Technology Accounts in the National Accounts

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Abstract

To make the system of national accounts (SNA) relevant to the economic and policy issues of the new era of globalization and digitization, this paper proposes that the future SNA creates technology accounts that can provide a consistent and improved measurement of the pace of technological progress across countries. Technological progress is the main driver of long-run economic growth. Economists have relied on the growth accounting framework to measure the multifactor productivity (MFP) growth, which serves as an indicator of a country's pace of technology progress. However, Griliches (1996) argues that the measurement of MFP growth is just a measurement of ignorance and economists have criticized that the MFP measurement is just a point estimate without a robustness check (Manski, 2014). Furthermore, as OECD countries have started capitalizing research and development (R&D) in national accounts, the change of the MFP growth after capitalizing R&D may cause more puzzles than reflect the true nature of technological progress across countries and across industries. For example, the change of U.S. new MFP growth between the period of 1998 to 2007 and the period of 2009 to 2012 are -0.20% for information technology (IT) producing industries, 0.05% for IT using industries, 0.51% for non-IT industries (Rosenthal et al., 2014). The latest result from the U.S. indicates that during the period of 1998 to 2012, the non-IT industries have experienced a faster pace of technological growth than the IT industries, which contradicts the general consensus.

Given that the MFP growth derived from the national accounts cannot provide a good indicator for the pace of technological progress, we propose to create technology accounts in the national accounts. The technology accounts can include key elements, such as R&D depreciation rates and high-skill immigration, related to technological progress. Currently, SNA has listed R&D as one of key capital assets, but the level of R&D investments cannot indicate a country's pace of technological progress, such as the case in China, and the growth rate of R&D capital stock depends on how reliable R&D depreciation rate is. Furthermore, to perform cross-country comparison, we need to have a consistent and reliable methodology to measure all key technology indicators.

For example, because most previous econometric models cannot provide a good methodology to estimate R&D depreciation rates, the OECD IPP manual recommends using expert opinions or surveys to estimate R&D depreciation rates (Peleg, 2012). The fidelity of past surveys has been seriously questioned. For example, a large scale survey on 39,968 U.S. firms in 2010 received an extremely low response rate of 2.45% (Li, 2012). The U.K. survey on 1701 firms in 2012 has shown very high uncertainty (Kerr, 2014). Expert opinions, on the other hand, can vary significantly from person to

[1] The views expressed herein are those of the author and do not necessarily reflect the views of Bureau of Economic Analysis.

person, and no known method can reconcile the differences. Therefore, neither suggested method can provide a true solution. Considering these difficulties, the OECD also suggests that a single average service life of 10 years should be retained if no good solution can be found (OECD, 2012). This suggestion implies that both developed and emerging countries have the same R&D productivity growth, which contradicts common sense. In addition, it is incorrect to assume that every country and industry have the same pace of technological progress.

Using R&D depreciation rates as an indicator of a country's relative technological status requires a consistent and reliable methodology for estimating the rates. In the U.S., we have developed a forward looking profit model to estimate R&D depreciation rates for all key industries (Li, 2012). The results are consistent with industry observers' observations, and can show the relative pace of technological progress and the degree of market competition across industries in the U.S.

Additionally, this new methodology and results have attracted increasing academic and industry interest not only in the traditional field of macroeconomics but also in other fields such as finance, innovation studies, and consulting. Academic scholars, such as Richard Freeman at Harvard and Rand Ghayad at MIT Sloan, have incorporated the materials and paper into their curricula.

Furthermore, the method has applied to Japan's data, and the results are consistent with the observations of Japan's technological progress in key industries relative to that of the U.S. (Li, 2014). During the data period of 1987 to 2012, R&D depreciation rates in the electrical machinery, equipment, and supplies industry are 33% for Japan and 30% for the U.S. Additionally, the rates are 30% for Japan and 29% for the U.S. in the information and communication electronic equipment industry. These findings indicate that, in those two industries, after considering standard error, the pace of technological progress and the degree of market competition in those two countries are close. However, the rates for the drugs and medicines industry, 10% for the U.S. and 13% for Japan, do show that the U.S. has a slight technological edge. This result is consistent with the U.S. International Trade Commission's report in the global medical device industry (U.S. International Trade Commission, 2007), where it finds that, in terms of technological advantage, the U.S. is ranked as the top in the world and Japan is close behind. Lastly, in the auto industry, Japan has a smaller R&D depreciation rate, 22%, than the U.S., 28%. This difference reflects the fact that Japan's auto industry has a clear technological edge and Japanese firms can better appropriate the returns from their investments in R&D. More cross-country comparisons, including time-varying estimates that can reveal the catch-up process, will be presented in the paper.

In the internet era, people are increasingly concerned about how technologies will affect their welfare. National accounts should have technology accounts composed of indices beyond the level of R&D investments and their impacts on the GDP and MFP growth rates, which cannot accurately inform countries' relative paces of the technological progress and technological environment. For countries to derive effective education and technology policies, it is important to establish reliable technology accounts for policy makers to assess where their countries stand in terms of the pace of technological growth and track their progresses.

Introduction

Technological progress drives long-term economic growth and improves standards of living (OECD, 1998a, 2000). In the era of internet, technologies have impacted our lives in many ways, ranging from personal finance management to medical treatments. Because of the importance of technologies to economic growth, we need to have a valid measurement of the dynamics of technological progress and environments. That is, policymakers need to have an effective technology indicator to track where the country's current level of technology is, whether its technology development moves forward, and how competitive it is in the world.

To track technological progress, economists often use the rate of MFP growth to measure technical changes. However, the OECD manual on productivity measurement (2001) points out that there is no straightforward link between the MFP growth and technical changes, and econometric studies show that R&D expenditures only explain a relative small portion of the overall annual movements in MFP. Empirically, not all facets of technological changes are captured by the MFP residual, and the measured MFP residual may contain other non-technology factors, such as adjustment costs and measurement errors. Moreover, the MFP 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). Alternatively, Jorgenson and Nishimizu (1978) develop the first translog nonparametric estimates of MFP levels for the comparison of two countries. Jorgenson et al. (2014) shows the MFP catch-up analysis between the U.S. and Japan for key industries from 1955 to 2010. As mentioned in the OECD manual, the method is still subject to the fact that the MFP level contains items unrelated to technology. For cross-country comparison of the MFP level, more measurement issues, such as currency conversion, will be encountered. As a result, we cannot explain the MFP gap between countries solely as a technological gap. Therefore, MFP and the MFP growth do not sufficiently and easily provide information on technological competitiveness for policymakers.

Other economists use data on patent and journal publication to infer the changes in a country's technological capacity and capability. But, it is well known that patents only cover a portion of technology innovation, and the distribution of patent values is highly skewed. The same concerns also apply to journal publication data. The journal article citation index can only account for a small portion of a country's innovation capacity, and it may be only useful for a limited number of industries but not for all major industries. Even for the pharmaceutical industry, the citation of journal articles has been used to measure a start-up's technological capacity. But, to deliver a new drug, it will take longer time and more investments in various processes, product technologies, and clinical trials. Not all countries can afford the financial and innovation resources required for the development.

Since there is no good technology indicator to track technological progress, this paper presents a new technology indicator, the industry-specific R&D depreciation rate, for an industry's technological competitiveness across countries. Business R&D depreciation rates are driven by an industry's pace of technological progress and the degree of market competition (Hall, 1997). R&D assets depreciate because their contributions to a firm's profit decline over time. Hence, a firm's R&D depreciation rate can indicate how much a firm can appropriate the return from its investments in R&D assets. Therefore, if a firm has a greater technological advantage within an industry, its R&D depreciation rate should be smaller than its counterparts in the same industry, which is a characteristic demonstrated in the study by Li (2015). Similarly, if an industry in country A has higher technological advantages than the same industry in country B, country A's R&D depreciation rate should be lower than country B's. Therefore, the R&D depreciation rate as a technology indicator can tell us the level of technological advantages and the technological gap between the countries. In addition, the R&D depreciation rate does not have the issue of measurement units, and we can use the time varying R&D depreciation pattern to track the industry's pace of technological progress within and between the countries as shown later in the paper.

In this paper, I use the methodology developed by Li (2012) for estimating the Depreciation of Business R&D Capital, as well as the data of annual industry outputs and annual industry R&D investments for four major high-tech industries across five countries. The four high-tech industries are the pharmaceutical industry, the computers, electronic, and optical products industry, the motors industry, and the electrical equipment industry. The five countries include the U.S., Germany, Japan, Korea, and China. 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.[2]

The estimates of the 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 consistent to the country ranking on Forbes' global 2000 list. Second, when I compare the results between the U.S. and Japan for four industries , the country with a lower industry-level R&D depreciation rate has a higher industry-level MFP. Third, the information derived from the time-varying R&D depreciation rates 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.[3]

This paper is organized as follows. Section 2 sets out the R&D investment model, 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 premise of my 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. R&D depreciation rate is a necessary and important component of a firm's R&D investment model. A firm pursuing profit maximization will invest in R&D optimally such that the marginal benefit equals the marginal cost. That is, in each period *i*, a firm will choose an R&D investment amount to maximize the net present value of the returns to R&D investment:

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

[3] This dataset only has two industry categories match Japan's industries. I, therefore, only use those two industries to run the time-varying pattern comparison. But, the data coverage period is very similar. The U.S. is from 1997 to 2013 and Japan is from 2002 to 2012.

$$\max_{RD_i} \pi_i = -RD_i + \sum_{j=0}^{J-1} \frac{q_{i+j+d} I(RD_i)(1-\delta)^j}{(1+r)^{j+d}} \quad , \qquad (1)$$

where RD_i is the R&D investment amount in period i, q_i is the sales in period i, $I(RD_i)$ is the increase in profit rate due to R&D investment RD_i, δ is the R&D depreciation rate, and d is the gestation lag and is assumed to be an integer which is equal to or greater than 0. Period i's R&D investment RD_i will contribute to the profits in later periods, i.e., $i+d, i+d+1, \ldots, i+d+(J-1)$, but at a geometrically declining rate. J is the length that should be large enough to cover at least the length of the service lives of R&D assets. r is the cost of capital.

It should be pointed out that J is not the length of the service lives of R&D assets. J can be ∞ in theory, but in practice any sufficiently large value can be used in calculations. We have confirmed that, with J greater than the service lives of R&D assets, the derived depreciation rates are very stable when we vary the number of J in small increments. In the analysis presented later, we have found that, with the same values of d and J, δ is different across industries.

It is necessary to note here that, when a firm decides the amount of R&D investment for period i, the sales q for periods later than i are not available but can be forecasted. In this study the past sales records are used to forecast the future sales to be included in the estimation of the depreciation rate. The time series of sales data is first taken logs and differenced in order to satisfy the stationary condition, and the converted time series is modeled by the autoregressive (AR) process. For the various types of industrial data included in this study, the optimal order of the AR model as identified by the Akaike Information Criterion [Mills, 1990] is found to range from 0 to 2. To maintain the consistency throughout the study, AR(1) is used to forecast future sales.

The forecast error of the AR model will also affect the estimation of the depreciation rate. To examine this effect, I performed a Monte Carlo calculation with 1000 replications. In each replication, the forecast error of AR(1) at k steps ahead, $\sum_{i=1}^{k} a_1^{k-i} \varepsilon_{t+i}$, was calculated with $\varepsilon_t \sim \mathcal{N}(0, \sigma^2)$ where σ was obtained by AR estimation. This error is then added to the forecast values based on the AR(1) model. For every industry included in this study, the 1000 estimates of the depreciation rate exhibit a Gaussian distribution.

In the following, the predicted sales in period *i* is denoted as $\hat{q}_i$. In addition, the choice of *J* can be a large number as long as it well covers the duration of R&D assets' contribution to a firm's profit. In this study, I use 20 for *J* except for the pharmaceutical industry where *J* = 40 is used due to the longer product life cycle.

To derive the optimal solution, I define $I(RD)$ as a concave function:

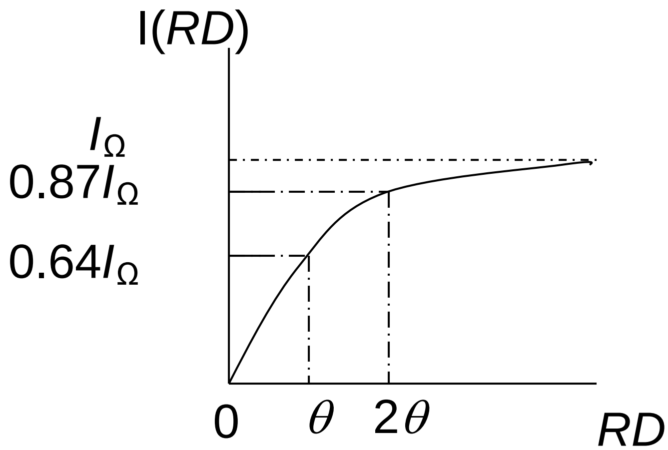
$$I[RD] = I_{\Omega}\left(1 - \exp\left[\frac{-RD}{\theta}\right]\right) \qquad (2)$$

$I'(RD) > 0$ and I''(RD) < 0. And, $\frac{dI}{dRD} = I_{\Omega} \times e^{\frac{-RD}{\theta}}\ where\ \frac{dI}{dRD} = I_{\Omega}\ when\ RD = 0.$ I(RD) $\rightarrow I_{\Omega}$ when $RD \rightarrow \infty$. The functional form of $I(RD)$ has very few parameters but still gives us the required concave property to derive the optimality condition, an approach adopted by Cohen and Klepper (1996).

I_{Ω} is the upper bound of increase in profit rate due to R&D investments. And, θ defines the investment scale for increases in *RD* and acts like a deflator to deflate the time trend of R&D investment. That is, θ can indicate how fast the R&D investment helps a firm achieve a higher profit rate. Note that based on equation (2)

$$I(RD) = \begin{matrix} 0.64 I_{\Omega},\ \ when\ RD = \theta \\ 0.87 I_{\Omega},\ \ when\ RD = 2\theta. \\ 0.95 I_{\Omega}, when\ RD = 3\theta \end{matrix} \qquad (3)$$

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



From the above graph, we can see that, for example, when *RD*, the current-period R&D investment amount, equals to θ, the increase in profit rate due to this investment will reach $0.64I_\Omega$. When *RD* equals to 2θ, the increase in profit rate due to this investment will reach $0.87I_\Omega$. The value of θ can vary from industry to industry; that is, we expect to see different industries have different R&D investment scales.

It will be shown in the next Section that the average R&D investment in some industries can increase by multiple folds over a period of two decades, and therefore we expect that the investment scale to achieve the same increase in profit rate should grow accordingly. For this reason I model the time-dependent feature of θ by $log\theta_t(\theta_{2000}, \alpha) = log\theta_{2000} + \alpha(t - 2000)$, in which θ_{2000} is the value of θ in year 2000. The coefficient α is estimated by linear regression of $\log(RD_i) = c + \alpha t$ for each industry. Note that *c* is a constant.

The R&D investment model becomes:

$$\begin{aligned}
\pi_i &= -RD_i + \sum_{j=0}^{J-1} \frac{\hat{q}_{i+j+d}\, I(RD_i)(1-\delta)^j}{(1+r)^{j+d}} \\
&= -RD_i + I_\Omega \left[1 - \exp\left(- \frac{RD_i}{\theta_i(\theta_{2000}, \alpha)} \right) \right] \sum_{j=0}^{J-1} \frac{\hat{q}_{i+j+d}(1-\delta)^j}{(1+r)^{j+d}}
\end{aligned} \quad (4)$$

The optimal condition is met when $\partial \pi_i / \partial RD_i = 0$, that is,

$$\frac{\theta_i(\theta_{2000}, \alpha)}{I_\Omega \exp\left(- \frac{RD_i}{\theta_i(\theta_{2000}, \alpha)} \right)} = \sum_{j=0}^{J-1} \frac{\hat{q}_{i+j+d}(1-\delta)^j}{(1+r)^{j+d}} \quad (5),$$

and through this equation we can estimate 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 the U.S., Japan, Germany, South Korea, and China. Each country covers four R&D intensive industries: the motors, the pharmaceutical, the computer, electronic, and optical products, and the electrical equipment industries.[4] 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. China's 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 outputs and annual industry R&D investments. Because of the data constraints, I chose five countries and four R&D intensive industries for the data analysis.

[4] Due to data constraints, for the electrical equipment industry, I only include the U.S., China, and Japan.

As a first step in our empirical analysis, I estimate the constant R&D depreciation rate δ_{RD} for the four R&D intensive industries by using the data from five countries, including the U.S., Japan, Germany, South Korea, and China. The four industries cover all R&D intensive industries in Japan and the five countries cover developed countries in the North America, Europe, East Asian, and the Asian developing country, China. Figures 2-6 display the time-series data of industry 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.

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

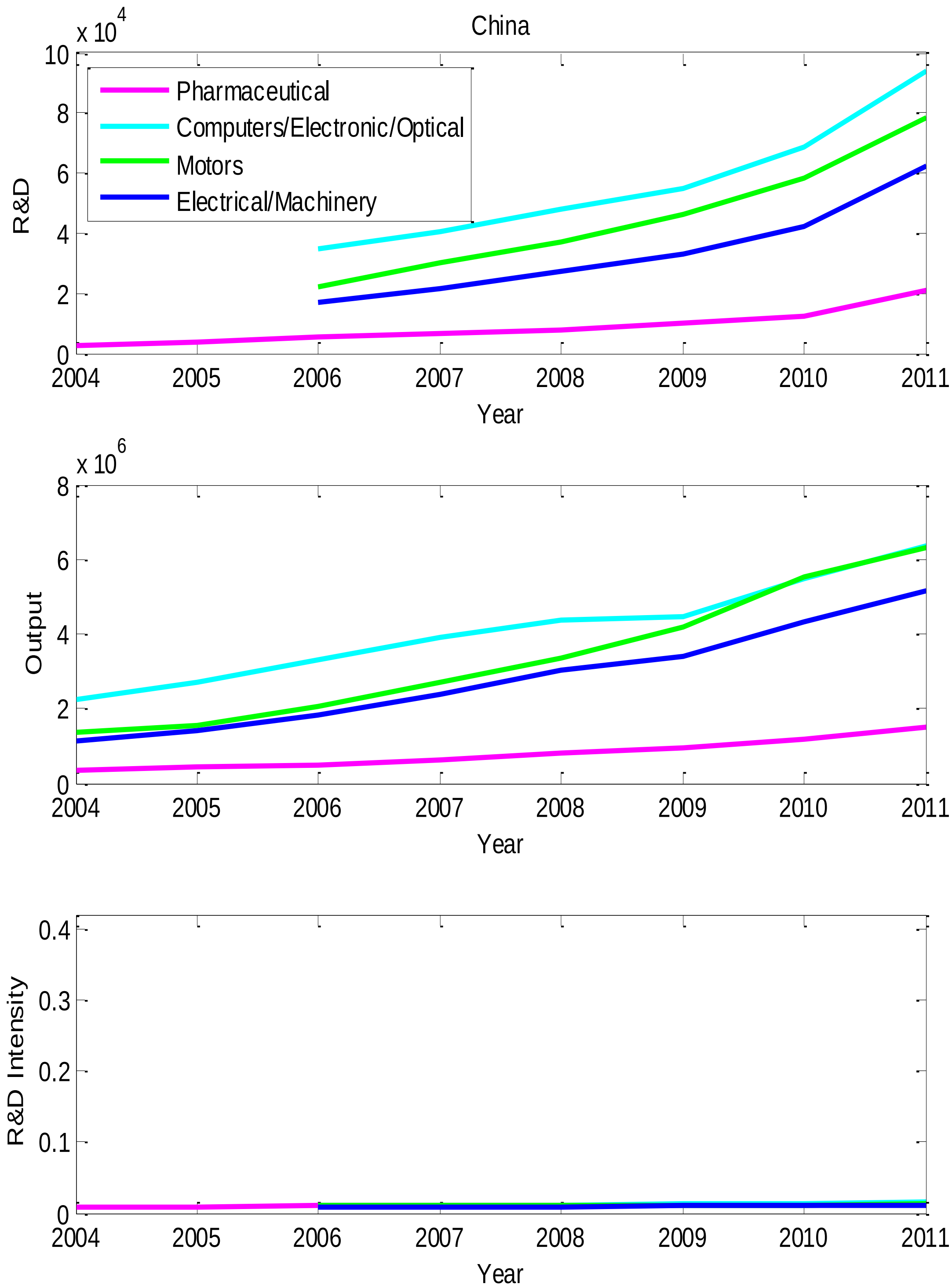


Figure 3: Annual Industry R&D Investment, Industry Output, and R&D Intensity: Germany

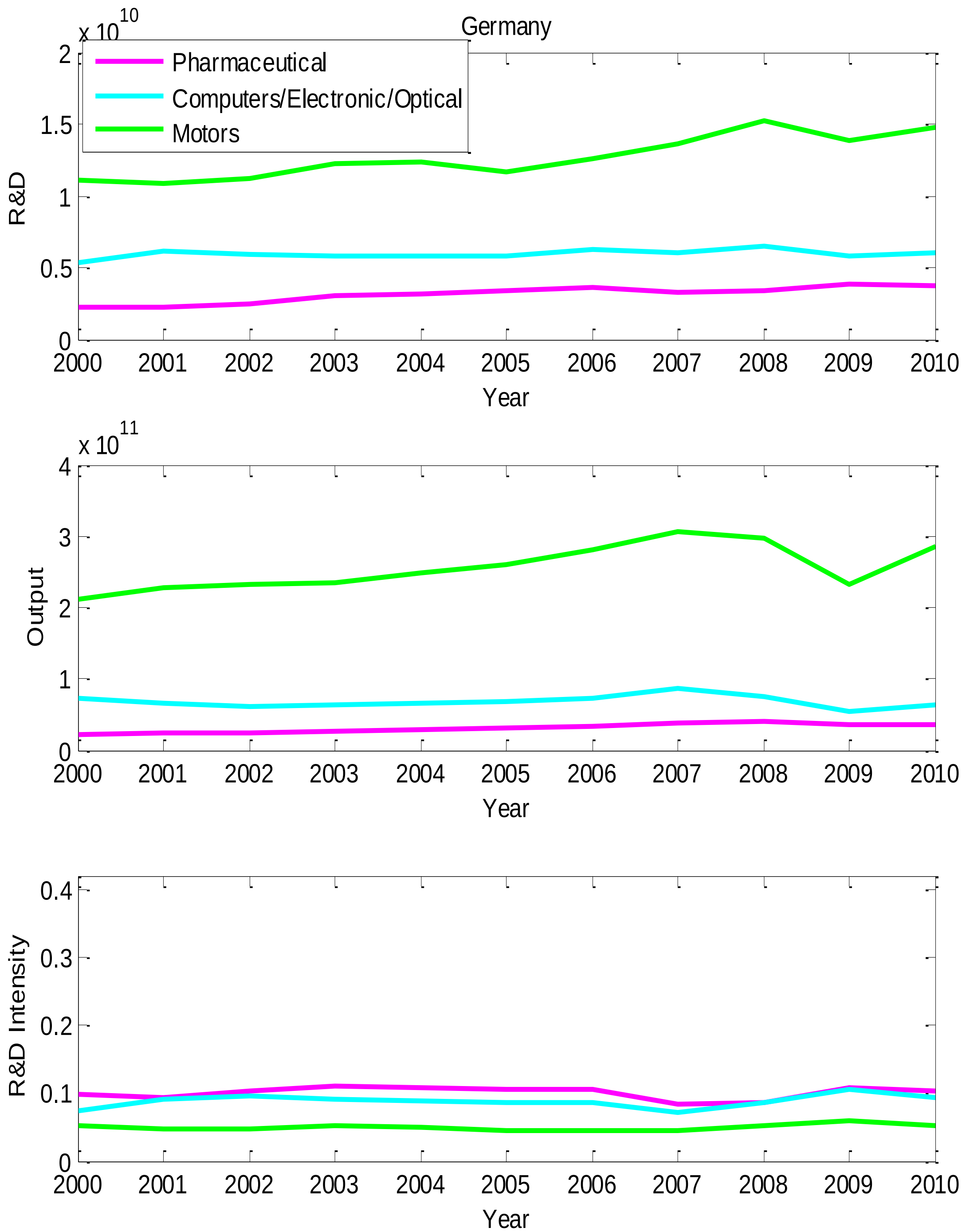


Figure 4: Annual Industry R&D Investment, Industry Output, and R&D Intensity: Japan

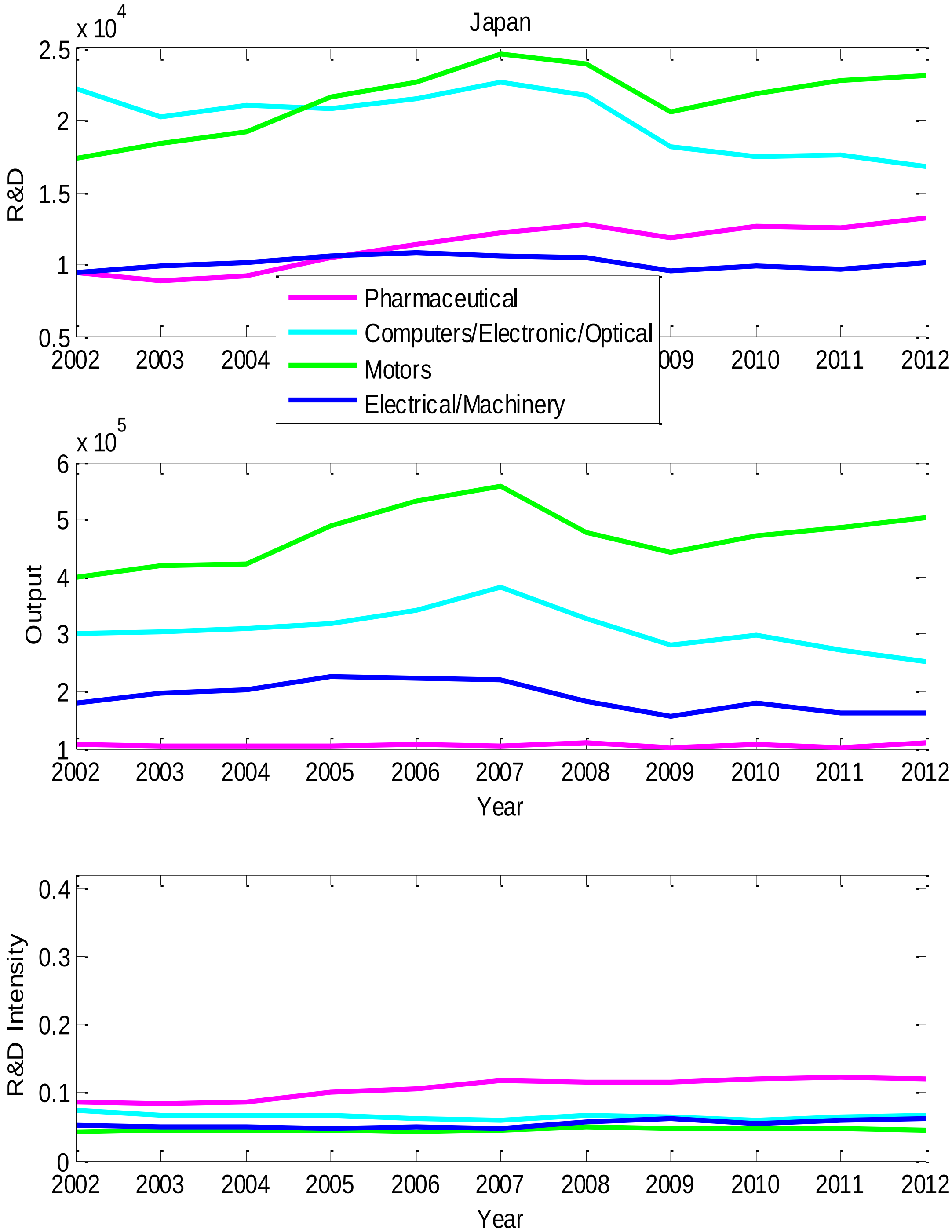


Figure 5: Annual Industry R&D Investment, Industry Output, and R&D Intensity:

South Korea

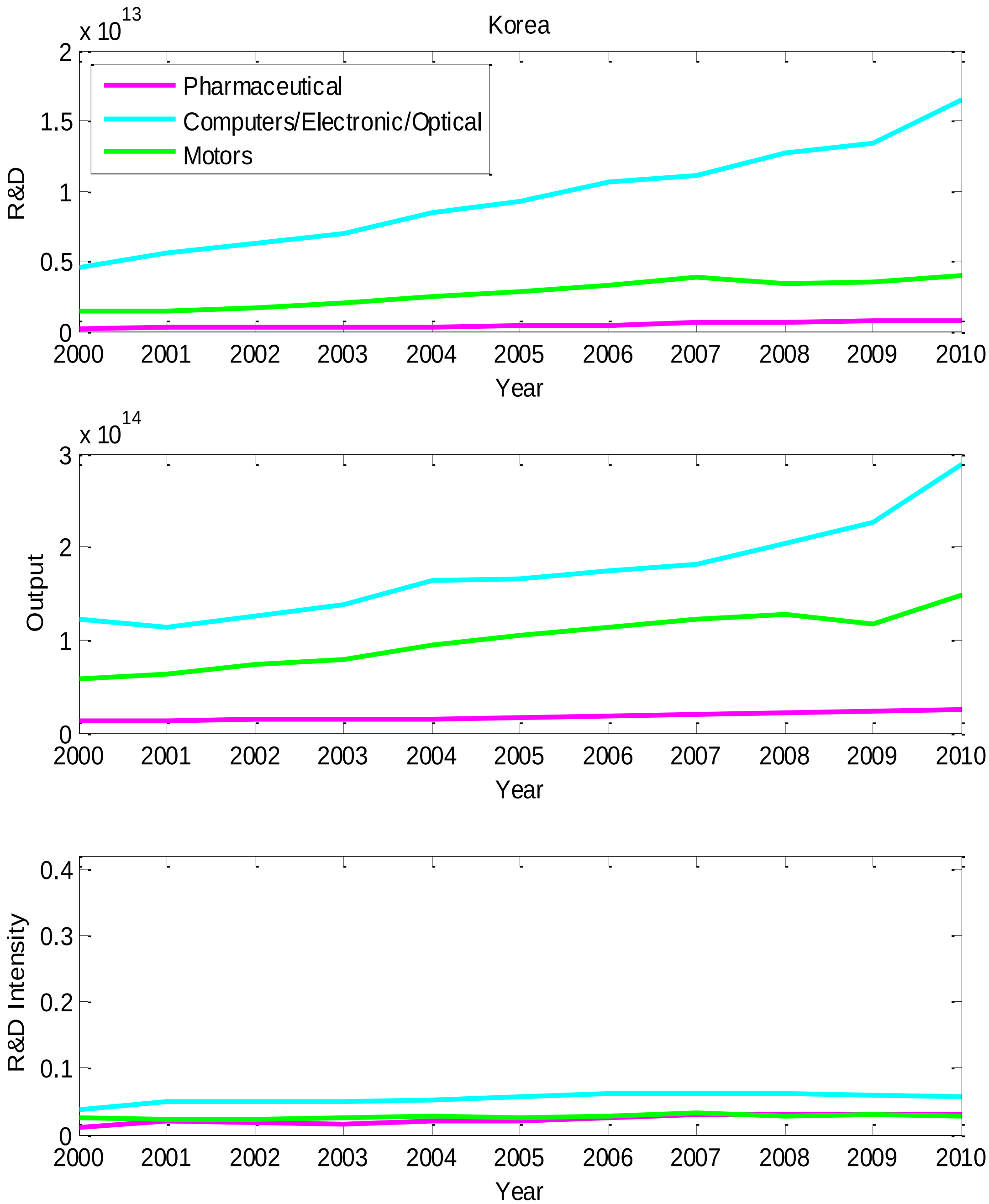


Figure 6: Annual Industry R&D Investment, Industry Output, and R&D Intensity: U.S.

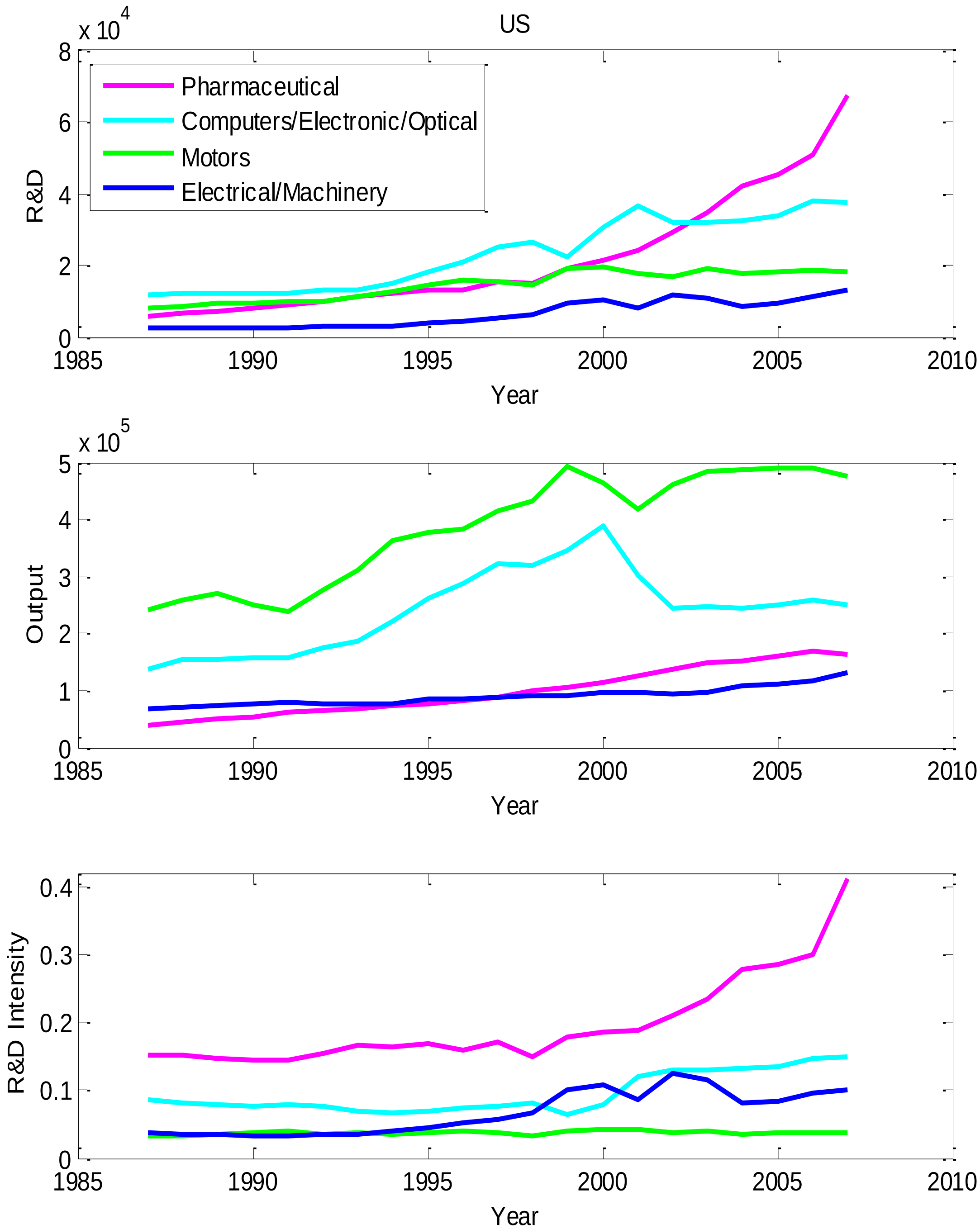
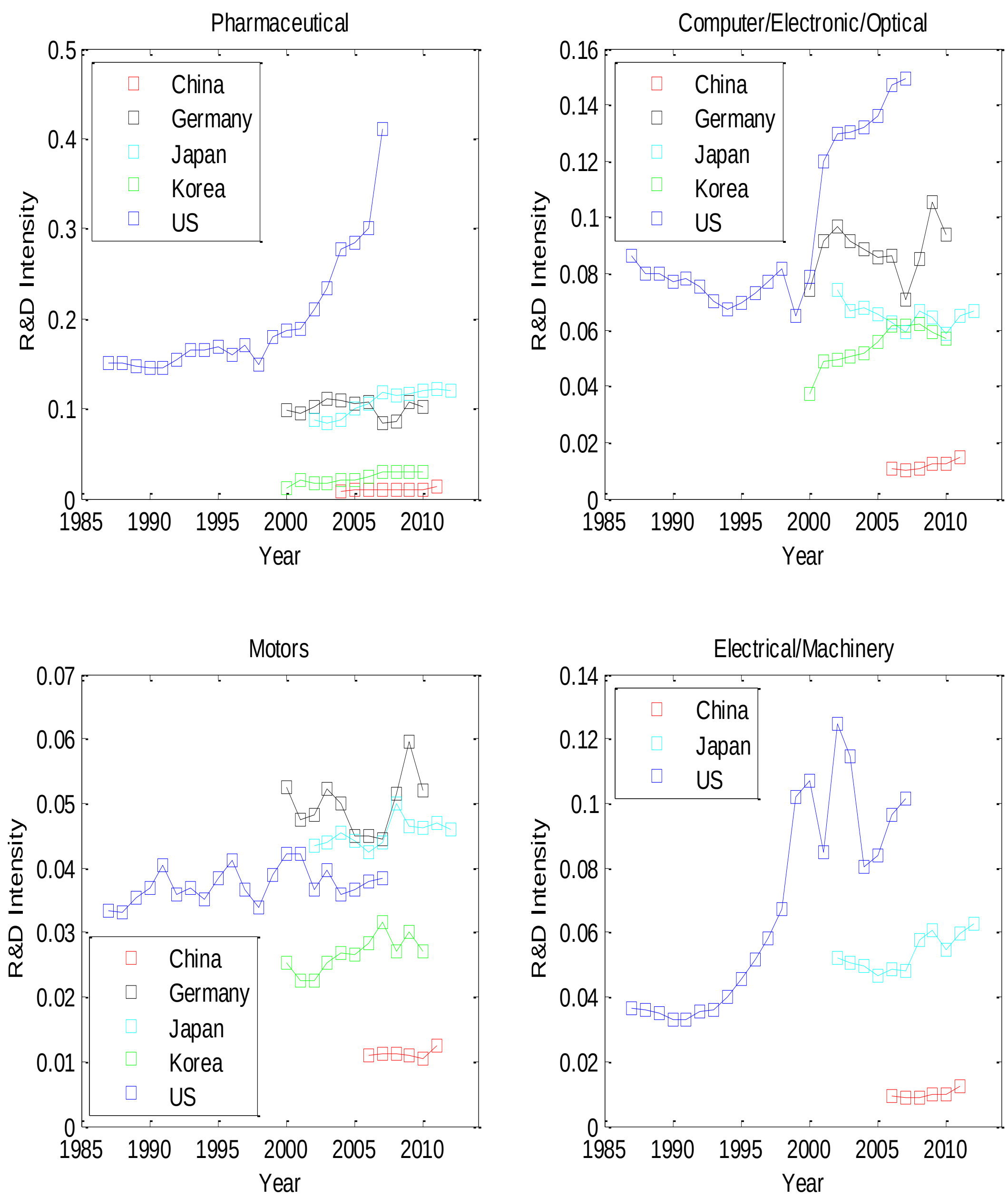


Figure 7: Annual R&D Intensity for Each Industry across Countries



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 overinvestment issue, the value of I_Ω is set to be 1% (Lee et al., 2012; Geng and N'Diaye, 2012).[5]

I use Equation (5) as the model to estimate the R&D depreciation rate from data. As $I_\Omega = r$, and as RD_i and q_i can be known from data, the only unknown parameters in the equation are δ and θ. These two parameters are expected to minimize the difference between the left hand side and the right hand side of Equation (5). That is, we can estimate these two parameters by minimizing the following quantity:

$$\sum_{i=1}^{N-5}\left[\frac{\theta_i(\theta_{2000},\alpha)}{I_\Omega \exp\left(-\dfrac{RD_i}{\theta_i(\theta_{2000},\alpha)}\right)}-\sum_{j=0}^{J-1}\frac{q_{i+j+d}(1-\delta)^j}{(1+r)^{j+d}}\right]^2 \qquad (6),$$

in which *N* is the length of data in years.

Minimizing Equation (6) is therefore the same as seeking the best fit between the model and the data. As the functional form is nonlinear, the calculation needs to be carried out

[5] 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.

numerically, and in this study the downward simplex method is applied. In each numerical search of the optimal solution of δ and θ, several sets of start values are tried to ensure the stability of the solution.

In this study I use a 2-year gestation lag, which is consistent with the finding in Pakes and Schankerman (1984) who examined 49 manufacturing firms across industries and reported that gestation lags between 1.2 and 2.5 years were appropriate values to use. Moreover, the 2010 U.S. survey indicates that the average gestation lag is 1.94 years for all U.S. R&D intensive industries. As mentioned previously, I set the value of J to 40 for pharmaceuticals and 20 for other industries.

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 the relative technological competitiveness that is consistent with industry rankings across countries.

[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.

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%	46%	4%
South Korea	20.99%	7.21%	2.27%	76%	3%
Japan	3.60%	0.31%	10.68%	13%	4%
Germany	5.60%	4.95%	10.07%	23%	1%
United States	18.68%	5.31%	18.42%	10%	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%	35%	9%
South Korea	13.92%	9.43%	5.41%	40%	3%
Japan	-2.55%	-1.41%	6.53%	30%	3%
Germany	1.38%	-0.30%	8.82%	32%	5%
United States	2.33%	-2.43%	13.47%	32%	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%	61%	10%
South Korea	11.14%	10.20%	2.66%	42%	5%
Japan	3.16%	2.66%	4.53%	22%	1%
Germany	3.18%	3.63%	4.98%	24%	5%
United States	-5.43%	-1.77%	3.40%	28%	2%

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%	55%	10%
Japan	0.85%	-0.62%	5.38%	33%	5%
United States	4.72%	1.21%	2.82%	26%	1%

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

Pharmaceutical Industry

Table 5: The Pharmaceutical Industry

Country	δ_{RD}	δ_{RD} Ranking	Forbes' Ranking
United States	10%	1	1
Japan	13%	2	2
Germany	23%	3	3
China	46%	4	4
South Korea	76%	5	5

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 this industry in the U.S. has the highest R&D intensity, absolute R&D investments (shown in Figure 6), higher growth rate of R&D investments, and higher growth rate of industry 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 the R&D depreciation rates. The U.S. is not only ranked as the number one in this industry, large initial endowment in technologies, but its growth rate in R&D investments is also relatively high compared with those for Germany and Japan.

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. Additionally, the ranking in R&D depreciation rates is consistent with the industry observations. In the Forbes' Global 2000 ranking, U.S. 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. 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. 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, it has no internationally recognized medicine. Lastly, South Korea does not have any pharmaceutical firm on the Forbes' list and its firms are not active in the global OEM drug market. Park et al. (2011) argue that China has outperformed South Korea in terms of technological capability, measured by R&D investment and the number of patents, in the pharmaceutical industry.

Computer, Electronic, and Optical Products Industry

Table 6: The Computer, Electronic and Optical Products Industry

Country	δ_{RD}	δ_{RD} Ranking
Japan	30%	1
Germany	32%	1
U.S.	32%	1
China	35%	4
South Korea	40%	4

Table 3 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 industry output. However, in the U.S., Germany, and Japan, this industry has experienced negative growth in industry output. In Japan, it even has a negative growth rate of R&D investments. Moreover, when the standard errors of the R&D depreciation rates are considered, Japan, 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' industry 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, and the U.S. leads the world. The Forbes' ranking does not include the optical industry, but it is expected 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.

Motors Industry

Table 7: The Motors Industry

Country	δ_{RD}	δ_{RD} Ranking	Forbes' Ranking
Japan	22%	1	1
Germany	24%	2	2
United States	28%	3	3
South Korea	42%	4	4
China	61%	5	5

For this industry, Table 7 indicates again that R&D depreciation rates and Forbes show the same country ranking, in which Japan's motors industry leads the world, followed by Germany as the 2nd and the U.S. 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. Indigenous brands without multinational collaboration are less popular, and cars manufactured in China are mainly sold domestically. 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 output in the U.S., Japan, and Germany. In terms of R&D intensity and the growth rate of R&D investments, Germany is slight higher than Japan. In the U.S., the industry has experienced negative growths in both R&D investments and industry outputs. In China, the growth rates of industry R&D investments and 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 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 worldclass auto makers. The degree of indigenous technologies is much lower than those of its counterparts in advanced countries. This can be seen in the Forbes' global 2000 ranking.

Electrical Equipment Industry

Table 8: The Electrical Equipment Industry

Country	δ_{RD}	δ_{RD} Ranking	Forbes'sRanking
U.S.	26%	1	1
Japan	33%	2	2
China	55%	3	3

In the electrical equipment industry, I only find three countries with data that fit the 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 outputs but the smallest R&D intensity rate. Japan has the smallest growth rate of R&D investments and industry outputs but 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 the competitiveness of high-tech industries among countries. In particular, it can rank the technological competitiveness of a country's industry in the world. Since R&D depreciation rate is not an index number, we can also assess technological gap between the countries.

As mentioned in the introduction, because MFP growth is far less useful for comparing the relative productivity of different countries (Hulten et al., 2001), some economists have conducted MFP estimates for the comparison between countries. 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 only have data on four Japanese industries, we compare the U.S. and Japan in those four industries.

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

Industry	$\delta_{RD, US}$	$\delta_{RD, Japan}$	MFP_{US}	MFP_{Japan}
Electrical equipment Industry	26%	33%	1.3%	1.1%
Computer, electronic, and optical products industry	32%	30%	19.5%	15%
Pharmaceutical industry	10%	13%	1.05%	0.9%
Motors industry	28%	22%	1.1%	1.3%

Note: 1. The R&D depreciation rates are calculated by this research. 2. The industry-level MFPs for the U.S. and Japan are from Jorgenson, Nomura, and Samuels (2014). The MFP levels are read from their presentation slides. 3. The industry definition is not exactly the same between the two studies.

Table 9 compares the U.S.'s and Japan's four R&D intensive industries in terms of their R&D depreciation rates and MFP levels. We can see that between the two countries, the industry has smaller R&D depreciation rate also has the higher MFP level. The only exception is in the computer, electronic, and optical products industry; however, the difference in R&D depreciation rate between the two countries is not statistically significant as shown in Table 2.

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, we 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 our method only requires two time series: R&D investment and output, we 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), we estimated the depreciation rates for a variety of artificial R&D and 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 output, and (3) the R&D intensity. In other words, these three values can determine an R&D depreciation rate. When we examine these three factors presented by the OECD data, we find that the R&D and 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 intensity.

With the above understanding about what affects the R&D depreciation rate (δ_{RD}), we now estimate the temporal variation of δ_{RD} when the duration of the time interval is limited. We first calculate the least squares moving averages of the R&D and 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 output data, which in turn can be used to estimate the annual δ_{RD}.

Figure 7: Time-Varying R&D Depreciation Pattern for the Motors Industry

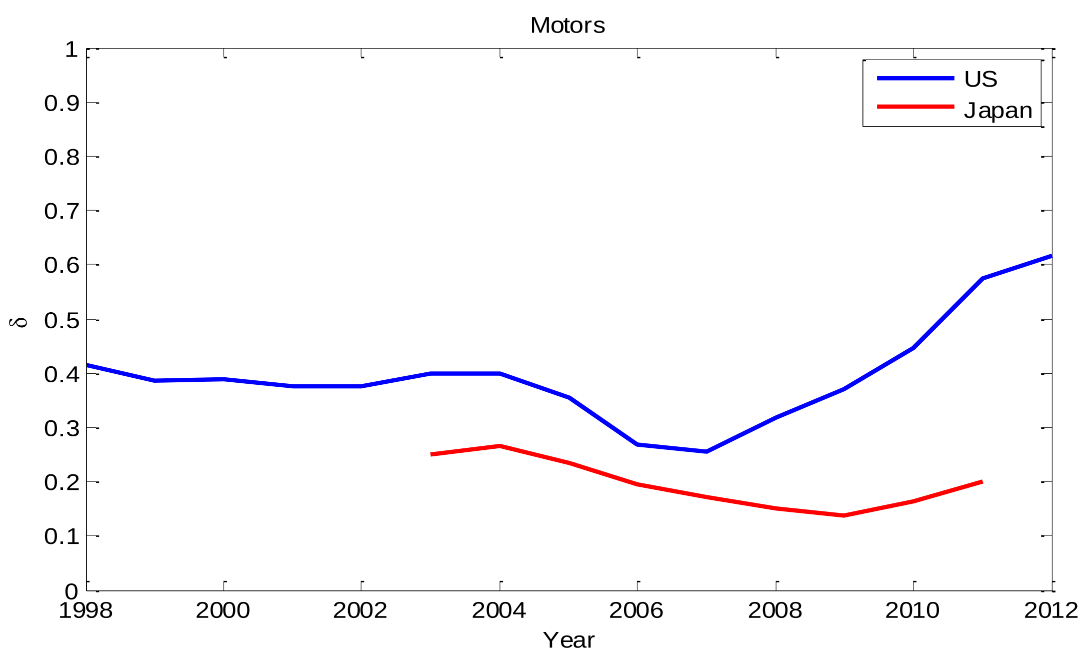
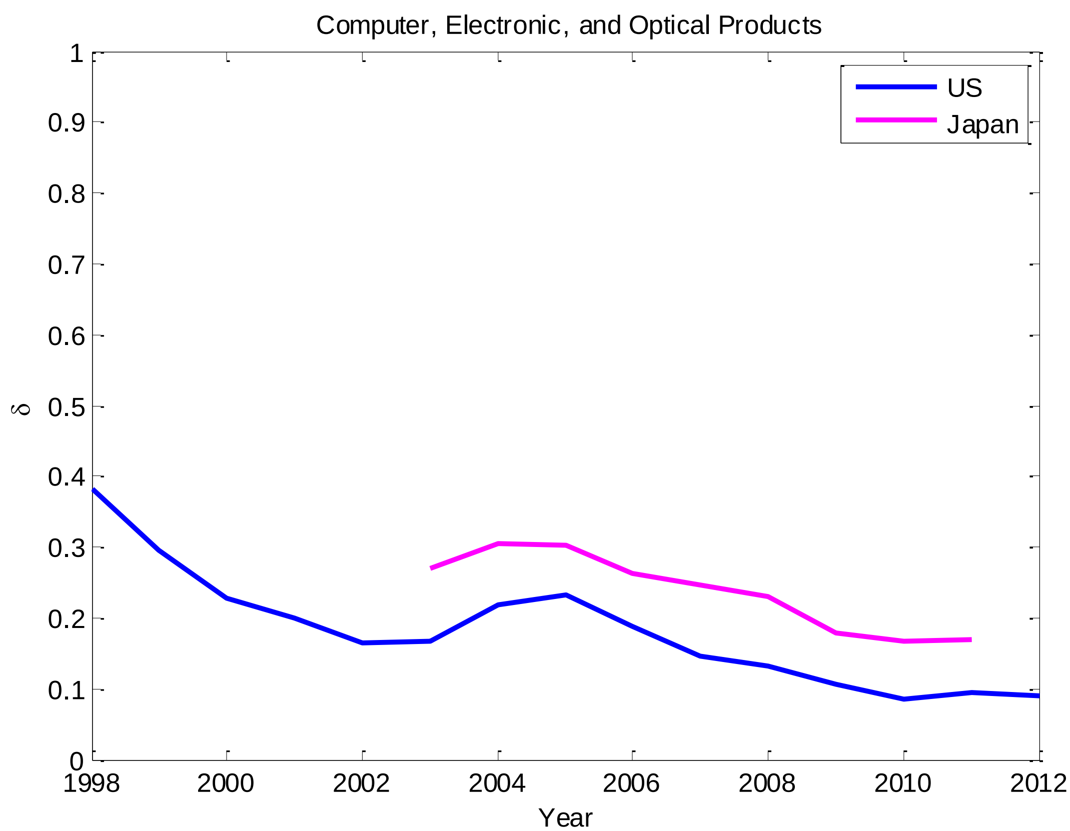


Figure 8: Time-Varying R&D Depreciation Pattern for the Computer, Electronic, and Optical Products Industry



Moreover, Figures 7 and 8 show the time-varying estimates for the motors, and the computer, electronic, and optical industries. [7] Figure 7 shows that during the data period, we can see that Japanese motor industry has maintained its technological competitiveness. During our data period, the R&D depreciation pattern has delivered the similar message as the MFP 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 8 shows that the U.S. has better technological competitiveness 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 MFP during the period of 1965 to 2005. Does this result can tell us anything about the historic technological gap between the two countries?

[7] Due to the data constraint, we can only cover the period of 2002 to 2012 for Japan. For the U.S., the data cover the period of 1997 to 2013. In the future, if there is more data length available, we can show the depreciation pattern better.

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 superior technology advantage over the period of time, which is consistent with the R&D depreciation pattern shown in Figure 5 but cannot be explained by Jorgenson et al.(2014)'s MFP-level catch-up analysis. Moreover, most countries do not publish the TFP level due to concerns, such as the large data requirement. This comparison indicates that the R&D depreciation pattern can better capture the trend of technological change between countries.

5. Conclusion

Since there is no straightforward link between MFP and technical changes, and since R&D investments only explain a small portion of overall annual movements in MFP, this paper proposes a new technology indicator, the R&D depreciation rate by country and by industry. As shown in this paper, the importance of the R&D depreciation rate is beyond the calculation of capital service flow and the construction of capital stock. The R&D depreciation rate can provide valuable information about the pace of technological progress and relative technological competitiveness across countries. Moreover, unlike MFP analysis with issues of measurement units and a multitude of data requirements, the R&D depreciation rate is easier to estimate and less subject to measurement errors.

In this research, I only conduct the study on four high-tech intensive industries over five different countries due to data constraints. Most OECD countries do not provide long-term time series data on industry gross output and R&D investments online. In addition, each set of the OECD data corresponds to an industry category (with an industry code for the first two or three digits) that contains several sub-industries, each might have a different pace of technological progress and a different degree of market competition. For a more accurate estimate of the industry-specific R&D depreciation rate, data for four-digit industry codes will be ideal. Furthermore, unlike the U.S., most countries do not publish the average profit rates for non-financial corporations, which is a parameter needed for the estimation. Fortunately, this research has the complete sets of data from the U.S. and Japan to perform reasonable analysis for five countries. For conducting further analysis across more countries, we need to have the data with similar details.

As shown in this paper, the U.S. has a technological edge in many high-tech industries over other developed and developing countries based on the industry-specific R&D depreciation rates across different countries. On the other hand, like productivity measurement, the new technology indicator does not provide enough information for us to understand the sources of scientific and technological advances. Neither does it identify the incentives and circumstances that caused those advances and that facilitated 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 a country's industry-specific technological performance and to reveal the relative technological competitiveness with its counterparts in other countries. However, it cannot tell us what motivated the progress or 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).

The U.S. is the leading country attracting worldwide inventors, according to the WIPO data that uses patent data to estimate the influx of inventor population to various countries. 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 immigrants account for a majority of the net increase in the U.S. STEM workforce since 1995. Immigrants represent an important and growing part of the U.S. workforce for innovation and entrepreneurship.

From the R&D depreciation rates, we see that the U.S. overall maintains the highest technological competitiveness among the four selected high-tech industries. As pointed out by Gierking and Mutti (1983), 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. 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. During the 1990s, the U.S. greatly increased the proportion of foreign-born workers among scientists and engineers. Nearly 60 percent of the growth in the number of U.S.-based Ph.D. scientists and engineers over this decade 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.

Countries such as the US, 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 US immigration rate is far more in line with other large OECD countries, suggesting that the popularity of the US 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 the internet era, people are increasingly concerned about how technologies affect their welfare. National accounts should have technology accounts composed of indicators, such as industry-specific R&D depreciation rates, beyond the level of R&D investments and their impacts on the GDP and MFP growth rates, which cannot accurately indicate the relative paces of the technological progress and technological environment among different countries. For countries to derive effective education and technology policies, it is important to establish reliable technology accounts for policy makers to assess the pace of technological growth as well as to track its progress.

References

Clemens, M.A. 2011. Economics and Emigration: Trillion-Dollar Bills on the Sidewalk? *Journal of Economic Perspectives*, 25(3), Summer, pp: 83-106.

Docquier, F. & Rapoport, H. 2012. Globalization, Brain Drain, and Development , *Journal of Economic Literature*, 2012, 50(3), 681-730.

Freeman, R.B. 2006. People Flows in Globalization, *Journal of Economic Perspectives,* 20(2), Spring, pp: 145-170.

Freeman, R. 2014. Immigration, International Collaboration, and Innovation: Science and technology policy in the global economy, *NBER working paper 20521*, September.

Hulten, C.R., Dean, E.R., & Harper, M. 2007. New Developments in Productivity Analysis.

Jorgenson, D. W., Nomura, K., & Samuels, J.D. 2014. "Industry Origins of the US-Japan Productivity Gap, 1955-2010," paper presented in the Third World KLEMS Conference, Tokyo, Japan, May 19-20.

Kerr, W.R. 2013. U.S. High-Skilled Immigration, Innovation, and Entrepreneurship: Empirical Approaches and Evidence, *Working Paper*, August.

Measuring Productivity, OECD Manual: Measurement of Aggregate and Industry-level Productivity Growth, OECD, 2001.

Meeker, M., & Wu, L. 2013. Immigration in America & the Growing Shortage of High-Skilled Workers, KPCB, May 29th, 2013 Presentation.

Miguelez, E. & Fink. Carsten. 2013. Working Paper No.8: measuring the international mobility of inventors: a new database, WIPO (World Intellectual property Organization) Economics &

Statistics Series.

Regets, M.C. 2007. Research Issues in the International Migration of Highly Skilled Workers: A Perspective with Data from the United States, National Science Foundation Working Paper, SRS 07-203, June.

Wendy C.Y. Li. 2012. “Depreciation of Business R&D Capital,” paper presented at the 32nd General Conference of the IAIRIW, Boston, USA.

Wendy C.Y. Li. 2015. “Organizational Capital, R&D Assets, and Offshore Outsourcing,” paper presented at the ASSA/SGE Conference, Boston, USA.

Science and Engineering Indicators, 2014, National Science Foundation.