DEPRECIATION OF BUSINESS R&D CAPITAL

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ABSTRACT

We develop a forward looking profit model to estimate the depreciation rates of business R&D capital. By using data from BEA and NSF between 1987 and 2007, and the newly developed model, we estimate both constant and time varying industry specific R&D depreciation rates. The results comprise a set of R&D depreciation rates for major U.S. high-tech industries. They align with the main conclusions from recent studies that the rates are in general higher than the traditionally assumed 15 percent and vary across industries. The relative ranking of the constant R&D depreciation rates among industries is consistent with industry observations and the industry specific time varying rates are informative about the dynamics of technological change and the levels of competition across industries. Lastly, we also present a cross country comparison of the R&D depreciation rates between the U.S. and Japan, and find that the results reflect the relative technological competitiveness in key industries.

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1. Introduction

In an increasingly knowledge-based U.S. economy, measuring intangible assets, including research and development (R&D) assets, is critical to obtaining a complete picture of the economy and explaining its sources of growth. Corrado *et al.* (2007) 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 and product accounts (NIPAs) and therefore to measure their impacts on economic growth. The difficulties arise because the capitalization involves several critical but difficult measurement issues. One of these is the measurement of the depreciation rate of intangible assets, including R&D assets.

The depreciation rate of R&D assets is required for capitalizing R&D investments in the NIPAs for two reasons. First, the depreciation rate is needed to construct knowledge stocks – it is 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.*, 2007, 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 order to measure the rate of return to R&D (Hall, 2005).

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 generally 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. Therefore it is difficult to independently compute the depreciation rate of R&D capital (Hall, 2005; Corrado *et al.*, 2007). Moreover, unlike tangible capital which depreciates partly due to physical decay or wear and tear, R&D capital depreciates mainly because its contribution to a firm's profit declines over time. The driving forces are obsolescence and competition (Hall, 2005), both of which reflect individual industry technological and competitive environments. Given that these environments can vary immensely across industries and over time, the resulting (private) R&D depreciation rates should also vary across industries and over time.

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In response to these measurement difficulties, previous research has adopted four major approaches to calculate R&D depreciation rates: patent renewal, production function, amortization, and market valuation (Mead, 2007). As noted by Hall et al. (1986) and summarized by Mead (2007), all approaches encounter the problem of insufficient variation in R&D spending over time and thus cannot separately identify R&D depreciation rates without imposing strong identifying assumptions. As discussed in Mead (2007), estimates from amortization models (Lev and Sougiannis, 1996; Ballister et al., 2003) are derived from a more general set of models that attempt to explain the returns on R&D investment. However, the estimates are subject to concerns related to the strong assumptions such as an assumed relationship between the amortization rate of R&D capital and its earnings, and operating income serving as a proxy for R&D benefits (Lev and Sougiannis, 1996).

Given the fact that firms' propensities to patent vary across industries and technology areas, the patent renewal approach cannot capture all innovation activities (Hall *et al.*, 2014). Moreover, innovations may remain valuable even if their patents have expired, given the other ways in which firms capture returns to R&D (Levin *et al.,* 1987). The patent renewal approach also suffers from the failure to observe the right hand tail of a very skewed value distribution due to the relatively low level of renewal fees. The identification problem can be mitigated by using citation-weighted patent data, but there is a truncation bias problem arising due to an incomplete observed citation life of patents (Hall *et al.*, 2000).

Using the production function and market value approaches has the advantage of incorporating all R&D rather than just that which is patented. However, these approaches generally rely on the assumption that the average realized rate of return is the same as the expected rate of return (Hall, 2005). This assumption allows one to back out the depreciation rate which makes the two consistent. We use a similar approach here, in that we assume a normal rate of return to R&D when computing the profit function, although we do not explicitly require it to be equal to the realized rate.

An additional complication is the question of a gestation lag for the output of R&D. Most earlier research has failed to deal with the issue of gestation lags by treating them as zero or one year to calculate the R&D capital stock (Corrado *et al.*, 2007, but see Hall and Hayashi, 1989 for an exception). Because the product development life cycle varies across industries, this treatment is questionable for R&D assets so we explore the use of a gestation lag here.

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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 familiar concept that R&D capital depreciates because its contribution to a firm's profit declines over time. Our forward-looking profit model rests on some relatively simple assumptions that are plausible given the nature of the data and allows us to estimate R&D depreciation rates by using only data on R&D investment and sales or industry output, which is often the only data available to statistical agencies for this purpose.

The model is applied to the BEA-NSF industry-level dataset to calculate constant R&D depreciation rates for all ten R&D intensive industries identified in BEA's R&D Satellite Account (R&DSA). This dataset contains BEA-NSF NAICS-based establishment-level industry output and R&D investments in ten R&D intensive industries. The estimates show that the derived R&D depreciation rates are consistent with the conclusion from recent studies that the rates should be higher than the traditional assumption (15 percent) and vary across industries. We also apply the model to estimate the industry-specific time-varying R&D deprecation rates for the ten R&D-intensive industries. The results are in general consistent with industry observations on the pace of technological change or reflect the appropriability condition of its intellectual property, although in some cases they are quite noisy due to the limited number of observations available.

The remainder of this paper is organized as follows. Section 2 sets out our new R&D investment model. Section 3 presents a firm and industry-level data analysis that assumes constant depreciation rates over time. Section 4 presents time-varying depreciation rates for five selected BEA's R&D intensive industries. Section 5 presents the first cross-country comparison of R&D depreciation rates between the U.S. and Japan for several key R&D intensive industries, and concluding remarks are given in Section 6.

2. Model

Our model assumes 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. This assumption ignores any spillover benefits that may continue past the life of the R&D assets in generating profits, but is an appropriate assumption when measuring the private rate of return to R&D

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investments. The expected R&D depreciation rate is a necessary and important component of a firm's R&D investment model. A profit-maximizing firm will invest in R&D such that the expected marginal benefit equals the marginal cost. That is, in each period *t*, a firm will choose an R&D investment amount to maximize the net present value of the expected returns to R&D investment:

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

where R_t is the R&D investment amount in period *t*, q_t is the sales in period *t*, $I(R_t)$ is the profit rate due to R&D investment, δ is the R&D depreciation rate, and *r* is the cost of capital. The parameter *d* is the gestation lag and is assumed to be an integer which is no less than 0.[1] R&D investment in period *t* will contribute to the profits in later periods but at a geometrically declining rate. We assume that the sales *q* for periods later than *t* grows at a constant growth rate, *g*. That is, $q_{t+j} = q_t(1+g)^j$. This assumption is consistent with the fact that the output of most R&D intensive industries grows fairly smoothly over time (See Figure A-1 in the appendices).

Place figure 1 here.

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

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

with $I''(R) < 0.$, $I'(R) = \frac{I_\Omega}{\theta}\exp(\frac{-R}{\theta}) > 0$, $I'(0) = \frac{I_\Omega}{\theta}$, and $\lim_{R\to\infty} I(R) = I_\Omega$. Figure 1 depicts how the function *I* gradually increases asymptotically to I_Ω with *R*, the current-period R&D investment. This functional form has few parameters but nevertheless shows the desired concavity with respect to *R*. In this, our approach is similar to that adopted by Cohen and Klepper (1996), who show that when there are fixed costs to an R&D program and firms

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[1] The paper has defined the gestation lag, *d*, as how long the R&D investment starts contributing the firm's profit. This definition follows what is defined in the U.S. National Science Foundation (NSF) 2010 Business R&D and Innovation Survey (BRDIS).

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have multiple projects, the resulting R&D productivity will be heterogeneous across firms and self-selection will ensure that the observed productivity of R&D will vary negatively with firm size. Our model incorporates the assumption of diminishing marginal returns to R&D investment implied by their assumptions, which is more realistic than the traditional assumption of constant returns to scale (Griliches, 1996). In addition, the model implicitly assumes that innovation is incremental, which is appropriate for industry aggregate R&D, most of which is performed by large established firms.

The function *I* includes a parameter θ that defines the investment scale for increases in R&D and acts as a deflator to capture the increasing time trend of R&D investment as a component of investment in many industries. The value of θ can vary from industry to industry, allowing different R&D investment scales for different industries. In Figure A-2, the BEA-NSF industry data show that the average R&D investment in most industries increases greatly over a period of two decades, and therefore we expect that the investment scale, θ, needed to achieve the same increase in profit rate should grow accordingly.

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

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

Note that we have assumed that *d, r,* and δ are known to the firm at time *t*. Because θ varies over time, we model the time-dependent feature of θ by $\theta_t \equiv \theta_0(1+G)^t$, where *G* is the growth rate of θ_t. To estimate G, we assume that the growth pattern of industry's R&D investment and its R&D investment scale are similar and we estimate *G* by fitting the data for R&D investment to the equation, $R_t = R_0(1+G)^t$. This approach is justified by the fact that BEA data on most industry R&D grows somewhat smoothly over time (See Figure A-2), Using this assumption, Equation (3) becomes:

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

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Assuming profit maximization, the optimal choice of R_t implies the following first order condition:

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

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

3. Estimation with constant R&D depreciation rates

As a first step in our empirical analysis, we estimate the time-constant R&D depreciation rates based on the industry-level BEA-NSF dataset from 1987 to 2007. The BEA-NSF data that we use are designed to measure true industry aggregates (correcting for such things as firm presence in multiple industries and multiple countries, something we are unable to do with Compustat data). [2] In addition, unlike the Compustat dataset which contains only the data of large publicly traded firms, the BEA-NSF data better represent the industry by including firms with 5 or more employees.[3]

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

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

Where $\hat{g}$ and $\hat{G}$ are estimated using the entire time period. In order to estimate, we need to make assumptions about I_Ω, r, and d. The value of I_Ω can be inferred from the BEA annual return rates of all assets for non-financial corporations. As Jorgenson and Griliches (1967) argue, in equilibrium the rates of return for all assets should be equal to ensure no arbitrage, and so we can use a common rate of return for both tangibles and intangibles (such as R&D assets). For simplicity, I_Ω is set to be the average return rates of all assets for non-financial corporations during 1987-2007, which is 8.9 percent. In addition, in equilibrium the rate of return should be equal to the cost of capital. Therefore, we use the same value for r. Later in the paper we perform a sensitivity analysis using time-varying rates of return, based both

[2] See Hall and Long (1999) for a full discussion of the differences between NSF and Compustat data.

[3] The R&D data come from the NSF's BRDIS. BRDIS is a nationally representative sample of all companies with 5 or more employees in all industries.

on the 3 month T-bill rate plus a risk adjustment of 4 per cent and on the BEA's own time-varying rate of return to assets.

We use a 2-year gestation lag d, 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 (see also Hall and Hayashi, 1989). In addition, according to the recent U.S. R&D survey conducted by BEA, Census Bureau and National Science Foundation (NSF) in 2010, the average gestation lag is 1.94 years for all industries. [4] We also report estimates using a gestation lag of zero years.

R_t and q_t are taken from the data and also used to compute the average growth rates of output (G) and of R&D (g), so the only unknown parameters in the equation are δ and θ_0. Given these assumptions, δ and θ_0 are estimated by nonlinear least squares (NLLS) and nonlinear generalized method of moments (GMM), using equation (6).

3.1 Nonlinear Least Squares Estimates

This section of the paper reports the results of NLLS estimation using our dataset. Table 2 shows the estimated industry-specific constant R&D depreciation rates based on the BEA-NSF establishment-based data. The depreciation rates are consistent with most industry observations. For example, the pharmaceutical industry has the lowest R&D depreciation rates in both sets of estimates, which reflects the long-term nature of pharmaceutical research and the fact that R&D resources in pharmaceuticals are more appropriable by the firms that fund the R&D than those in other industries due to effective patent protection and other entry barriers. Because a higher entry barrier works similarly as patent protection, we expect the R&D depreciation rate will be lower (De Rassenfosse and Jaffe, 2017). In addition, as mentioned earlier in the paper, two of the main drivers of R&D depreciation rates are the industry's pace of technological progress and its degree of market competition. Therefore, a higher entry barrier, in general, implies a lower degree of market

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[4] The average gestation lag is based on the responses from 6,381 firms across 38 industries in the NSF 2010 Business R&D and Innovation Survey (BRDIS). Based on the NSF survey in 2010, the average gestation lag is 1.94 years for 6,381 firms across industries. Only 1.35% of firms have gestation lags larger than 3 years. The pharmaceutical industry, 0.9% of the population, has the longest gestation lag, which is 4 years. The majority of firms have gestation lags around or less than 2 years.

competition, which may drive down the industry-level R&D depreciation rate. Compared with the pharmaceutical industry, the various ICT sectors have higher R&D depreciation rates, which is consistent with industry observations that the ICT industry has adopted a higher degree of global outsourcing to source from few global suppliers (Li, 2008). Module design and efficient global supply chain management has made the products introduced in the ICT industry more like commodities, which have shorter product life cycles.

Place tables 1 and 2 here.

Table 1 showed the time-constant R&D depreciation rates estimated by other recent studies. Comparing Table 2 with Table 1, we can see several key results from this study. First, the estimated industry-specific R&D depreciation rates 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 and paces of technology change. Second, most industries have R&D depreciation rates higher than the traditionally assumed 15 percent that has been the benchmark for much of the empirical work (Griliches and Mairesse, 1984, Bernstein and Mamuneas, 2006, Corrado *et al.,* 2007, Hall, 2007, Huang and Diewert, 2007, Warusawitharana, 2010). Third, the R&D depreciation rate in the scientific research and development industry is much higher than that in the pharmaceutical industry.[5] This is consistent with industry observations that in the past two decades, there has been little innovation in the traditional pharmaceutical industry and biopharmaceuticals has faster growth rate of innovation. For example, in 1988, only 5 proteins from genetically engineered cells had been approved as drugs by the U.S. FDA, but the number has skyrocketed to over 125 by the end of 1990s (Colwell, 2002).

Among the R&D depreciation rates in the ten analyzed R&D intensive industries, the values for the aerospace and auto industries are usually large compared to those for other industries. For example, the estimated R&D depreciation rate for the auto industry is 73.3 percent. This result is not inconsistent with the result of the UK's ONS (Office of National Statistics) survey of the R&D service lives (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 R&D

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[5] According to NSF's BRDIS in 2009, biotech firms account for over 65% of R&D investments in the scientific research and development industry. Other firms related to physical, engineering, and life sciences account for around 34.5% of R&D investments.

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depreciation at a geometric declining rate of 40 percent. Note that the response rate of the UK's ONS survey, however, is reported to be low.[6]

In our formulation of the R&D investment model, there is an implicit tradeoff between the assumed *ex ante* rate of return and the computed depreciation rate. Essentially the depreciation rate for private business R&D is determined by the competitive environment of the firms that do it, and if the rate of return turns out to be lower than expected, the implication is that the value of the R&D has depreciated. We illustrate this tradeoff by re-estimating our model for the aerospace and auto industries with an assumed rate of return to R&D of 1 percent. This is justified by two facts: First, the U.S. auto industry had negative return rates during the data period.[7] Second, in its August 2011 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 (Department of Commerce, 2011).[8]

Table 2 reports estimates for these two industries that use the lower rates of return in italics and they are much lower, around 7-15 percent, confirming our intuition about the tradeoff between rates of return and depreciation. It is also worth noting that the data quality of R&D expenses in the auto and the aerospace industries are poor and the R&D data based on 10-K & 10-Q reports do not cover the industry well. For example, in the aerospace industry, some firms clearly report their own investment in R&D, but others report R&D expenses that combine federally funded and company-funded R&D (Hall and Long, 1999).

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[6] In 2011 and 2012, the UK's ONS conducted two back-to-back surveys on 1701 firms and found a median R&D service life of 6 years for all industries. Compared with 2.1% in the U.S. similar survey in 2010, the two surveys have better response rates at around 43%. However, the survey result has a very high degree of uncertainty (Kerr, 2014; Li, 2014). For example, the average answer difference from the same correspondent for the same company is 3.9 years and the average difference from different correspondents is 4.5 years. The UK's survey result is consistent with the U.S.'s finding that most respondents could not answer questions related to the R&D service lives correctly (Li, 2012). In the end, the UK's ONS adopts 16% as the R&D depreciation rate for all industries.

[7] Private communication with Brian Sliker at BEA, an expert in the return rate of industry assets, confirmed this negative trend in the auto industry.

[8] After using the new modified model, our new estimate is 29% higher than the rate in Huang and Diewert (2007). However, in the later section of cross-country comparison, the estimates between the U.S. and Japan in this industry are reasonable. Diewert reports in private communication that they found computing the optimal rate in this sector difficult.

Table 3 presents the results of a sensitivity analysis for the gestation lag and *ex ante* rate of return. The first two sets of columns compare gestation lags of two and zero years.[9] In general, the estimated depreciation rates do not differ a great deal, and those for the zero lag are slightly higher, except in the software, computer system design, and scientific research and development. Interestingly, these three sectors are the only service sectors. A possible interpretation of the general result is the following: if the gestation lag is zero rather than two, effectively there is a greater stock of R&D over which to spread the same profits, so it must depreciate more rapidly to explain the same rate of return. The fact that the service sectors do not follow this pattern is somewhat puzzling but is doubtless due to the specific trends in R&D and output in those sectors.

Place table 3 here.

The estimates are not sensitive to allowing a variable cost of capital (although as we saw earlier, they are sensitive to a change in the overall level. The last two sets of columns in Table 3 show results when the cost of capital/rate of return is set to (1) the risk free 3-month treasury bill rate plus a risk premium of 4 percent or (2) BEA's own measured average rate of return to assets during the year. Figure A-3 displays these time series. There is little difference in the estimates across these columns. Figure 2 graphs the sensitivity of the estimated depreciation rate of R&D assets to the assumed cost of capital for each industry separately. There are clear differences across the industries, with autos, computer hardware and services, aerospace, and instruments the most sensitive to the assumption, and the other sectors much less sensitive.

Place figure 2 here.

3.2 Nonlinear GMM

We may be concerned that simultaneity between current output and R&D (due to cash flow or demand shocks) could bias estimates of the relation in equation (6). To check this possibility we estimated the equation using nonlinear GMM, choosing lagged values of R&D, output, and the 3-month Treasury bill rate as instruments. The choice of instrument variables is based on the assumption that (given a forward-looking profit model) previous

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[9] BEA adopts a zero gestation lag, on the grounds that when a firm invests in R&D, the R&D investment should contribute immediately to the firm's knowledge stock.

R&D investments and output are not related to any shocks (ε) to the optimal R&D plan described by equation (6). The T-bill rate is included as a proxy for the lagged cost of capital, which is similarly unrelated to the shocks.

Place table 4 here.

Table 4 compares the estimates based on nonlinear least squares and nonlinear GMM, both computed with a two-year gestation lag and an expected rate of return equal to 8.9%. In general, the nonlinear GMM estimates have higher standard errors than those associated with the nonlinear least squares estimates, although not always. With the exception of the motor vehicle sector, where the estimated depreciation rate is much lower, the estimates are somewhat similar to those obtained using nonlinear least squares. The main difference is a much lower variance in the estimates across the sectors. We also report the results of a test of the over-identifying restriction (degrees of freedom equal to two), which passes for all the sectors except software, computer system design, and motor vehicles. If future datasets are larger in size and we are able to find better instruments, the nonlinear GMM approach might provide a more robust estimation, but for the current data these results suggest that the nonlinear least squares estimates are adequate.

4. Estimation with time-varying R&D depreciation rates

Since the technological and competition environments change over time, the R&D depreciation rates are expected to vary through the 21 years of data studied. Therefore, there is a need to calculate industry-specific and time-dependent R&D depreciation rates. We use the same industry output and R&D investment data from the BEA-NSF dataset. 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, with a step of 2 years in progression. As a result, the data-model fit is carried out nine times for 21 years of data, and each estimated depreciation rate is assigned to the center of a time window. The values of d, I_Ω, and r are defined in the same manner as before. Although there are only 5 data points to estimate the two parameters, the estimates generally converged well and the standard error estimates are not that large, except in a few cases.

Place figure 3 here.

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Figure 3 shows the best-fit time-varying R&D depreciation rates for all ten industries together with their ± 1 standard errors; the figures are plotted on the same scale to facilitate comparison. Based on ± 3 standard errors, we can still see that the industries differ in their volatility considerably, with software, pharmaceuticals, semiconductors, and scientific R&D being relatively stable, whereas the industries strongly affected by hardware-related technical change during this time period are much more volatile (e.g., communication equipment and computer system design). One concern with these results may be the underlying data: industries like semiconductors whose R&D is dominated by very large firms may be somewhat better measured than the communication equipment sector.

Figure 3 also reveals some other facts about the industries we studied. First, the pharmaceutical industry has a somewhat declining depreciation pattern. The declining deprecation pattern could be either due to a slower pace of technological change or a reduced degree of market competition. However, the history of technology development in this industry suggests that the driving force is a slower pace of technological change. For example, stricter FDA approval guidelines have negatively affected the industry's productivity growth in R&D in recent years. As a result, the industry has been experiencing a negative productivity growth in R&D in recent years. For example, during the period of 1990 to 1999, the FDA approved an average of 31 drugs per year, but this number dropped to 24 during the period of 2000 to 2009 (Rockoff and Winslow, 2011) and further went down to 21 in 2010 (Lamattina, 2011). In addition, Bloom at al. (2017) use data from U.S. Food and Administration, and Pharmaceutical Research and Manufacturers of America and find that the research productivity in this industry has fallen by a factor of 11 by 2007 and that the overall decline by 2014 is a factor of 5. However, the scientific R&D industry, which contains a large share of biotech firms, has a higher level of depreciation rates that has not declined since 1990. This echoes the fact mentioned previously that, in the past two decades, there has been little innovation in the traditional pharmaceutical industry and the biopharmaceuticals industry has faster growth rate of innovation.

Second, the R&D depreciation rate of the semiconductor industry shows a clear declining trend after 2000. This depreciation pattern is consistent with several research results. For example, since 2000, the rate of technological change in the microprocessor industry has slowed (Flamm, 2007). By combining our depreciation pattern with the evidence of a slower pace of productivity growth in the semiconductor industry after 2000 (Jorgenson *et*

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al., 2012), we find that our result supports Jorgenson's hypothesis (2001) that the increase in the pace of technological change in this sector is positively related to faster productivity growth.

Third, the communication equipment industry had a declining R&D depreciation pattern after early 1990s. It is helpful to recall the result by Hall (2005) who shows a pattern of decreasing depreciation for the computers, communication equipment, and scientific instrument industries during the period of 1989 to 2003. Since Hall's result is based on the data including two additional high-tech industries, it is not adequate to directly compare the depreciation patterns between the two studies.

Lastly, the R&D depreciation of the software industry also experienced a declining trend during the period from early 1990s to early 2000s. The declining trend reflects the fact that, compared with the variable technology environment during the period from 1980s to early 1990s, the Wintel system provided a more stable development environment starting from mid-1990s.[10]

5. Cross-country Comparison: U.S. vs. Japan

The R&D depreciation rate is one of the critical elements in computing R&D stock for the analysis of a country's productivity and economic growth. At the present time, however, there is no consistent methodology to estimate industry-specific R&D depreciation rates across countries. When no survey and/or research information is available, Eurostat recommends that a single average service life of 10 years should be retained (Eurostat, 2012). As a result, many OECD countries adopted R&D depreciation rates close to either Eurostat's recommendation (a 10 year service life corresponds roughly to a geometric depreciation rate of 20 percent) or the traditional assumed 15 percent. The lack of variations in R&D depreciation rates across countries and across industries implies that countries, no matter in technology frontier or not, have a similar pace of technological progress and degree of market competition across countries. This result contradicts existing trade and growth theories.

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[10] Wintel is a computer trade industry term for personal computers based on the Intel microprocessor and one of the Windows operating system from Microsoft. The term "PC" has often been used for this purpose. http://searchwindowsserver.techtarget.com/definition/Wintel

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Our method is an attempt to provide a consistent and reliable way to estimate industry-specific R&D depreciation rates across countries and to enable cross-country comparisons. We applied our model to Japanese data on four R&D-intensive industries: drugs and medicines, electrical machinery, equipment and supplies, information and communication electronic equipment, and transportation equipment. The estimates were based on a 2-year gestation lag, and the values of I_Ω and r are assumed to be 0.06, which is the value provided by Japan's National Accounts Department for the rate of return. Table 5 shows the estimated R&D depreciation rates for the period 2002-2012. The choice of period is dictated by data availability limitations.

Place table 5 here.

In general, the estimates in Table 5 are consistent with those in Table 2. Unfortunately, the electrical machinery, equipment, and supplies, and information and communication electronic equipment industries in Japan are not exactly comparable to the US industries, although the results do seem in the same range as those for computers and peripheral equipment, communication equipment, semiconductor, and navigational, measuring, electro-medical, and control instruments industries in the US. The arithmetic average depreciation rate for these four categories of IT hardware in the US is 28%, and the average for Japan is 34%. In the case of the US, the number is pulled down by the depreciation rate in the communication equipment sector, where a few US firms are able to sustain relatively high profits.

The U.S. pharmaceutical industry has a lower R&D depreciation rate, implying that U.S. pharmaceutical firms have a slight technology edge in this field and can better appropriate the returns from their investments in R&D assets. This result is consistent with the U.S. International Trade Commission's report on the global medical device industry, where it finds that, in terms of technological advantage, the U.S. is ranked first in the world and Japan is a close second (USITC, 2007). Second, Japan's lower R&D depreciation rate in the auto industry suggests that Japan has a clear technological edge and can better appropriate the return from its investments in R&D in this sector. Note, however, that we also show results for the transport equipment sector that use the 1% rate of return we used for the US, and in this case the depreciation rate for Japan is only slightly lower.

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6. Conclusions

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. Although important, measuring R&D depreciation rates is extremely difficult because both the price and output of R&D capital are generally unobservable.

In this paper, we developed a forward-looking profit model to derive industry-specific R&D depreciation rates. Our model uses only data on R&D and output together with some assumptions on the role of R&D in generating profits for the firm. This allows us to calculate not only industry-specific constant R&D depreciation rates but also time-varying rates. We used both nonlinear least squares and nonlinear GMM to fit the model to the data. Both gave similar results, although GMM passed the over-identification test only part of the time and resulted in fairly large standard errors. Future work would be useful to find better instruments and to improve the quality of the underlying data.

Our research results highlight several promising features of the new forward-looking profit model: First, the derived constant industry-specific R&D depreciation rates are consistent with the 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 (Bernstein and Mamuneas, 2006; Corrado et al., 2007; Hall, 2005; Huang and Diewert, 2007; Warusawitharana 2010). Second, the time-varying results capture the heterogeneous nature of industry environments in technology and competition. Third, our method provides a consistent way to perform cross-country comparisons of R&D depreciation rates, which can inform countries' relative paces of technological progress and technological environments as exemplified in the U.S.-Japan comparison.

Note that when capitalizing R&D investments into the U.S. national accounts, the U.S. Bureau of Economic Analysis adopts the concept that failed research projects also generate useful knowledge, so all R&D is included in R&D capital, not just successful R&D. Moreover, as mentioned earlier, the main drivers of R&D depreciation rates are the industry's pace of technological progress and the degree of market competition. To understand whether the failure of a research project affects the firm-level R&D depreciation rate, Li (2015) studied U.S. high-tech industries and found that, in each industry, the R&D depreciation rates of

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market leaders were lower than those of market followers. This pattern is present in all U.S. high-tech industries, a result consistent with the resource based theory (Barney, 1991) in that market leaders can better maintain the value of their assets than their followers. The resource based theory tells us that, if a firm has a better competitive advantage in any resources, such as R&D assets and organizational capital, the firm is more capable of maintaining the value of its assets in those areas. That is, a leading firm in technology will enjoy a smaller (private) depreciation rate of its technology than its follower. The industry level data we use here aggregates over both leaders and followers.

While this study provides the first complete set of industry-specific business R&D depreciation rates for all ten R&D intensive industries identified in BEA's R&D Satellite Account, future research can make improvements in several areas. First, current estimation uses nominal R&D and output data. When the industry-specific price index of R&D assets becomes available, we can improve the estimates by explicitly incorporating the price level change. Second, the current model assumes the decision maker has perfect foresight. Future research can relax this assumption by including uncertainty in the model. Third, the current model assumes decreasing marginal returns to R&D investments and that innovations are incremental. This seems appropriate when dealing with National Income Account data. However, future research could explore these two assumptions and potentially modify the model to be applicable to the industry with increasing marginal returns to R&D investments and drastic innovations. Fourth, the current model assumes that the growth rate of θ is equal to that of R&D investment, but this assumption could be relaxed if better data are available for the proper estimation of the growth (or decline) of R&D productivity.[11]

Lastly, it has been argued that other intangible assets, such as organizational capital, can also contribute to a firm's productivity growth (Lev and Radhakrishnan, 2005; Corrado et al., 2009; Eisfeldt and Papanikolaou, 2013). It should be noted that intangibles other than R&D and software are not included in national accounts, and measuring intangible assets, including resolving the critical issue of data availability, is still a topic of active research. As to the investment timing of R&D assets and organizational capital, as reported in Lev and Radhakrishnan (2005), market leaders tend to invest more in R&D assets and

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[11] We are grateful to a referee for this insightful suggestion. We experimented with a model of this type in Appendix B.

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organizational capital in a recession period. Following Lev and Radhakrishnan (2005) and Eisfeldt and Papanikolaou (2013), Li (2016) and Li et al. (2017) use the selling and general administrative (SG&A) expenditure as a proxy for the investment in organizational capital, and they applied the same methodology to estimating the depreciation of organizational capital across all high-tech industries. The estimated depreciation rates of organizational capital are very different from those of R&D assets not only at the firm level but also at the industry level. In general, the firm-level and industry-level depreciation rates of organizational capital are found to be much smaller than those of R&D assets, implying that changes in profitability due to competition in the market are not the main drivers. Future work can enrich the model to allow the flows of other types of tangible and intangible investments and the interactions between the investments, especially when the data is available.

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Table 1: Summary of previous estimates of R&D depreciation rates

Study	Industry	Estimate	Method	Data
Lev and Sougiannis (1996)	Chemicals	11%	Amortization	825 U.S. firms over the period of 1975-1991
	Electrical equipment	13%		
	Industrial machinery	14%		
	Scientific instruments	20%		
	Transportation equipment	14%		
Ballester et al. (2003)	Chemicals	14%	Amortization	652 U.S. firms over the period of 1985-2001
	Electrical equipment	13%		
	Industrial machinery	14%		
	Scientific instruments	14%		
	Transportation equipment	17%		
Knott et al. (2003)	Pharmaceuticals	88-100%	Production function	40 U.S. firms over the period of 1979 -1998
Berstein and Mamuneas (2006)	Chemicals	18%	Production function	U.S. industries over the period of 1954-2000
	Electrical equipment	29%		
	Industrial machinery	26%		
	Transportation equipment	17%		
Hall (2005)	Computers and scientific instruments	-5%	Production function	16750 U.S. firms over the period of 1974-2003
	Electrical equipment	-3%		
	Chemicals	-2%		
	Drugs and medical instruments	-11%		
	Metal and machinery	-2%		
Hall (2005)	Computers and scientific instruments	31%	Market valuation	16750 U.S. firms over the period of 1974-2003
	Electrical equipment	36%		
	Chemicals	19%		
	Drugs and medical instruments	15%		
	Metal and machinery	32%		
Huang and Diewert (2007)	Chemicals	1%	Production function	U.S. industries over the period of 1953-2001
	Electrical equipment	14%		
	Industrial machinery	3%		
	Transportation equipment	27%		
Warusawitharana (2010)	Semiconudctors	34%	Market valuation	U.S. industries over the period of 1987-2006
	Computer hardware	28%		
	Medical equipment	37%		
	Pharmaceuticals	41%		
	Software	37%		

Note: With the exception of Berstein and Mamuneas (2006) and Huang and Diewert (2007), all of the studies are based on US Computstat data.

Table 2: Nonlinear Least Squares estimates of the R&D depreciation rate

Time period Industry	BEA-NSF Data 1987-2007	
	Estimate	s.e.
Computers and peripheral equipment	36.3%	3.8%
Software	30.8%	0.5%
Pharmaceutical	11.2%	4.8%
Semiconductor	22.6%	3.7%
Aerospace products and parts	33.9%	6.5%
Aerospace products and parts with ROR = 1%	*6.3%*	*0.6%*
Communication equipment	19.2%	3.3%
Computer system design	48.9%	7.9%
Motor vehicles, bodies and trailers, and parts	73.3%	2.9%
Motor vehicles, bodies and trailers, and parts, with ROR = 1%	*11.9%*	*0.4%*
Navigational, measuring, electromedical, and control instruments	32.9%	7.4%
Scientific research and development	29.5%	2.6%

Note: Gestation lag is 2 years; assumed interest rate = ex ante rate of return = 8.9%

Table 3: Sensitivity of the depreciation rate to assumptions

| Gestation lag in years | 0 | | 2 | | 2 | | 2 | |
| Interest rate | 8.9% | | 8.9% | | Tbill + 4% | | BEA return | |
	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.	Estimate	s.e.
Computers and peripheral equipment	28.7%	3.7%	24.0%	3.2%	24.4%	3.7%	23.5%	4.1%
Software	37.3%	0.7%	40.0%	0.8%	41.7%	0.6%	40.1%	0.7%
Pharmaceutical	17.4%	17.1%	16.9%	16.6%	23.5%	6.4%	20.4%	6.2%
Semiconductor	31.4%	13.4%	28.4%	12.2%	29.4%	12.1%	28.1%	16.3%
Aerospace	23.3%	4.5%	19.9%	4.0%	21.6%	5.1%	21.1%	4.7%
Communication equipment	19.5%	3.4%	16.8%	3.0%	17.0%	2.7%	16.6%	2.3%
Computer system design	25.5%	5.1%	26.4%	5.3%	27.7%	3.3%	27.0%	3.7%
Motor vehicles, bodies and trailers, and parts	31.3%	1.5%	27.7%	1.4%	29.5%	1.8%	27.8%	1.3%
Navigational, measuring, electromedical, & control instruments	18.1%	3.9%	15.8%	3.5%	18.3%	4.0%	15.8%	2.5%
Scientific research and development	21.4%	4.9%	21.5%	5.0%	31.1%	5.0%	28.0%	3.7%

Method of estimation is nonlinear least squares.

Table 4: Comparing estimation methods

Industry	NLLS		NL GMM			
	Estimate	*s.e.*	*Estimate*	*s.e.*	*Test#*	
Computers and peripheral equipment	36.3%	3.8%	27.8%	5.5%	0.988	
Software	30.8%	0.5%	33.5%	4.8%	0.045	*
Pharmaceutical	11.2%	4.8%	14.5%	11.7%	0.908	
Semiconductors	22.6%	3.7%	31.3%	6.4%	0.039	*
Aerospace products and parts	33.9%	6.5%	26.3%	5.0%	0.260	
Communication equipment	19.2%	3.3%	23.9%	18.3%	0.514	
Computer system design	48.9%	7.9%	25.1%	12.4%	0.290	
Motor vehicles, bodies and trailers, and parts	73.3%	2.9%	33.1%	5.0%	0.018	**
Navigational, measuring, electromedical, & control instruments	32.9%	7.4%	23.2%	11.1%	0.115	
Scientific research and development	29.5%	2.6%	32.0%	2.0%	0.400	

Notes:

Assumed gestation lag is two years; interest rate is 8.9%.

Estimates shown are for the depreciation rate and its standard error.

Instruments are R&D and the T-bill rate, lagged once and twice.

\# The p-value of a test for overidentifying restrictions is reported in these columns. *, **, *** denote significance at 10%, 5%, 1% respectively

Table 5: Estimates for Japan

Industry	Estimate	s.e.
(1) Drugs and medicines	16.4%	5.4%
(2) Electrical machinery, equipment, and supplies	38.8%	7.6%
(3) Information and communication electronic equipment	28.4%	1.3%
(4) Transportation equipment	50.0%	2.0%
(4) Transportation equipment (r=3%)	*26.9%*	*1.0%*

Notes:

1. The estimates are based on a 2-year gestation lag, and an interest rate of 6%.

2. The data cover the period 2002 to 2012.
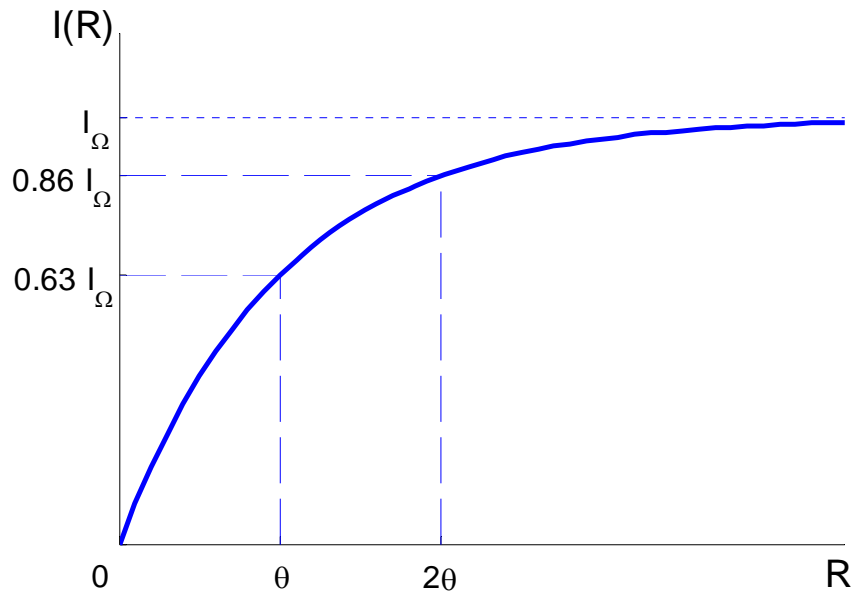
Figure 1: The Concavity of $I(RD)$

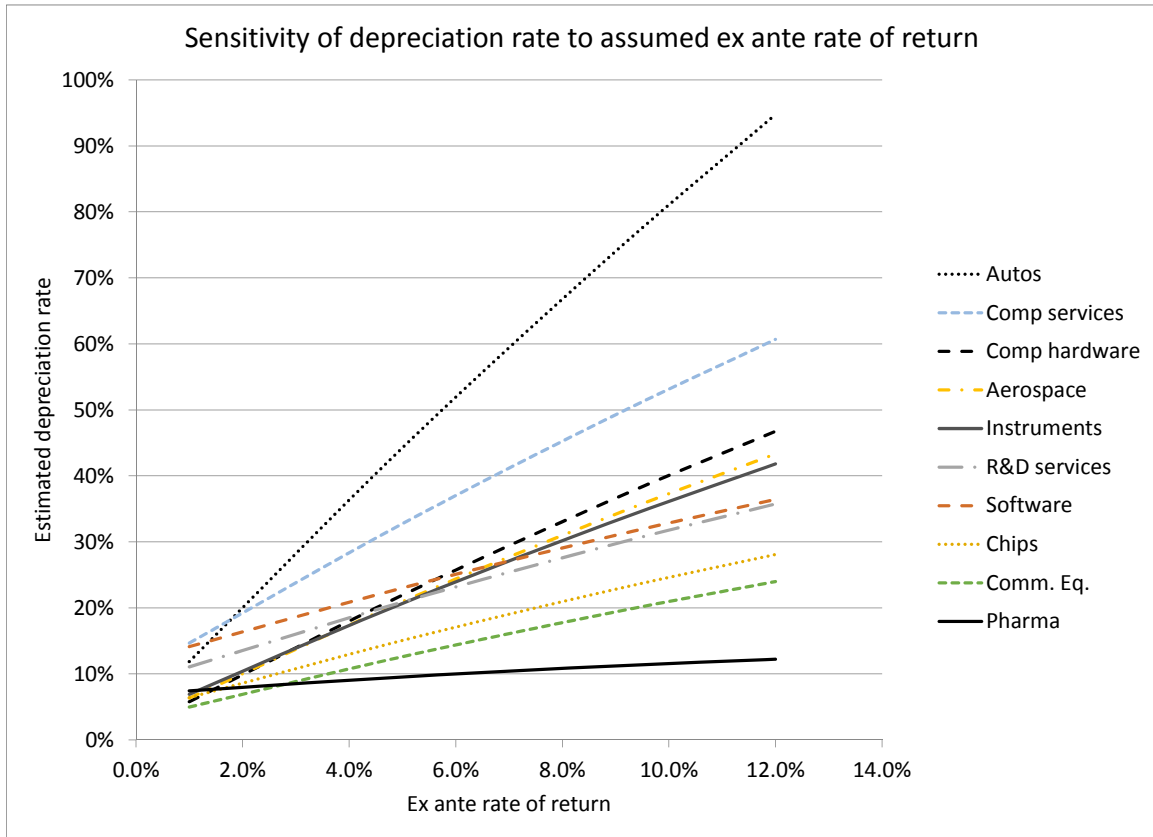**Figure 2: Sensitivity of the depreciation rate of R&D Assets to the Cost of Capital**
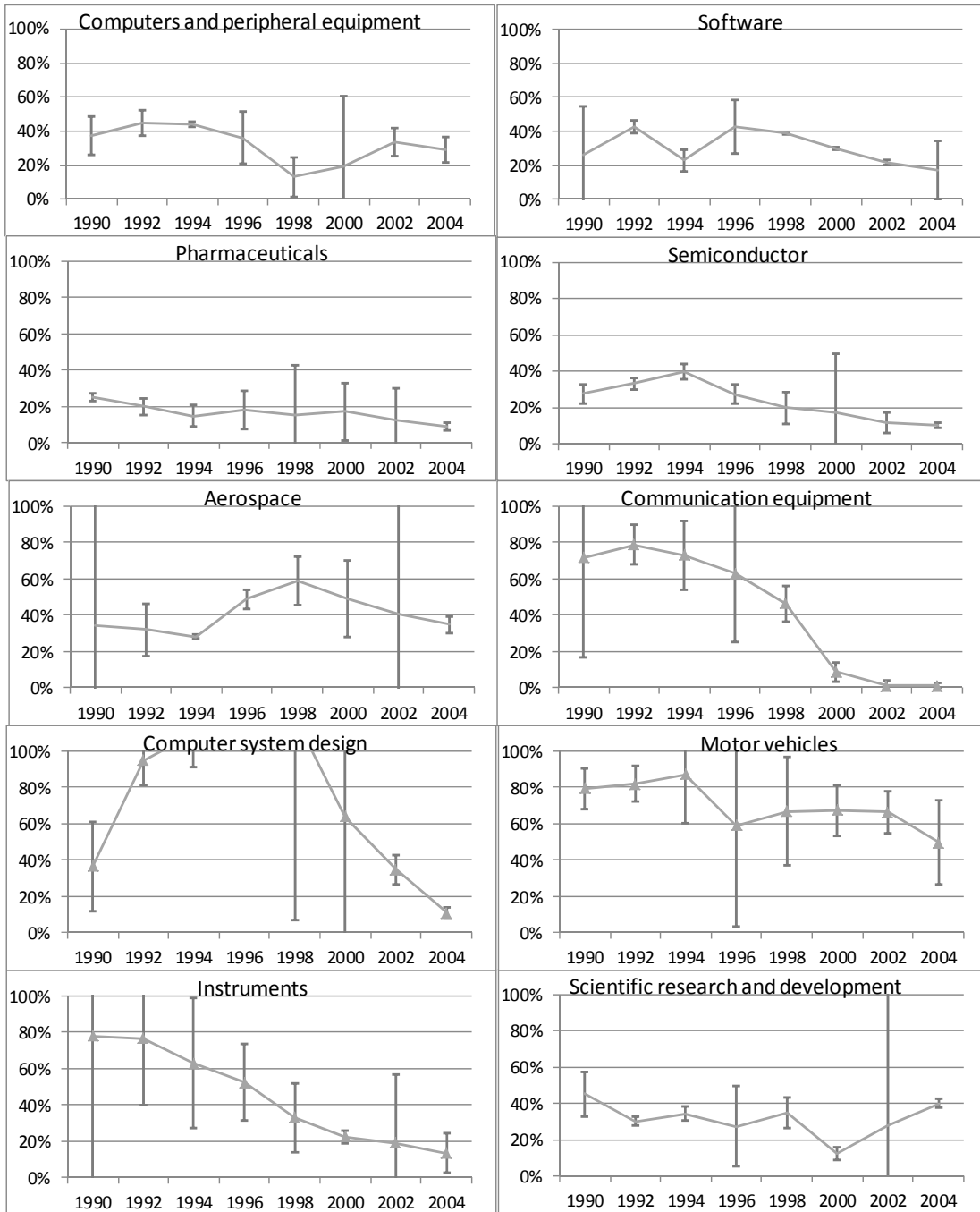
Figure 3: Time-varying R&D Depreciation Rates

Estimated Time-varying Depreciation Rate by Sector - BEA-NSF data
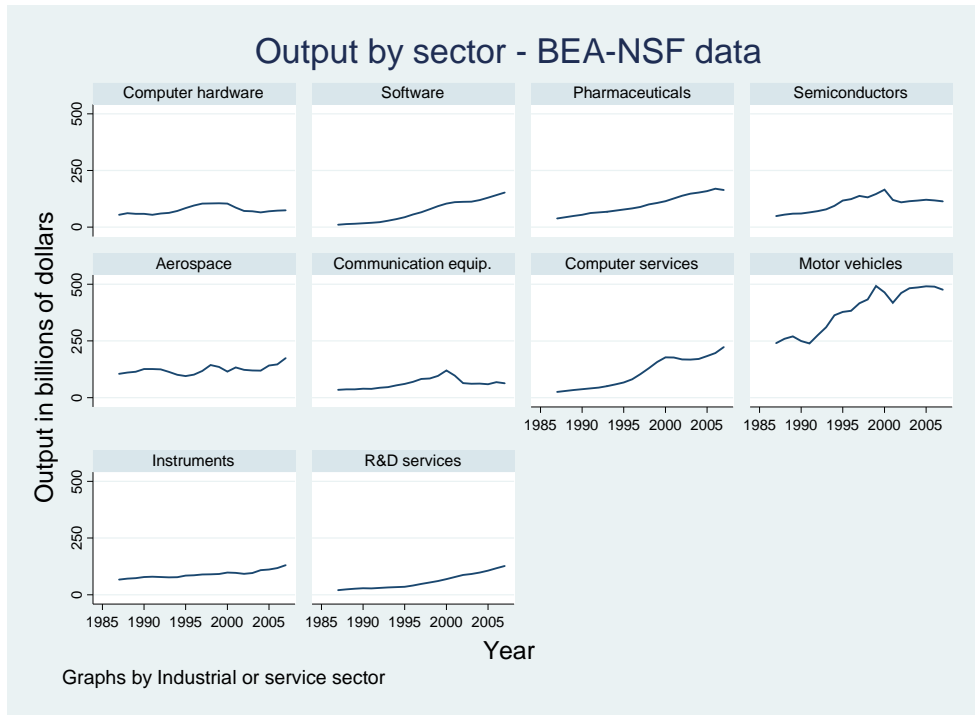
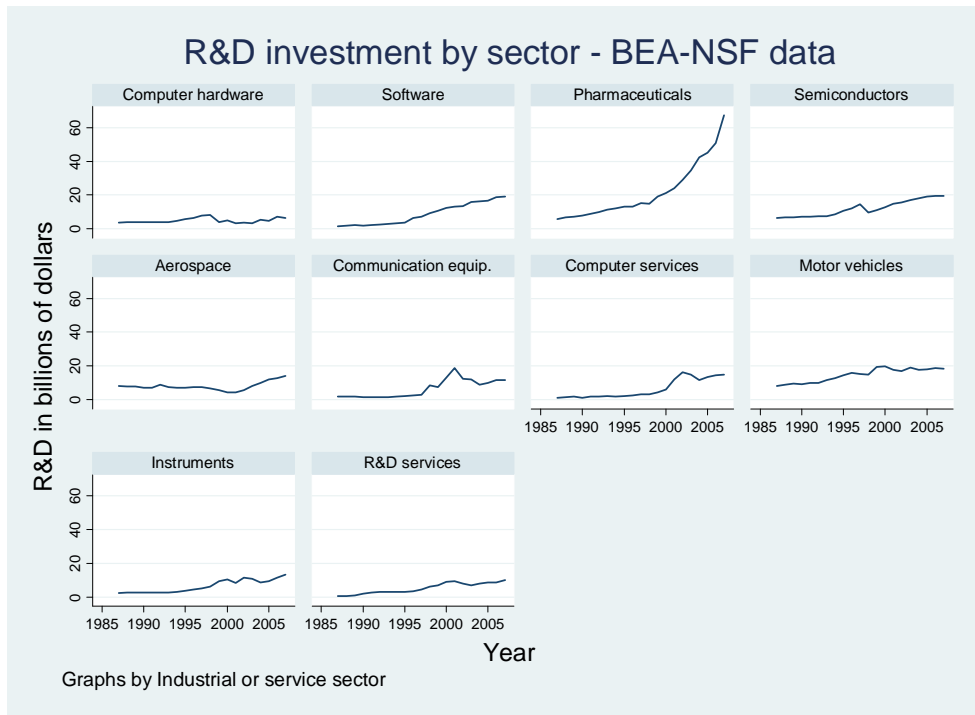# Appendix A: Additional tables and figures

Figure A-1

Output by sector - BEA-NSF data

Figure A-2

R&D investment by sector - BEA-NSF data

Figure A-3

Interest rates

14				
12				
10				
8				
6				
4				
2				
0				

1987   1992   1997   2002   2007

——— Fixed rate of 8.9%   – – – 3-month T-bill rate plus 4%

– – – BEA rate of return on assets
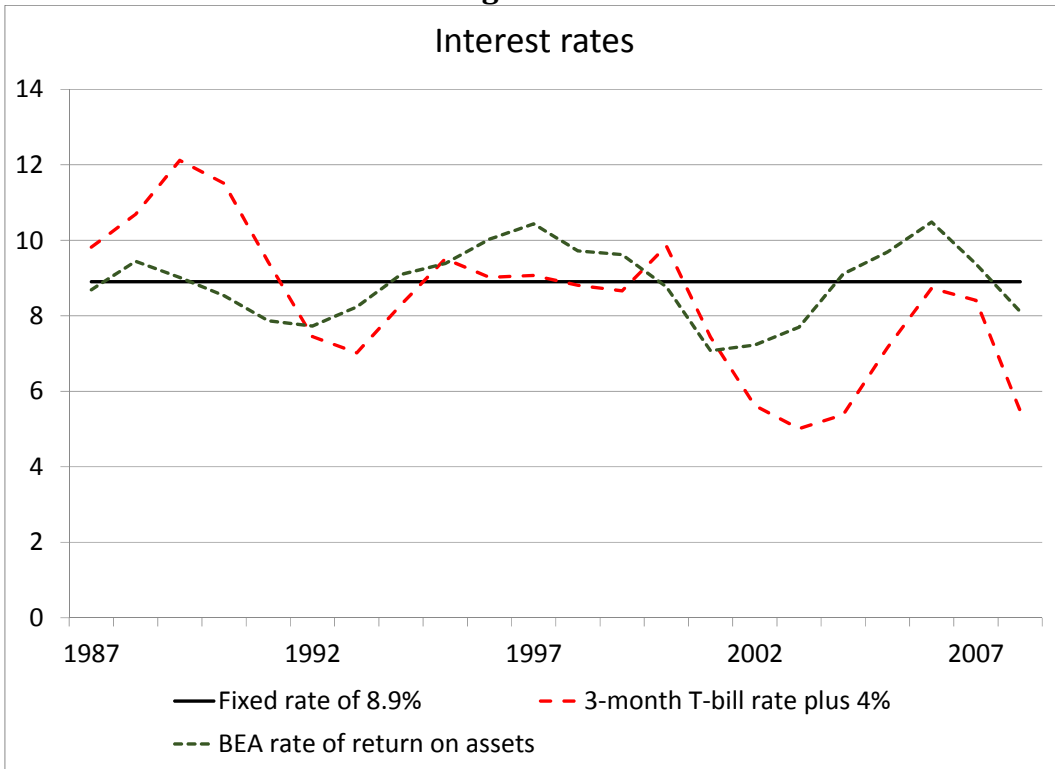
Appendix B: a three parameter model

In the main body of the paper, we estimated the profit model in the following form:

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

The parameters to be estimated were δ and θ_0, while $\hat{G}$, $\hat{g}$, and $r = I_\Omega$ were fixed at plausible values. Thanks to a suggestion from a referee, we found that $\hat{G}$, which corresponds to the growth or decline in R&D productivity in generating profits, was also identified in our data, at the cost of some additional imprecision. Estimates for this three parameter model ($\hat{G}$, δ and θ_0) are shown in Table B-1, using a gestation lag of 2 and interest rate of 8.9%. The estimated depreciation rates are somewhat lower than those in Table 2, but generally similar.

<div align="center">Table B-1: Estimation of the three parameter model</div>

	Depreciation (delta)	s.e.	Inflation (growth in theta)	s.e.	Base theta (US$B)	s.e.
Computers and peripheral equipment	35.4%	4.4%	1.1%	2.0%	7.37	2.42
Software	30.8%	0.6%	9.8%	2.4%	3.46	0.85
Pharmaceutical	6.7%	7.4%	4.9%	4.3%	48.71	39.02
Semiconductor	20.6%	9.3%	1.5%	8.9%	16.98	6.93
Aerospace	30.7%	5.6%	0.6%	1.1%	17.24	4.32
Communication equipment	15.4%	2.8%	-0.6%	2.7%	18.43	4.38
Computer system design	45.8%	9.4%	6.4%	2.9%	7.70	2.29
Motor vehicles, bodies and trailers, and parts	72.9%	3.2%	3.3%	0.8%	14.49	2.23
Navigational, measuring, electromedical, & control instruments	22.2%	4.6%	-0.5%	1.5%	20.70	3.08
Scientific research and development	22.1%	5.1%	10.8%	0.7%	5.34	2.07

The interpretation of the G and θ_0 estimates are the following: θ_0 varies across industry to the extent that the profit productivity of R&D varies. The industry with the highest value, pharmaceuticals, is the industry where the largest amount of R&D is needed to generate an additional dollar of profit. That is, θ_0 is related to but not the same as the R&D intensity in the industry (the correlation is 0.69). G measures how this productivity changes over the period, with a positive value indicating the R&D is becoming less productive and a negative value the reverse. The estimates suggest that R&D productivity is increasing in two sectors: communication equipment and instruments, while declining in others. The industries with the greatest declines in the ability of R&D to generate profits are software, semiconductors (the slowdown of Moore's Law) and computer system design, followed by pharmaceuticals. These results seem plausible, and with more data, worth pursuing.