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**Depreciation of Business R&D Capital**

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# **Depreciation of Business R&D Capital**

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## **Abstract**

R&D depreciation rates are critical to calculating the rates of return to R&D investments and capital service costs, both of which are important for capitalizing R&D investments in the national income and product accounts. Although important, measuring R&D depreciation rates is extremely difficult because both the price and output of R&D capital are generally unobservable. To resolve these difficulties, economists have adopted various approaches to estimate industry-specific R&D depreciation rates, but the differences in their results cannot easily be reconciled. In addition, many of their calculations rely on unverifiable assumptions.

Unlike tangible capital which depreciates due to physical decay or wear and tear, business R&D capital depreciates because its contribution to a firm's profit declines over time. Based on this understanding, I develop a forward-looking profit model with a gestation lag to derive both constant and time-varying industry-specific R&D depreciation rates for ten R&D intensive industries that are identified in BEA's R&D Satellite Account. I used two data sources, Compustat SIC based database and BEA-NSF NAICS based database, to perform model calculations. The data cover the period from 1989 to 2008. The results align with the major conclusions from recent studies that R&D depreciation rates are higher than the traditionally assumed 15 percent and vary across industries. Moreover, the industry-specific time-varying R&D depreciation rates provide information about the dynamics of technological evolution and competition across industries.

**Acknowledgments.** I would like to thank Ernie Berndt, Wesley Cohen, Erwin Diewert, Bronwyn Hall, Brian Sliker, and many seminar participants in 2010 NBER Summer Institute CRIW Workshop and 2011 ASSA Conference for helpful comments. I am grateful to Brian Moyer and Carol Moylan for their support to this project, and to Jennifer Lee and Jeff Young for excellent assistance with data compilation. The views expressed herein are those of the author and do not necessarily reflect the views of Bureau of Economic Analysis.

## **1. Introduction**

In an increasingly knowledge-based U.S. economy, measuring intangible assets, including R&D assets, is critical to capturing this development and explaining its sources of growth. Corrado et al. (2006) pointed out that after 1995, intangible assets reached parity with tangible assets as a source of growth. Despite the increasing impact of intangible assets on economic growth, it is difficult to capitalize intangible assets in the national income accounts and capture their impacts on economic growth. The difficulties arise because the capitalization involves several critical but difficult measurement issues. One of them is the measurement of the depreciation rate of intangible assets, including R&D assets.

The depreciation rate of R&D assets is critical to capitalizing R&D investments in national income and product accounts for two reasons. First, the depreciation rate is required to construct knowledge stocks and is also the only asset-specific element in the commonly adopted user cost formula. This user cost formula is used to calculate the flow of capital services (Jorgenson (1963), Hall and Jorgenson (1967), Corrado et al. (2006), Aizcorbe et al. (2009)), which is important for examining how R&D capital affects the productivity growth of the U.S. economy (Okubo et al (2006)). Second, the depreciation rate is required in the current commonly adopted approaches of measuring the rate of return to R&D (Hall 2007).

As Griliches (1996) concludes, the measurement of R&D depreciation is the central unresolved problem in the measurement of the rate of return to R&D. The problem arises from the fact that both the price and output of R&D capital are unobservable. Additionally, there is no arms-length market for most R&D assets and

the majority of R&D capital is developed for own use by the firms. It is, hence, hard to independently calculate the depreciation rate of R&D capital (Corrado et al. 2006). Moreover, unlike tangible capital which depreciates due to physical decay or wear and tear, R&D, or intangible, capital depreciates because its contribution to a firm's profit declines over time. And, the main driving forces are obsolescence and competition (Hall 2007), both of which reflect individual industry technological and competitive environments. Given that these environments can vary immensely across industries and over time, the resulting R&D depreciation rates should also vary across industries and over time.

In response to these measurement difficulties, previous research adopted four major approaches to calculate R&D depreciation rates: patent renewal, production function, amortization, and market valuation approaches (Mead 2007). As summarized by Mead (2007), all approaches encounter the problem of insufficient data on variation and thus cannot separately identify R&D depreciation rates without imposing strong identifying assumptions. In addition, the patent renewal approach cannot capture all innovation activities and suffers from the identification problem of an unknown skewed distribution of patent values. Lastly, the production function approach relies on the questionable assumption of initial R&D stock and depreciation rate (Hall, 2007). Currently, there is no consensus on which approach can provide the best solution.

Furthermore, because of the complexity involved in incorporating the gestation lag into the model, most research fails to deal with the issue of the gestation lag by treating it as zero or one to calculate the R&D capital stock (Corrado et al. 2006).

Because product life cycle varies across industries, this treatment is questionable for R&D assets.

To capitalize R&D investments into its Input-Output accounts and other core accounts by 2013, the Bureau of Economic Analysis (BEA) has established an R&D Satellite Account (R&DSA) and continues to develop methodologies to measure R&D depreciation rates. In the 2006 R&DSA, BEA used an aggregate depreciation rate for all R&D capital. In the baseline scenario, BEA used 15 percent as the annual depreciation rate for all R&D capital. In the alternative scenarios, BEA used the depreciation rate of nonresidential equipment and software for all R&D capital before 1987 and the depreciation rate of information processing equipment after that date. In the 2007 R&DSA, BEA adopted a two-step process to derive industry-specific R&D depreciation rates. In the first step, BEA chose the midpoints of the range of estimates given by existing studies calculated for each industry (Mead 2007). In the second step, those midpoints were scaled down so that the recommended rates were more closely centered on a value of 15 percent and that the overall ranking of industry-level rates suggested by the literature was preserved. The resulting R&D depreciation rates are: 18 percent for transportation equipment, 16.5 percent for computer and electronics, 11 percent for chemicals, and 15 percent for all other industries. However, this approach assumes that each set of estimates from the existing research is equally valid and future depreciation patterns will be identical to those in the study period. Moreover, the most recent studies conclude that depreciation rates for business R&D are likely to be more variable due to different competition environments across industries and higher than the traditional 15 percent assumption (Hall 2007).

This paper introduces a new approach by developing a forward-looking profit model that can be used to calculate both constant and time-varying industry-specific R&D depreciation rates. The model is built on the core concept that, unlike tangible assets which depreciate due to physical decay or wear and tear, R&D capital depreciates because its contribution to a firm's profit declines over time. Without employing any unverifiable assumptions adopted by other methods, this forward-looking profit model contains very few parameters and allows us to utilize data on sales, industry output, and R&D investments.

To test the new model, I first use my model to derive industry-specific R&D depreciation rates for pharmaceutical, IT hardware, semiconductor, and software industries. The Compustat data used cover the period from 1989 to 2008. The constant industry-specific R&D depreciation rates are:  $11.82 \pm 0.73$  percent for the pharmaceutical industry,  $37.64 \pm 1.00$  percent for the IT hardware industry,  $17.95 \pm 1.78$  percent for the semiconductor industry, and  $30.17 \pm 1.89$  percent for the software industry. The calculation results show that, first, the derived R&D depreciation rates fall within the range of estimates from existing literature. Second, they align with the major conclusions from recent studies that the rates should be higher than the traditional assumption, 15 percent, and vary across industries. Third, each industry's time-varying R&D depreciation rates exhibit its depreciation pattern, which is normally consistent with the industry's observations on the pace of technological progress or reflects the appropriability condition of its intellectual property.

The above test demonstrates the capability of the new model in estimating R&D depreciation rates from industry data. The model is then applied to two independent

datasets to calculate the R&D depreciation rates for all ten R&D intensive industries identified in BEA's R&DSA. One is the Compustat SIC-based dataset containing firm-level sales and R&D investments in nine R&D intensive industries. The other is the BEA-NSF NAICS-based dataset containing establishment-level industry output and R&D investments in ten R&D intensive industries.

This paper is organized as follows. Section 2 sets out the R&D investment model, followed by the description of data analysis. The industry-level analysis is carried out in Section 3. Section 4 presents the set of recommended R&D depreciation rates for BEA's ten R&D intensive industries, and concluding remarks are given in Section 5.

## 2. Forward-looking Profit 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:

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

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  $RD_i$ ,  $\delta$  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.,  $i+d$ ,  $i+d+1$ , ...,  $i+d+(J-1)$ , 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  $\infty$  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  $J$ ,  $\delta$  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  $\sigma$  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  $J = 25$  is used due to the longer product life cycle.

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

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

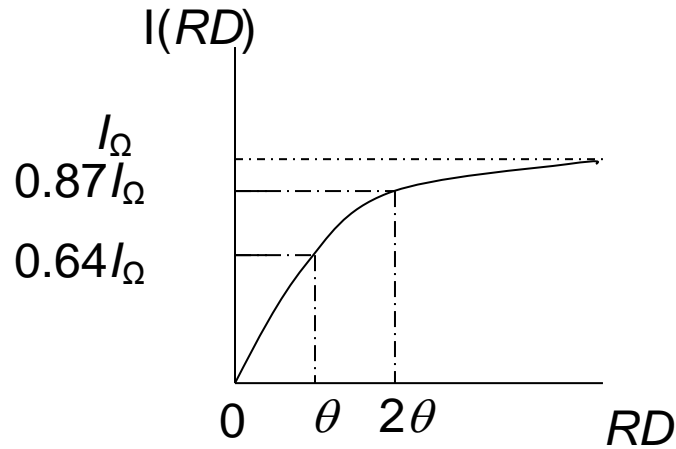
$I'(RD) > 0$  and  $I''(RD) < 0$ . And,  $\frac{dI}{dRD} = I_\Omega \times e^{\frac{-RD}{\theta}}$  where  $\frac{dI}{dRD} = I_\Omega$  when  $RD = 0$ .

$I(RD) \rightarrow I_\Omega$  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).

$I_\Omega$  is the upper bound of increase in profit rate due to R&D investments. And,  $\theta$  defines the investment scale for increases in  $RD$ . That is,  $\theta$  can indicate how fast the R&D investment helps a firm achieve a higher profit rate. Note that based on equation (2)

$$I(RD) = \begin{cases} 0.64I_\Omega, & \text{when } RD = \theta \\ 0.87I_\Omega, & \text{when } RD = 2\theta \\ 0.95I_\Omega, & \text{when } RD = 3\theta \end{cases} \quad (3)$$

Figure 1: The Concavity of  $I(RD)$



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

As the data demonstrate an increase in R&D investment by multiple folds in two decades, we also expect that  $\theta$  gradually grows with time. I model the time-dependent feature of  $\theta$  by  $\log\theta_t(\theta_{2000}, \alpha) = \log\theta_{2000} + \alpha(t - 2000)$ , in which  $\theta_{2000}$  is the value of  $\theta$  in year 2000. The coefficient  $\alpha$  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  $\delta$ .

### 3. Industry-Level Analysis – Initial Test

As a first step in our empirical analysis, I estimate the constant R&D depreciation rate  $\delta$  for four industries (pharmaceuticals, semiconductor, IT hardware, and software) by using the data from 1989 to 2008 to check whether my model gives us R&D depreciation rates in line with rates in past studies. These industries are important for the initial test of my model because the combined R&D investments of these four industries account for 54.56% of U.S. total business R&D investments in 2004. I take the average values of annual sales and R&D investment in each industry from Compustat for estimation.<sup>1</sup>

The Compustat dataset contains firm-level sales and R&D investments for SIC-based industries: pharmaceutical, IT hardware, semiconductor, and software. Their corresponding SIC codes listed below:

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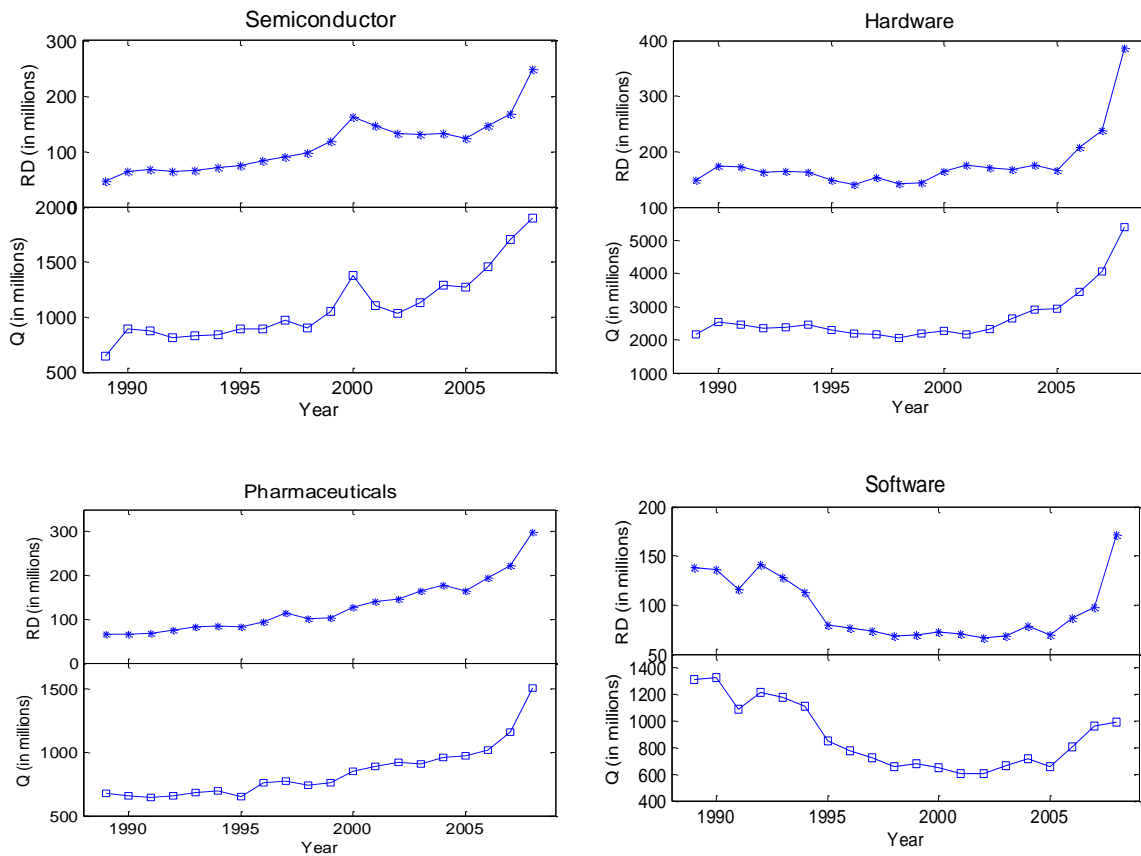
<sup>1</sup> I conduct this calculation from the data of 463 firms in semiconductor industries (SIC codes 3622, 3661-3666, 3669-3679, 3810, 3812), 153 firms in IT hardware (SIC codes 3570-3579, 3680-3689, 3695), 651 firms in software (SIC code 7372), and 551 firms in pharmaceuticals (SIC codes 2830, 2831, 2833-2836).

**Table 1: Industry and Its Correspondent SIC Codes**

Industry	SIC codes
Pharmaceuticals	2830, 2831, 2833-2836
IT Hardware	3570-3579, 3680-3689, 3695
Semiconductor	3622, 3661-3666, 3669-3679, 3810, 3812
Software	7372

The data covers the period from 1989 to 2008. Figure 1 displays the time-series plots of four industries for each dataset.

**Figure 2: Compustat Firm-level Dataset; Mean Value and Company Based; Period: 1989-2008**



The value of  $I_{\Omega}$  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 1987-2008, 8.9 percent, for  $I_\Omega$ . In addition, in equilibrium the rate of returns should be equal to the cost of capital. Therefore, I use the same value for  $r$ .

I use Equation (5) as the model to estimate the R&D depreciation rate from data. As  $I_\Omega = r = 0.089$ , and as  $RD_i$  and  $q_i$  can be known from data, the only unknown parameters in the equation are  $\delta$  and  $\theta$ . Because Equation (5) holds when the true values of  $\delta$  and  $\theta$  are given, the difference between the left hand side and the right hand side of Equation (5) is expected to be zero or close to zero when we conduct a least square fitting to derive the optimal solution. Therefore, we can estimate these unknowns by minimizing the following quantity:

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

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

Minimizing Equation (6) is therefore least squares fitting between the model and the data. As the functional form is nonlinear, the calculation needs to be carried out numerically, and in this study the downward simplex method is applied. In each numerical search of the optimal solution of  $\delta$  and  $\theta$ , 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

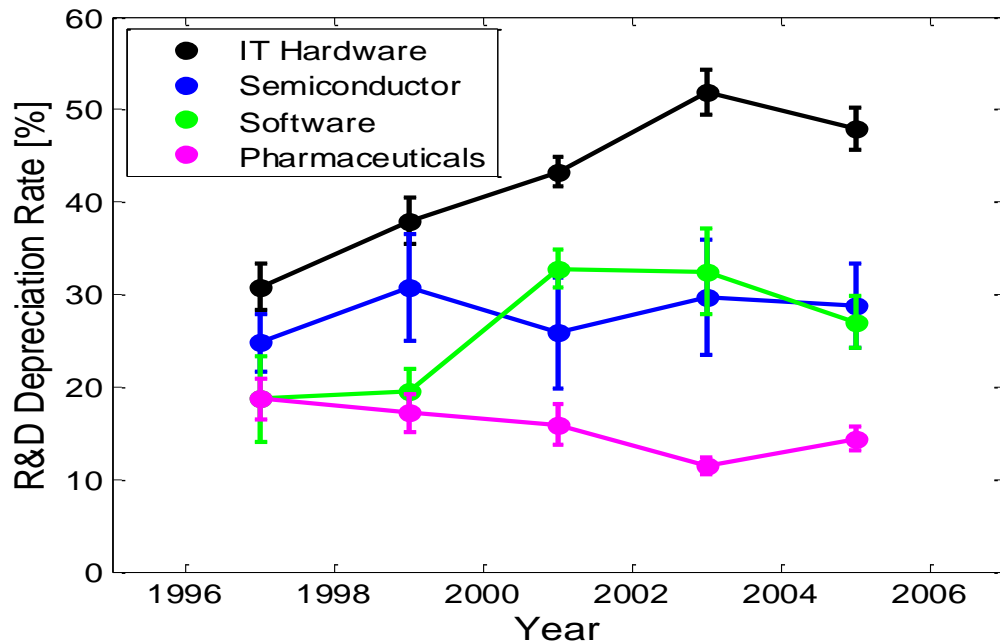
and reported that gestation lags between 1.2 and 2.5 years were appropriate values to use. As mentioned previously, the value of  $J$  is set to be 25 for pharmaceuticals and 20 for other industries. The estimated value of constant  $\delta$  is  $11.82 \pm 0.73$  percent for the pharmaceutical industry,  $37.64 \pm 1.00$  percent for the IT hardware industry,  $17.95 \pm 1.78$  percent for the semiconductor industry, and  $30.17 \pm 1.89$  percent for the software industry. These results indicate that the ranking of R&D depreciation rates across industries in a descending order is: IT hardware, software, semiconductor, and pharmaceutical industries.

Since the technological and competition environments change over time, the R&D depreciation rates are expected to vary through the 20 years of data studied. Therefore there is a need to calculate industry-specific and time-dependent R&D depreciation rates. I use the same industry average sales and R&D investment data from Compustat. The time-dependent feature of  $\delta$  was obtained by minimizing Equation (6) with subsets of data. Instead of using all years of data, I performed least squares fitting over a five-year interval each time, in addition to the five prior years used for sales forecasts. Four more subsets of data are examined in the same way, each with a step of 2 years in progression. As a result there are five subsets of data where data-model fit is carried out, and the estimated depreciation rates are the mid-years of time windows, which are years of 1997, 1999, 2001, 2003, and 2005. The values of  $d$ ,  $J$ ,  $I_\Omega$ , and  $r$  are defined in the same manner as before.

The best-fit time-varying R&D depreciation rates for the studied four industries show that the ranking order of the depreciation rates is in general maintained over time

(See Figure 3). The vertical error bar is the standard deviation of the estimated R&D depreciation rate estimated through the Monte-Carlo calculation in the same fashion.

**Figure 3: Depreciation Rates for Four R&D Intensive Industries (Compustat)**



The results of the time-varying R&D depreciate rates indicate that (1) the pharmaceutical industry has the lowest R&D depreciation rate, which may reflect the fact that R&D resources in pharmaceuticals are more appropriable than in other industries due to effective patent protection and other entry barriers; (2) the IT hardware industry has the highest R&D depreciation rate, which is consistent with the industry’s observations that, compared with other industries, the IT hardware industry has adopted a higher degree of global outsourcing to source from few global suppliers. In addition, the module design and efficient global supply chain management has made the industry products introduced like commodities, which have shorter product life cycle; (3) the R&D depreciation rate of the semiconductor industry has slightly declined since early 2000.

This is consistent with the industry's consensus that the rate of technological progress in the microprocessor industry has slowed down after 2000<sup>2</sup>.

Table 2 compares the constant R&D depreciation rates estimated by this study with those obtained from other recent studies. The comparison highlights several key results from this study. First, the derived industry-specific R&D depreciation rates fall within the range of recent research estimates based on commonly-adopted production function and market valuation approaches (Berstein and Mamuneas, 2006; Hall, 2007; Huang and Diewert, 2007; Warusawitharana, 2008). Second, my results are consistent with those of recent studies, which indicate that depreciation rates for business R&D are likely to vary across industries due to the different competition environments that each industry faces. Third, most industries have R&D depreciation rates higher than the traditional 15% assumption derived using the data of the 1970s (Berstein and Mamuneas, 2006; Corrado et al., 2006; Hall, 2007; Huang and Diewert, 2007; Warusawitharana, 2008; Grilliches and Mairesse, 1984).

Given that the results based on Compustat dataset align with the conclusions with existing studies and industry observations on the pace of technological progress and the degree of market competition, the next step is to perform the same calculations for all ten R&D intensive industries identified in BEA's R&D Satellite Account.

#### **4. Industry-Level Analysis – All Ten BEA R&D Intensive Industries**

There are two steps to derive a complete set of the recommended depreciation rates of business R&D assets. In the first step, I estimate two sets of the industry-specific

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<sup>2</sup> Professor Pillai, who used to work for AMD and is now at SUNY University at Albany, confirmed this trend.



R&D depreciation rates based on the Compustat company-based data and the BEA-NSF establishment-based data (See Table 3). The numbers based on the two datasets are plausible for most industries. Among the R&D depreciation rates in the ten analyzed R&D intensive industries, the numbers for the aerospace and auto industries stand above the rest. For example, based on both Compustat and BEA-NSF datasets, the estimated R&D depreciation rates for the auto industry are 39.88% and 61.57%, respectively, and these results are not inconsistent to the result of the UK's ONS (office of National Statistics) survey on the R&D service life (Haltiwanger et al., 2010). The average R&D service life for the auto industry in the UK's ONS survey is 4.3 years, which implies an R&D depreciation rate over 40 percent. Note that the response rate of the UK's ONS survey, however, is merely 10-200 firms out of 989 firms, or equivalently 1.0-20.2 percent of the surveyed firms.

In the second step, because the profit rates of these two industries are significantly lower than those of other industries, I relax the criterion based on the argument by Jorgenson and Griliches' with regard to using the common rate of return for both tangible and intangible assets and reduce the upper bound of the return rate by 50% in the model. The justifications are given by the two facts: First, the U.S. auto industry had negative return rates during the data period<sup>3</sup>. Second, in its August latest report on the Aerospace and Defense industrial base assessments, the Office of Technology Evaluation at Department of Commerce reports that the industry's profit margin is around 1% and may be only 10% of the performance of high-tech industries in Silicon Valley. After the relaxation, for the auto industry, the estimated result based on the BEA-NSF dataset is

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<sup>3</sup> Brian Sliker at BEA, an expert in the return rate of industry assets, indicated this negative trend in the auto industry.

close to the estimated range by Bernstein and Mamuneas (2006) and by Huang and Diewert (2007).

Table 4 is the summary of the recommended depreciation rates of R&D assets based on the BEA-NSF dataset. The results in this table are based on two scenarios of the average gestation lag of R&D projects. In addition, I assume that the R&D assets depreciate at this rate geometrically. Lastly, it is considered that when a firm invests in R&D, whether the investment is successful or not, the R&D investment should contribute to the firm's knowledge stock. Therefore, we recommend the use of the calculated rates with a zero gestation lag.

**Table 2: Summary of Studies on R&D Depreciation Rates**

Study	$\delta$ : R&D Depreciation Rate	Approach	Data
Lev and Sougiannis (1996)	Scientific instruments: 0.20 Electrical equipment: 0.13 Chemical: 0.11	Amortization	825 U.S. firms over the period of 1975-1991; Compustat dataset
Ballester, GarciaAyuso, and Livnat (2003)	Scientific instruments: 0.14 Electrical equipment: 0.13 Chemicals: 0.14	Amortization	652 U.S. firms over the period of 1985-2001 for preferred specification; Compustat dataset
Knott, Bryce and Posen (2003)	Pharmaceuticals: 0.88-1.00	Production function	40 U.S. firms over the period of 1979 -1998; Compustat dataset
Berstein and Mamuneas (2006)	Electrical equipment: 0.29 Chemicals: 0.18	Production function	U.S. manufacturing industries over the period of 1954-2000
Hall (2007)	Computers and scientific instruments: 0.05 Electrical equipment: 0.03 Chemicals: 0.02	Production Function	16750 U.S. firms over the period of 1974-2003; Compustat dataset
Hall (2007)	Computers and scientific instruments: 0.42 Electrical equipment: 0.52 Chemicals: 0.22	Market valuation	16750 U.S. firms over the period of 1974-2003; Compustat dataset
Huang and Diewert (2007)	Electrical equipment: 0.14 Chemicals: 0.01	Production function	U.S. manufacturing industries over the period of 1953-2001
Warusawitharana (2008)	Chips: 0.344 Hardware: 0.277 Medical Equipment: 0.369 Pharmaceutical: 0.409 Software: 0.366	Market valuation	U.S. manufacturing industries over the period of 1987- 2006; Compustat dataset
This study	Semiconductor: $0.1795 \pm 0.0178$ IT hardware: $0.3764 \pm 0.01$ Software: $0.3017 \pm 0.0189$ Pharmaceutical: $0.1182 \pm 0.0073$	R&D investment model	U.S. manufacturing industries over the period of 1989-2007; Compustat dataset

**Table 3: Summary of R&D Depreciation Rates**  
**Based on A Steady-State Model**

Industry	Compustat Data	BEA-NSF Data
Computers and peripheral equipment	$0.3764 \pm 0.01$	$0.4073 \pm 0.0136$
Software	$0.3017 \pm 0.01$	$0.2420 \pm 0.0030$
Pharmaceutical	$0.1182 \pm 0.0073$	$0.0812 \pm 0.0040$
Semiconductor	$0.1795 \pm 0.0178$	$0.2708 \pm 0.0175$
Aerospace product and parts	$0.6131 \pm 0.0200$	$0.4539 \pm 0.0314$
Communication equipment	$0.2783 \pm 0.0457$	$0.3089 \pm 0.0223$
Computer system design	$0.2860 \pm 0.0290$	$0.4272 \pm 0.0056$
Motor vehicles, bodies and trailers, and parts	$0.3988 \pm 0.0105$	$0.6157 \pm 0.0227$
Navigational, measuring, electromedical, and control instruments	$0.3408 \pm 0.0216$	$0.2602 \pm 0.0067$
Scientific research and development	NA	$0.1627 \pm 0.0038$

**Table 4: Summary of Depreciation Rates of Business R&D Assets  
Based on BEA-NSF Dataset**

<b>Industry</b>	<b><math>\delta</math> (d=2)</b>	<b><math>\delta</math> (d=0)</b>
Computers and peripheral equipment	41%	40%
Software	24%	20%
Pharmaceutical	8%	8%
Semiconductor	27%	25%
Aerospace	21%	21%
Communication equipment	31%	28%
Computer system design	43%	36%
Motor vehicles, bodies and trailers, and parts	28%	29%
Navigational, measuring, electromedical, and control instruments	26%	29%
Scientific research and development	16%	15%

Note:

1.  $d$  refers to the gestation lag of a typical R&D investment and  $\delta$  refers to the depreciation rate of the R&D investment.

## 5. Conclusion

R&D depreciation rates are critical to calculating rates of return to R&D investments and capital service costs, which are important for capitalizing R&D investments in the national income accounts. Although important, measuring R&D depreciation rates is extremely difficult because both the price and output of R&D capital are generally unobservable. BEA adopted two simplified methods based on existing studies to temporarily resolve the problem of measuring R&D depreciation rates in its 2006 Research & Development Satellite Account (R&DSA) and 2007 R&DSA. BEA chose the rates following two rules: First, the rates were close to traditional 15 percent assumption. Second, the overall ranking of the rates suggested by the literature was preserved. However, the most recent studies conclude that depreciation rates for business R&D are likely to be more variable due to different competition environments across industries and higher than the traditional 15 percent assumption.

In this research, I develop a forward-looking profit model to derive industry-specific R&D depreciation rates. Without any unverifiable assumptions adopted by other methods, this model contains very few parameters and allows us to utilize Compustat data on sales and R&D investments, and BEA-NSF data on industry output and R&D investments. The new methodology allows us to calculate not only industry-specific constant R&D depreciation rates but also time-varying rates.

My research results highlight several promising features of the new forward-looking profit model: First, the derived constant industry-specific R&D depreciation rates fall within the range of estimates from previous studies. The time-varying results also

capture the heterogeneous nature of industry environments in technology and competition. In addition, the results are consistent with conclusions from recent studies that depreciation rates for business R&D are likely to be more variable due to different competition environments across industries and higher than traditional 15 percent assumption (Berstein and Mamuneas 2006, Corrado et al 2006, Hall 2007, Huang and Diewert 2007 and Warusawitharana 2008). Lastly, for the purpose of implementation, this paper recommends a preliminary set of R&D depreciation rates for the ten R&D intensive industries identified in BEA's R&D Satellite Account.

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