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, which are important for capitalizing R&D investments in the national income accounts and harmonizing BEA statistics with those of the productivity program of BLS. 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 or oversimplified assumptions. As of now, measuring R&D depreciation rates remains an unresolved problem.

To incorporate the effect of industries' technological and competition environments, as well as gestation lags, I develop an R&D investment model to derive industry-specific R&D depreciation rates for four R&D intensive industries, the pharmaceutical industry, the IT hardware industry, the semiconductor industry, and the software industry. Based on Compustat company-based dataset, the model has produced results that not only align with conclusions from most recent literature but also indicate the dynamic technological changes across industries. The data cover the period from 1989 to 2008. The constant industry-specific R&D depreciation rates are: 11.82 ± 0.73 % for the pharmaceutical industry, 37.64 ± 1.00 % for the IT hardware industry, 17.95 ± 1.78 % for the semiconductor industry, and 30.17 ± 1.89 % for the software industry. The industry rankings of these R&D depreciation rates are consistent with the conclusions in most recent literature. Time-varying industry-specific R&D depreciation rates are also presented in this paper, and they further enhance our understanding about the dynamics of technological change and competition across industries.

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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) point out that after 1995, intangible assets reached parity with tangible assets as a source 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 or R&D assets.

The depreciation rate of R&D assets is critical to capitalizing R&D investments in national income 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 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, economists have adopted four major approaches to calculate R&D depreciation rates: production function, amortization, patent renewal, 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; the production function approach relies on the questionable assumption of initial R&D stock and depreciation rate. Currently, no consensus exists 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. The majority of research also ignores the risky nature of R&D investments.

Failure to include this risk factor leads to inconsistent estimates of the returns to R&D and its implied R&D deprecation rates because the differences in the realized profitability levels fail to reflect the true marginal impact of R&D investment (Warusawitharana 2008).

To capitalize R&D investments into its Input-Output accounts around 2012 and other core accounts around 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 deprecation rate for all R&D capital. In the baseline scenario, BEA used 15% as the annual depreciation rate for all R&D capital. In the alternative scenarios, BEA used the deprecation 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 deprecation 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% and that the overall ranking of industry-level rates suggested by the literature was preserved. The resulting R&D depreciation rates are: 18.0% for transportation equipment, 16.5% for computer and electronics, 11.0% for chemicals, and 15.0% 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% assumption (Hall 2007).

The purpose of this paper is to develop an R&D investment model to derive industry-specific R&D depreciation rates by incorporating individual industry's gestation lags, as well as technological and competition environments. 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 model contains very few parameters and allows us to utilize data on sales and R&D investments.

In this research, I use my model to derive industry-specific R&D depreciation rates for pharmaceutical, IT hardware, semiconductor, and software industries. The Compustat data cover the period 1989 to 2008. The constant industry-specific R&D depreciation rates are: 11.82 ± 0.73 % for the pharmaceutical industry, 37.64 ± 1.00 % for the IT hardware industry, 17.95 ± 1.78 % for the semiconductor industry, and 30.17 ± 1.89 % for the software industry. The results demonstrate the promising potential of the model in that: these derived R&D depreciation rates fall within the range of estimates from the existing literature. The time-varying industry-specific R&D depreciation rates are also presented. The industry rankings of constant and time-varying R&D depreciation rates are consistent with the conclusions in most recent literature. In addition, the time-varying industry-specific R&D depreciation rates further enhance our understanding about the dynamics of technological change and competition across industries.

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 concludes and discuss topics for future investigation.

2. R&D Investment Model

The premise of my model is that business R&D capital depreciates because its contribution to a firm's profit declines over time (Hall 2007). 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:

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

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 percentage 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 1. 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.

In the analysis presented later, we have found that, with the same values of d and J, δ is different across industries. 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.

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, we 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, we 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, we define $I(RD)$ as a concave function:

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

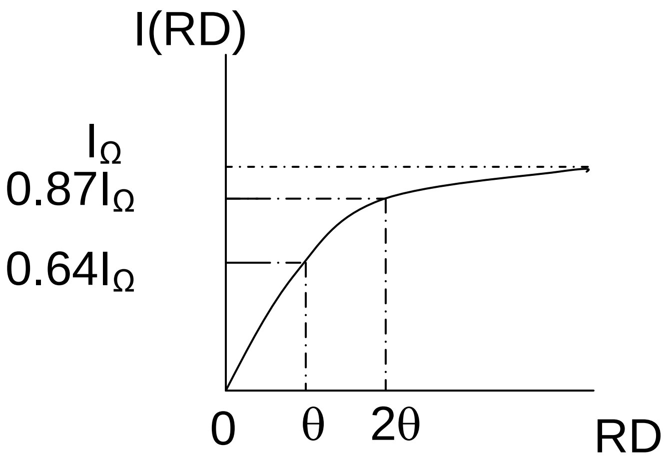
$I'(RD) > 0$ and $I''(RD) < 0$. And, $\frac{dI}{dRD} = I_{\Omega} \times e^{\frac{-RD}{\theta}}$ $where$ $\frac{dI}{dRD} = I_{\Omega}$ $when$ $RD = 0$.

The functional form of $I(RD)$ has very few parameters but still gives us the required concave property to derive the optimality condition.

I_{Ω} is the upper bound of increase in profit rate due to R&D investments. And, θ defines the curvature of I_{Ω} and is a reference number. 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) , we have

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

From the graph below, 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 $0.87I_{\Omega}$. We should be able to see different industries have different R&D investment scales reaching I_{Ω}.



The value of θ can vary from industry to industry, and, as the data demonstrate an increase in R&D investment by multiple folds in two decades, θ is expected to gradually grow with time as well. We model the time-dependent feature of θ by $\log\theta = \log\theta_{2000} + \alpha t$, in which θ_{2000} is the θ value for year 2000. The coefficient α is estimated by a linear regression of log(*RD*) for the associated industry.

The R&D investment model becomes:

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

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

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

and through this equation we can estimate the depreciation rate δ.

3. Industry-Level Analysis

As a first step in our empirical analysis, we estimate the constant R&D depreciation rate δ for four industries (pharmaceuticals, semiconductor, IT hardware, and software) by using the data from 1989 to 2008 to check whether our model gives us R&D depreciation rates in line with rates in past studies. These industries are important for the initial test of our 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. We take the average values of annual sales and R&D investment in each industry from Compustat for estimation.[1]

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

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

[1] We 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).

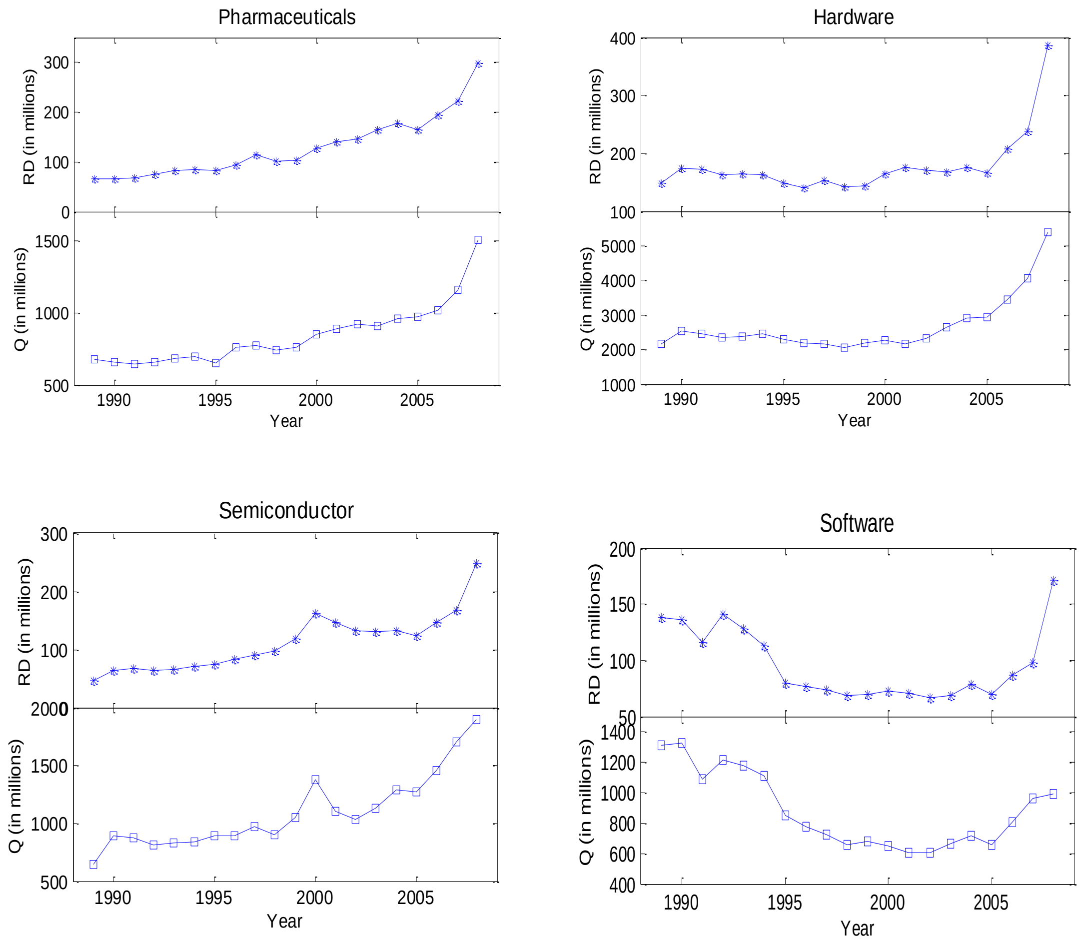


Figure 1. Mean values of industrial R&D investments and sales for years 1989-2008 calculated from the Compustat firm-level database

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, we 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, we use 8.9% for r.

We 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 δ and θ. Because Equation (5) holds when the true values of δ and θ 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:

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

in which N is the total duration of data. In practice N is a large number relative to $J + d$ and therefore multiple least squares should be summed over in Equation (6).

Minimizing Equation (6) is therefore the same as 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 δ and θ_{2000}, several sets of start values are tried to ensure the stability of the solution.

In this study we 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 are appropriate values to use. As mentioned previously, we set the value of J to 20 (for pharmaceuticals we use 25 due to the longer product life cycle in this industry) to derive δ for all the combinations of d and J.

The estimated value of constant δ is 11.82 ± 0.73 % for the pharmaceutical industry, 37.64 ± 1.00 % for the IT hardware industry, 17.95 ± 1.78 % for the semiconductor industry, and 30.17 ± 1.89 % 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 deprecation rates are expected to vary through the 20 years of interval covered by our database. Therefore we need to calculate industry-specific and time-dependent R&D depreciation rates. The time-dependent feature of δ was obtained by minimizing Equation (6) with subsets of data. Instead of using all years of data, we performed least squares fitting over a five-year interval each time, in addition to the five prior years used for sales forecasts. Three more subsets of data are examined in the same way, each with a step of 3 years in progression. As a result there are four subsets of data where the data-model fit is carried out, and the estimated depreciation rates are the mid-years of time windows, which are years 1995, 1998, 2001, and 2004.

The main data for carrying out the data-model fit are the industry average sales and R&D investment data between 1989 and 2008 from Compustat. The BEA annual return rates to all assets for non-financial corporations are used for the values of I_{Ω} and r. We use $(d, J) = (2, 20)$ for all industries except pharmaceuticals. When we alter the value of these parameters we obtain qualitatively similar results.

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

Figure 2). The vertical and horizontal error bars are the standard deviation of the estimated R&D depreciation rate resulting from the errors associated with sales forecasts.

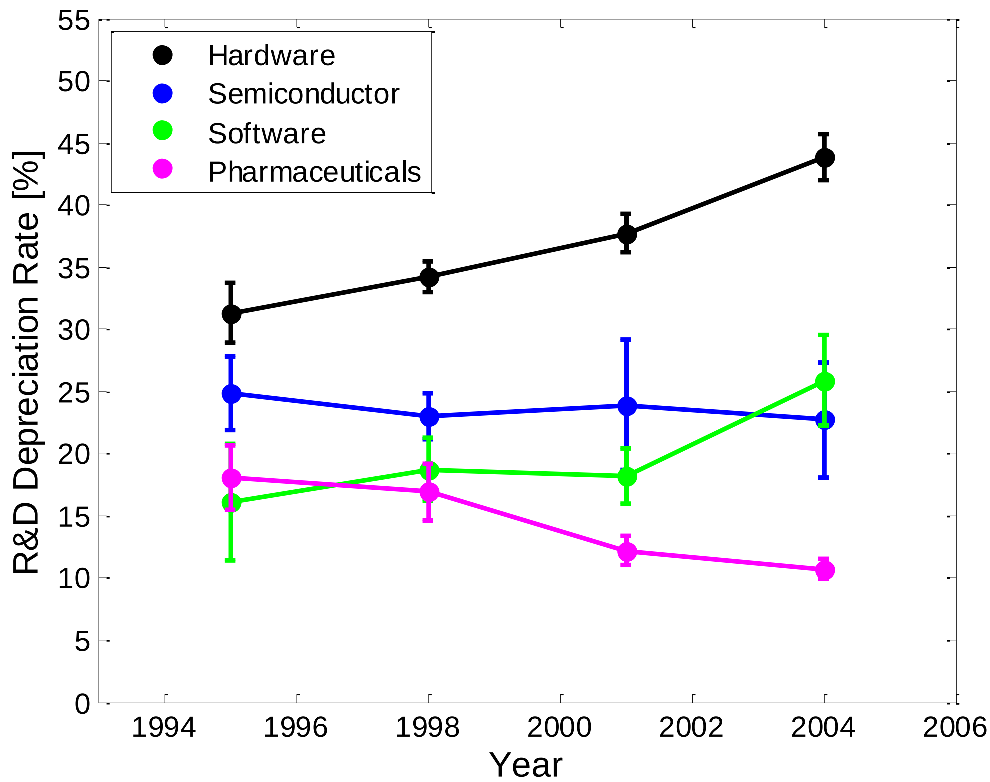


Figure 2. Depreciation rates for four R&D intensive industries

The results of the time-varying R&D depreciate rates indicate that (1) R&D resources in pharmaceuticals are more appropriable than in other industries due to effective patent protection and other entry barriers; (2) Compared with other industries, the IT hardware industry has been adopted a higher degree of global outsourcing to source from few global suppliers and the module design and efficient global supply chain management has made the industry products introduced like commodities, which have shorter product life cycle. Therefore, the IT hardware industry has the highest R&D depreciation rate; (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.

Table 2 compares the constant R&D depreciate rates estimated by this study with those obtained from other recent studies. The comparison points to several favorable features of our model. 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). Also, the 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 different competition environments each industry faces, and are 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).

4. 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. As of now, measuring R&D depreciation rates remains an unresolved problem. Given that no good solution is available, BEA has adopted two simplified methods based on existing studies to temporarily resolve the problem of

Table 2. Summary of studies on R&D depreciation rates

Study	δ: 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 ± 0.0178 IT hardware: 0.3764 ± 0.01 Software: 0.30.17 ± 0.0189 Pharmaceutical: 0.1182 ± 0.0073	R&D investment Model	1167 U.S. firms over the period of 1989-2007; Compustat dataset

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% assumption. Second, the overall ranking of the rates suggested by the literature was preserved. The methods, however, implicitly assume that all studies are equally valid and that 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% assumption.

To incorporate the effect of individual industry technological and competition environment, as well as gestation lags, I develop an R&D investment model to derive industry-specific R&D deprecation rates. The premise of my model is that a business R&D asset depreciates because its contribution to a firm's profit declines over time. Without any problematic assumptions adopted by other methods, this model contains very few parameters and allows us to utilize Compustat data on sales and R&D investments. Unlike previous studies, it does not rely on the capital accumulation formula, thus avoiding the problem of ignoring productivity gain from R&D investments.

My research results highlight several promising features of my 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% assumption (Berstein and Mamuneas 2006, Corrado et al 2006, Hall 2007, Huang and Diewert 2007 and Warusawitharana 2008).

Our analysis can be expanded to all thirteen R&D intensive industries, as well as the comparison with the results calculated with Compustat and BEA-NSF datasets. In addition, to capture the dynamic nature of industry technology and competition environments over time, it requires BEA to build a longer time-series data set with both

R&D investments and industry outputs based on a consistent industry classification method. BEA currently has NAICS-based R&D investment and industry output data from 1987 to 2008 and SIC-based industry output data from 1977 to 1997. However, in order to capitalize R&D investments into the national income accounts, it is important for us to establish the dataset of R&D investments and industry output with a longer time series.

References

Aizcorbe, A., Moylan, C., and Robbins, C. Toward Better Measurement of Innovation and Intangibles, Survey of Current Business, January 2009, pp. 10-23.

Copeland, A., & Fixler, D. Measuring the Price of Research and Development Output, *U.S. Bureau of Economic Analysis Working Paper*, October, 2008.

Corrado, C., Hulten, C., & Sichel, D. Intangible Capital and Economic Growth, *National Bureau of Economic Research working paper 11948*, January 2006.

Griliches, Z. 1996. *R&D and Productivity: The Econometric Evidence*, Chicago: Chicago University Press.

Hall, B. Measuring the Returns to R&D: The Depreciation Problem, *National Bureau of Economic Research Working Paper 13473*, October 2007.

Huang, N. and Diewert, E. 2007. Estimation of R&D Depreciation Rates for the US Manufacturing and Four Knowledge Intensive Industries, *working paper for the Sixth Annual Ottawa Productivity Workshop held at the Bank of Canada, May 14-15, 2007.*

Jorgenson, D. and Griliches, Z. 1967. The Explanation of Productivity Change, *Review of Economic Studies*, 34 (July): 349-83.

Mead, C. R&D Depreciation Rates in the 2007 R&D Satellite Account, *Bureau of Economic Analysis/National Science Foundation: 2007 R&D Satellite Account Background Paper*, November 2007.

Mills, T. C. 1990. *Time Series Techniques for Economists*. Cambridge: Cambridge University Press.

Robbins, C., and Moylan, C. 2007. Research and Development Satellite Account Update: Estimates for 1959-2004, New Estimates for Industry, Regional, and International Accounts, *Survey of Current Business*, October 2007.

Sliker, B. 2007 R&D Satellite Account Methodologies: R&D Capital Stocks and Net Rates of Return, *Bureau of Economic Analysis/National Science Foundation: R&D Satellite Account Background Paper*, December 2007.

Sumiye, O., Robbins, C., Moylan, C., Sliker, B., Schultz, L., and Mataloni, L. BEA's 2006 Research and Development Satellite Account: Preliminary Estimates of R&D for 1959-2002 Effect on GDP and Other Measures, Survey of Current Business, December 2006, pp. 14-27.

Warusawitharana, M. Research and Development, Profits and Firm Value: A Structural Estimation, Federal Reserve Board working paper, December 2008.