

Offshoring and U.S. Innovation Capacity

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Abstract

The degree of offshoring has increased rapidly in past decades. Because of this trend, economists have been debating whether offshoring is reducing U.S. innovation. To shed light on this question, I used Compustat data and a model developed by Li and Hall (2016) to measure investment and capital stock in R&D and organizational capital for all key non-financial U.S. industries during the period of 1995 to 2011. Then, I used the world input-output database to calculate the annual value added per export ratio, a measure of an industry's degree of offshoring, for all key U.S. non-financial industries. Lastly, I used those estimates to examine how the increasing degree of offshoring impacts the U.S. innovation capacity.

The results show that: first, as the degree of offshoring increases, U.S. industry-level TFP increases as well. Second, as the degree of offshoring increases, most U.S. high-tech industries increase the intensity of their intangible assets. Industries with a higher degree of offshoring invest more in intangibles. Third, in addition to R&D assets, organizational capital contribute positively to an industry's TFP as well. And, both R&D assets and organizational capital are complementary in terms of the contribution to a firm's TFP. Last but not least, although low cost import competition affects the innovation rates of OECD developed countries (Bloom et al., 2015) in the area of technology, U.S. industries, especially high-tech industries, have been increasingly invested more resources on organizational capital.

1. Introduction

The scale and scope of offshoring has increased rapidly in past decades, and the globalization of innovation is particularly proceeding at an exceptionally fast pace (Li, 2008; Kerr and Kerr, 2015). As shown in the Bureau of Economic Analysis multinational firms' data, the share of R&D for U.S. companies conducted by their foreign operations rose from 6% in 1982 to 14% in 2004. As a result, the central debate on the impact of offshoring is whether or not the increasing global division of labor is reducing U.S. innovations (Keller, 2010). Freeman (2006) argues that the globalization of science and engineering can threaten U.S. economic and technological leadership and diminish U.S. comparative advantage in high-tech sectors. However, other leading economists have long argued that, according to the traditional trade theory, the increasing global division of labor has enabled innovations to become a principal driver of the competitiveness of U.S. industries (Bhagwati, 2004). In other words, under globalization, the U.S. industries will still specialize in higher value added activities, innovations. Therefore, given the fact that U.S. firms are increasing offshoring innovations and that U.S. industries will still specialize in innovations, it is important to examine what the impacts of offshoring on the dynamic features of U.S. innovations are.

To understand what happens to U.S. innovations, we need to adopt the broad definition of innovation (Keller, 2010). Innovation is the attempt to try out new or improved products, processes, or ways to do things (Bell and Pavitt, 1993; Kline and Rosenberg, 1986; Keller, 2010). It includes not only technologically new products and processes but also improvements in areas such as logistics, distribution, and marketing. That is, the innovation is defined as intangibles¹ which include R&D assets and organizational assets. Most existing studies on the impacts of offshoring on innovations are mainly focused on the part of R&D assets, measured by the proxy of R&D investments and/or patents. However, as U.S. firms increase offshoring R&D activities, what becomes the main content of the U.S. innovations? That is, what type of intangibles is increasing dominant in the U.S. innovations?

¹ 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).

Therefore, the key outstanding question is whether industries with a higher degree of offshoring invest more in intangibles, invest differently among intangibles, and how the investment behavior affects the resulting composition of U.S. intangibles. Specifically, if the U.S. industries place specialization and comparative advantage at the center of trade growth, as predicted by trade theories, we should see that, as the degree of offshoring increases, U.S. investments in intangibles increase and positively contribute to the U.S. value added in exports. In addition, the rise of offshoring may affect the investment behavior among different types of intangibles unevenly, and previous research has shown that the intensity of intangibles is positively correlated to productivity growth (Griliches, 1986; Eifeldt and Papanikolaou, 2013). Therefore, it is important to examine how the increasing degree of offshoring affects the intensity of intangibles. Moreover, as the global division of labor in innovation continues to increase, we need to further examine how it shapes the composition of U.S. innovation across industries and whether certain types of innovations become more important for the industry-level TFP growth. To my knowledge, no prior research has answered any of the above questions.

This paper aims to fill in the gaps in our understanding about the impact of offshoring on U.S. innovations. Before conducting the analysis, we need to measure the innovations of U.S. industries, defined as intangibles, including R&D assets and organizational capital. To measure intangibles, economists generally encounter the problems that there is no arms-length market for most intangibles and that 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 research in this area interest is due largely to the dearth 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) have made a significant step forward by collecting related data through a new pilot survey on U.S. management practices in 2011. The collected data include qualitative measurements of structured management practices, which raise the concern of measurement units, and cover the years between 2005 and 2010. To achieve the goal of this research, panel data on a long spending time series is needed to construct the stock of organizational capital.

Following earlier research, I use 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 ways clearly support this approach.

In this research, I adopt the R&D depreciation model that Li and Hall (2016) developed, which improves the original model developed by Li (2012) to estimate the depreciation rate of the organizational capital. I also use the perpetual inventory method to construct the stock of organizational capital for all U.S. industries. The same procedure is applied to the estimation of R&D depreciation rates and the construction of R&D capital stock for all U.S. industries as well.

As to the measurement of the degree of offshoring, economists used to rely on the data on gross trade. However, gross trade data include substantial double-counting, especially for the goods that enter and exit national borders multiple times, which have become more typical under the increasing degree of international production fragmentation. As a result, gross exports tend to overstate the amount of domestic value-added in export (Johnson, 2014), and

gross trade is an increasingly misleading guide to how value added is exchanged between countries.

In this paper, I use the value-added per export (VAX) ratio to measure the degree of offshoring. Developed by Noguera and Johnson (2012), this new index removes the double counting issues in the gross trade data and better measures the degree of international production fragmentation. The calculated VAX ratio can serve as an index to reflect the degree of offshoring. For example, the ratio of value-added to gross trade has declined over time, down from around 85 percent in the early 1970s (Johnson and Noguera 2014). This decline implies that there is more double counting in gross trade data now than in the past. And, compared with the service sector, the manufacturing sector in general has a smaller VAX ratio because it has a higher degree of offshoring (Johnson, 2014). Since the VAX ratio varies and the growth of intangibles varies across industries, I construct the industry-level panel data for the analysis on the relationship between the VAX ratio and the intangibles.

This paper has several key contributions and findings. First, I construct the industry panel data on R&D assets, organizational capital, and the VAX ratios for 18 U.S. non-financial industries during the period of 1995 to 2011, a period with a rapid increase in offshoring. It should be noted that Johnson and Noguera (2014) find that the decline in value-added relative gross exports occurs almost entirely after 1990 (Johnson and Noguera 2014). Second, using the newly constructed data, I find that as the degree of U.S. offshoring increases, U.S. industry-level TFP increases as well. Third, as the degree of offshoring increases, most high-tech industries increase the intensity of their intangible assets. In particular, the computer and peripheral industry, which is the highest offshoring industry in the high-tech sector, shows the most dramatic increase in the intensity of intangible assets and in the ratio of organizational capital to R&D assets. That is, in the rise of globalization, U.S. high-tech sector has become more intangible intensive. Third, even in R&D intensive industries, the estimated size and the growth rate of organizational capital are larger than those of R&D assets. Lastly, as the degree of offshoring increases, U.S. intensity of intangibles increases as well. That is, as the degree of offshoring increases, U.S. still increases its innovations.

The rest of paper proceeds as follows. Section 2 describes the theoretical models for deriving the VAX ratio and the depreciation rates of intangibles. Section 3 describes the data, the estimations of depreciation rates, and the VAX ratio. Section 4 shows the panel regression analysis for the degree of offshoring and U.S. innovation intensity. Section 5 concludes.

2. Models for measure VAX ratio and depreciation rates of intangibles

2.1 The Measurement of the VAX ratio

The Derivation of the Value Added Per Export (VAX) Ratio

In this section, I briefly describe the derivation of the VAX ratio as introduced by Johnson and Noguera (2012). Here, I define i as the source country, j the destination country, s the source industry, s' as the destination industry and t as the year. The market clearing condition in value terms is:

$$y_{it}(s) = \sum_j f_{ijt}(s) + \sum_j \sum_{s'} m_{ijt}(s, s')$$

where $y_{it}(s)$ is the value of total output in industry s of country i , $f_{ijt}(s)$ is the value of final goods shipped from country i to country j in industry s , and $m_{ijt}(s, s')$ is the value of intermediate goods from industry s used in industry s' . Following Johnson and Noguera, we define the exports $x_{ijt}(s)$ as the total number of final goods and intermediate goods exported to country j . Then, the market clearing condition states that total output is divided between gross exports (sum of $x_{ijt}(s)$, domestic final use $f_{ijt}(s)$ and domestic intermediate use (sum of $m_{iit}(s, s')$)).

Stacking the market clearing conditions by country, we have both total output, $y_{it}(s)$ and final goods $f_{ijt}(s)$ as $S \times 1$ vectors, while the intermediate goods, $m_{ijt}(s, s')$ are an $S \times S$ matrix.

Then, we define $A_{ijt}(s, s')$ as the proportion of intermediate inputs used in total output where

$A_{ijt}(s, s') \equiv \frac{m_{ijt}(s, s')}{y_{jt}(s')}$. This allows us to rewrite the market clearing conditions as an $S \times N$ matrix

where:

$$y_t = A_t y_t + f_t$$

where $A_t = \begin{pmatrix} A_{11t} & \dots & A_{1Nt} \\ \vdots & \ddots & \vdots \\ A_{N1t} & \dots & A_{NNt} \end{pmatrix}$, $y_t = \begin{pmatrix} y_{1t} \\ \vdots \\ y_{Nt} \end{pmatrix}$, and $f_t = \begin{pmatrix} \sum_j f_{1jt} \\ \vdots \\ \sum_j f_{Njt} \end{pmatrix}$.

Next, we solve for the total output and rewrite the total output vector as:

$$y_t = (I - A_t)^{-1} f_t.$$

We define the ratio of total intermediate inputs in country l as the total amount of inputs collected from all other industries and countries divided by the total output in country i , so that the ratio $r_{it}(s)$ is defined as

$$r_{it}(s) = 1 - \sum_j \sum_{s'} A_{jit}(s', s),$$

Then we multiply this ratio by the individual elements of the total output vector to obtain the measure of value-added trade from country i to country j ,

$$va_{ijt}(s) = r_{it}(s) y_{ijt}(s).$$

As Johnson and Noguera (2012) noted, the framework above provides details of a circular process of production where inputs and outputs are continuously transferred from one country-industry to another, which implies an infinite number of production stages. Using a two-stage sequential production process, Johnson and Noguera (2012) construct values of gross exports and value-added exports using the input output tables with the following components:

$$\bar{x}_{ij} = f_{ij} + A_{ij} f_{jj} + A_{ij} f_{ji} + \sum_k A_{ij} f_{jk}, \text{ and}$$

$$\bar{v}a_{ij} = f_{ij} + A_{ij} f_{jj} + A_{ii} f_{ij} - \sum_k A_{ki} f_{ij} + \sum_{k \neq i, j} A_{ik} f_{kj}.$$

We can then define the approximate VAX ratio as:

$$\overline{VAX}_{ij} = \frac{\bar{v}a_{ij}}{\bar{x}_{ij}}.$$

2.2 The Measurement of Depreciation Rates of Intangibles

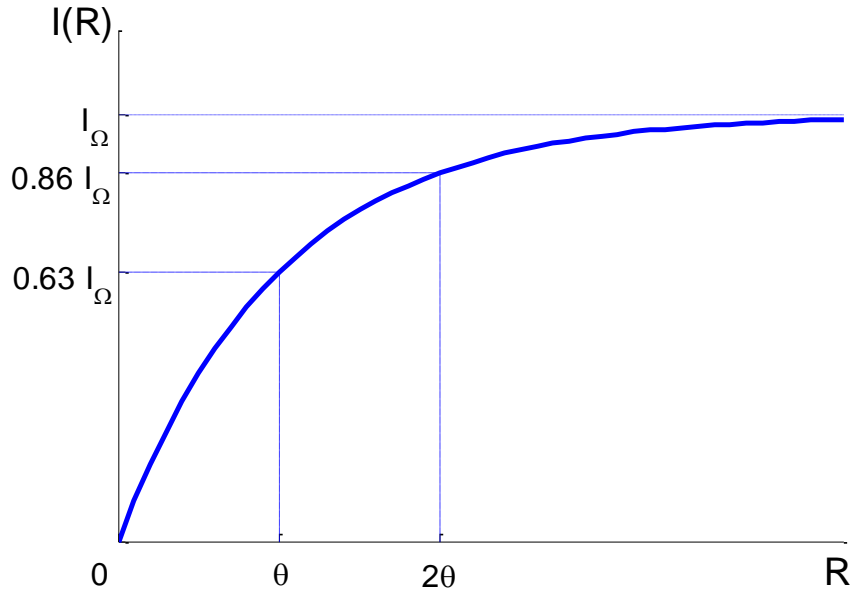
The R&D investment model follows the forward-looking profit model in Li and Hall (2016). The premise of the model is that business R&D capital depreciates because its contribution to a

firm's profit declines over time. R&D capital generates privately appropriable returns; thus, it depreciates when its appropriable return declines over time (Hall, 2007). 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:

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

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 increase in 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. 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.

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



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

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

with $I''(R) < 0$. $I'(R) = I_{\Omega} \exp \left(\frac{-R}{\theta} \right) > 0$, and $I'(0) = I_{\Omega} = \lim_{R \rightarrow \infty} I(R)$. Figure 1 depicts how the

function I gradually increases asymptotically to I_{Ω} with R , the current-period R&D investment.

The increase in profit rate due to R&D investments, $I'(R)$, has an upper bound at I_{Ω} when $R = 0$.

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 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.

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

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

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. Using this assumption, Equation (3) becomes:

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

Note that because of our assumptions of constant growth in sales and R&D, there is no longer any role for uncertainty in this equation, and therefore no error term. Assuming profit maximization, the optimal choice of R_t implies the following first order condition:

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

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 .

Data

3.1 Data on International Trade

For the measurement of offshoring, I use the data from the World Input Output Database (WIOD). The database contains data for 35 industries and 41 countries, including the rest of world (ROW) as a country, and covers the period of 1995 to 2011. The data is used to construct bilateral value-added trade. Therefore, the data for each year are essentially a 1435 x 1435 matrix.

Data on Investments in innovation, R&D Assets and Organizational Capital

As mentioned earlier, there has been a dearth of data for organizational capital. To resolve this 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, and the survey collected data on structured management practices in 2005 and 2010. Nonetheless, the qualitative questions in the survey raise concerns about the measurement units for the answers to these questions. 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). A large panel data set from an improved survey in the future will no doubt enhance our understanding 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 in the survey data.

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 concept 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; Bloom et al., 2012). 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; Tronconi and Vittucci Marzetti, 2011; Eisfeldt and Papanikolaou, 2013; Chen and Inklaar, 2015). Firms report this expense in their annual income statements, and 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.

Eisfeldt and Papanikolaou (2013) use five ways to validate SG&A expenditures as a measure for a firm's investment in organization capital, and the results indicate that four out of five methods show clear support to this approach. For example, this 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 all U.S. industries. The data is from the company-based Compustat dataset and covers the period of 1996 to 2015. People might be concerned whether the Compustat dataset that only covers public firms can represent the whole economy well. In fact, as indicated by the NSF survey data for 1999 (NSF 2005), 83% of all manufacturing R&D belongs to the parent companies of U.S. multinational firms. The NSF survey data implies that larger companies account for a significant portion of R&D activities in the economy and that the use of Compustat data should well represent the

economy as a whole. Moreover, the latest OECD science, technology and industry scoreboard indicates that more than 60 percent of global R&D is done by only 250 companies (Financial Times, November 2015).

Additionally, to conduct analysis under the framework of the world IO table, we need to make the industry classification consistent between the data from the Compustat dataset based on SIC codes and the WIOD based on NAICS codes. Following the industry classification in the World KLEMS, I classify the SIC codes into NAICS code and group them into the 35 industry categories listed in the world IO table. The level of details in the SIC codes is 4-digit industry level, which is critical to calculate the more accurate and reliable depreciation rate of intangible capital, given the fact that different industries exhibit different paces of technological progress and degrees of market competition. After compiling the detailed table of the 35 world IO industries and their correspondent SIC codes, I compiled the industry-level data on sales, R&D expenditures, SG&A expenditures, gross profits, market values, and PP&E (which is the tangible asset and a stock concept), at the 4-digit SIC codes. The data cover the whole economy.

To conduct the estimation, I use the annual average sales, R&D investments, and SG&A expenditures for each industry. The depreciation rates of R&D capital and organizational capital, both at the 4-digit SIC level, are computed separately. I then constructed the industry-level stocks of organizational capital and R&D capital at the 4-digit SIC level and aggregated them to the industries following the world input-output industry categories.

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

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

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, l_Ω is set to be the average return rates of all assets for non-financial corporations during 1987-2008, 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 .

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.² As to the gestation lag for organizational capital, I use a one-year gestation lag for organizational capital. No previous research has developed a model to estimate the depreciation rate of organizational capital. Corrado et al. (2005) assumes a 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 as adopted by Fraumeni and Okubo (2005) in their work on R&D investments. 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 . Given these assumptions, δ and θ are estimated by nonlinear least squares (NLLS), using equation (6).

Industry-level VAX Ratios

With the VAX ratio defined, I use the world input output database to calculate the value added trades between the U.S. industries and other countries in each year. I then use the value added trade data to calculate the VAX ratio between the U.S. industries and other countries in each year. Same procedures are applied to calculate the VAX ratio between China's, Germany's, and Japan's industries and the U.S. in each year. Additionally, for the general VAX ratio between the U.S. industries and other countries to summarize the results and avoid the problem of

² The NSF 2010 Business R&D and Innovation Survey (BRDIS) received 6,381 responses from 39,968 firms across 38 industries.

outliers, I calculate the annual median value of the VAX ratio in each U.S. industry for the period of 1995 to 2011. The results cover 35 different industry sectors.

In general, as shown in Johnson and Noguera (2012), the manufacturing sector has a smaller VAX ratio than non-manufacturing sector, which implies that the manufacturing sector has a higher degree of international production fragmentation. And, among the manufacturing sector, the industry that has a higher degree of technology capability also has a higher value of VAX ratio, reflecting that the industry is engaging in higher value added activities.

3.4 Industry-level Constant Depreciation Rates of R&D Assets and Organizational Capital

In this research, we construct the stock of R&D assets and organizational capital from 1995 to 2015. The innovation data from Compustat cover the whole period of the data in the world input output table (WIOT). I apply the steady-state model as described in the previous section to estimate the depreciation rates of R&D assets and organizational capital for the industries covered in the WIOT. Table 1 shows the depreciation rates of R&D assets and organizational capital for the industries where data are available for conducting the estimation.

**Table 1: Depreciation Rates of R&D Assets and Organizational Capital
for U.S. Non-financial Industries**

Industry	NAICS Group or single NAICS	δ_{RD} [%]	δ_{OC} [%]
1 Agriculture, Hunting, Forestry and Fishing	11	N/A ³	N/A
2 Mining and Quarrying	21	68.60	50.70
3 Food, Beverages and Tobacco	311, 3122	N/A	8.41
4 Textiles and Textile Products	313, 314	N/A	4.5
5 Leather, Leather and Footwear	316	N/A	N/A
6 Wood and Products of Wood and Cork	321, 337	70.84	37.21
7 Pulp, Paper, Paper , Printing and Publishing	322, 323, 5111	82.6	15.80
8 Coke, Refined Petroleum and Nuclear Fuel	324	N/A	75.27
9 Chemicals and Chemical Products	325 (x 3254)	65.93	8.93
	3254	9.94	2.59
10 Rubber and Plastics	326	N/A	14.10
11 Other Non-Metallic Mineral	327	N/A	N/A
12 Basic Metals and Fabricated Metal	331	N/A	67.80
	332	43.73	18.98
13 Machinery, Nec	333	61.49	17.79
14 Electrical and Optical Equipment	3341	27.98	12.88
	3344	27.18	31.59
	3342	34.55	18.80
	3343-6	42.24	11.09
	335	36.97	20.39
15 Transport Equipment	3361-3	26.24	16.20
	3364	34.50	25.90
	3366, 3369	35.38	6.64
16 Manufacturing, Nec; Recycling	339	85.78	3.70
17 Electricity, Gas and Water Supply	22	N/A	N/A
18 Construction	23	37.29	32.10
19 Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel	441	N/A	12.90
20 Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	42	N/A	50.73
21 Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	44 (exclude 441)	N/A	14.10
22 Hotels and Restaurants	721, 722	N/A	27.40

³ N/A indicates no data or data are insufficient for calculating the R&D stock and OC stock.

23-25 Inland, Water, and Air Transport, and other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	48	N/A	42.46
27 Post and Telecommunications	515, 5175	N/A	11.50
	517(x5175)	69.12	9.45
29 Real Estate Activities	531	N/A	33.70
30 Renting of M&Eq and Other Business Activities	5112	16.90	7.83
	5182	30.32	13.99
	532_533	18.86	21.52
	5411	N/A	N/A
	5415	42.45	15.11
	5417	32.60	22.25
	541 (x5411, x5415, x5417), 561	N/A	23.40
31 Public Admin and Defense; Compulsory Social Security		N/A	N/A
32 Education		N/A	N/A
33 Health and Social Work	621-4	N/A	40.12
34 Other Community, Social and Personal Services	512, 562, 711, 713	N/A	36.10
35 Private Households with Employed Persons		N/A	N/A

The results in Table 1 show at least two patterns. First, R&D assets depreciate faster than organizational capital in all industries in the world input output table⁴. Second, most U.S. service industries, except some sub-industries in industry No. 30, do not have R&D assets⁵ but do have significant organizational capital stock. Because those industries have consistently invested in the areas such as marketing and business models, we expect them to have accumulated a significant portion of organizational capital.

3.5 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 all industries. To construct the stock of each type of intangible capital

⁴ Some industries do not have data on R&D assets so we cannot compare the depreciation rates between the two assets.

⁵ Most service industries show no or very little investment data on R&D assets.

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. 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. I set the initial capital stock at the beginning to be zero and conduct the analysis without the first three-year data that were more influenced by the initial value. The time series of the stocks of R&D assets and organizational capital cover the period of 1990 to 2015.

There are several key findings from the newly constructed stocks of R&D assets and organizational capital. First, in the industries with both R&D assets and organizational capital, except the semiconductor industry, the growth rate of organizational capital is greater than that of R&D assets. Second, high-tech industries with a higher degree of offshore outsourcing have become more intangible intensive and organizational capital intensive. Figure 2 shows that the computer and peripheral equipment industry has the fastest growth rate of intangible capital and the fastest growth rate of the ratio of organizational capital to total intangible capital among the high-tech sector. As shown in Li (2008), compared with other high-tech industries, this industry also has the highest degree of offshore outsourcing. Navigational, measuring, electromedical, control instrument manufacturing industry has a mild increase in the organizational capital ratio. The organizational capital is quite steady in the pharmaceutical, the software, and the communication industries. Lastly, in addition to R&D assets, organizational capital has a statistically positive relationship with each industry's TFP level. Table 2 shows the panel regression results for 18 U.S. non-financial industries, for the manufacturing sector only, and for the high-tech sector only. The results indicate that the organizational capital of high-tech sector contributes more to each industry's TFP level than those of other sectors do.

Figure 2: The Intensity of Intangible Capital and the Ratio of R&D Assets to Organizational Capital for U.S. High-tech Industries

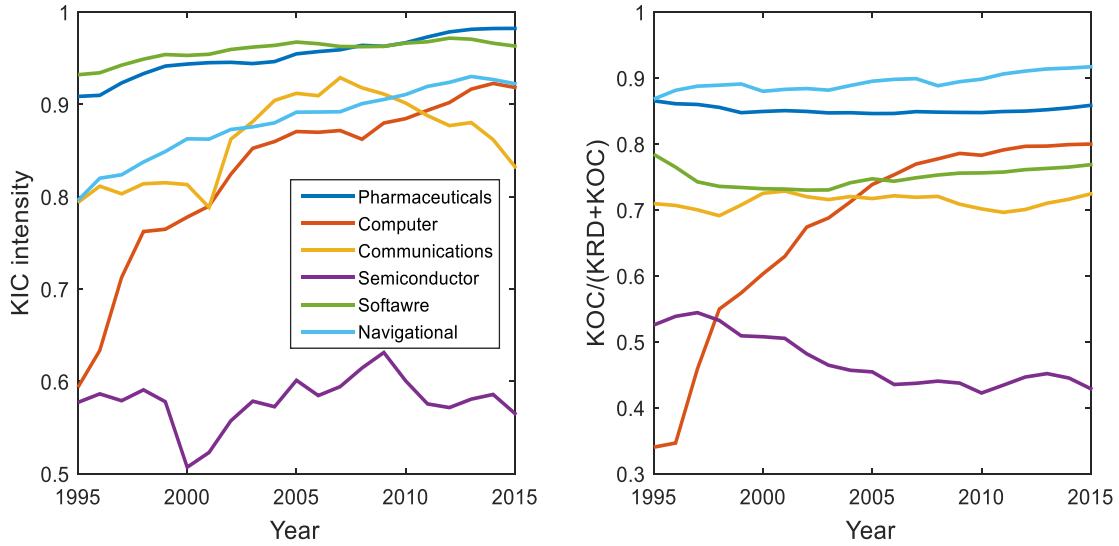


Table 2: Panel Regression of TFP Level on the Stock of Organizational Capital

InTFP	The Whole Economy (18 Industries)	Manufacturing Sector (12 Industries)	High-Tech Sector (5 Industries)
InKOC	0.063 (0.008)	0.060 (0.010)	0.084 (0.013)
P > t	0.000	0.000	0.000

Note: 1. The panel data is strongly balanced and covers the period of 2006 to 2011.
 2. The annual TFP data from BLS are already adjusted for R&D assets.

4. Degree of Offshoring, U.S. Innovations, and TFP Growth

In order to understand the impacts of increasing offshoring on the U.S. innovation capacity, we need to examine the relationship between the degree of offshoring and the innovation capacity. The conventional trade theory predicts that industries in each country will focus on where they have comparative advantages. That is, the U.S., as a leader in many industries, will focus on higher value-added products. As indicated by many researchers, the most highly value

added sections in the global supply chain in each industry are in the sections of R&D and marketing, where the value added output depends on the industry's capability in two intangibles -- R&D and organizational capital. However, the debate discussion and relevant data have suggested that more overseas suppliers are conducting innovation jobs for U.S. firms and that they are moving up in the global value chain. However, Brynjolfsson et al. (2002) studied the PC industries and found a complementarity relationship between PC capital and organizational capital. That is, a firm's performance depends not only on the level of intangible capital but also the interaction between different types of intangible capital. Since the interrelation between intangibles will affect a firm's performance, it then affects a firm's motivation to invest in different types of intangible capital. That is, although we see the increase of offshoring in innovations, especially R&D, by U.S. multinational firms, the rate of the increase may be slow if there is a complimentary relationship between R&D and organizational capital within the firm or the industry. Therefore, we need to examine not only how the degree of offshoring relates to firm's innovations but also the relationship between intangibles within a firm.

To examine the relationship between the degree of offshoring and an industry's innovation capacity, I use the VAX_UStoOthers ratio to measure each U.S. industry's degree of offshoring. In addition, Bloom et al. (2015) examined the impact of Chinese import competition on twelve European countries's technical change, measured by patenting, IT, and TFP, from 1996 to 2007, and they found that Chinese import competition led to increased technical change within firms. They also found that, in contrast to low-wage nations like China, developed countries had no significant effect on innovation. Because the U.S. is the world leader in several technological frontiers, I'd like to examine how the import competition from China, and from other tech leading countries such as Germany and Japan, affects the U.S. technical change. I construct a panel data which includes the time series of each industry's annual TFP level from BLS which has adjusted for R&D assets, average annual stock of organizational capital, annual median VAX ratio (each U.S. industry to industries in other countries), annual VAX_ChinatoUS (the VAX ratio of each Chinese industry to the industries in the U.S.), annual VAX_JapantoUS (the VAX ratio of each Japanese industry to the industries in

the U.S.), and annual VAX_GermanytoUS (the VAX ratio of each Germany industry to the industries in the U.S.). To smooth the time series data, I use natural logarithms for TFP level and the stock of organizational capital. Since the panel data contain data from 18 non-financial U.S. industries, we need to control the problems of the omitted variables and unobserved heterogeneity in the panel regression analysis. The panel regression results are shown in Table 3.

Table 3: Panel Regression Results – Offshoring, Organizational Capital, and TFP

InTFP	1	2	3	4	5	6
InKOC	0.063* (0.007)	0.066* (0.010)	0.059* (0.009)	0.061* (0.009)	0.058* (0.010)	0.057* (0.010)
VAX_UStoOthers		-0.184*** (0.108)				
VAX_ChinatoUS					-0.022 (0.015)	-0.014 (0.016)
VAX_GermanytoUS				-0.016** (0.008)		
VAX_JapantoUS			-0.080** (0.038)			-0.069*** (0.040)

Note: * p < 0.01, ** p < 0.05, ***p < 0.10

From Table 3, we can see: First, in model 2, it tells that as the degree of offshoring increases, the U.S. TFP level increases. Second, as shown in model 5, Chinese import competition does not affect the U.S. TFP level significantly. Instead, import competition from Japan and Germany negatively affects the U.S. TFP level with statistical significance. Third, in all models, organizational capital positively affects the U.S. TFP level with statistical significance.

The above analysis shows that as offshoring increases, U.S. industry-level TFP level increases. That is, as globalization rises, U.S. technical change increases. The next step is to examine the relationship between intangibles within a firm. To examine the relationship, I

construct a panel data which includes the time series of each firm’s annual TFP level, annual stocks of organizational capital, R&D assets, tangible assets for high-tech industries with sufficient data for analysis. To smooth the time series data, I take a natural logarithm. Because the average firm size varies across industries, I use the variables of asset intensities to control the size. That is, for the independent variables, I calculate the total assets of each firm as the sum of all assets, including R&D assets, organizational capital, and tangible assets. The R&D intensity is defined as the ratio of R&D assets to total assets. The organizational capital intensity is defined as the ratio of organizational capital to total assets. The tangible intensity is defined as the ratio of PP&E to total assets. Note that each firm’s annual TFP level is calculated following the approach by Imrohorglu and Tuzel (2013), who adopted the semiparametric method by Olley and Pakes (1996).

Table 4: Firm-level Panel Regression: Complementary Relationship Between Organizational Capital and R&D Assets

lnTFP	Pharmaceuticals	Computer	Communication	Semiconductor	Software	Navigational
R&D Intensity	0.007 (0.007)	-0.010 (0.008)	-0.033* (0.014)	-0.031* (0.004)	-0.031** (0.019)	-0.050* (0.005)
OC Intensity	0.009* (0.004)	0.001 (0.004)	-0.007 (0.006)	0.001 (0.003)	0.007 (0.005)	0.005* (0.002)
R&D Intensity* OC Intensity	0.014 (0.011)	0.038* (0.014)	0.014 (0.021)	0.069* (0.010)	0.054* (0.026)	0.050* (0.007)

After the firm heterogeneity and size are controlled, the results for the interaction term between the intensities of R&D capital and organizational capital show clearly that, for most high tech industries, organizational capital and R&D assets have a complementary relationship. Therefore, although the globalization of innovations increases as shown in BEA’s data, the rate of increase may not be fast. As a consequence, although some developing countries are moving upward in the global value chain by conducting more R&D activities, a phenomenon that is well known in IT industries, it is still difficult for them to compete with industries in the U.S. and other developed countries in the segment of marketing and the consumer end of global value chain. Studies in the trade literature (e.g., Keller, 2010) have found that, because of its tacit

nature, the cost of technology transfers in multinational firms is substantial (Teece, 1977), and hence, it is difficult to transfer technology across borders. And, based on the studies on the depreciations of intangible capitals (Li, 2015) and the study on the U.S. multinationals in the U.K. (Bloom et al., 2012), we find that it is even more difficult to transfer organizational capital across firms even within the same country.

5. Conclusion

In the era of globalization, U.S. 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. Under this trend, the central debate on the impacts of offshoring is whether or not the increasing degree of globalization is reducing U.S. innovations. To contribute to the understanding of this topic, I adopt the new index developed by Johnson and Noguera (2012) for measuring the degree of offshoring and construct a new data set of R&D capital, organizational capital, and the value added per export ratio to examine whether, under globalization, U.S. firms invest more in innovation, and under the trend of increasing of offshoring in innovation, U.S. firms invest differently among different types of innovations, and what the resulting feature of U.S. innovations.

I find that, under globalization, most high-tech firms invest more in intangibles. Freeman (2006) argues that the globalization of science and engineering can threaten U.S. economic and technological leadership and diminish U.S. comparative advantage in high-tech sectors. However, Bloom, Draca, and Van Reenen (2016) study OECD countries and find that import competition from low-cost countries positively affects innovation rates in developed countries. My research results find that as the degree of offshoring increases, U.S. industries' TFP level increases as well. This is consistent to the finding by Bloom et al. that demand-driven through the exploration of overseas markets and competition-driven innovation through offshoring are helping firms in advanced countries to increase investing in innovation and make technological progress.

Moreover, the two types of intangibles, organizational capital and R&D assets, are complementary. Literature shows that it is not easy to internationally transfer technology, and

it is even more difficult to transfer organizational capital across countries (Keller, 2010, Bloom et al., 2012, Li, 2015, 2016). The slow international transfer in knowledge, specifically in organizational capital, combining with the complementary relationship between R&D assets and organizational capital, implies that U.S. industries with a stronger complementary relationship between the two assets and the industries with a higher investment growth in organizational capital will tend to outsource R&D assets more slowly.

I construct a new times series on both intangible capitals, R&D assets and organizational capital, and industry-level VAX ratio for all U.S. industries covering the period of 1995 to 2011. Using this newly constructed data, I examine whether under the increasing degree of offshoring, U.S. industries are reducing their innovations and whether the composition of U.S. innovations varies. My analyses show that, under the increasing degree of offshoring, the U.S. exports have becoming more intangible embodied, as indicated by the increasing intensity of intangible capital across U.S. industries. This finding is consistent with the industry observations that even in the high-tech industries, although low-cost competitors from countries such as China are moving upward along the global value chain, the key segments of marketing and end-market are dominated by the U.S. and developed countries (Dedrick et al., 2011). Moreover, R&D and organizational capital are complementary in terms of the contribution to each industry's TFP. That is, the contribution of R&D assets to an industry's TFP also depends on its organizational capital, and vice versa. U.S. industries compete not only in the dimension of technologies but also in the dimension of organizational capital.

While this study provides the first complete set of business R&D capital and organizational for all U.S. industries and the value added per export derived from the world input output dataset, future research can make improvements on this topic. The current research only examines whether as the degree of offshoring rises, U.S. industries have higher intensities of intangibles. When more detailed data for offshoring in intangibles are available, the causal relationship between offshore outsourcing and intangible investments can be further examined.

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