Papanikolaou, 2013, Li, 2015).

Table 5 indicates that in the pharmaceutical industry, U.S. is ranked as the first among the five countries in terms of the R&D depreciation rates and Japan is the 2nd. This result is consistent with the U.S. International Trade Commission report that in the global medical device industry, the U.S. is ranked as the first in technological competitiveness, and Japan is close behind (US International Trade Comission, 2007). Additionally, the ranking in R&D depreciation rates is consistent with the industry observations. In the Forbes' Global 2000 ranking, US firms have the highest share on the Forbes' list, Japan is the 2nd, Germany's Merck ranked as 15th, China's Sinopharm Group ranked as 25th and Yunnan Baiyao Group ranked as 40th. No Korean pharmaceutical firms are on the list.

The high R&D depreciation rates in the pharmaceutical industry for both China and South Korea are not unexpected for the following reasons. First, in the past decade, Chinese firms have been increasingly involved in the manufacturing of generic drugs or have been performing OEM production and clinical trials for international pharmaceutical industries

(Zhang et al., 2012). Since China's pharmaceutical industry is focused on generic drugs and OEM production, it is reasonable to expect that the depreciation rates of its R&D assets will be much higher than those of their counterparts in the U.S., Japan, and Germany. In 2011, China has the world's third largest pharmaceutical market, following the U.S. and Japan; however, most Chinese pharmaceutical firms are small- and medium-sized and lack sufficient financial and human resources to develop new drugs. As a result, it has no internationally recognized medicine. Second, South Korean firms are not on the list of Forbes' global ranking at this point and not active in the global OEM market even for the generic drugs and clinical trials. Park et al. (2011) show that in the pharmaceutical industry, China has outperformed South Korea in terms of technological capability, measured by R&D investments and the number of patents. Third, countries are different in technology. In the U.S., compared with other high-tech intensive industries, the pharmaceutical industry has the lowest R&D depreciation rate. It does not imply that the pharmaceutical industry in other countries will have the same performance. Given the high level of entry barriers and investment scale in this industry, countries with low initial technology endowment such as China and South Korea, will have hard time to develop the world recognized products and enjoy the high level of appropriateness from their investments in R&D.[8]

3.2 Computer, Electronic, and Optical Products Industry

place "Table 6: The Computer, Electronic and Optical Products Industry" here

Table 2 shows that in the computer, electronic, and optical products industry, the U.S. has the highest R&D intensity ratio and that Germany and Japan have the second and third highest ratios. Again, China and South Korea have much higher double-digit growth rates in R&D investments than the low single-digit growth rates of Germany and the U.S., where the industry has highest R&D intensity, R&D investment, and gross output. However, in the U.S.,

[8] However, it is well known that few countries such as India have strict regulations on issuing patents for world famous drugs from developed countries and tend to award the patents to the local pharmaceutical firms that develop generic version of the world famous drugs. This will not fall in the open free trade framework, and we expect that the R&D depreciation rate for the Indian pharmaceutical industry to be lower than their counterparts in China and South Korea. Data in India will be needed to verify this expectation.

Germany, and Japan, this industry has experienced negative growth in gross output. In Japan, it has even a negative growth rate of R&D investments. Moreover, when the standard errors of the R&D depreciation rates are considered, the U.S., and Germany have a similar level of technological competitiveness. South Korea and China, on the other hand, are on a lower level of technological competitiveness, after considering the standard error.

Because this industry category combines several sub-industries, such as semiconductor, computer hardware, electronics, and optical industries, there is no clear Forbes' country ranking for this aggregate industry. In the semiconductor industry, the U.S. leads the world. In the computer hardware industry, the U.S. and Japan surpass other three countries. In the consumer electronics, Japan leads the world but in the communication equipment industry, the U.S. leads the world. The Forbes' ranking does not include the optical industry, but it is well known that Germany's optical companies are very competitive in the global market. In summary, it is noted that the U.S. and Japan are always ranked in the top three of each sub-industry available on the Forbes' global 2000 list.

3.3 Motors Industry

place "Table 7: The Motors Industry" here

For this industry, Table 7 indicates again that R&D depreciation rates and Forbes show the similar country ranking. In terms of R&D depreciation rate, when the standard errors of the R&D depreciation rates are considered, Japan and Germany have a similar level of technological competitiveness. The U.S. is ranked as the third. South Korea is ranked at the fourth place and China is ranked at the bottom. Most of the automobiles produced in China are made by joint ventures between Chinese firms and world famous auto manufacturers, such as General Motors and Toyota. Car manufactured in China are mainly sold domestically and local brands without multinational collaboration are less popular. Most technologies in this field still rely on the technology transfers from foreign companies through joint ventures.

In Japan, the motors industry has the highest level of R&D investments. And, the motors industry has the largest annual average industry gross output in the U.S., Japan, and

Germany. In terms of R&D intensity and the growth rate of R&D investments, Germany is slightly higher than Japan. In the U.S., the industry has experienced negative growths in both R&D investments and industry gross outputs. In China, the growth rates of industry R&D investments and gross outputs are both greater than 25%, but its R&D intensity is very low. Compared with China, South Korea has a higher R&D intensity rate, but smaller growth rates of R&D investments and industry gross outputs. In addition, South Korean auto industry has expanding its world market share in the past decade. In contrast, most Chinese automobiles companies started with joint ventures with world-class auto makers. The degree of indigenous technologies is much lower than those of its counterparts in advanced countries. This can be also seen in the Forbes' global 2000 ranking.

3.4 Electrical Equipment Industry

place "Table 8: The Electrical Equipment Industry" here

In the electrical equipment industry, I only find three countries with data that fit into this industry category. Both the country ranking in terms of R&D depreciation rates and Forbes' ranking are the same. The U.S. is ranked as the first in terms of R&D depreciation rate, Japan the second, and China the third. Table 4 shows that China has the highest growth rates of R&D investments and industry gross outputs but the smallest R&D intensity rate. Japan has the smallest growth rate of R&D investments and industry gross outputs but the highest R&D intensity rate.

From the above comparison, we know that the industry-specific R&D depreciation rate can serve as a useful technology indicator for an industry's international technological competitiveness. Moreover, because countries are different in technology, we expect in each industry, countries have different R&D depreciation rate. And, it is not true that the pharmaceutical industry has always the lowest R&D depreciation rate than other industries within a country. Countries, such as China, mainly focused on the production of OEM and generic drugs will expect to have higher R&D depreciation rates. Countries, such as South Korea, with small domestic market and limited resources to invest, may devote more R&D

investments in industries that it has more comparative advantage, such as the motors and computers industries.

Lastly, as mentioned in the introduction, because TFP growth is far less useful for cross-country comparisons (Hulten et al., 2001), some economists have adopted the approach of TFP estimates. Jorgenson et al. (2014) use industry-level TFP from 1955 to 2010 to analyze the catch up in manufacturing sectors between the U.S. and Japan. Because I have data for only four Japanese industries, we compare the U.S. and Japan in these four industries.

place "Table 9: Comparison on R&D Depreciation Rate and TFP Level between the U.S. and Japan" here

Table 9 compares US's and Japan's four R&D intensive industries in terms of their R&D depreciation rates and TFP levels. The main purpose of this comparison is to show that both constant indicators can deliver the same message about the relative technological competitiveness between the two countries' industries. We can see that between the two countries, the industry has smaller R&D depreciation rate also has the higher TFP level.

4. Time-varying R&D Depreciation Pattern

Since the technological and competition environments change over time, the R&D deprecation rates are not expected to remain constant. It is desirable to estimate how the depreciation rate changes with time, even though the optimization in Equation (6) prefers a long time series to obtain a solution with a smaller uncertainty. As the multi-nation OECD data and the data from Japan have lengths between 8 and 11 years, dividing the data makes the subsets too short to yield useful estimates. In the following, I describe an alternative approach that can provide a quick estimate of the approximate time-dependent depreciation rate throughout the time interval of available data.

Because my method only requires two time series: R&D investment and gross output, I first inspect a simple scenario where both time series have constant growth rates. In many occasions, this scenario does represent the industry time series data if short-term variations are removed. Using the same optimal condition indicated in Equation (5), I estimate the depreciation rates for a variety of artificial R&D and gross output time series with constant growth rates. When $I_{\max}$ and r are given, as in the case for each nation, the resulting R&D depreciation rates are found to depend only on three factors: (1) the growth rate of R&D, (2) the growth rate of gross output, and (3) the R&D intensity. In other words, when other things equal, these three values can determine an R&D depreciation rate. When I examine these three factors presented by the OECD data, I find that the R&D and gross output growth rates are between –10% and +20% in most cases, whereas the data across different industries and nations present a wide range of R&D intensities.

With the above understanding about what affects the R&D depreciation rate, δ_{RD}, I now estimate the temporal variation of δ_{RD} when the duration of the time interval is limited. I first calculate the least squares moving averages of the R&D and gross output time series data with a window of five years, as variations shorter than five years are not expected to make a significant influence on the δ_{RD} for the entire industry. These smoothed time series represent the trends in the annual R&D and gross output data, which in turn can be used to estimate the annual δ_{RD}.

place "Figure 8: Time-Varying R&D Depreciation Pattern for the Motors Industry" here

place "Figure 9: Time-Varying R&D Depreciation Pattern for the Computer, Electronic, and Optical Products Industry" here

Moreover, Figures 8 and 9 show the time-varying estimates for the motors, and the computer, electronic, and optical industries. [9] Figure 8 shows that during the data period, we can see that the Japanese motors industry has maintained its technological competitiveness. During our data period, the R&D depreciation pattern has delivered the similar message as the TFP catch-up analysis does for the motors industry in Jorgenson et al. (2014). However, in the computer, electronic, and optical products industry, the two methods show opposite results for period of 2000 to 2005. Figure 9 shows that the U.S. has better technological competitiveness

[9] Due to the data constraint, my analysis only covers the period from 2002 to 2012 for Japan. For the U.S., the data cover the period from 1997 to 2013. A longer depreciation pattern can be estimated when more data are available in the future.

during the period of early 2000 to 2012. Jorgenson et al. (2014) showed that the U.S. was behind Japan in terms of the industry-level TFP during the period of 1965 to 2005. Can this result tell us anything about the historic technological gap between the two countries?

There are several important historic facts about the computer and electronics over the period of 1960 to 1980s that can answer our question (Ruttan, 2001). First, in the mainframe computer technology frontiers, the U.S. has lead in the technology in terms of cycle time in nanoseconds from 1960 to early 1980s. Japan did not catch up with the U.S. until early 1980s. Second, in the semiconductor industry, although Japan has dominated the memory chips since 1970s to 1980s, the U.S. has dominated the product architecture for the microprocessors all the time. Third, in the personal computer industry, the U.S. has technological advantage over Japan since 1980s. This shows that in the majority of the computer and electronic industry, the U.S. has a greater technological advantage over the period of time, which is consistent with the R&D depreciation pattern shown in Figure 8 but cannot be explained by the TFP-level catch-up analysis by Jorgenson et al. (2014). Moreover, most countries do not publish the TFP level due to concerns like the requirement of large data and measurement errors. This comparison indicates that the R&D depreciation pattern can better capture the trend of relative technological competitiveness between countries.

5. Conclusion

Demand for international comparability of innovations is increasing; however, it is difficult to achieve (Hall and Jaffe, 2012). Currently, economists commonly use TFP to measure technical change. But, empirical studies show that there is no straightforward link between TFP and technical change, and R&D investments only explain a small portion of overall annual movements in TFP. Given the drawbacks of TFP in measuring technical change, this paper proposes a new technology indicator, the R&D depreciation rate by industry and country. This paper shows that the importance of the R&D depreciation rate is beyond the calculation of capital service flow and the construction of capital stock. The industry-level R&D depreciation rate can provide valuable information about a country's pace of technological progress and its international technological competitiveness in an industry. Moreover, unlike TFP analysis with issues of measurement units and a multitude of data requirements in cross-country performance comparison, the R&D depreciation rate is easier to estimate and less subject to measurement errors.

In this research, due to data constraints, I only conduct the study on four high-tech intensive industries over five different countries. Most OECD countries do not provide long-term time series data on industry gross output and R&D investment online. In addition, in the OECD dataset, the industry data are reported at the two- or three-digit industry code, which contains several sub-industries with very different paces of technological progress and degrees of market competition. For a more accurate estimate of the industry-specific R&D depreciation rate, data for four-digit industry codes, such as the U.S. data at the 4-digit NAICS codes, will be ideal. Furthermore, unlike the U.S., most countries do not publish the average return rates of all assets for non-financial corporations, which is a parameter needed for the estimation. To conduct analyses covering more countries, we need more country data with similar details.

The cross-country, cross-industry performance comparison based on the new technology indicator indicates that countries are different in innovation capabilities. For an industry, R&D depreciation rate can vary a lot across countries. In a free trade environment, countries with a stronger technology advantage will have a lower R&D depreciation rate. Cohen and Levinthal (1990) point out that firms are different in absorptive capacity, defined as the capability to recognize the value of new, external information, assimilate it, and apply it to commercial ends. The same reasoning can apply to countries as well. Cross-country data show that industry-level R&D intensity ratio and R&D investment vary a lot across countries, which are important for building innovation capability and capacity. The development of absorptive capacity and innovation capability are path-dependent (Cohen and Levinthal, 1990). Unlike the U.S. which leads in many industries, countries with limited innovation resources will allocate resources among industries differently. For example, in the U.S., the pharmaceutical industry has the lowest R&D depreciation rate than other industries. However, for late-coming countries like China and South Korea, which have very skewed distribution of talents among industries, their pharmaceutical industries may not have the lowest R&D depreciation rate within their countries. Compared with its pharmaceutical industry mainly focusing on the production of OEM and generic drugs, China's computer and electronic industry can has a lower R&D depreciation rate due to the abundant supply of computer and electronics talents from Taiwan and overseas (Li, 2008). Similarly, countries with a small domestic market and limited resources to invest, such as South Korea, may devote more R&D investments in industries that it has more comparative advantage, such as the motors and computers industries.

Despite the fact that the new technology indicator can track an industry's technological progress and international competitiveness, like productivity measurement, it cannot provide enough information for us to understand the sources of scientific and technological advances. Neither can it identify the incentives and circumstances causing those advances and facilitating their implementation and diffusion. To provide a clear picture about technological environments and the dynamics of technological progress, we need to resort to other studies that can complement the information provided by this new technology indicator. In other words, the new technology indicator can provide an objective tool to trace an industry's technological progress and international competitiveness. However, it cannot tell us what drives the progress and what incentive mechanisms could facilitate the progress. To answer to these questions, we need to include other statistics pertinent to a country's technological capacity and capability, such as high-skilled immigrants (Kerr, 2013, Freeman, 2006, 2014, Clemens, 2011, Regets, 2007, Miguelez and Fink, 2013, Docquier and Rapoport, 2012, Meeker and Wu, 2013, NSF, 2012 and 2014).

Immigrants represent an important and growing part of the U.S. workforce for innovation and entrepreneurship. Immigrants account for roughly a quarter of U.S. workers in the field of innovation and entrepreneurship, and they have a similar contribution in terms of output measures like patents or startups (Kerr, 2013, Saxenian, 1999, Wadhaw et al. 2007b). Moreover, Kerr and Lincoln (2010) estimate that since 1995, immigrants account for a majority of the net increase in the U.S. Scientists, Technology professionals, Engineers and Mathematicians (STEM) workforce. During the 1990s, the U.S. greatly increased the proportion of foreign-born workers among scientists and engineers. Over the 1990s, nearly 60 percent of the growth in the number of U.S.-based Ph.D. scientists and engineers were born in foreign countries (Freeman, 2006). The 2000 Decennial Census also shows that a large proportion of highly skilled U.S. workers are foreign born (Regets, 2007), including 25.7% of all employed doctorate holders and 37.6% of doctorate holders in science and engineering (S&E) occupations.

When an advanced economy uses more productive technology than a developing country, returns to labor and capital will both be higher in the advanced economy, and both factors will migrate there (Gierking and Mutti, 1983). The U.S. is a prime example of a country where immigration has responded to the country's technological edge and has added to its comparative advantage. The U.S. has a comparative advantage in exporting relatively high-tech products. It imports science and engineering specialists who help the country maintain its position as the technological frontier (Freeman, 2006). The U.S. is not only the leading country attracting worldwide inventors (Miguelez and Fink, 2013) and in general, maintains the highest technological competitiveness among the four selected high-tech industries as shown in this paper.

Countries such as the U.S., Canada, Australia or New Zealand stand out as exhibiting the largest shares of immigrant workers, while European economies are lagging in attracting talents (Miguelez and Fink, 2013). The WIPO data shows that the U.S. immigration rate is far more in line with other large OECD countries, suggesting that the popularity of the U.S. might be unique to inventors. While at the forefront of technological innovation, Germany and France have consistently seen lower inventor immigration rates. Germany even has negative net immigration. Japan has even lower immigration rates than those for Germany and France. This may imply that high-skilled immigrants in Germany, France, and Japan only account for a small part of a nation's technological innovation.

In sum, in the digital era, people are increasingly concerned about how technologies affect their welfare, such as technology unemployment (Brynjolfsson and McAfee, 2014). National accounts should have indicators related to innovations, such as industry-specific R&D depreciation rate, organizational capital, and human capital, which are increasingly important for the traditional growth accounting framework of national accounts to be well equipped to provide a complete picture of the new economy (Corrado et al., 2015, Li, 2015) and help countries to derive effective education and technology policies.

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Figure 1: The Concavity of $\boldsymbol{I(RD)}$

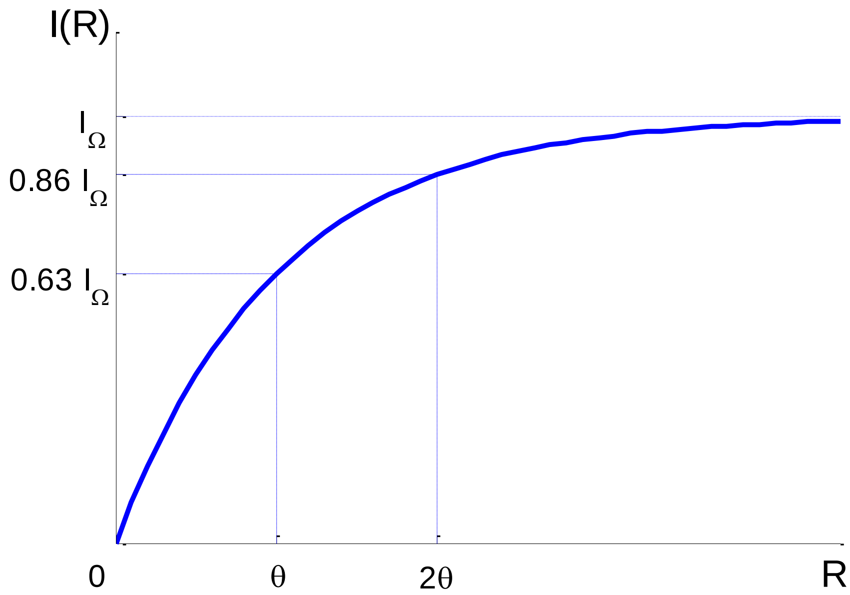

Figure 2: Annual Industry R&D Investment, Gross Output, and R&D Intensity: China

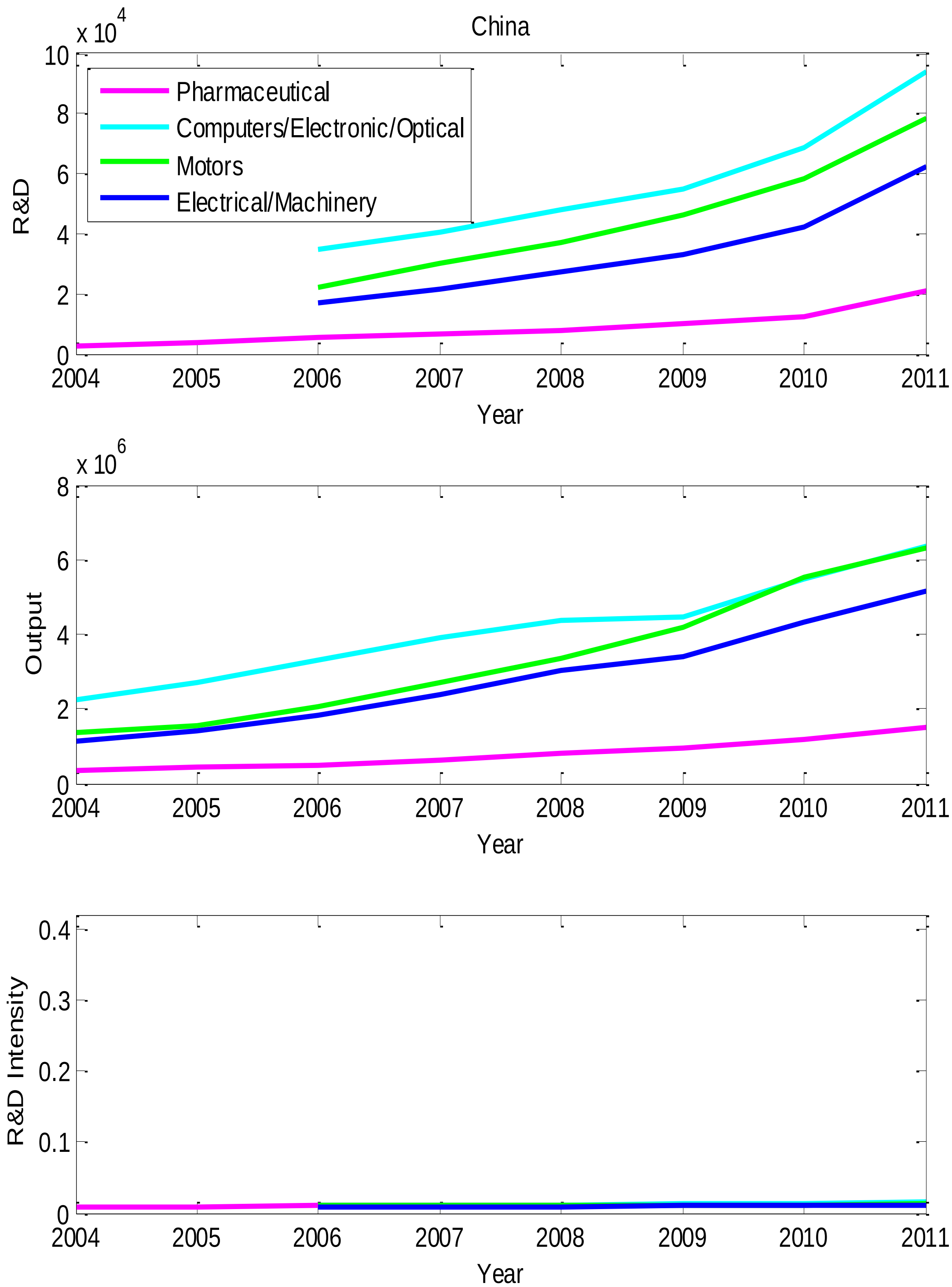

Figure 3: Annual Industry R&D Investment, Gross Output, and R&D Intensity: Germany

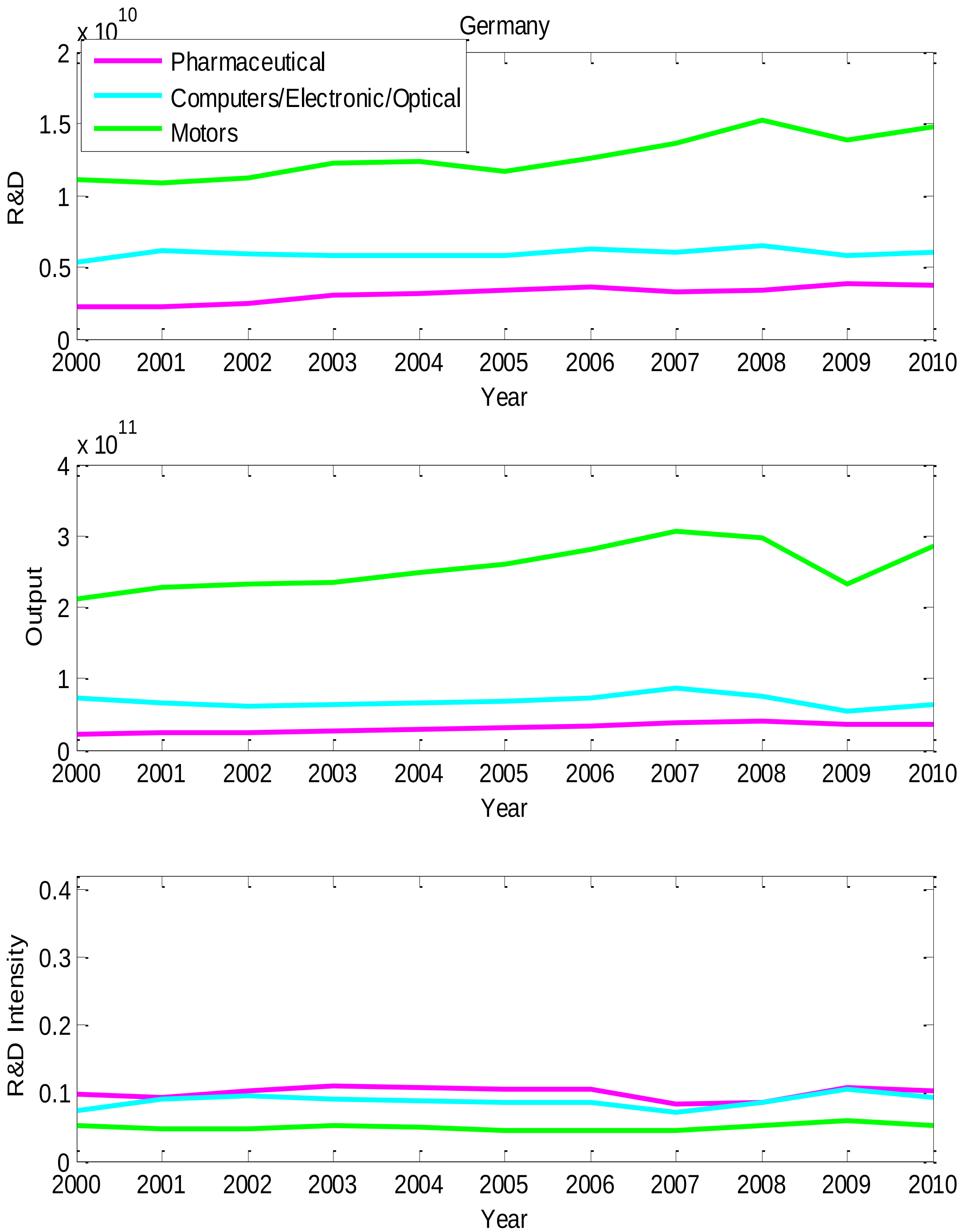

Figure 4: Annual Industry R&D Investment, Gross Output, and R&D Intensity: Japan

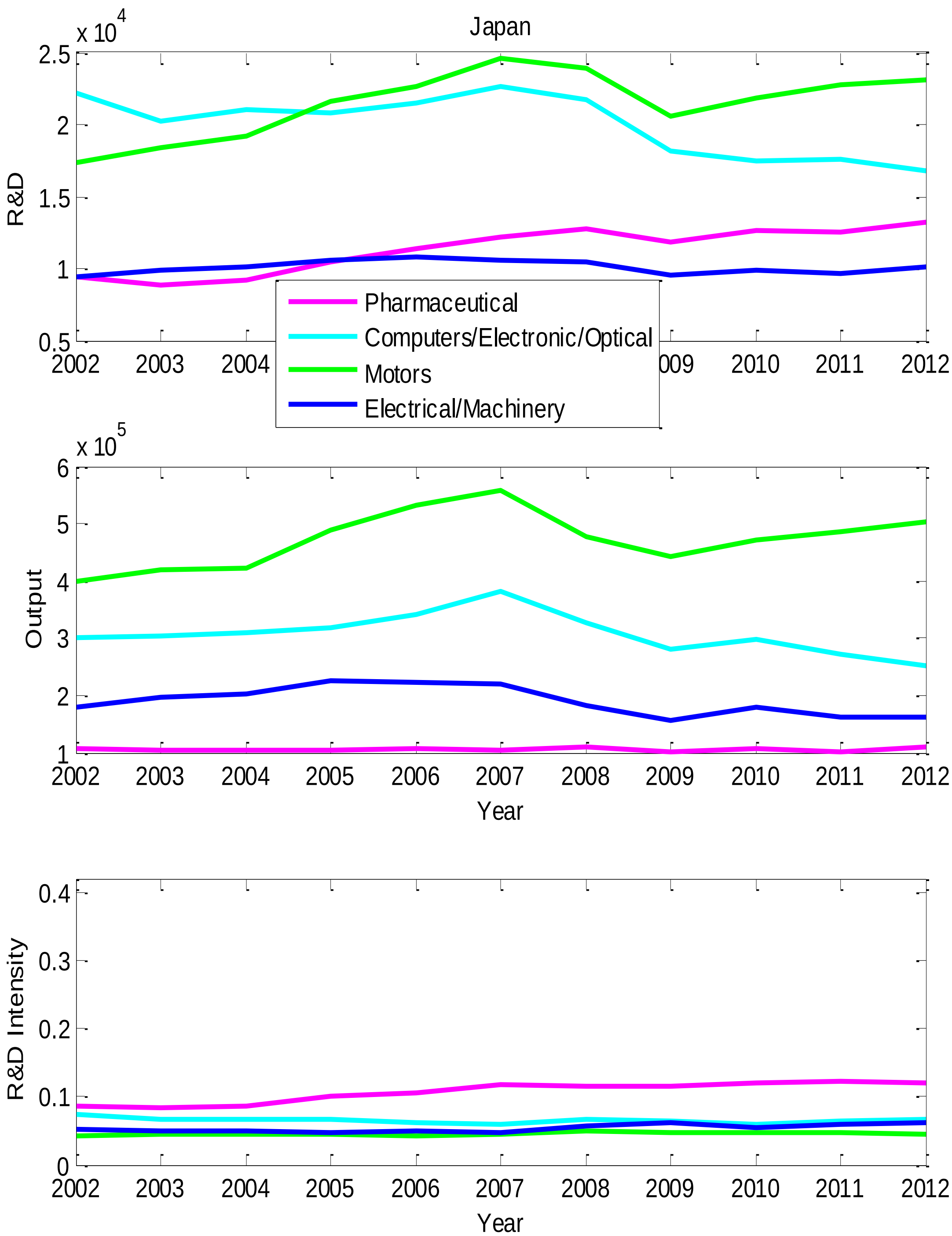

Figure 5: Annual Industry R&D Investment, Gross Output, and R&D Intensity: South Korea

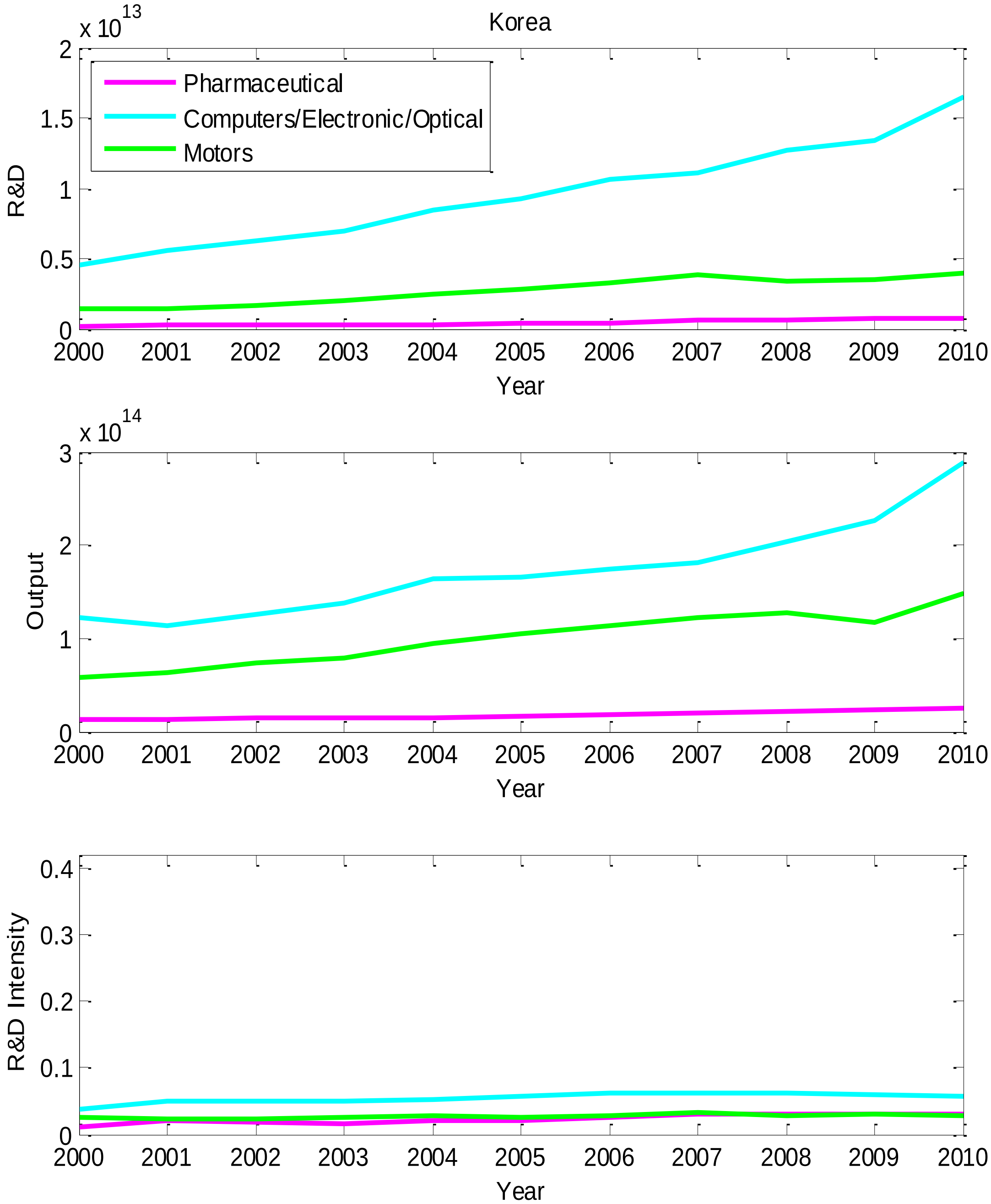

Figure 6: Annual Industry R&D Investment, Gross Output, and R&D Intensity: U.S.

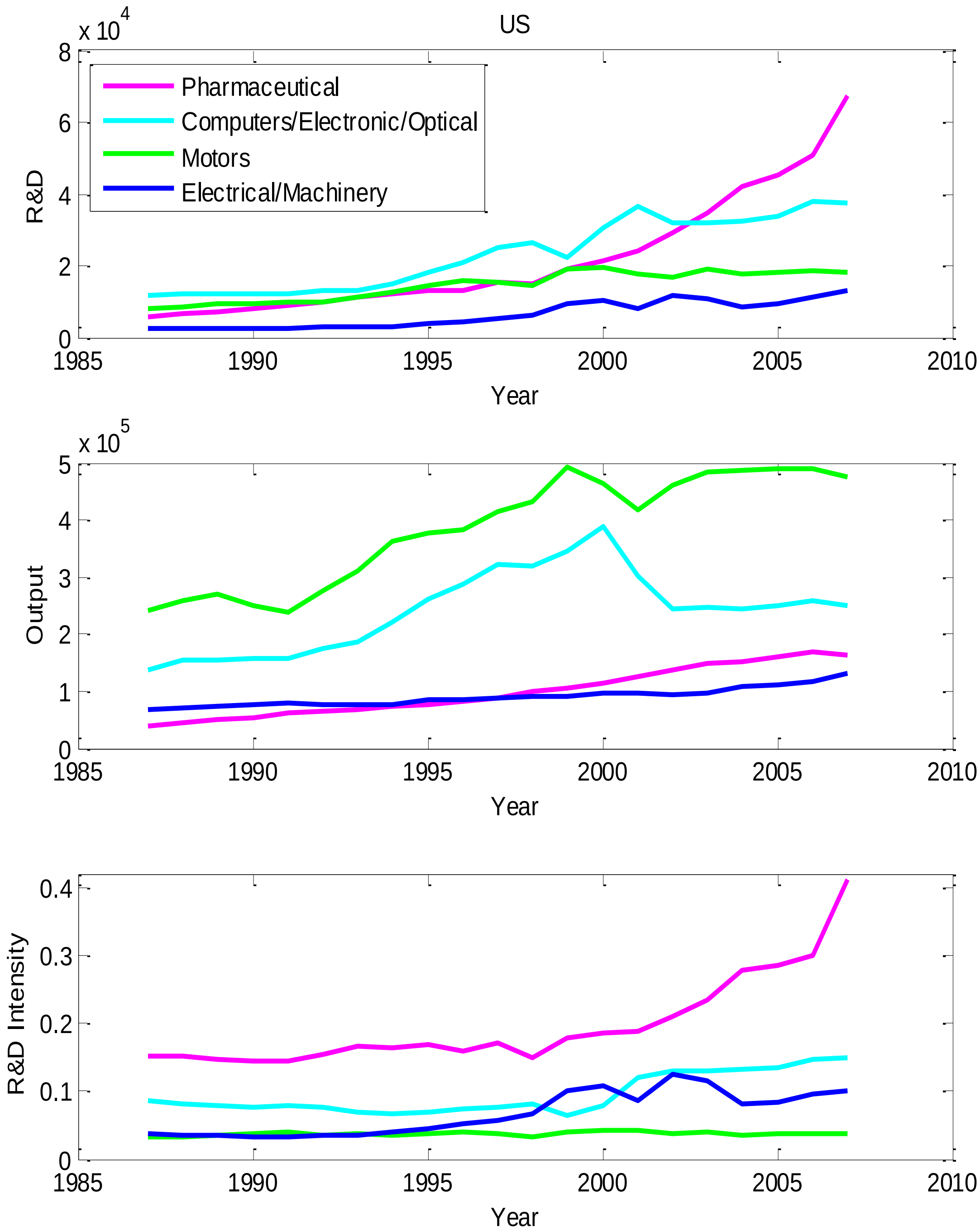

Figure 7: Annual R&D Intensity for Each Industry across Countries

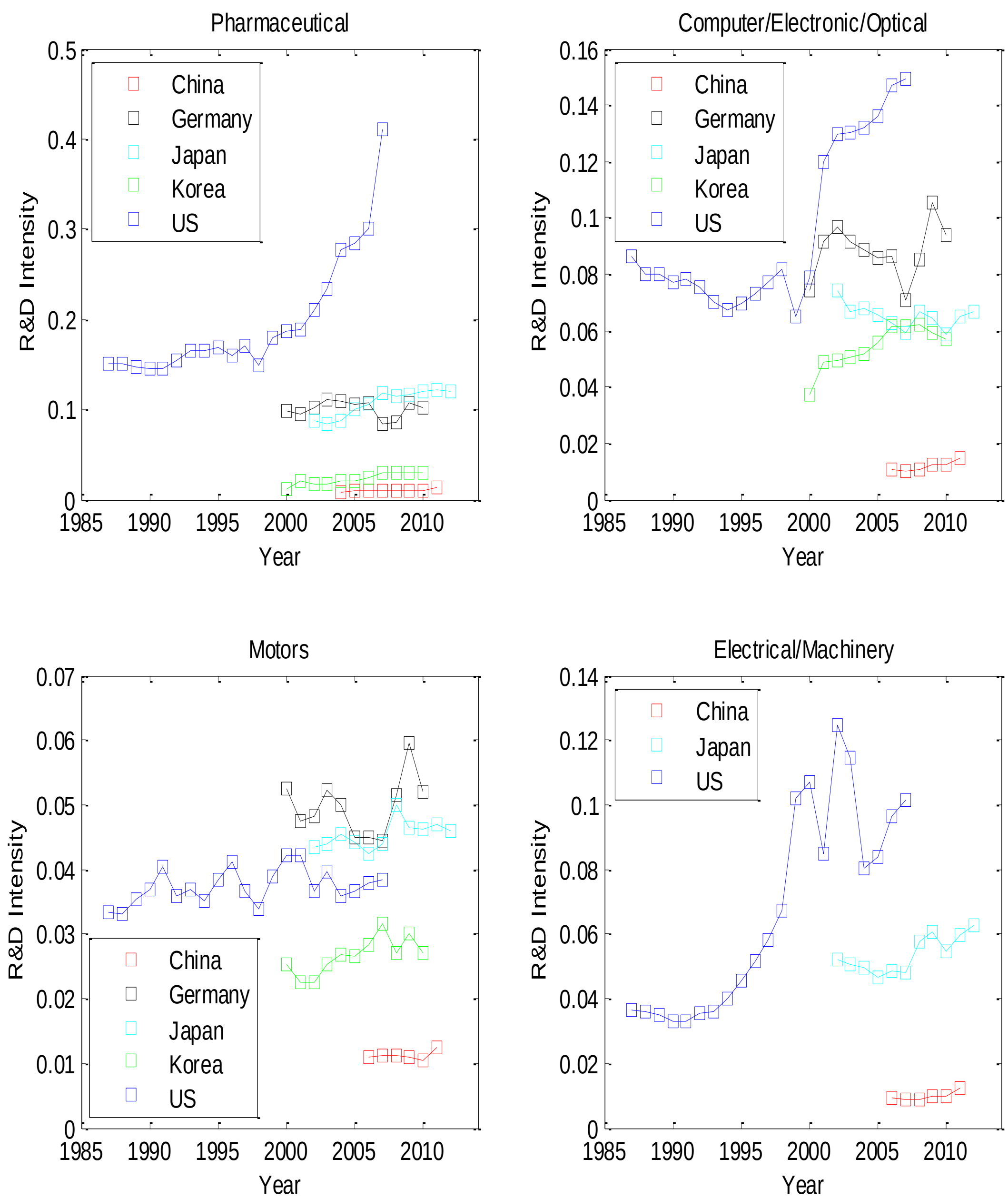

Figure 8: Time-Varying R&D Depreciation Pattern for the Motors Industry

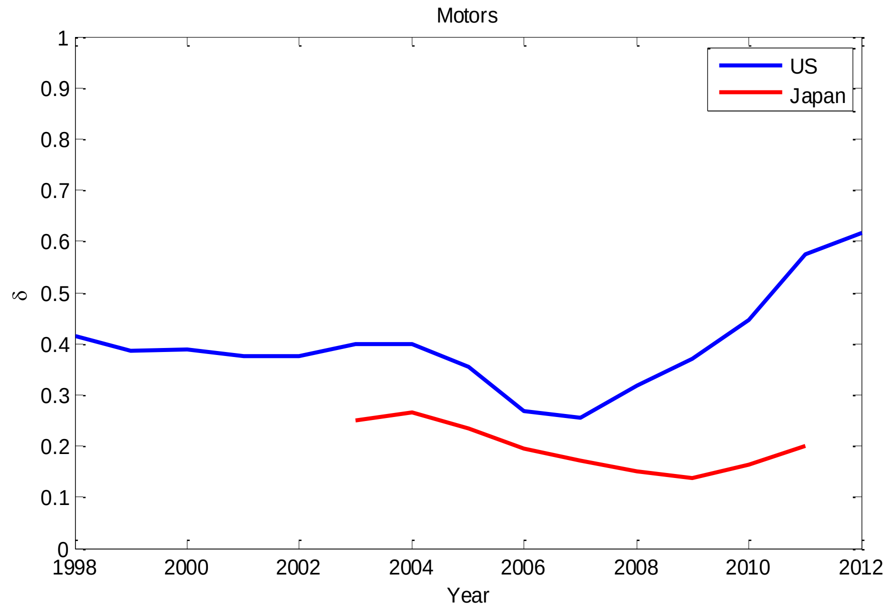

Figure 9: Time-Varying R&D Depreciation Pattern for the Computer, Electronic, and Optical Products Industry

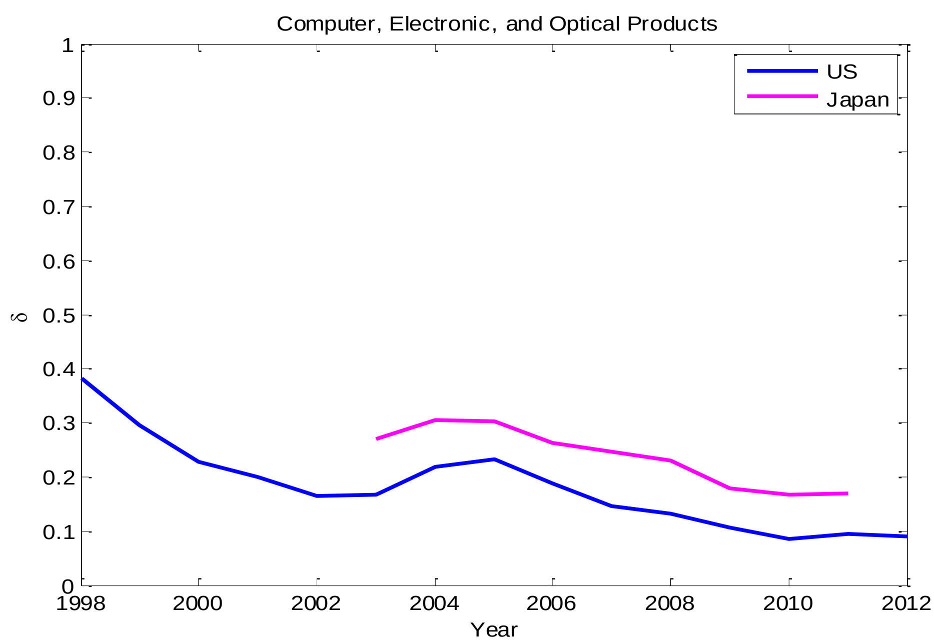

Table 1: R&D Statistics for the Pharmaceutical and Medical Device Industry

Country	G(RD)	G(Output)	R&D Intensity	δ_{RD}	$s(\delta_{RD})$
China	34.29%	24.47%	1.05%	52%	4%
South Korea	20.99%	7.21%	2.27%	89%	7%
Japan	3.60%	0.31%	10.68%	14%	1%
Germany	5.60%	4.95%	10.07%	20%	1%
United States	18.68%	5.31%	18.42%	12%	1%

Note: 1. G(RD) is the average growth rate of annual R&D investments. 2. G(Output) is the average growth rate of annual industry output. 3. δ_{RD} is the R&D depreciation rate. 4. $s(\delta_{RD})$ is the standard error of the R&D depreciation rate.

Table 2: R&D Statistics for the Computer, Electronic, and Optical Products Industry

Country	G(RD)	G(Output)	R&D Intensity	δ_{RD}	$s(\delta_{RD})$
China	22.25%	14.29%	1.19%	36%	4%
South Korea	13.92%	9.43%	5.41%	43%	2%
Japan	-2.55%	-1.41%	6.53%	23%	1%
Germany	1.38%	-0.30%	8.82%	18%	1%
United States	2.33%	-2.43%	13.47%	16%	1%

Table 3: R&D Statistics for the Motors Industry

Country	G(RD)	G(Output)	R&D Intensity	δ_{RD}	$s(\delta_{RD})$
China	28.62%	25.62%	1.12%	52%	2%
South Korea	11.14%	10.20%	2.66%	43%	4%
Japan	3.16%	2.66%	4.53%	20%	1%
Germany	3.18%	3.63%	4.98%	19%	1%
United States	-5.43%	-1.77%	3.40%	35%	1%

Table 4: R&D Statistics for the Electrical Equipment Industry

Country	G(RD)	G(Output)	R&D Intensity	δ_{RD}	$s(\delta_{RD})$
China	30.47%	23.38%	0.98%	53%	2%
Japan	0.85%	-0.62%	5.38%	26%	4%
United States	4.72%	1.21%	2.82%	19%	3%

Table 5: The Pharmaceutical Industry

Country	δ_{RD}	δ_{RD} Ranking	Forbes' Ranking
United States	12%	1	1
Japan	14%	2	2
Germany	20%	3	3
China	52%	4	4
South Korea	89%	5	5

Table 6: The Computer, Electronic and Optical Products Industry

Country	δ_{RD}	δ_{RD} Ranking
U.S.	16%	1
Germany	18%	1
Japan	23%	3
China	36%	4
South Korea	43%	5

Table 7: The Motors Industry

Country	δ_{RD}	δ_{RD} Ranking	Forbes' Ranking
Germany	19%	1	2
Japan	20%	1	1
United States	35%	3	3
South Korea	43%	4	4
China	52%	5	5

Table 8: The Electrical Equipment Industry

Country	δ_{RD}	δ_{RD} Ranking	Forbes' Ranking
U.S.	20%	1	1
Japan	26%	2	2
China	53%	3	3

Table 9: Comparison on R&D Depreciation Rate and TFP Level between the U.S. and Japan

Industry	$\delta_{RD, US}$	$\delta_{RD, Japan}$	TFP_{US}	TFP_{Japan}
Electrical equipment Industry	20%	26%	1.3	1.1
Computer, electronic, and optical products industry	16%	23%	19.5	15
Pharmaceutical industry	12%	14%	1.05	0.9
Motors industry	35%	20%	1.1	1.3

Note: 1. The R&D depreciation rates are calculated by this research. 2. The industry-level TFPs for the U.S. and Japan are from Jorgenson, Nomura, and Samuels (2014). The TFP levels at 2005 are read from their presentation slides. But the relative TFP levels for each industry between these two countries are the same during our sample coverage period. 3. The industry definitions are not exactly the same between the two studies.