Organizational Capital, R&D Assets, and Offshore Outsourcing

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Abstract

The degree of offshore outsourcing in the high-tech industries has increased rapidly in past decades. Because of this trend, economists have been debating whether offshore outsourcing is hollowing out U.S. high-tech firms' core competencies in intangibles. To contribute to the debate, I first develop a forward-looking profit model and use Compustat dataset to measure the capital stock and depreciation rate of R&D and organizational capital for major U.S. R&D-intensive industries. Then, I use the estimates to analyze whether industries with a higher degree of offshore outsourcing exhibit a different investment pattern in intangibles. In general, I find that industries with more intangibles are more competitive in the global market. Even in R&D intensive industries, the estimated size of organizational capital is larger than that of R&D assets. Moreover, in industries with a lower degree of offshore outsourcing, R&D assets and organizational capital are complementary. However, industries with a higher degree of offshore outsourcing invest less in both R&D and organizational capital but have higher productivity growth. Lastly, R&D assets contribute to a firm's market value but U.S. top high-tech market performers maintain a close ratio of R&D assets to organizational capital.

Key words: Intangible Asset Relationship, Offshore Outsourcing, Intangibles, R&D, Organizational Capital

1. Introduction

The scale and scope of offshore outsourcing has increased rapidly in past decades (Li, 2008). As a result, the central debate on the impact of offshore outsourcing is whether or not the increasing global division of labor is hollowing out U.S. high-tech firms' core competencies in intangibles. Economists have argued that the increasing global division of labor has enabled intangibles, such as R&D assets and organizational capital, to become a principal driver of the competitiveness of U.S. high-tech firms. Past research has also shown that the intensity of intangibles is positively related to productivity growth (Griliches, 1981; Eisfeldt and Papanikolaou, 2013).

Despite the fact that the estimated size of U.S. business spending on intangibles has increased significantly and reached 13.1% of GDP by 2000 (Corrado et al., 2005), to contribute to the debate research needs to show, in the high-tech industries, whether industries with a higher degree of offshore outsourcing invest more in intangibles. Moreover, since the scale and the scope of offshore outsourcing vary across industries, we need to examine whether the intangible investment pattern varies across industries as well and how that relates to the scale and scope of offshore outsourcing in each industry. Currently, to my knowledge, no research has shown any of the above.

This paper aims to fill in these gaps. Before conducting the above analysis, we need to measure the sizes of intangible assets of high-tech industries. To measure intangible assets, economists generally encounter the problem that: there is no arms-length market for most intangibles and the majority of them are developed for a firm's own use. Many economists have been working on the measurement of R&D assets. The Bureau of Economic Analysis (BEA) has developed methodologies to measure R&D assets and computer software capital (Li, 2012; Robbins et al., 2012). In 2013, BEA started publishing R&D assets. Organizational capital, with annual business spending of at least 1.5 times that of R&D assets (Corrado et al. 2005), however, has not received equal attention in the economic community. The lack of interest is due to the lack of systematic data on organizational capital across firms and countries, and the misunderstanding about the application and innovation of management practices (Bloom and van Reenen, 2010). Organizational change and innovation is not a straightforward process.

To resolve the issue of the dearth of data on organizational capital, the Census Bureau, the National Science Foundation (NSF), and the National Bureau of Economic Research (NBER) made a significant step forward in collecting related data by conducting a new pilot survey on U.S. management practices in 2011. The survey collects data including qualitative measurements of structured management practices, which raise the concern of measurement units, and covering the years 2005 and 2010. To achieve the goal of this research, panel data on spending with a long time series is needed to construct the stock of organizational capital.

Following earlier research, I use sales, general, and administrative (SG&A) expense as a proxy for a firm's investment in organizational capital (Lev and Radhakrishnan, 2005; Eisfeldt and Papanikolaou, 2013). Firms report this expense in their annual income statements. It includes most of the expenditures that generate organizational capital, such as employee training costs, brand enhancement activities, consulting fees, and the installation and management costs of supply chains. Because SG&A expenditures may include some items that are unrelated to improving a firm's organizational efficiency, people might question whether it is a valid measure of a firm's investment in organizational capital. Eisfeldt and Papanikolaou (2013) use five ways to validate their measure and the results show that four out of five clearly support this approach.

In this research, I develop a forward looking profit model to estimate the depreciation rate of the organizational capital and then use the perpetual inventory method to construct the stock of organizational capital for nine R&D intensive industries. The same procedure is applied to the estimation of R&D depreciation rates and the construction of R&D capital stock for the nine industries as well. After constructing the stocks of intangibles for those industries, I conduct panel regression analysis to examine how different types of intangibles relate to firms' economic performances and find out whether industries with a higher degree of offshore outsourcing have a different investment pattern from their counterparts.

In this paper, there are several key findings. First, organizational capital in general depreciates slower than R&D assets across industries, which supports Brynjolfsson et al. (2002)'s finding that because of explicit and implicit complementariness among each collection of business practices, it is difficult for other firms to imitate the winners' best practices. Second, in general, market leaders have smaller depreciation rates of both types of intangibles, R&D assets and organizational capital, than their followers. The finding indicates that market leaders

can have a higher appropriation of their investments in intangibles than their followers. It is also consistent with Bloom and van Reenen (2010)'s finding that bigger firms have better economic performances and management practices, which implies that *ceteris paribus*, their appropriable return to their investments in organizational capital declines more slowly, i.e., a lower depreciation rate of organizational capital.

Third, firms in the high-tech industries need both R&D assets and organizational capital to compete in the market[1]; however, how the two intangibles interact with each other matters for a firm's outsourcing decision. During the sample period, organizational capital has a positive relationship with a firm's profitability for all high-tech industries.[2] Furthermore, U.S. top high-tech market performers maintain a close ratio of R&D assets to organizational capital. These results support the fact that in the era of globalization, organizational capital is the core competence of U.S. high-tech firms. Even though U.S. high-tech firms may outsource production and R&D activities (Li, 2008), they always keep their organizational capital in-house. Based on this fact, my empirical analyses show that in general, when the return to R&D investment is positively related to investment in organizational capital, we observe that the industry has a lower degree of offshore outsourcing in R&D activities. The observed industries are the non IT-hardware industries, such as the pharmaceutical industry. The opposite scenario is observed in the IT hardware industries, such as the communication and computer and peripherals industries, where there exists a negative relationship between the return of investment in R&D and investment in organizational capital, and a higher degree of offshore outsourcing in R&D activities.

Lastly, even in R&D intensive industries, the estimated size of organizational capital is larger than that of R&D assets. In addition, in the industry ranking in terms of the stock of intangibles, the top three industries in R&D assets are the pharmaceutical, the software, and the

[1] Lev and Radhakrishnan (2002) point out that in McKinsey Global institute's 2002 report, it studies the performance of 1000 firms during the period of 1982 to1999 and concludes that industry leaders tend to increase not only R&D expenses but also SG&A expenses significantly above average during recessions. The McKinsey study indicates that both organizational capital and R&D capital are important for industry leaders to develop and maintain their competence during recessions.

[2] Here, we ignore the results from the aerospace and the motor industries since the Compustat has poor data coverage for those industries.

semiconductor industries and the top three ones in organizational capital are the pharmaceutical, the software and the navigational industries, a ranking that is consistent with our understanding of the relative competitiveness of U.S. high-tech firms in the global market (See Table 4).

The rest of paper proceeds as follows. Section 2 describes the theoretical model for deriving the depreciation rates of intangibles. Section 3 describes the data and the estimations of depreciation rates. Section 4 presents the construction of annual stocks of both types of intangibles for the nine R&D intensive industries. Section 5 shows the panel regression analysis for the industry profitability and three types of major tangible and intangible assets. Section 6 examines the relationship between the market values of firms, their R&D assets, and the ratio of their R&D assets to organizational capital. Section 7 concludes. An appendix is included on a new approach of estimating the depreciation rates of intangibles with a non-linear generalized method of moments.

2. Forward-looking Profit Model

To construct the stocks of R&D assets and organizational capital, we need the depreciation rates of both intangibles for the nine R&D intensive industries. Previously, I use BEA data to estimate R&D depreciation rates for the ten R&D intensive industries defined in BEA's R&D satellite account, which has been released in late 2013 (Li, 2012). However, no research has worked on the depreciation rates of organizational capital for all major R&D intensive industries.

To construct the stock of organizational capital, Eisfeldt and Papanikolaou (2013) subjectively chose 15% as the depreciation rate of organizational capital, a number estimated by Griliches (1981) for the depreciation rate of R&D assets for major manufacturing industries during the 1970s. However, since each industry has a different competition environment, business practices, and technological progress, the depreciation rates of organizational capital and R&D assets should vary across industries as well. Furthermore, although both organizational capital and R&D assets are intangibles, the nature of their productions and their relationships with market competition should be different. That is, we should expect that even within the same industry, the depreciation rate of R&D assets should be different from that of organizational capital.

To estimate the depreciation rates of both intangibles, I develop a forward-looking profit model. The premise of my model is that business intangible capital depreciates because its contribution to a firm's profit declines over time. Intangible capital generates privately appropriable returns; thus, it depreciates when its appropriable return declines over time. The depreciation rate of intangible capital is a necessary and important component of a firm's intangible investment model. A firm pursuing profit maximization will invest in intangibles optimally such that the marginal benefit equals the marginal cost. That is, in each period *i*, a firm will choose an intangible investment amount to maximize the net present value of the returns to this investment:

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

where IC_i is the intangible investment amount in period *i*, q_i is the sales in period *i*, $I(IC_i)$ is the increase in profit rate due to the intangible investment IC_i, δ is the depreciation rate of the intangible, and *d* is the gestation lag and is assumed to be an integer which is equal to or greater than 0. Period *i*'s the intangible investment IC_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 intangible assets. *r* is the cost of capital.

It should be pointed out that *J* is not the length of the service lives of intangible assets. *J* can be ∞ in theory, but in practice any sufficiently large value can be used in calculations as long as it well covers the duration of intangible assets' contribution to a firm's profit. In this study, I use 20 for *J* except for the pharmaceutical industry where $J = 40$ is used due to the longer product life cycle. I have confirmed that, with *J* greater than the service lives of intangible assets, the derived depreciation rates are very stable when we vary the number of *J* in small increments. In the analysis presented later, I have found that, with the same values of *d* and *J*, δ is different across industries.

It is necessary to note here that, when a firm decides the amount of the intangible 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 as logs and differenced in order to satisfy the stationary condition, and the converted time series is modeled by the autoregressive (AR) process. For the various types of industrial data included in this study, the optimal order of the AR model as identified by the Akaike Information Criterion [Mills, 1990] is found to range from 0 to 2. To maintain the consistency throughout the study, AR(1) is used to forecast future sales.

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

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

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

$I'(IC) > 0$ and I"(IC) < 0. In addition, $\frac{dI}{dIC} = I_{\Omega} \times e^{\frac{-IC}{\theta}}$ where $\frac{dI}{dIC} = I_{\Omega}$ when $IC = 0$. I(IC) → I_{Ω} when $IC \to \infty$. The functional form of $I(IC)$ 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). The model incorporates the assumption of diminishing marginal returns to intangible investments, which is more realistic than the traditional assumption of constant returns to scale in intangible investments by accounting for the decreasing productivity growth of intangible investments. In addition, the model assumes that innovation is incremental.

I_{Ω} is the upper bound of increase in profit rate due to intangible investments. In addition, θ defines the investment scale for increases in *IC*. That is, θ can indicate how fast the intangible investment helps a firm achieve a higher profit rate. Note that based on equation (2),

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

From Figure 1, we can see that, for example, when *IC*, the current-period intangible investment amount, equals θ, the increase in profit rate due to this investment will reach $0.64I_{\Omega}$. When *IC* equals 2θ, the increase in profit rate due to this investment will reach $0.87I_{\Omega}$. The value of θ can vary from industry to industry; that is, we expect to see different industries have different intangible investment scales.

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

The intangible investment model becomes:

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

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

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

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

3. Data and the Estimation of Depreciation Rates

As mentioned earlier, there is an issue of the dearth of data on organizational capital. To resolve the data issue, the Census Bureau, the National Science Foundation (NSF), and the National Bureau of Economic Research (NBER) made a significant step forward in collecting related data by conducting a new pilot survey of U.S. management practices in 2011. The pilot survey has a 78% response rate from 47,534 establishments. The survey collected data on structured management practices in 2005 and 2010. Because the survey contains qualitative questions, answers based on them raise the concern of measurement units. Additionally, the establishment-based survey population raises another concern of the selection bias. That is, because larger firms tend to have multiple and more establishments, they have a higher chance of responding to the survey (Brynjolfsson et al., 2013). No doubt a large panel data set of this type of survey in the future will greatly increase our understanding of some of the complicated facets of organizational capital. To achieve the goal of this research, however, we need to use spending data on organizational capital with a long time series to construct the stock of organizational capital, an approach which can mitigate the concerns of measurement units and sample selection bias.

To explore the availability of spending data, we first need to define the terms of organizational capital. Organizations develop and accumulate knowledge affecting their production technology. The accumulated knowledge is distinct from the concepts of physical or human capital in the standard growth model (Arrow, 1962; Rosen, 1972; Tomer, 1987; Ericson and Pakes, 1995; Atkeson and Kehoe, 2005). That is, organizational capital is firm-embodied and provides firms a sustainable competitive advantage, a type of advantages that cannot be completely codified, transferred to other firms, and imitated by other firms (Lev and Radhakrishnan, 2005). It contains business models, organizational practices, and corporate culture (Brynjolfsson et al., 2002). Following the definition, researchers have used the sales, general, and administrative (SG&A) expense as a proxy for a firm's investment in organizational capital (Lev and Radhakrishnan, 2005; Eisfeldt and Papanikolaou, 2013). Firms report this expense in their annual income statements. It includes most of the expenditures that generate organizational capital, such as employee training costs, brand enhancement activities, consulting fees, and the installation and management costs of supply chains. Because SG&A expenditures

may include some items that are unrelated to improving a firm's organizational efficiency, people might question whether it is a valid measure of a firm's investment in organizational capital.

Eisfeldt and Papanikolaou (2013) use five ways to validate their measure and the results show that four out of five clearly support it. For example, their measure of organizational capital is informative about the quality of management practices across firms. Firms with a higher ratio of organization capital to assets are also more productive. To construct the stock of organizational capital, Lev and Radhakrishnan (2002) also use the SG&A expenditure as a proxy for the investment of organizational capital and adopt a production residual approach to measure firm-level organizational capital. However, because the production residual may contain other types of intangibles, the approach may overestimate the size of organizational capital (Bresnahan, 2002).

Following earlier research (Lev and Radhakrishnan, 2002; Eisfeldt and Papanikolaou, 2013), I use sales, general, and administrative (SG&A) expense as a proxy for a firm's investment in organizational capital. As a first step in my empirical analyses, I estimate the constant depreciation rates of R&D assets and organizational capital for the nine U.S. high-tech industries. The data is from the company-based Compustat dataset and covers the period of 1987 to 2010. To conduct the estimation, I use the annual average sales, R&D investments, and SG&A expenditures for each industry.

The value of I_Ω can be inferred from the BEA average 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. For simplicity, I use the average return rates of all assets for non-financial corporations during 1987-2010, 8.9 percent, for I_Ω. In addition, in equilibrium the rate of returns should be equal to the cost of capital. Therefore, I use the same value for r.

I use Equation (5) in Section 2 as the model to estimate the depreciation rate of each type of intangibles from the data. As $I_\Omega = r = 0.089$, and as IC_i and q_i can be known from data, the only unknown parameters in the equation are δ and θ. Under our assumptions, Equation (5)

holds when the true values of δ and θ are given and we can therefore estimate these unknowns by minimizing the following quantity for each industry:

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

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

Equation (6) defines a minimum distance estimator with two unknown parameters. 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, several sets of start values are tried to ensure the stability of the solution.

In this study I use a two-year gestation lag for R&D investments, which is consistent with the finding in Pakes and Schankerman (1984) who examined 49 manufacturing firms across industries and reported that gestation lags between 1.2 and 2.5 years were appropriate values to use. In addition, in a recent U.S. R&D survey conducted by BEA, Census Bureau and National Science Foundation (NSF) in 2010, the average gestation lag is 1.94 years for all industries.[3] As to the gestation lag for organizational capital, I use a one-year gestation lag for organizational capital. No research has developed a model to estimate the depreciation rate of organizational capital before. Corrado et al. (2004) assumes zero gestation lag for the construction of the stocks of all types of intangible capital. Given that it takes time for the investment in organizational capital to become productive, I assume a one-year gestation lag which is adopted by Fraumeni and Okubo (2005) in their work on R&D investments. Lastly, as mentioned previously, the value of *J* is chosen based on the tests that the increase in the value of *J* does not change the optimal solution.

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

3.1 Industry-level Constant Depreciation Rates

I apply the static model in the previous section to estimate the depreciation rates of R&D assets and organizational capital for the ten R&D intensive industries identified in BEA's R&D Satellite Account. Table 1 shows the estimated depreciation rates and their associated standard errors of both intangibles for the ten R&D intensive industries. The standard errors are calculated by the bootstrap method with 300 resamples.

Table 1: The Comparison Table of the Depreciation Rates of R&D Assets and Organizational Capital

Industry	$\delta_{R\&D,\ BEA}$ with 2-year gestation lag	$\delta_{R\&D}$ with 2-year gestation lag	δ_{OC} with 1-year gestation lag
Aerospace	21% (3%)	22.0% (0.7%)	21.6% (0.7%)
Communication	31% (2%)	21.8% (4.5%)	17.7% (3.9%)
Computer System Design	43% (1%)	28.6% (2.0%)	11.6% (1.1%)
Computer & peripherals	41% (1%)	24.6% (3.9%)	8.5% (3.1%)
Motor	28% (2%)	18.3% (1.0%)	15.1% (0.9%)
Navigational	26% (1%)	29.5% (2.0%)	6.3% (1.3%)
Pharmaceutical	10% (0.4%)	12.5% (0.9%)	3.3% (0.8%)
Scientific R&D	16% (1%)	26.7% (1.7%)	9.1% (1.5%)
Semiconductor	27% (2%)	22.2% (4.6%)	24.2% (4.6)
Software	24% (1%)	24.9% (1.2%)	11.1% (0.9%)

Note:

1. The depreciation rates of R&D assets on the second column are estimated based on the BEA dataset.
2. The depreciation rates of R&D assets and organization capital are estimated based on the Compustat dataset.
3. Both datasets cover the period of 1987-2011.

Table 1 shows the two sets of the industry-specific depreciation rates of R&D assets based on the BEA and Compustat data and one set of the industry-specific depreciation rates of organizational capital based on the Compustat data. There are two key findings. First, R&D assets in general depreciate faster than organizational capital in all R&D intensive industries. Second, the estimates are plausible for most industries. For example, the pharmaceutical industry has the lowest depreciation rates of both intangibles, which may reflect the fact that through effective patent protections and high entry barriers in clinical stages and marketing stages, pharmaceutical firms can better appropriate the return from their investments in both intangibles than firms in other industries. Compared with the pharmaceutical industry, the computer and peripherals industry has higher depreciation rates in both assets, a finding that is consistent with the industry's observations that the computers and peripheral 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 similar to commodities, which implies a shorter product life cycle and a higher depreciation rate for intangibles (Li, 2008). Lastly, compared with the traditional pharmaceutical industry, the scientific R&D industry, the majority of which are composed of the biotech firms, has higher depreciation rates in both R&D assets and organizational capital. The higher depreciation rates reflect the fact that in the past three decades including our sample period, the biotech industry has a faster pace of technological progress than the traditional pharmaceutical industry and its organizational capital including brand name, marketing and supply chain are not as well established as its counterpart.

3.2 Comparison of the Constant Depreciation Rates: Leader vs. Follower

I further divide each industry into two groups, the leader and the follower. The group of the leader is composed of the top five percent of firms in terms of sales in 2000. Table 2 compares the depreciation rates of R&D assets and organizational capital for the two groups in each industry. Note that all estimates are based on the Compustat dataset.

Table 2: Comparison between the Industry Leader and Its Follower in the Depreciation Rates of R&D Assets and Organizational Capital

Industry	$\delta_{R\&D,\ Leader}$	$\delta_{R\&D,\ Follower}$	$\delta_{OC,\ Leader}$	$\delta_{OC,\ Follower}$
Aerospace	29% (2%)	28% (1%)	19% (1%)	37% (1%)
Communication	29% (5%)	27% (6%)	23% (4%)	20% (4%)
Computer System Design	17% (3%)	27% (1%)	6% (2%)	16% (1%)
Computer & peripherals	26% (4%)	36% (14%)	6% (3%)	19% (9%)
Motor	21% (1%)	23% (1%)	13% (1%)	14% (1%)
Navigational	27% (2%)	34% (5%)	7% (1%)	10% (3%)
Pharmaceutical	9% (1%)	38% (13%)	4% (0.3%)	23% (12%)
Semiconductor	26% (3%)	26% (4%)	26% (3%)	30% (5%)
Software	21% (2%)	29% (1%)	7% (1%)	16% (1%)

Note: All estimates are based on the Compustat dataset.

There are several key findings. First, except in the aerospace and the semiconductor industries, in both groups across industries, R&D assets depreciate faster than the organizational capital, which is consistent with the earlier result. Second, except in the aerospace and the communication industries, both the intangibles of the industry leaders depreciate slower than those of the followers. This result indicates that the leaders can better appropriate the return from their investment in intangibles than their followers across industries.[4] Moreover, it supports the finding by Brynjolfsson et al. (2002) that because of explicit and implicit complementariness among each collection of practices, it is difficult to imitate the winner's best practices. Third, except in the navigational and the pharmaceutical industries, the depreciation gap in organizational capital is greater than that in R&D assets. This indicates that in most R&D intensive industries, industry leaders can maintain their advantage of organizational capital better than that of R&D assets.

[4] Note that it is well known that the aerospace data in the Compustat is poor in the coverage of R&D expenditures.

4. The Construction of Annual Stocks of R&D Assets and Organizational Capital

Before conducting further analysis, I first construct the stocks of R&D assets and organizational capital for the nine R&D intensive industries.[5] To construct the stock of each type of intangible capital in an industry, I follow the method of constructing the annual stock of R&D assets for U.S. manufacturing industries in Hall (1998). First, I deflate each industry's annual R&D investments and SG&A expenditures by using the GDP deflator with 2005 as the base year.[6] Then, I apply our estimated depreciation rates and the perpetual inventory method to construct the annual stock of each intangible capital. Lastly, I use the GDP deflator again to bring back the real number to the correspondent nominal value in that year.

Table 3: The Industry Ranking in Intangible Capital

Rank	R&D Assets	Organizational Capital
1	Pharmaceutical	Pharmaceutical
2	Software	Software
3	Semiconductor	Navigational
4	Communication	Computer System Design
5	Computer System Design	Computer & Peripherals
6	Navigational	Communication
7	Computers & Peripherals	Semiconductor

Note: 1. The industry ranking is valid over the sample period.

2. Because the Compustat has poor data coverage for the aerospace and the motor industries, the ranking does not include those two industries.

Table 3 shows the industry ranking of the seven R&D intensive industries in terms of the annual stock sizes of R&D assets and organizational capital. I set the initial capital stock at the beginning as zero and conduct the analysis without the first three-year data. The time series of

[5] Because of the unclear industry definition for the scientific R&D industry in the Compustat dataset, I will not conduct analysis for that industry.

[6] BEA develops the R&D price index by adopting the input cost method with the adjustment of a multifactor productivity (MFP) growth rate. However, because the Bureau of Labor Statistics (BLS) currently only estimates MFP growth rate for three R&D intensive industries, the method requires additional assumptions on the MFP growth rate for the rest R&D intensive industries. Moreover, because the MFP growth rate is estimated by the residual approach, the approach cannot deliver the standard error of an estimated MFP growth rate. That is, the approach cannot guarantee a robust estimation.

the stocks of R&D assets and organizational capital cover the period of 1990 to 2013. In the ranking of R&D assets, the pharmaceutical industry has the largest stock of R&D assets, the software industry is the second, and the semiconductor industry is the third. In the ranking of organizational capital, the pharmaceutical industry has the largest stock of organizational capital, the software industry is the second, and the navigational is the third. The ranking seems to reflect the relative competitiveness of U.S. industries in the global market. Table 4 shows the industry ranking in terms of the stock sizes of R&D assets, organizational capital, and the share of the global top ten public companies. In general, U.S. industries with a higher ranking in the stock size of intangible capital have a higher degree of dominance in the global market. The only exception is the communication industry. The relationship is less clear in the communication industry. Compared with other industries, this industry has a higher degree of regulations across countries. Interestingly, the semiconductor is ranked as the last in terms of the stock of organizational capital. Figure 1 indicates that the average ratio of R&D assets to organizational capital is the highest among all R&D intensive industries. Moreover, compared with their counterparts in other high-tech industries, the top market performers in the semiconductor industry have a higher average ratio of R&D assets to organizational capital. Lastly, it is well known that the computer and peripherals industry has the highest degree of offshore outsourcing. And, this industry is ranked as the last in terms of the stock of R&D assets and the third from the bottom in terms of the stock of organizational capital.

Table 4 The Industry Ranking in Intangibles and Global Competitiveness

Rank	R&D Assets	Organizational Capital	Global Top Ten Share
1	Pharmaceutical	Pharmaceutical	Software (8)
2	Software	Software	Medical Equipment and Supplies (7) Pharmaceutical (4)
3	Semiconductor	Navigational	Semiconductor (5; 3 out of top 5)
4	Communication	Computer System Design	Computer System Design (3)
5	Computer System Design	Computer & Peripherals	Computers & Peripherals (3)
6	Navigational	Communication	Communication (3)
7	Computers & Peripherals	Semiconductor	

Source: Forbes, 2013. http://www.forbes.com/global2000/.

5. The Relationship Between Assets and Profitability

5.1 Pooled Industry-level Analysis

In order to understand why firms invest in different types of intangibles, we need to examine the relationship between asset types and firm performance. Brynjolfsson et al. (2002) find that firm performance depends both on the level of overall intangible capital and also on the interaction between different categories of intangible capital in the computer adoption industries. So, we need to examine not only how different types of intangibles relate to firm performance but also find out the relationship between intangibles within a firm.

To examine the relationship between intangibles and firm performance, in this section, I construct a panel data which includes the time series of each industry's average annual stock of R&D assets, annual stock of organizational capital, annual stock of physical assets, and annual

gross profit[7]. To smooth the times series data, I use natural logarithms. Since the panel data contain data from nine different R&D intensive industries, we need to control the problems of the omitted variables and unobserved heterogeneity in the panel regression analysis. Additionally, because the contribution of one asset to a firm's profitability may depend on other assets, we need to examine the interactive relationships among the two intangibles, R&D assets and organizational capital, and one tangible capital, the physical assets. I conduct panel regression analyses with the fixed effect model, the random effect model, and the Hausman test to choose the correct model. The results are shown in Tables 5 to 7.

[7] The industry's average gross profit is an absolute number not a percentage.

Table 5: Pooled Industry Panel Regression – Fixed Effect Model

```
. xtset Industry Year
       panel variable:  Industry (strongly balanced)
        time variable:  Year, 1990 to 2010
                delta:  1 unit

. xtreg lnGrossProfit lnKRD lnKOC lnPPE lnKRDlnKOC lnKRDlnPPE lnKOClnPPE, fe

Fixed-effects (within) regression               Number of obs      =       189
Group variable: Industry                        Number of groups   =         9

R-sq:  within  = 0.8546                         Obs per group: min =        21
       between = 0.9490                                        avg =      21.0
       overall = 0.9017                                        max =        21

                                                F(6,174)           =    170.39
corr(u_i, Xb)  = -0.8341                        Prob > F           =    0.0000
```

lnGrossPro~t	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
lnKRD	1.439998	.3983047	3.62	0.000	.6538673	2.226128
lnKOC	-1.333184	.3005843	-4.44	0.000	-1.926445	-.7399235
lnPPE	.2757458	.4162582	0.66	0.509	-.5458195	1.097311
lnKRDlnKOC	-.0021448	.019092	-0.11	0.911	-.0398265	.0355369
lnKRDlnPPE	-.2055516	.0437451	-4.70	0.000	-.2918911	-.1192122
lnKOClnPPE	.2387186	.0568547	4.20	0.000	.1265049	.3509324
_cons	1.680433	1.822427	0.92	0.358	-1.916476	5.277342
sigma_u	.40355291					
sigma_e	.18246931					
rho	.8302572	(fraction of variance due to u_i)				

```
F test that all u_i=0:     F(8, 174) =    18.00                 Prob > F = 0.0000
```

Table 6: Pooled Industry Panel Regression – Random Effect Model

```
. xtreg lnGrossProfit lnKRD lnKOC lnPPE lnKRDlnKOC lnKRDlnPPE lnKOClnPPE, re

Random-effects GLS regression                   Number of obs      =       189
Group variable: Industry                        Number of groups   =         9

R-sq:  within  = 0.8506                         Obs per group: min =        21
       between = 0.9492                                        avg =      21.0
       overall = 0.9093                                        max =        21

                                                Wald chi2(6)       =   1052.16
corr(u_i, X)   = 0 (assumed)                    Prob > chi2        =    0.0000
```

lnGrossPro~t	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
lnKRD	1.509717	.3526263	4.28	0.000	.8185819	2.200852
lnKOC	-1.022344	.2649475	-3.86	0.000	-1.541631	-.5030563
lnPPE	.3882375	.3482767	1.11	0.265	-.2943723	1.070847
lnKRDlnKOC	-.0132347	.0161187	-0.82	0.412	-.0448269	.0183575
lnKRDlnPPE	-.2073083	.0407877	-5.08	0.000	-.2872507	-.1273659
lnKOClnPPE	.2230232	.0497514	4.48	0.000	.1255123	.3205341
_cons	-.8268244	1.737075	-0.48	0.634	-4.231429	2.57778
sigma_u	.16453014					
sigma_e	.18246931					
rho	.4484398	(fraction of variance due to u_i)				

```
.
```

Table 7: Pooled Industry Panel Regression – The Hausman Test

```
. hausman fixed random

                 ---- Coefficients ----
              |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
              |    fixed        random       Difference          S.E.
--------------+----------------------------------------------------------------
        lnKRD |   1.439998     1.509717       -.0697189        .1852061
        lnKOC |  -1.333184    -1.022344       -.3108404         .141964
        lnPPE |   .2757458     .3882375       -.1124917        .2279786
    lnKRDlnKOC |  -.0021448    -.0132347        .0110899        .0102318
    lnKRDlnPPE |  -.2055516    -.2073083        .0017567        .0158115
    lnKOClnPPE |   .2387186     .2230232        .0156954        .0275184
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(6) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       26.65
                Prob>chi2 =      0.0002
                (V_b-V_B is not positive definite)

.
```

Table 5 shows the result from the fixed effect analysis. After controlling for industry heterogeneity, R&D capital has a positive relationship with the industry's profitability and organizational capital has a negative relationship with the industry's profitability. Both are statistically significant. However, there is a negative but statistically insignificant relationship between R&D capital and organizational capital. Table 6 shows the result from the random effect analysis, which is similar to that from the fixed effect model. The Hausman Test is conducted to determine which model is appropriate to use. The test result is shown in Table 7. Based on the test result, we should use the fixed effect model estimation. Because the existence of industry heterogeneity, I conduct further analysis on the firm-level data for each industry.

5.2 **Industry-level Analysis**

In this section, I further divide the data by industry and conduct additional analysis. For each industry, I run a fixed effect model, a random effect model, and the Hausman test to determine which model estimation to use. Table 8 is a summary of the analysis results for the nine R&D intensive industries.

Table 8: Summary of Impacts of R&D Assets, Organizational Capital, Physical Assets, and Their Relationship on Profitability

Industry	RD	OC	PPE	RD*OC	RD*PPE	OC*PPE
Aerospace	-/	-/**	+/**	+/**	-/**	+/**
Communication	+/**	+/**	+/**	-/**	+/**	+/
Computer and Peripherals	+/**	+/**	-/	-/**	-/	+/**
Computer Systems Design	-/**	+/**	+/**	-/	+/**	-/**
Motor	-/	+/	+/**	+/**	-/*	+/
Navigational	-/**	+/**	+/**	+/	+/	-/
Pharmaceutical	-/**	+/**	+/**	+/**	+/**	-/**
Semiconductor	+/	+/	+/**	+/**	-/**	-/
Software	-/**	+/**	+/**	-/	+/	-/

Note: * 10% significant level. ** 5% significant level.

Table 8 shows that except for the communication, the computer peripheral and the semiconductor industries, the other six high-tech industries have negative R&D relationships with the industry's profitability.[8] However, during the same period of time, with the exception of the aerospace industry, industries have positive organizational capital contributions to the industry's profitability.[9] In general, there is a significant positive relationship between organizational capital and firm performance. Further, in Section 3 I show that the industry leader can better appropriate the returns from their investments in both intangibles, and maintain their advantage of organizational capital than that of R&D assets. Then, the question follows, why will high-tech firms still invest in R&D assets? Why not just invest in organizational capital and outsource R&D activities?

The answer seems to be related to the relationship between organizational capital and R&D assets. Brynjolfsson et al. (2002) find that firm performance depends both on the level of overall intangible capital and also on the interaction between different categories of intangible capital. They confirm a complementary relationship between computer investments and organizational capital. The complementary relationship indicates that the return of a firm's

[8] Note that the negative relationship is not statistically significant in the motor and the aerospace industries.
[9] Note that the positive relationship in the motor and the semiconductor industries are not statistically significant.

investment in computers also depends on its investment in organizational capital. Their finding is based on the study of the computer adoption industries, an information technology (IT) adoption industry instead of an IT producing industry. That is, they focus on examining the relationship between the adopted technology and organizational capital for the IT adoption industry. The debate on the impact of offshoring on the competitiveness of U.S. firms, however, is focused on the technology producing industries. In this research, I instead focus on examining the relationship between technology output, such as R&D assets, and organizational capital in the technology producing industries. Table 8 shows a substitute relationship between R&D assets and organizational capital in the communication, the computer and peripherals industries, the computer system design, and the software industries, and a complementary relationship for the other five R&D intensive industries.[10]

Combining the research results from this study and Brynjolfsson et al. (2002), we can summarize my findings as: among the technology producers, in the non IT-hardware industries, R&D capital has a complementary relationship with organizational capital; in the IT hardware industries, the relationship is substitute. Among the technology users, in the non-IT producing industries, computer capital has a complementary relationship with organizational capital.

If we ignore the industries with non-significant coefficients on R&D assets, organizational capital, and their interaction term, we can categorize the industries into two groups, the industries with a significant complementary relationship between the two intangibles and the industries with a significant substitute relationship. The former is the non IT-hardware industries, such as the pharmaceutical industry, and the latter is the IT hardware industries, such as the computer and peripherals and the communication industries.[11] Compared with the non-IT hardware industries, it is well recognized that the IT hardware industries have increasingly

[10] Note that the relationships in the computer system design, the navigational, and the software industries are not statistically significant.

[11] The only exception is the semiconductor industry, which belongs to the IT hardware sector. However, it is well known that unlike other industries in the IT hardware sector, the majority of offshore outsourcing contracts in the semiconductor industry go to the overseas foundries in Asia, which only conduct activities related to production. So, in this research, we categorize it into the non-IT hardware sector.

increased their scale and scope of offshoring outsourcing not only in production but also in R&D activities during the sample period (Li, 2008).

The relationship between intangibles is negatively related to the scale and the scope of offshore outsourcing in R&D activities. My analysis shows that, in the U.S. high-tech industries, organizational capital has a positive relationship with a firm's profitability.[12] Currently, U.S. firms in those high-tech industries keep organizational capital in house. However, in the IT hardware industries, return to R&D investment is negatively related to investment in organizational capital and we observe the industries with a higher degree of offshore outsourcing in R&D activities. In addition, in the non IT-hardware industries, return to R&D investment is positively related to investment in organizational capital and the industries are observed to have a lower degree of offshore outsourcing in R&D activities. Because the positive contribution of organizational capital to firms' profitability also depends on R&D assets, this motivates U.S. firms to keep R&D in house even though R&D assets have a negative contribution to their profitability during the sample period. Additionally, as argued by Brynjolfsson et al. (2000), certain organizational capital can facilitate the process of knowledge creation. A positive interaction relationship between R&D assets and organizational capital therefore provides U.S. firms with an incentive to invest R&D in house. However, in the IT hardware industries, because the negative contribution of organizational capital to a firm's profitability is related to investment in R&D assets, it tends to outsource R&D even though R&D assets have a positive contribution to its profitability during the sample period. For example, compared with firms in other industries, even though R&D assets have a positive relationship with a firm's profitability, U.S. firms in the computer and peripherals industry have a higher degree of outsourcing not only in production but also in R&D activities during the sample period (Li, 2008).

Lastly, combining the above findings with the industry ranking in terms of the annual stock size of R&D assets and organizational capital, I find that the IT hardware industries have a lower ranking in the stock of intangibles and the non IT-hardware industries have a higher ranking. The findings show that in the globalization era, industries with a higher degree of offshore outsourcing will invest less in intangibles. Interestingly, combining this finding with

[12] The only exception is the aerospace industry, where the relationship between organizational capital and a firm's profitability is negative but not statistically significant.

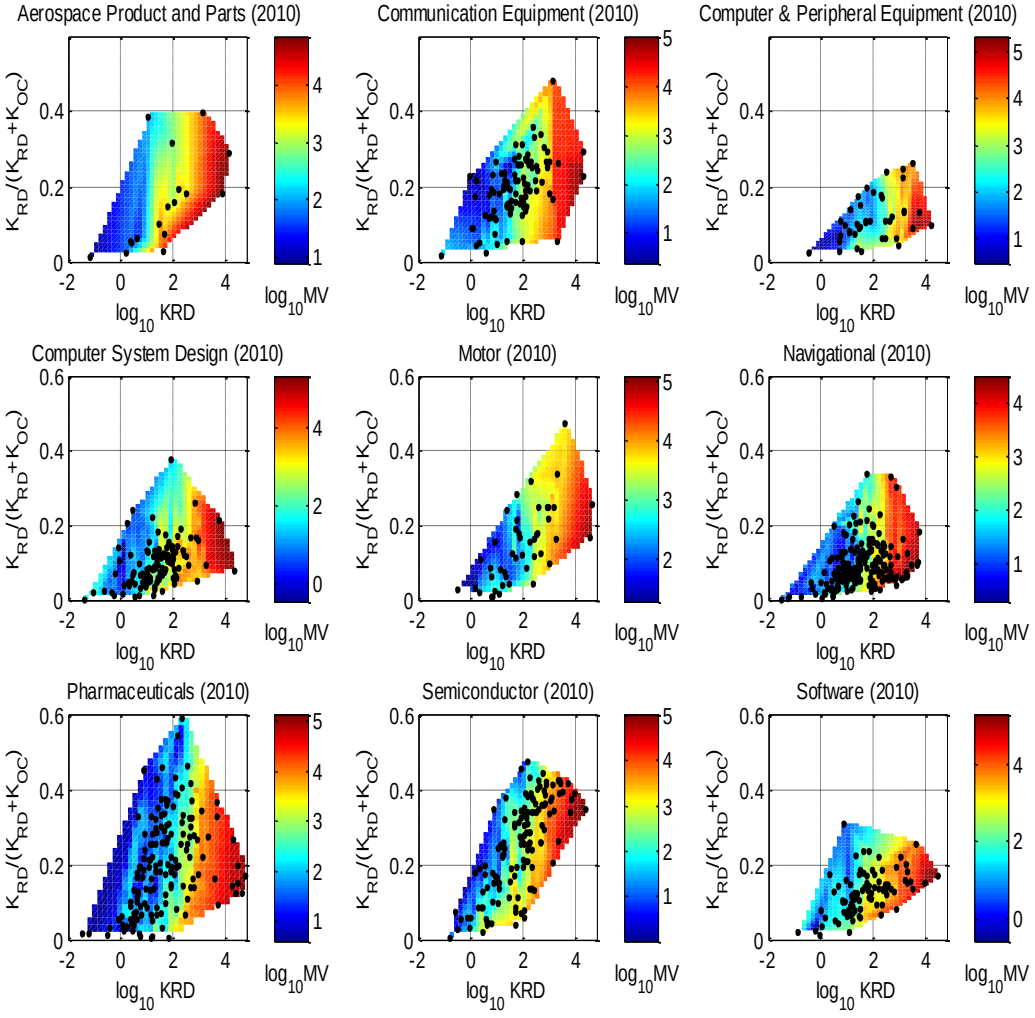
productivity growth rates for the corresponding industries during the sample period (Jorgenson et al., 2014), I find that industries with a higher degree of offshore outsourcing have higher productivity growth.

6. Market Value, R&D Assets and the Ratio of R&D to Organizational Capital

In this section, I examine the relationship between the market values of firms and the ratio of their R&D assets to organizational capital. Figure 1 shows the three-dimensional relationship between the market values, the ratio of R&D assets to organizational capital, and the log value of R&D assets of firms across the nine R&D intensive industries in 2010. Note that the ratio of R&D assets to organizational capital is a parameter that indicates the relative share between the R&D assets and organizational capital. Different colors indicate the market values of firms with the red color indicating highest market values and the blue color the lowest ones.

Figure 1shows several important facts: First, for all R&D intensive industries, firms with higher R&D assets have higher market values. Second, relative to the semiconductor industry, the computer and peripherals industry has a lower ratio of R&D assets to organizational capital. The result is consistent to the industry ranking in terms of stocks of organizational capital and R&D assets in Table 4. Third, in the pharmaceutical industry, the ratio of R&D assets to organizational capital varies a lot across firms. However, the ratio converges to a much narrower range for firms with top market values. The ratio is apparently lower than the ratios for most firms. Given these top firms have highest level of R&D assets, the stock of their organizational capital is much larger than most firms as well. Last but not least, compared with the software and the computer and peripherals industries, the pharmaceutical and the semiconductor industries have more firms with higher ratios of R&D assets to organizational capital.

Figure 1: Market Value, R&D Assets, and Ratio of R&D to Organizational Capital



7. Conclusion

In the era of globalization, U.S. high-tech firms have increasingly expanded the scale and scope of their offshoring activities to reap the advantages of lower production costs, and greater strategic and operational flexibilities (Li, 2008). Under this trend, the central debate on the impacts of offshore outsourcing is whether U.S. high-tech firms can maintain its core competencies in intangibles, such as R&D assets and organizational capital. To contribute to the debate, this paper focuses on nine R&D intensive industries, which are the major technology producing industries in the U.S. I develop a forward-looking profit model to estimate the depreciation rates of R&D assets and organizational capital to construct the stocks of both intangibles. This paper uses the data on constructed stocks of intangibles and firm performance to examine whether industries with a higher degree of offshoring outsourcing have a different investment pattern in intangibles from their counterparts.

My analyses show that higher intangible intensive industries are more competitive in the global market. The industry ranking in terms of the annual stock of R&D assets and organizational capital are the same and the ranking is in general consistent with the relative global competitiveness of U.S. industries. This result indicates that in the global market, U.S. high-tech industries cannot compete successfully only with technology. Organizational capital does matter as well. In addition, even in the nine U.S. R&D intensive industries, the estimated size of organizational capital is larger than that of R&D assets[13] However, note that U.S. top high-tech market performers maintain a close ratio of R&D assets to organizational capital.

Moreover, the relationship between intangibles is negatively related to the degree of offshore outsourcing in intangibles. My empirical analysis shows that return to investment in organizational capital is negatively related to investment in R&D in the IT hardware industries and positively related in the non IT-hardware industries.[14] Given the fact that compared with the non IT-hardware industries, the IT-hardware industries have a much higher degree of offshore outsourcing in R&D activities, we can reasonably conclude the negative relationship between

[13] This study shows that even in the high-tech industries, the size of organizational capital is larger than that of R&D assets. Given the fact that in the non high-tech industries, firms will invest more in organizational capital than in R&D assets, we can reasonably reach the conclusion that in the U.S. economy, the size of organizational capital is larger than that of R&D assets.

[14] The result differs from that in Brynjolfsson et al. (2002) where they examine the computer adoption industry and find a complementary relationship between computer investments and organizational capital. The study here focuses on the technology producing industries.

intangibles and the degree of offshore outsourcing in R&D activities. This phenomenon is further observed by the industry ranking in terms of the stock of intangibles. U.S. high-tech industries with a higher degree of offshore outsourcing invest less in intangibles than their counterparts.

My analysis shows that U.S. high-tech industries with a higher stock of intangibles perform better in the global market. However, when we combine the results with the industry-level productivity growth rates calculated in Jorgenson et al. (2014), surprisingly, industries with a higher degree of offshore outsourcing have a higher productivity growth rate than their counterparts during the sample period. This may be mainly due to the substitution effect that firms with a higher degree of offshore outsourcing can reap more advantages of cheaper inputs and production costs.[15]

While this study provides the first complete set of industry-specific depreciation rates of business R&D capital and organizational capital for all U.S. major R&D intensive industries, future research can make improvements in several areas. First, the current model assumes that intangibles can provide a firm only the benefits of profit increase but not demand expansion. In future research, we can modify the model to relax the assumption. Second, the current model assumes decreasing marginal returns in intangible investments and innovations to be incremental. Future research can relax these two assumptions and modify the model to be applicable to the industry with increasing returns in intangible investments and drastic innovations. Lastly, the current research only examines whether industries with a higher degree of offshore outsourcing have a different investment pattern from their counterparts. When a more detailed level of offshore outsourcing in intangibles data is available, future research can conduct an analysis to identify the causal relationship between offshore outsourcing and intangible investments.

[15] The result is also consistent to the finding in Berndt and Morrison (1995) using data on two-digit manufacturing industries from 1968 to 1986 to find a negative relationship between productivity growth and the high-tech intensity of capital stock.

Appendix: The Non-linear Generalized Method of Moments Approach

I simplify and estimate the model with the nonlinear generalized method of moments (GMM) approach. In Equation (4),

$$\frac{\theta_i}{I_\Omega \exp\left[-\frac{IC_i}{\theta_i}\right]} = \sum_{j=0}^{J-1} \frac{q_{i+j+d}(1-\delta)^j}{(1+r)^{j+d}}. \tag{A.1}$$

Define $f(IC;\theta,\delta) \equiv \frac{\theta_i}{I_\Omega \exp\left[-\frac{IC_i}{\theta_i}\right]} - \sum_{j=0}^{J-1} \frac{q_{i+j+d}(1-\delta)^j}{(1+r)^{j+d}}$, and $\theta_i \equiv \theta_0(1+G)^i$, where G is the growth rate of θ_i. Still describing the exponential growth, θ_i is now written as $\theta_0(1+G)^i$. To reduce the number of parameters, we estimate G by fitting the data of the intangible investment to the equation, $IC_i = IC_0(1+G)^i$. Therefore, $\frac{\theta_i}{I_\Omega \exp\left[-\frac{IC_i}{\theta_i}\right]} = \frac{\theta_0(1+G)^i}{I_\Omega \exp\left[-\frac{IC_i}{\theta_0(1+G)^i}\right]}$ or $\frac{(1+G)^i}{I_\Omega} \cdot \theta_0 \cdot \exp\left[\frac{IC_i}{\theta_0(1+G)^i}\right]$. In addition, by changing the range of j from $[0, J]$ to $[0, \infty)$, we get:

$$\begin{aligned}\sum_{j=0}^{J-1} \frac{q_{i+j+d}(1-\delta)^j}{(1+r)^{j+d}} &= \sum_{j=0}^{\infty} \frac{q_{i+j+d}(1-\delta)^j}{(1+r)^{j+d}} \\ &= \frac{q_i(1+g)^d}{(1+r)^{d-1}(r+\delta-g+g\delta)} \\ &\cong \frac{q_i(1+g)^d}{(1+r)^{d-1}(r+\delta-g)},\end{aligned} \tag{A.2}$$

with the assumption that $d = 1$ and $q_{i+j} \equiv q_i(1+g)^j$.

We can define the nonlinear residual as:

$$\varepsilon_i \equiv \frac{(1+G)^i}{I_\Omega} \cdot \theta_0 \exp\left[\frac{IC_i}{\theta_0(1+G)^i}\right] - \frac{q_i(1+g)^d}{(1+r)^{d-1}(r+\delta-g)}, \tag{A.3}$$

and choose the instrument variables as $z_i = [1\ IC_{i-1}\ q_{i-1}]'$. The choice of instrument variables is based on the model assumption that in a forward-looking profit model, the previous intangible investments and sales will not affect the decision of intangible investments in the current period and the future sales related to current period's investment decision.

Let $m(\Theta) \equiv z_i \varepsilon_i$ and $s(\Theta) \equiv E(m(\Theta)m(\Theta)')$.

The corresponding analog sample moments are:

$$\widehat{m(\Theta)} = \frac{1}{n-1}\sum_{i=2}^{n} \begin{bmatrix} \frac{(1+G)^i}{I_\Omega} \cdot \theta_0 \exp\left[\frac{IC_i}{\theta_0(1+G)^i}\right] - \frac{q_i(1+g)^d}{(1+r)^{d-1}(r+\delta-g)} \\ IC_i \cdot \quad \frac{(1+G)^i}{I_\Omega} \cdot \theta_0 \exp\left[\frac{IC_i}{\theta_0(1+G)^i}\right] - \frac{q_i(1+g)^d}{(1+r)^{d-1}(r+\delta-g)} \\ q_i \cdot \frac{(1+G)^i}{I_\Omega} \cdot \theta_0 \exp\left[\frac{IC_i}{\theta_0(1+G)^i}\right] - \frac{q_i(1+g)^d}{(1+r)^{d-1}(r+\delta-g)} \end{bmatrix}, \qquad \text{(A.4)}$$

and $\widehat{s(\Theta)} = \frac{1}{n-1}\sum_{i=2}^{n} m\left(\widehat{\Theta}\right)m(\widehat{\Theta})'$.

Define $\Theta \equiv [\Theta_1 \ \Theta_2]' \equiv [\theta_0 \ \ \delta]'$ and

$$M(\Theta) \equiv \frac{\partial m(\Theta)}{\partial \Theta} = \begin{bmatrix} \frac{\partial m_1}{\partial \Theta_1} & \frac{\partial m_1}{\partial \Theta_2} \\ \vdots & \vdots \\ \frac{\partial m_5}{\partial \Theta_1} & \frac{\partial m_5}{\partial \Theta_2} \end{bmatrix}. \qquad \text{(A.5)}$$

The corresponding sample analog is:

$$\widehat{M(\Theta)} \equiv \frac{1}{n-1}\sum_{i=2}^{n} \begin{bmatrix} m_{11}(\widehat{\Theta}) & m_{12}(\widehat{\Theta}) \\ \vdots & \vdots \\ m_{51}(\widehat{\Theta}) & m_{52}(\widehat{\Theta}) \end{bmatrix}. \qquad \text{(A.6)}$$

Note that GMM estimators are asymptotic normal: $\widehat{\Theta} \sim N\left(\Theta, \frac{V}{n-1}\right)$ where $V = [M' s^{-1} M]^{-1}$.

To derive the optimal solution for Θ, we solve the following optimization problem by using an iterative GMM estimation approach with the initial weight matrix as an identity matrix:

$$\widehat{\Theta} = \underset{\Theta}{argmin}\ m(\Theta)'\widehat{W}_K m(\Theta) \qquad \text{(A.7)}$$

I continue the iterative operations until the change of the value of the objective function is stabilized.

Table 10 is the comparison of the estimations between organizational capital and R&D capital based on the nonlinear GMM approach with a 1-year gestation lag. We can see that most of the nonlinear GMM estimates and standard errors are higher than those of the NLLS ones across industries shown in the earlier section.

Table 9: Depreciation Rates of R&D Capital and Organizational Capital Based on the Non-Linear GMM Approach

Industry	Organizational Capital	R&D Capital
Computers and peripheral equipment	15% (11%)	36% (15%)
Software	7% (1%)	31% (4%)
Pharmaceutical	1% (12%)	18% (32%)
Semiconductor	15% (3%)	26% (5%)
Aerospace	12% (1%)	4% (84%)
Communication equipment	16% (2%)	40% (17%)
Computer system design	4% (7%)	87% (70%)
Motor vehicles, bodies and trailers, and parts	10% (9%)	31% (26%)
Navigational, measuring, electromedical, and control instruments	8% (1%)	28% (8%)
Scientific research and development		34% (5%)

Notes: 1. In the nonlinear GMM approach, we use a 1-year gestation lag for the typical intangible investment. 2. In general, the nonlinear GMM estimates have higher standard errors than those associated with the nonlinear lease square estimates due to the lack of large sample.

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