Columbia Business School

CENTER ON JAPANESE ECONOMY AND BUSINESS

日本経済経営研究所

Working Paper Series

September 2009, No. 285

The Great Realignment: How the Changing Technology of Technological Change in Information Technology Affected the U.S. and Japanese IT Industries, 1983-1999

Ashish Arora, Lee G. Branstetter, and Matej Drev

This paper is available online at www.gsb.columbia.edu/cjeb/research/ac

COLUMBIA UNIVERSITY IN THE CITY OF NEW YORK

The Great Realignment: How the Changing Technology of Technological Change in Information Technology Affected the U.S. and Japanese IT Industries, 1983-1999

Ashish Arora

Lee G. Branstetter

Matej Drev

First Version: January 2009

This Version: July 2009

PRELIMINARY AND INCOMPLETE

Abstract

This paper empirically shows that innovation in Information Technology (IT) has become increasingly dependent on and intertwined with innovation in software. This change in the nature of IT innovation has had differential effects on the performance of the United States and Japan, two of the largest producers of IT globally. We document this linkage between software's contribution in IT innovation and the differential innovation performance of US and Japanese electronics, semiconductors, and hardware firms. We collect patent data from USPTO in the period 1980-2002 and use a citation function approach to formally show the trend of increasing software dependence of IT innovation. Then, using a broad unbalanced panel of the largest US and Japanese publicly listed IT firms in the period 1983-1999, we show that (a) Japanese IT innovation relies less on software advances than US IT innovation, (b) the innovation performance of Japanese IT firms is increasingly lagging behind that of their US counterparts, particularly on IT sectors that are more software intensive, and (c) that US IT firms are increasingly outperforming their Japanese counterparts, particularly in more software intensive sectors. The findings of this paper could provide a fresh explanation for the relative decline of the Japanese IT industry in the 1990s.

Key Words: innovation, technological change, IT industry, software innovation, Japan

Acknowledgements: This research was supported by the Software Industry Center at Carnegie Mellon University and benefitted from the research assistance of Ms. Kanako Hotta of UCSD. We acknowledge with gratitude extremely useful comments from Hiroyuki Chuma, Kyoji Fukao, Shane Greenstein, Susumu Hayashi, Toshiaki Kurokawa, Mark Kryder, Koji Nomura, Jeffrey Smith, David Weinstein and participants in the 2009 Spring Meeting of the NBER Productivity Program and the 2009 NBER Japan Project Conference.

I. Introduction

The surge of innovation in Information Technology (IT) is one of the great economic stories of the last two decades. This period also coincides with the unexpected resurgence of the United States IT sector, belying the gloomy predictions about the US IT industry popular in the late 1980s and early 1990s (e.g. Cantwell, 1992; Arrison and Harris, 1992).

In this paper, we argue that a shift in the nature of the innovation process in IT occurred. Starting in the late 1980s and accelerating in the 1990s, technological change in IT has taken on a trajectory that is increasingly software intensive. We show that non-software IT patents are significantly more likely to cite software patents, even after controlling for the increase in the pool of citable software patents. We also show that employment of software professionals has increased in IT industries. While these shifts are broad-based, we also see substantial differences across IT sub-sectors in the degree to which they taken place. We exploit these differences to sharpen our empirical analysis in the manner described below.

If the innovation process in IT has indeed become more dependent on software competencies and skills, then firms better able to use software advances in their innovation process will benefit more than others. Indeed, we argue that the shift in software intensity of IT innovation has differentially benefited American firms over their Japanese counterparts. Our results from a sizable unbalanced panel of the largest publicly traded IT firms in US and Japan for the period 1983-1999 show that US IT firms have started to outperform their Japanese counterparts, both as measured by productivity of their innovative activities, and as measured by their stock market performance.[1]

[1] These results parallel the findings of Jorgenson and Nomura (2007), who demonstrate that Japanese TFP rose rapidly for decades, converging to U.S. levels, but then began diverging from it around 1995. Their industry level analysis suggests that a change in the relative performance of the IT-producing industries (which we study in this paper) and the IT-using industries were particularly important in driving the shift from convergence to divergence. Jorgenson and Nomura do not attempt to explain the mechanisms behind relative declines in productivity.

The timing and the concentration of this improvement in relative performance appears to be systematically related to the software intensity of IT innovation. We show that the relative strength of American firms tends to grow in the years after the rise in software intensity had become well established. Furthermore, the relative improvement of the U.S. firms is greatest in the IT sub-sectors in which the measured software intensity of innovation is the highest. Finally, we present evidence suggesting that much of the measured difference in financial performance declines disappears when we separately control for the software intensity of IT innovation at the firm level.

This paper is structured as follows. Section II provides evidence and documents the existence of a shift in the technological trajectory of IT, Section III empirically explores its implications for innovation performance of US and Japanese IT firms, while Section IV discusses the possible explanations for the trends we observe in our data. We conclude in Section V with a summary of the key results and an outline of the limitations of our study with avenues for future work.

II. Changing Technology of Technological Change in IT

A survey of the computer and software engineering literature points to an evident increase in the role of software for successful innovation and product development in various parts of the IT industry. The share of software costs in product design has increased steadily over time (Allan et al, 2002) and software engineers have become more important as high-level decision-makers at the system design level in telecommunications, semiconductors, hardware, and specialized industrial machinery (Graff, Lormans, and Toetenel, 2003). Graff, Lormans, and Toetenel (2003) further argue that software will increase in importance and complexity in a wide range of products, such as mobile telephones, DVD players, cars, airplanes, and medical systems. Industry observers claim that software development and integration of software applications has become a key differentiating factor in the mobile phone and PDA industry (Express Computer, 2002). A venture capital report by Burnham (2007) forcefully argues that that the central value proposition in the computer business has shifted from hardware to systems and application software.

Similarly, De Micheli and Gupta (1997) assert that hardware design is increasingly similar to software design, so that the design of hardware products requires extensive software expertise. Gore (1998) argues that peripherals are marked by the increasing emphasis on the software component of the solution, bringing together hardware and software into an integrated environment.[2] Kojima and Kojima (2007) suggest that Japanese hardware manufacturers will face increasing challenges due to the rising importance of embedded software in IT hardware products. In sum, there is broad agreement among engineering practitioners and technologists about the increasing role of software in various parts of IT. In the next section, we validate this assertion formally, using data on citation patterns of IT patents.

Measuring the Shift in the Technology of Technological Change in IT

Approach

We use citations by non-software IT patents to software patents as a measure of the software intensity of IT innovation. Patents have been used as a measure of innovation in mainstream economic research at least since the early 1960s (e.g., Griliches and Schmookler, 1963). The possible uses of patent citations in economic research have been well documented (Jaffe and Trajtenberg, 2002), and although problems in using citations to measure knowledge

[2] Personal discussions with Mark Kryder, former CTO of Seagate, confirmed that software has become an increasingly important driver of product functionality and product differentiation in the hard disk drive industry.

flows have been identified (Alcácer and Gittelman, 2006), they are still extremely useful in the context of our research project. We cannot simply use time trends in software patenting by IT sector because (a) patent counts are a very crude measure of innovation output through time, (b) the patentability of software has changed dramatically over our sample period, and (c) tracking patent counts does not tell us much about the connections between different types of IT innovation.

The citation patterns we observe are an end result of the interplay of several determinants: the size of the citing knowledge pool expressed by the number of citing patents, the availability of citable knowledge expressed by the number of possible cited patents, and the rates of knowledge diffusion and obsolescence (Hall, Jaffe, and Trajtenberg, 2001). In order to get an unbiased view of knowledge flows, we need to purge citation patterns of the impact of these factors. [3]

The citation function has been pioneered in the work of Caballero and Jaffe (1993) and Jaffe and Trajtenberg (1996, 2002). Following these authors, we model the probability that a particular patent, P, applied for in year t, will cite a particular patent, a, granted in year T. This probability is determined by the combination of an exponential process by which knowledge diffuses and a second exponential process by which knowledge becomes superseded by subsequent research (Jaffe and Trajtenberg, 2002). The probability, $p(a, P)$, is a function of the attributes of the citing patent (P), the attributes of the cited patent (a), and the time lag between them (t-T), as depicted formally below:

$$p(a,p) = \alpha(a,p) \cdot \exp(-\beta_1 (t-T) \cdot (1-\exp(-\beta_2 (t-T)) \qquad (1)$$

[3] The possible biases in patent citations due to examiners (Alcacer and Gittelman, 2006) or due to the strategy behavior of patent applicants (Mowery, Oxley, and Silverman, 1996) are well known. Still, there is substantial evidence validating these data as useful indicators of knowledge spillovers (Duguet and MacGarvie, 2005; Jaffe, Trajtenberg, Fogarty, 2000).

We sort all potentially citing patents and all potentially cited patents into cells corresponding to the attributes of articles and patents. The attributes of the citing patents that we incorporate into our analysis include the citing patent's grant year, its geographic location, and its technological field (IT, software). The attributes of the cited patents that we consider are again the cited patent's grant year, its geographic location, and its technological field. Thus, the expected value of the number of citations from a particular group of citing patents to a particular group of cited patents can be expressed as the following:

$$E(c_{abcdef}) = n_{abc} \cdot n_{def} \cdot \alpha_{abcdef} \cdot \exp(-\beta_1(t-T) \cdot (1-\exp(-\beta_2(t-T)) \qquad (2)$$

where the dependent variable measures the number of citations made by patents in the appropriate categories of grant year (a), geographic location (b), and technological field (c) to patents in the appropriate categories of grant year (d), geographic location (e), and technological field (f). The alpha terms are multiplicative effects estimated relative to a benchmark or "base" group of citing and cited patents. Rewriting equation (2) gives us the Jaffe – Trajtenberg (2002) version of the citation function:

$$p(c_{abcdef}) = \frac{E(c_{abcdef})}{n_{abc} \cdot n_{def}} = \alpha_{abcdef} \cdot \exp(-\beta_1(t-T) \cdot (1-\exp(-\beta_2(t-T)) \qquad (3)$$

Adding an error term, we can estimate this equation using the nonlinear least squares estimator. The estimated equation thus becomes the following:

$$p(c_{abcdef}) = \alpha_a \cdot \alpha_b \cdot \alpha_c \cdot \alpha_d \cdot \alpha_e \cdot \alpha_f \cdot \exp(-\beta_1(t-T) \cdot (1-\exp(-\beta_2(t-T)) + \varepsilon_{abcdef} \ldots\ldots \qquad (4)$$

In estimating equation (4) we adjust for heteroscedasticity by weighting the observations by the square root of the product of potentially cited patents and potentially citing patents corresponding to the cell, that is

$$w = \sqrt{(n_{abc}) \cdot (n_{def})} \qquad (5)$$

Data

We use patents granted by the United States Patent and Trademark Office (USPTO) between 1980 and 2002. We use the geographic location of the first inventor to determine the "nationality" of the patent.[4] We identified patents belonging to IT, broadly defined, by using a classification system based on USPTO classes, developed by Hall, Jaffe, and Trajtenberg (2001). They classified each patent into one of six broad technological categories: (1) chemical, (2) computers & communications, (3) drugs & medical, (4) electrical & electronic, (5) mechanical, and (6) others. They further broke down each category, generating a total of 36 technological subcategories. We applied their system and identified IT patents broadly defined as those belonging to any of the following categories: computers & communications category, electrical devices, or semiconductor devices. We obtained these data from the updated NBER patent dataset.[5]

Next, we identified software related patents. The most pressing challenge is the definition and identification of software patents. There have been three significant efforts to define a large set of software patents. Graham and Mowery (2003) defined software patents as an intersection of those falling within a narrow range of IPC classes and those belong to packaged software firms. This created a sample that was severely under-inclusive according to Allison et al, (2006).

The second effort was that of Bessen and Hunt (2007), who define a software invention as one in which the data processing algorithms are carried out by code either stored on a magnetic storage medium or embedded in chips. They rejected the use of official patent classification systems for defining the set of software patents, and used a keyword search method instead. They identified a small set of patents that adhered to their definition, and then used a

[4] Patents with inventors from multiple countries currently represent a small fraction of the total patent population, so using first inventor's location only is not likely to introduce noticeable measurement error into our data.
[5] Downloaded from the following link: http://elsa.berkeley.edu/~bhhall/bhdata.html (12/15/2007)

machine learning algorithm to identify similar patents in the patent population, using a series of keywords in the patent title and abstract. Recently, Arora et al. (2007) use a similar approach that connects the Graham-Mowery and Bessen-Hunt definitions.[6]

We use a combination of a broad keyword-based and patent class strategy to identify software patents. First, we generated a set of patents, applied for after January 1st 1980 and granted before December 31st 2002, that used the words "software" or "computer program" in the patent document. Then, we defined the population of software patents as the intersection of the set of patents the query returned and IT patents broadly defined as described above, granted in the period 1980-2002. This produced a dataset consisting of 104,407 patents.

These data are potentially affected by a number of biases. Not all invention is patented, and special issues are raised by changes in the patentability of software over the course of our sample period – this makes it all the more important for us to control for the expansion in the pool of software patents over time, as we do. We also rely on patents generated by a single authority – the USPTO – to measure invention for both U.S. and Japanese firms. However, Japanese firms have historically been among the most enthusiastic foreign users of the U.S. patent system. Evidence suggests that examination of the U.S. patents of Japanese firms does provide the researcher with a reasonably accurate portrayal of their inventive activity (Branstetter, 2001; Sakakibara and Branstetter, 2000; Nagaoka, 2007). This is particularly likely to be true in IT, given the importance of the U.S. market in the various components of the global IT industry.

[6]Allison et al. (2006) rejected the use of both the standard classification system and keyword searches, resorting to the identification of software patents by reading through them manually. Although potentially very accurate, this method is inherently subjective and not scalable.

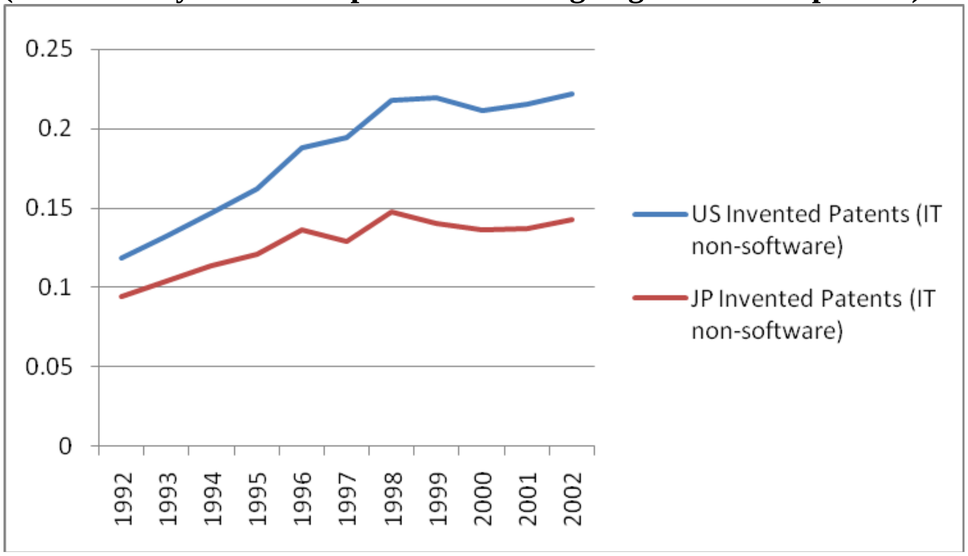
Results

The unit of analysis in Table I is an ordered pair of citing and cited patent classes. In this regression, we are primarily interested in the coefficient on the software patent dummy. Our regression model is multiplicative, so it is not a "zero" coefficient on a dummy variable but rather a coefficient of 1 that indicates no change relative to the base category. Our coefficients are reported as deviations from 1. The software patent dummy is large, positive, statistically significant, and indicates that IT patents in the 1990s are 1.34 times more likely to cite software patents than other IT patents, controlling for the sizes of available IT and software knowledge pools. The second specification in Table I includes only software patents in the population of possibly cited patents. The coefficients on the citing grant years show a sharp increase in citation probabilities from 1992 to 2002. An IT patent granted in 1996 is 1.74 times more likely to cite a software patent than an IT patent granted in 1992. Furthermore, an IT patent granted in 2002 is almost 4 times more likely to cite a software patent than that granted in 1992. Comparing this trend to that of the specification in the left-hand column of Table I, we see that this trend is much more pronounced, suggesting that software patents are becoming increasingly important for IT innovation broadly defined. In Table I, we also explore citation differences between Japanese and non-Japanese invented IT inventions. The specification in the left-hand column indicates that Japanese invented IT patents are 34 percent less likely to cite other IT patents than non-Japanese IT patents. However, they are 93 percent less likely to cite software patents than non-Japanese IT patents. This result is corroborated by the regression in the right-hand column, where the coefficient on the Japanese dummy again shows that Japanese invented IT patents are significantly less likely to cite software patents than non-Japanese patents.

The citation function results were subjected to a number of robustness checks. Concerned that our results might be driven by large numbers of U.S.-invented software patents appearing in the later years of our sample, we estimated the propensity of U.S. IT patents to cite non-U.S. software patents and found a rise in this propensity qualitatively similar to that depicted in Table 1. We also directly controlled for the disproportionately high likelihood that patents cite patents from the same country, but our result that Japanese IT hardware patents are systematically less likely to cite software over time was robust to this.

The citations function's complexity makes it difficult to estimate different tendencies for Japanese and American firms to increase their propensity to cite software patents over time, holding all other factors constant, but we see evidence consistent with this in the raw data. Figure 1 shows trends over time in the fraction of total (non-software) IT patents' citations that are going to software patents. While the trends for both Japanese and U.S. firms rise significantly over the 1990s, then level off a bit in the 2000s, the measured gap between Japanese and U.S. firms rises substantially over the period. A one-tailed t-test reveals that these differences are statistically significant at conventional levels for every year shown.

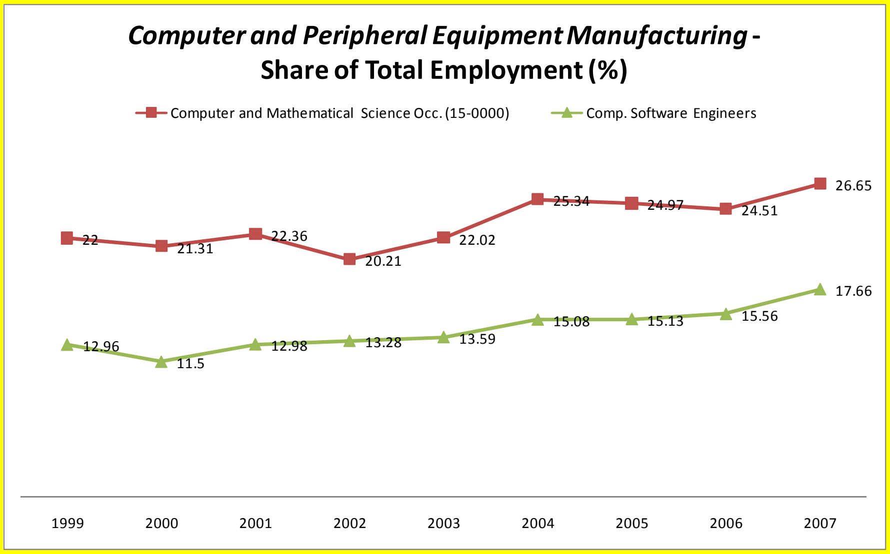
Figure 1: Software Intensity of Non-Software IT Patents
(Measured by fraction of patent citations going to software patents)



The results from the two specifications in Table I portray an interesting picture: software innovation is (increasingly) important for IT innovation broadly defined, and this appears to be especially true in the U.S. If this is true, then we might expect to see supporting evidence in patterns of employment in IT industries. The U.S. Bureau of Labor Statistics conducts periodic surveys of U.S. employment by occupation and industry. Inspection of the data from 1999-2007[7] reveal trends consistent with a rising importance of software in IT innovation. For instance, Figure 2 illustrates how two measures of the share of software engineers in total employment in the computer and peripheral equipment manufacturing industry have trended upward over time. We see similar trends in other IT subsectors. Interestingly, the relative share of software engineers in total employment across subsectors appears to accord with patent citation-based measures of software intensity. The share is highest in computers and peripherals, lowest in audio and visual equipment manufacturing, and at intermediate levels in semiconductors.

[7] Methodological changes in the survey make it difficult to track occupational employment in the U.S. IT industry in a consistent way over time, particularly in comparing the periods before and after 1999.

Figure 2 Trends in Software Engineering Employment



Source: Bureau of Labor Statistics, Occupational Employment Survey, 1999-2007
Note: Data include domestically employed H1-B visa holders

III. Comparing US and Japanese Firm-Level Innovation Performance in IT

We use two of the most commonly employed empirical approaches to compare firm-level innovation performance of US and Japanese IT firms: the innovation (patent) production function and the market valuation of R&D. While the former approach relates R&D investments to patent counts and allows us to study the patent productivity of R&D, the second approach relates R&D investment to the market value of the firm and explores the impact of R&D on the value of the firm (Tobin's Q). This allows us to tie together firm-level results reported in this section with the reported shift in IT innovation of the previous section.

Patent Production Function

This approach builds on Pakes and Griliches (1984) and Hausman, Hall, and Griliches (1984). We begin by specifying a functional relationship between research and development effort, proxied by R&D expenditures, and innovation resulting from this effort, proxied by the number of patents taken out by a firm. We use a log-log form of the patent production function.

$$P_{it} = r_{it}^{\beta} \Phi_{it} \, e^{\varphi JP_i} \tag{6}$$

where

$$\Phi_{it} = e^{\sum_c \vartheta_c D_c} \tag{7}$$

In equation (6), P_{it} are patents taken out by firm i in period t, r_{it} are research and development expenditures, JP_i indicates if the firm is Japanese, and Φ's represent innovation-sector-specific technological opportunity and patenting propensity differences across c different innovation sectors D, which follow a functional form as specified in (7). Substituting (7) into (6), taking logs of both sides, and expressing the sample analog we obtain the following:

$$p_{it} = \beta r_{it} + \sum_c \vartheta_c D_c + \varphi JP_i + \mu_{it} \tag{8}$$

where p_{it} is the natural log of new patents (flow) and the error term which is defined below.

$$\mu_{it} = \xi_i + u_{it} \tag{9}$$

We allow the error term in (9) to contain a firm-specific component, ξ_i, which accounts for the intra-industry firm-specific unobserved heterogeneity, and an *iid* random disturbance, u_{it}. The presence of the firm-specific error component suggests using random or fixed effect estimators. Since the fixed effects estimator precludes time-invariant regressors, including the firm origin indicator, we feature the pooled OLS and random effects estimators, and use the fixed effects estimator as a robustness check.

Private Returns to R&D and Tobin's Q

Griliches (1981) pioneered the use of Tobin q regressions to measure the impact of R&D on a firm's economic performance (see also Jaffe, 1986; Cockburn and Griliches, 1988; Hall and Oriani, 2006).[8] In this approach, efficient capital markets are assumed, so that the market value

[8] See Hall (2000) for a detailed review.

of the firm represents the value maximizing combination of its assets. We can represent the market value V of firm i at time t as a function of its assets:

$$V_{it} = f(A_{it}, K_{it}) \tag{10}$$

where A_{it} is the replacement cost of the firm's tangible assets, typically measured by their book value, and K_{it} is the replacement value of the firm's technological knowledge, typically measured by stocks of R&D expenditures[9]. The functional form of f is not known, and we follow the literature, which assumes that the different assets enter additively..:

$$V_{it} = q_t(A_{it} + \beta * K_{it})^{\sigma} \tag{11}$$

where q_t is the average market valuation coefficient of the firm's total assets, β is the shadow value of the firm's technological knowledge measuring the firm's private returns to R&D, and σ is a factor measuring returns to scale. Again following practice in the literature (e.g. Hall and Oriani, 2006), we assume constant returns to scale (σ = 1). Then, by taking natural logs on both sides of (11) and subtracting $\ln A_{it}$, we obtain the following expression that relates a firm's technological knowledge to its value above and beyond the replacement cost of its assets, Tobin's Q:

$$\ln Q_{it} = \ln\left(\frac{V_{it}}{A_{it}}\right) = \ln q_t + \ln\left(1 + \beta_t * \left(\frac{K_{it}}{A_{it}}\right)\right) \tag{12}$$

Following Hall and Kim (2000), Bloom and Van Reenen (2002) and others, we estimate a version of (12) using the nonlinear least squares estimator, with time dummies and a firm origin indicator. We were unable to estimate a specification with firm-fixed effects because the NLS algorithms did not converge. As a robustness check, we estimated a linearized version of (12) with fixed effects.

[9] The construction of variables is explained in greater detail in subsequent sections.

Data and Variables

Sample

Our sample consists of large publicly traded IT companies in the United States and Japan, observed from 1983 to 1999. We obtained the sample of US firms from historical lists of constituents of Standard & Poor's (S&P) US 500 and S&P 400 indices. The resulting set of firms was refined using Standard & Poor's Global Industry Classification Standard (GICS) classification[10] so that only firms appearing in "electronics", "semiconductors", "IT hardware" and "IT software and services" categories remained in the sample. This produced an initial set of approximately 220 firms. The sample was narrowed further in the following way: (a) only firms that were granted at least 10 patents in the 1983-1999 period were retained, (b) US firms in "IT software and services" were removed from the estimation samples in order to achieve compatibility with the sample of Japanese firms,[11] and for Tobin's Q regressions, only (c) firms for which at least 3 consecutive years of positive R&D investment and sales data were available were kept in the sample. This produced a final unbalanced panel of 140 and 135 US IT firms for patent production function and Tobin's Q regressions respectively.

The sample of large publicly traded Japanese IT firms was derived from the Development Bank of Japan (DBJ) database, which gave us an initial unbalanced panel of 154 publicly listed Japanese IT firms in the period 1983-1999.[12] The sample was supplemented by an additional 37 firms that were listed as constituents of Standard & Poor's Japan 500 index as of January 1st 2003[13], and that were listed as belonging to either "electronics", "semiconductors", "IT

[10] GICS, the Global Industry Classification System, is constructed and managed by Moody's in collaboration with Compustat.
[11] NTT is the only Japanese firms in "IT services and software" in our sample.
[12] We thank the Columbia Business School Center on the Japanese Economy and Business for these data.
[13] January 1st, 2003 was the date of creation of this index.

hardware", or "IT software and services" based on their GICS code. This created an unbalanced panel of 191 Japanese firms.

Japanese accounting standards do not force firms to report R&D data in a uniform way, which rendered the R&D investment data from the DBJ database unusable. As a consequence, we were forced to obtain self-reported R&D expenditure data for Japanese firms from annual volumes of the Kaisha Shiki Ho[14] survey. Lack of reliable R&D expenditure data for some firms led to their exclusion from our sample. We further restricted the sample by (a) dropping all firms without at least 10 patents in the observed period, (b) dropping Nippon Telephone and Telegraph, and, for Tobin's Q regressions, (c) all firms for which at least three consecutive years of R&D investment and positive output data were not available in DBJ. This produced a final sample of 98 and 89 Japanese IT firms for the patent production function and Tobin's Q regressions respectively.

Locating Firms in Software Intensity Space

To explore how innovation performance differentials between US and Japanese firms vary with software intensity, we classify firms into industry segments. GICS provided us with a classification of all US firms in our sample into four sectors – "electronics", "semiconductors", "IT hardware", and "IT software and services". Japanese firms were classified manually using the two-digit GSIC classification data from the S&P Japan 500 along with the data from Japan's Standard Industrial Classification (JSIC), supplemented by manual Google Finance, Yahoo! Finance and corporate websites.

[14] *Kaisha Shiki Ho* (Japan Company Handbooks) is an annual survey of Japanese firms, published by the Japanese equivalent of Dow Jones & Company, *Toyo Keizai* Inc. We thank Ms. Kanako Hotta for assistance in obtaining these data from the collections at the School of International Relations and Pacific Studies of the University of California at San Diego.

We construct two separate measures of software intensity, both of which suggest a similar ranking of IT subsectors. First, we use the shares of software patents in total patents taken out by the firms in our sample to construct a firm-level measure of software intensity, then we average these across firms in an industry category. Second, we calculate the fraction of citations to software parents that appear in the non-software IT patents of our sample firms, and average these across firms within a sample category. Table II presents summary statistics for both these measures of software intensity. As expected, electronics is the least software intensive, followed by semiconductors and IT hardware. A two-sided test for the equality of means rejects that the intensities are the same in any pair of sectors when we use the share of software patents as our measure. The second measure, citations to software patents, yields similar results, albeit at lower levels of significance in some cases. Tables III and III-2 calculate the industry averages of our measures of software intensity separately for U.S. and Japanese firms. In general, the ranking of industries in terms of software intensity suggested by the overall sample appears to apply to the country-specific subsamples.[15] Japanese firms' measures of software intensity tend to be far lower than that of their US counterparts, consistent with the findings of the previous section that showed Japanese firms were less likely to use software innovation than their foreign counterparts.[16] We also find that large Japanese IT firms are disproportionally located in less software-intensive sectors.

Taking the assignment of firms to the different IT industries as given, we test whether US firms outperform Japanese firms, and whether this performance gap is more marked in IT industries that are more software intensive.

[15] Depending on the measure, statistical tests of equality are not always significant at the conventional threshold levels when we disaggregate by country of origin, and when Japanese software intensity is measured by citations to software in non-software patents, electronics is (insignificantly) more software intensive than semiconductors.
[16] This is true in five out of six cases, although the measured differences are not always statistically significant.

Construction of Variables

Patent Counts: Patent data for our sample of firms were collected from the updated NBER patent dataset containing patents granted by the end of 2002. Compustat firm identifiers were matched with assignee codes based on the original and updated matching as constructed and available on Bronwyn Hall's website.[17] The matching algorithm was manually updated by matching strings of Compustat firm names and strings of assignee names as reported by the USPTO. An identical procedure was used for matching Japanese firms to their patents, except that we based it on a Tokyo Stock Exchange (TSE) code - assignee code matching algorithm previously used in Branstetter (2001). Next, we computed patent counts for all firm-year observations based on patent application years. In addition to total patent counts, counts of IT and software patents, as defined in the previous sections, were collected.

R&D Investment: Annual R&D expenditure data for US firms were collected from Compustat, and a set of self-reported R&D expenditure data for Japanese firms were collected from annual volumes of the Kaisha Shiki Ho survey. We deflated R&D expenditures following Griliches (1984), and constructed a separate R&D deflator for US and Japanese firms that weighs the output price deflator for nonfinancial corporations at 0.51 and the unit compensation index for the same sector at 0.49. Using data on wage price indexes for service-providing and goods-producing employees,[18] we constructed a single unit compensation index for each country, and then applied the proposed weights and appropriate producer price indexes to compute the R&D deflators and deflate the R&D expenditure flows.

R&D stocks: We calculated R&D capital stocks from R&D expenditure flows using the perpetual inventory method,with a 15% depreciation rate (Hall and Vopel, 1997; Mairesse and

[17] Downloaded from the following link: http://elsa.berkeley.edu/~bhhall/bhdata.html (12/15/2007)

[18] We obtained these data from the Bureau of Labor Statistics and Statistics Bureau of Japan, respectively.

Hall, 1996; Hall, 1993).[19] We used 5 pre-sample years of R&D expenditures to calculate the initial stocks.[20]

Market Value of the Firm: Market value of a firm equals the sum of market value of its equity and market value of its debt (Perfect and Wiles, 1994). Market value of equity equals the sum of the value of outstanding common stock and the value of outstanding preferred stock. The value of outstanding common (preferred) stock equals the number of outstanding common (preferred) shares multiplied by their price. For US firms, we used year-close prices, year-close outstanding share numbers, and year-close liquidating values of preferred capital. For Japanese firms, the only available share price data were year-low and year-high prices, and we used the arithmetic average of the two to obtain share price for each firm-year combination. In addition, preferred capital data was not available for Japanese firms. Although this can introduce a source of measurement error in our dependent variable, as long as preferred capital does not systematically vary with time and across technology sectors in a particular way, our results regarding sector and sector-origin differences will remain valid. Market value of debt was calculated following Perfect and Wiles (1994) as a sum of the value of long-term and short-term debt. For U.S. firms, we used total long-term debt as a proxy for the former and debt due in one year as a proxy for the short term debt. In the case of Japanese firms, we used fixed liabilities as a proxy for the value of long-term debt and short-term borrowings as a proxy for the value of short-term debt.[21]

---

[19] See Griliches and Mairesse (1984) and Hall (1990) for a detailed description and discussion of this methodology. We used several depreciation rates between 10% and 30%, with little change in the results..

[20] When the expenditure data was not available, we used first 5 years of available R&D expenditure data, "backcast them" using linear extrapolation, and calculated the initial R&D capital stock based on the projected R&D expenditures.

[21] We use the book value of debt as our measure of debt. Although this might introduce measurement error, the results in Perfect and Wiles (1994) using a variety of measures provide us with some reassurance as they do not differ much, regardless of the measure used. Similarly, complicated recursive methods have been suggested for calculating the market value of short-term debt. Using book value approximations could again introduce measurement error to our data, but we again rely on the discussion in Perfect and Wiles (1994) for reassurance that this error will not be severe.

Replacement Cost of Assets: The replacement cost of the firm's assets is the deflated year-end book values of total assets.[22] where the deflator is a country-specific capital goods deflator obtained from the Bureau of Labor Statistics and the Statistics Bureau of Japan, respectively.

Patent Production Function

Figure 3 compares the number of patents per firm for the US and Japanese firms in our sample. We observe that Japanese firms obtain more non-software IT patents than their US counterparts. Between 1983 and 1988, the average number of non-software IT patent applications were almost identical for Japanese and US firms. Between 1988 and 1993, patent applications by Japanese firms outpaced those of US firms, after which both grew at the same pace. By contrast, Japanese firms file fewer and increasingly fewer software patents than their US counterparts. The difference has grown steadily since the late 1980s and at an increasing pace in the mid and late 1990s.

22 Perfect and Wiles (1994) note that different calculation methodologies do result in different absolute replacement cost values, but do not seem to bias coefficients on R&D capital. In a discussion particular to calculating replacement cost of assets in Japan, found in Hayashi and Inoue (1991) and Hoshi et al. (1991), several complex methodologies were proposed. For the purpose of this paper, we did not compare our results against the alternative of using replacement cost calculated with their methodology.

Figure 3: Average Number of non-software IT and Software Patents Per Firm

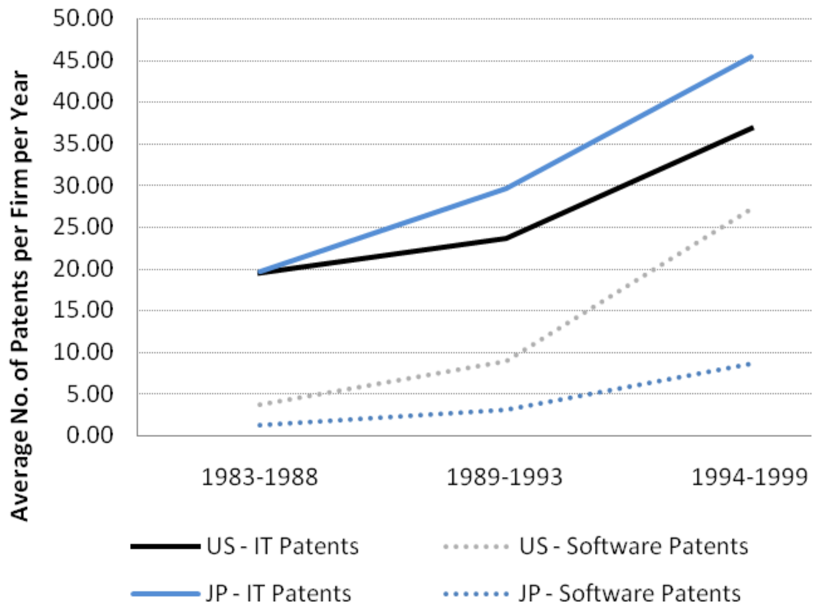
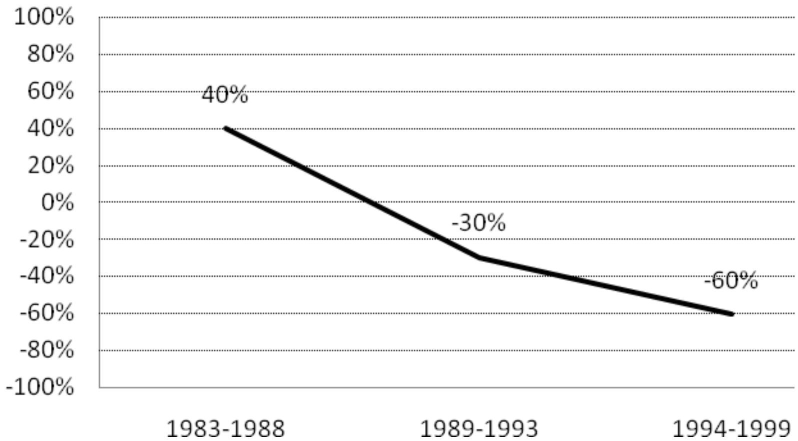


Table V in the Appendix reports the estimates of the patent production functions of Japanese and US IT firms. Our first key result is presented in Figure 4 below, which plots the pooled OLS average difference in log patent production per dollar of R&D, between Japanese and US firms in our sample through time, controlling for time and sector dummies,.[23] We see that R&D spending by Japanese firms was 40% more productive than in their US counterparts during 1983-1988, but 30% less productive during 1989-1993. This trend accelerated in the 1990s, resulting in Japanese IT firms producing 60% fewer patents, controlling for the level of R&D spending, than their US counterparts in the period 1994-1999.

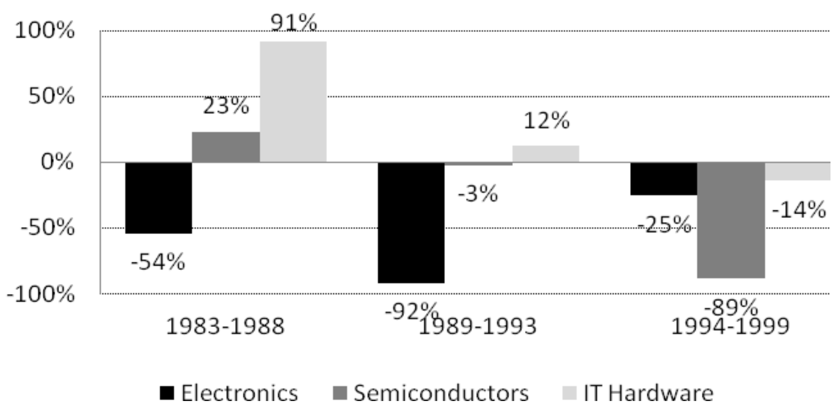
[23] Detailed results are found in Table IV in the Appendix.

Figure 4: Average Japan-US Productivity Differences, Entire Sample



Based on results from Table V. of the Appendix. Reported are pooled OLS estimation coefficients.

Figure 5: Average Japan-US Productivity Differences, By Software Intensity Sector



Based on results from Table V. of the Appendix. Reported are selected pooled OLS coefficients.

Figure 5 reports Japan-U.S. differences in average R&D productivity by IT sector, where the measure of R&D productivity is based on patent output controlling for R&D input. In electronics, previously shown to be the least software intensive, and where average software intensity is similar between US and Japanese firms, Japanese firms have been less productive in patent production in the 1980s and early 1990s, but have been catching up to their US counterparts in the mid and end 1990s.[24] On the other hand, in semiconductors and IT hardware,

[24] In the mid-2000s, Japanese electronics firms received a boost from the rapidly growing sale of so-called digital appliances, such as DVD recorders, digital cameras, and LCD televisions. Industry observers, such as Ikeda (2003),

which have significantly higher software intensity than electronics, and where average software intensity of US firms is greater than of Japanese firms, Japanese firms exhibited higher productivity in the mid 1980s, lost all of their advantage by the turn of the 1990s, and increasingly started to lag behind their US counterparts in the mid to end 1990s.

All of the results are statistically significant at the 5% level and robust to changes in the particularities of estimation techniques. Random effects and fixed effects estimators, which take into account firm-specific unobserved differences in patent productivity, do not produce qualitatively different results, suggesting that our results are not driven by unobserved firm-specific research productivity or patent propensity differences.

Robustness checks: These results have as the dependent variable the log of total patents applied for by firm i in year t. We estimated our regressions using the log of IT patents, and the log of IT patents excluding software patents, with no qualitative change in the results. We also weighted total patent output by subsequent citations and by the number of claims appearing in the patent documents, with no qualitative change in the results.[25]

One might argue that the bursting of the Japanese asset price bubble at the break of the 1990s and the economic slowdown that followed might distort our results, for instance by reducing Japanese R&D investments. Note however that we are estimating the productivity of R&D in producing patents, rather than merely the number of patents produced. Further, insofar as Japanese firms reduced their R&D, diminishing returns to R&D should have resulted in higher not lower measured productivity. Alternatively, Japanese firms may have changed patent propensity, filing fewer but higher quality patents. However, estimates using citation weighted patents (not reported here) yield similar results. But most telling of all, no simple story about the

---

warned of imminent commoditization of these new products – a prediction that has been born out in the latter years of the decade.

[25] We do not report these results in the paper, but are available from the authors upon request.

bubble can explain the observed pattern, wherein the relative decline in productivity is greater in more software intensive segments.

A related stream of research, much of it authored by Japanese economists, has addressed the perceived relative weaknesses of the Japanese R&D system more generally.[26] Goto (2000), Goto and Odagiri (2003), Nagaoka (2007) and many others have stressed the importance of effective university-industry linkages in science-based industries and noted that these linkages have taken a different form in the U.S. and Japan, possibly contributing to relative weakness in certain areas. Together with these authors, Hamada (1996) and many others have pointed to the importance of venture capital as a driving force in American innovative dynamism and the lack of a similar system in Japan as a serious impediment to growth. Chuma and Hashimoto (2007) and Tanaka (2003) have focused on the decline in the Japanese semiconductor industry in particular, suggesting that a shift in the technological trajectory of this industry undermined Japanese relative performance. We find these analyses to be plausible and persuasive, but these views do not explain why the pattern of Japanese relative performance in IT is so closely linked to the software intensity of various IT market segments.

Our empirical approach does have certain limitations. One is that we have estimated the patent production regressions based on a relatively narrow sample of Japanese firms, especially in the semiconductor sector. Entry of privately held firms has been limited in Japan, making it unlikely that we are missing a significant part of important Japanese IT firms in our data. A more serious problem is that the same firms often contain business units operating in different IT

[26] See Branstetter and Nakamura (2003) for a discussion of these issues and some attempt at quantification.

market segments, but do not separately report the revenues and R&D expenditures of these units, making it difficult to assess their R&D productivity.[27]

Another limitation is that we are do not attempt to compare the research productivity of US and Japanese firms in the packaged software industry, *per se*, which is the sector where we might expect differences to be most pronounced.[28] This is driven partly by our interest in explaining the divergence of Japanese and U.S. performance in IT hardware, where Japanese firms have traditionally been strong. We are also constrained by the relatively small numbers and relatively late appearance of publicly traded software firms in Japan, making a direct comparison difficult. If we were to include such firms, the productivity differences would likely be favorable to US firms.[29]

Finally, if Japanese firms exhibited lower propensities to patent in the United States than their US counterparts, this would bias the estimated Japan-US research productivity differences upwards. We have a two-fold response. First, a survey of patenting activity in the US suggests that Japanese IT firms have patented extensively in the US in our sample period, accounting for up to 30% of total IT patents filed at the USPTO (e.g. Arora et al, 2007). Secondly, in order for our time-period and industry-period differences to be biased, one would have to construct a viable story for why the patent propensity of Japanese firms dropped significantly in the 1990s, and more so in more software-intensive sectors.

---

[27] We are currently seeking to address this, in part, by exploring the impact of alternative firm classifications on our results

[28] This means that U.S. software powerhouse firms such as Microsoft, Oracle, and Google are all omitted from the data set and play no role in our results.

[29] Towards the end of the 1990s, a small number of publicly listed firms that we could classify as software firms appeared on the Tokyo Stock Exchange. Softbank is a canonical example. We could not include these firms in our analysis as we are only looking at the period 1983-1999. The Japanese videogame industry includes a handful of software-intensive game developers, but they are sufficiently different from their U.S. counterparts to make a comparison problematic. Motohashi (2009) uses a different data set to explore productivity trends in the Japanese software industry, but does not attempt an international comparison.

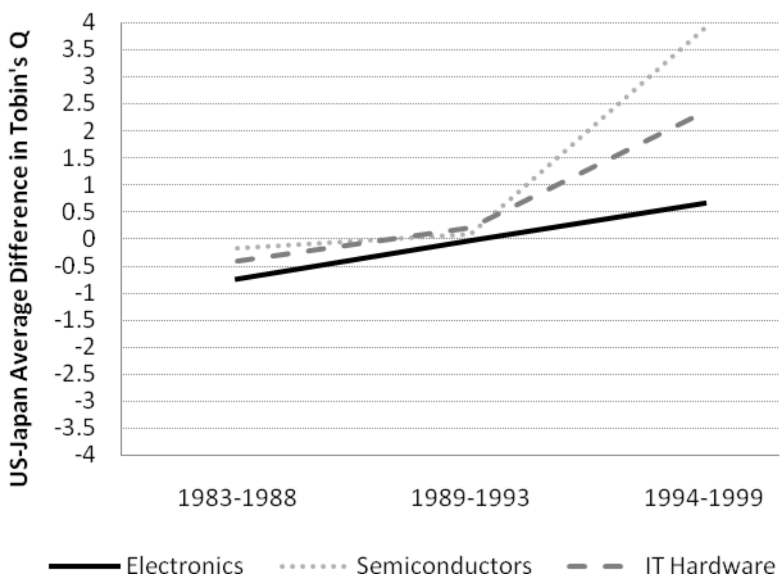
Private Returns to R&D

We begin by plotting the average difference in Tobin's Q between our sample of US and Japanese firms through time, shown in Figure 6 below. We observe that Japanese firms, on average, have had higher Q values than US firms in the mid 1980s, particularly in what would become more software intensive sectors – semiconductors and IT hardware. These differences diminished with the bursting of the Japanese economic bubble at the dawn of the 1990s, and Japanese Q values have lagged throughout the 1990s, especially in semiconductors, and to a lesser extent, also in IT hardware. Thus trends in average Tobin's Q values by sector parallel those in patent production.

Moving beyond the descriptive analysis, we regress Tobin's Q on the ratio of R&D stocks by total assets to estimate private returns to R&D (shadow value of R&D). Table IV reports estimates of equation (12) by period using nonlinear least squares. It shows that the shadow price of R&D/Assets for US firms was negative and statistically significant in the period 1983-1988, but rose to positive and statistically significant levels by the mid to end 1990s. On the other hand, the coefficient on R&D/Assets for Japanese firms has not followed this trend. It has hovered just above 0 in the 1980s and dropped to just below 0 in the mid 1990s. In none of the periods was it statistically significantly different from 0. This is consistent with what we observed when plotting the values of Tobin's Q through time, except that we see that it is not the Japanese who experienced a drop in returns, but that it is the US firms who exhibited a hike in private returns to R&D.

Interestingly, this "reversal of fortune" for the market valuation of U.S. firm R&D appears to be sensitive to the inclusion of a direct measure of software intensity. Table IV-2 reports the results of a regression in which we add the software intensity (measured by average firm citations to software in non-software IT patents), and also interact with R&D/Assets. This additional regressor changes our results. The R&D/Assets coefficient for U.S. firms is positive in the last period, but not statistically significant from zero. These results support the view that the relative increase in U.S. performance is related to software intensity.

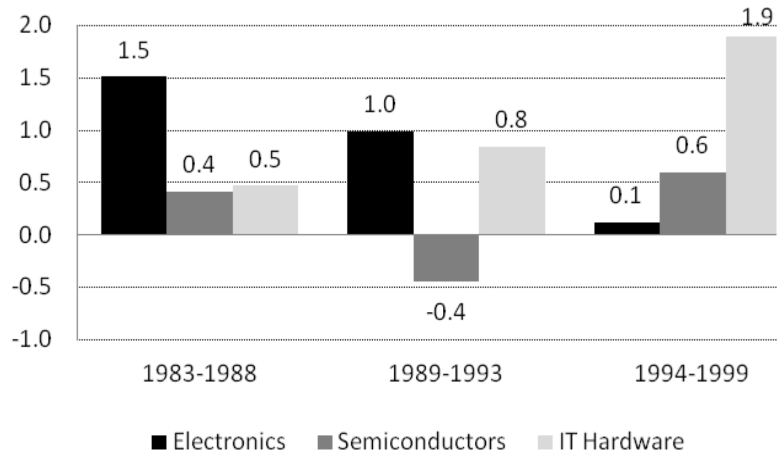
Figure 6: Average Difference in Tobin's Q, By Sector



Tobin's Q as calculated in the database, averaged across sector. Calculated as JP average subtracted from US average.

Figure 7 compares private returns to R&D for Japanese and US firms by IT sector. As with patent productivity, we find that results differ by sector. In electronics, the least software intensive sector, the US firms started off with an advantage in the mid 1980s, before losing it all by the mid to end 1990s. The reverse is true in IT hardware, the most software-intensive sector. We report detailed regression results in Tables VII-IX of the Appendix.

Figure 7: Average Difference in Private Returns to R&D, By Sector



Shadow values of R&D as estimated by NLS by sector. Calculated as JP average subtracted from US average.

We conducted several robustness checks. We first estimated versions of (12) and (13) using NLS and FE estimators, where we directly estimated time trends for private returns to R&D separately for US and Japanese firms. Table VI shows that the direction of the trends remains unperturbed, but they lose their statistical significance when we use the NLS estimator on the sample of US firms. Private returns to R&D for Japanese firms linger, as before, around 0, and have no significant trend over time. In the left columns of Tables VII-IX, we report estimates of the linear approximation using firm fixed effects. Again, we observe that the signs of the coefficients remain essentially unchanged, except in the case of US semiconductors, where the FE reveals a highly statistically significant positive trend in private returns to R&D.

Finally, we estimate a linearized version where we split US and Japanese firms into quartiles according to the share of software patents in total patents. Table X of the Appendix provides summary results of this effort. We observe that US firms' private returns to R&D increase with software intensity, while they fall in the case of Japanese firms. This is consistent with our results from above. However, when we perform the same exercise by sector, we observe that, in semiconductors and IT hardware this no longer holds, suggesting that our results might be driven by trends in electronics. This is plausible since Japanese firms are disproportionally located in this sector. Interestingly, we also observe that US firm's private returns to R&D increase with the software intensity of the sector when they are also in the top quartile of software intensity. The same is true for Japanese firms. Conversely, private returns to R&D decrease with the software intensity of the sector for firms located in the bottom quartile of software intensity.

IV. Discussion

The empirical part of our paper documents three key observations. First, we show that IT innovation has become more software intensive. Second, Japanese firms produce significantly fewer software inventions and rely less on software knowledge in innovation production than their US counterparts. Third, the innovation performance of Japanese IT firms is increasingly lagging behind particularly in software intensive sectors. This suggests, but does not conclusively demonstrate, a causal link running from the changing technology of technical change in IT to an inability of Japanese firms to respond adequately to the shift, leading to worsening performance.

The question is what prevented Japanese firms from using software advances as effectively as U.S. firms? There are at least two explanations, not mutually exclusive. The first is a resource constraint argument: software-intensive IT innovation necessarily requires access to large numbers of software engineers at various skill levels. U.S.-based firms have access to a much larger specialized labor pool than do their Japanese counterparts for reasons that are largely exogenous to the wishes or actions of Japan-based firms. Japanese firms are not able – or, at least, have not yet been able -- to completely overcome their national labor resource constraints by offshoring their software-intensive R&D. The second explanation is one rooted in the failure of Japanese managers to understand and adequately respond to the changing nature of technological change in IT. Under this alternative hypothesis, Japanese firms would have lost ground even in a world where they had equal access to specialized software engineering labor.

Japan's relative weakness in many kinds of software has been widely recognized in the literature, and many scholars have pointed to human resource constraints as a partial explanation for this.[30] Finan and Williams (1992) argued that Japan's lack of an adequate training pipeline for software engineers would constrain its prospects in some areas of IT. The authors also quoted Japanese researchers as having noted a critical shortage of software engineering talent in Japan since at least 1988. Cusumano (1991) showed how Japan's electronics and hardware companies took special steps to increase the productivity of their scarce software labor. Other studies, citing reasons as diverse as the structure of the Japanese language and weak university-level computer science education programs, all pointed to the relatively weak software competence of many Japanese firms, the relatively weak software skills of many Japanese software workers, and the inadequate supply of highly skilled software labor in Japan (e.g., Fransman, 1995; Baba et al, 1996; Japanese Ministry of Internal Affairs and Communications, 2005; D'Costa (2007); Kurokawa and Hayashi (2008).

In spite of this general state of affairs, there are clusters of Japanese firms that have maintained their strong international market positions in software-intensive segments of IT, the most conspicuous example of which is probably the Japanese videogame sector.[31] Does the strength of Japanese firms in this sector refute the generalizations both Western and Japanese

[30] Anchordoguy (2000) and Tanaka (2003) have described in detail the relative weaknesses of the Japanese software industry in systems and applications software. Kojima and Kojima (2007) discuss weakness in embedded systems software.

[31] Japanese firms also maintain a strong position in robotics, one that they have held for years. The Japanese mobile phone service industry has been characterized by a high degree of software-intensive innovation, but these Japanese innovations have had little impact to date outside of the Japanese home market.

scholars have made regarding the relative weakness of software in Japan?[32] We do not think so. As an entertainment industry, videogames sales are driven by artistic factors as well as purely technological ones, and Japanese developers have a rich local cultural tradition of *manga* (a Japanese art form akin to comic books in the West) and *anime* (animated films) to draw upon. In terms of economics, the global revenues of the Japanese industry have been dominated by hardware sales rather than software in recent years, and hardware sales have been dominated by two console manufactures, Nintendo and Sony Computer Entertainment (a subsidiary of consumer electronics giant Sony). An analysis of patenting and patent citations by the important Japanese players in this sector reveals that they are extremely software intensive. This is consistent with our results that the performance differentials between Japanese and U.S. firms diminish when one controls for software intensity. Our analysis also reveals that that Japanese videogame manufacturers and developers cite a much narrower set of patent classes than firms elsewhere in IT. The ability of a handful of firms to pursue a narrowly focused but software-intensive innovation strategy would not seem to contradict the general picture of software weakness painted by the work of the Western and Japanese scholars who have looked at the Japanese IT industry. Nor would it seem to necessarily contradict the existence of a general shortage of software workers that impacts less highly specialized firms.

If we assume for the moment that an adequate supply of software workers is usually important for success in an increasingly software-intensive IT industry and that Japan's domestic supply of such workers has been limited, it is still not necessarily the case that a local labor shortage would constrain multinational firms. The level of local human capital would not be a constraint if knowledge flowed freely across countries. Unfortunately, it is widely

[32] This Japanese industry is not a focus of our empirical analysis because of the difficulty of finding U.S. firms with which the leading Japanese console manufacturers and game developers can be compared. The issues are somewhat similar to those encountered in packaged software.

acknowledged that tapping into foreign knowledge pools can be difficult (Jaffe, Trajtenberg, and Henderson 1993). Belderbos (2001) and Odagiri and Yasuda (1997) document the relatively limited extent of Japanese R&D activity outside Japan during the years from which our data are taken; Belderbos, Fukao and Kwon (2006) examine the drivers of Japanese R&D expenditure outside Japan. The results of this research are consistent with the view that Japanese foreign R&D spending was a relatively small fraction of total R&D spending during the years of our sample period. Branstetter (2006) measures the impact of Japanese R&D subsidiaries in the U.S. on the research productivity of Japanese firms at home, finding it to be positive but limited in magnitude. Anchordoguy (2000) provides circumstantial evidence that tapping into foreign software knowledge pools might be particularly difficult for Japanese firms due to language barrier, labor market frictions, and important differences between Japanese and other firms in terms of the institutional environment and business conduct conventions.[33] All of these considerations suggest significant barriers to the ability of Japanese firms to move abroad to tap foreign knowledge or expertise.[34] Japan's relatively restrictive immigration laws and its long history as an ethnically homogenous society mitigate against large-scale importation of skilled labor from foreign countries, creating barriers to bringing the foreign expertise (or experts) to Japan.[35]

---

[33] An important strand of literature in international economics argues that country-specific factor endowments are crucial for explaining comparative differences in innovation performance of industries in national economies. For instance Acemoglu (2001, 2002), Dudley and Moenius (2007) and others, argue that not only do countries specialize in the production of goods intensive in factors they are abundant in, but that they also specialize in innovation activities intensive in factors they are abundant with, a phenomenon they dub "factor-biased technical change".

[34] Kojima and Kojima (2007) examine the available data on Japanese offshoring of software development to other countries. While the data are highly problematic, they suggest a very low level of offshoring relative to the U.S. – something as low as 5-10% of the U.S. level – even by the mid-2000s.

[35] See D'Costa (2008).

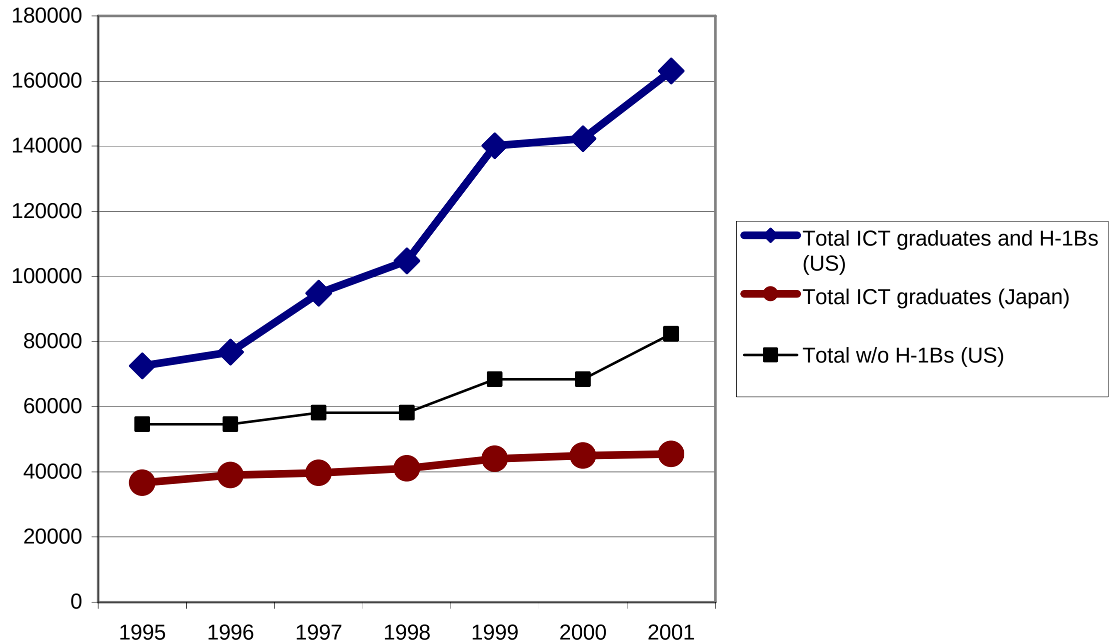
What if local labor resources really do matter?[36] The available data make it difficult to precisely quantify the differences in software human resources between the U.S. and Japan, but the gap between the two is clearly large. Figure 8 presents data from a number of sources comparing the flows of new (potential) domestic IT workers during the latter years of our sample period. The U.S. National Science Foundation's SESTAT survey, conducted every two years, tracks science and engineering graduates across fields and disciplines from U.S. universities. The Japanese Ministry of Education, Sports, and Welfare's Basic School Survey does the same for Japanese universities, albeit with a slightly different breakdown of fields and disciplines. To make the figures as comparable as possible, we aggregate over IT software and hardware related disciplines to produce a count of total IT bachelors and masters level graduates for both countries.[37] In the U.S., the software related disciplines have consistently accounted for far more than half of this total, at both the bachelors and masters levels – anecdotal evidence suggests this is not true for Japan. The U.S. Citizenship and Immigration Service and the Department of State maintain data on H-1B visa applications, approvals, and issuances; using these data, we create estimates of the number of temporary workers joining the U.S. labor force for the first time under an H-1B visa in order to work in "computer-related fields."[38] While Japanese immigration law also provides work visas to highly skilled foreigners, the numbers of workers imported into Japan under these visa categories to work in the IT sector has been extremely limited – so much so that inclusion of reasonable estimates of such workers would not materially affect the totals. In this paper, we have omitted such estimates.

[36] Kerr and Lincoln (2008) examine the impact of fluctuations in H-1B immigrants on innovation at the city level; Hunt and Gauthier-Loiselle (2008) examine the impact of immigration more generally on innovation at the state level. We conjecture here that this impact has been highly concentrated, with software innovation and diffusion being particularly impacted by H-1B visa immigration from India. Broader studies may find a weaker impact.

[37] Our Japanese graduation data come from a report by the Japanese Ministry of Internal Affairs and Communications, (2006).

[38] Our data are drawn from reports by Lowell (2000) and Kirkegaard (2005).

Figure 8 ICT Human Resources, U.S. vs. Japan
(ICT graduates and H-1B immigrants into computer related-professions, 1995-2001)



These data are obviously imperfect in many respects – only a fraction of IT graduates will enter employment in IT industries in the countries in which they study, and only a fraction of those who obtain employment in the IT industry will be engaged in research. Likewise, our estimates of H-1B temporary workers include individuals employed in IT companies as well as individuals working for banks and insurance companies, and only a fraction of the H-1Bs employed in IT companies are involved in research. These data track new entrants to the IT workforce, not the total stocks of workers available for employment in the sector. Despite these caveats, the picture painted by Figure 8 is quite striking. During the crucial years of the mid-to-late 1990s, new software technologies were being rapidly created and deployed in both countries, and it is plausible that newly trained workers were especially important and in especially short supply. Our graph indicates that the estimated pool of domestic new IT labor from which the two countries we study could draw expanded at very different rates. In 1995, the inflows of new onshore IT labor in the U.S. were about 98% greater than those in Japan. By 2001, the inflows in the U.S. were nearly 3.6 times bigger than those in Japan. And the graph makes it clear that most of the difference is driven by H-1Bs. In the latter years of the sample period, the U.S. was importing more IT specialists on an annual basis than it was graduating from all IT-related bachelors and masters programs combined.

Figure 9 US Software Outsourcing to India, 1995-2001

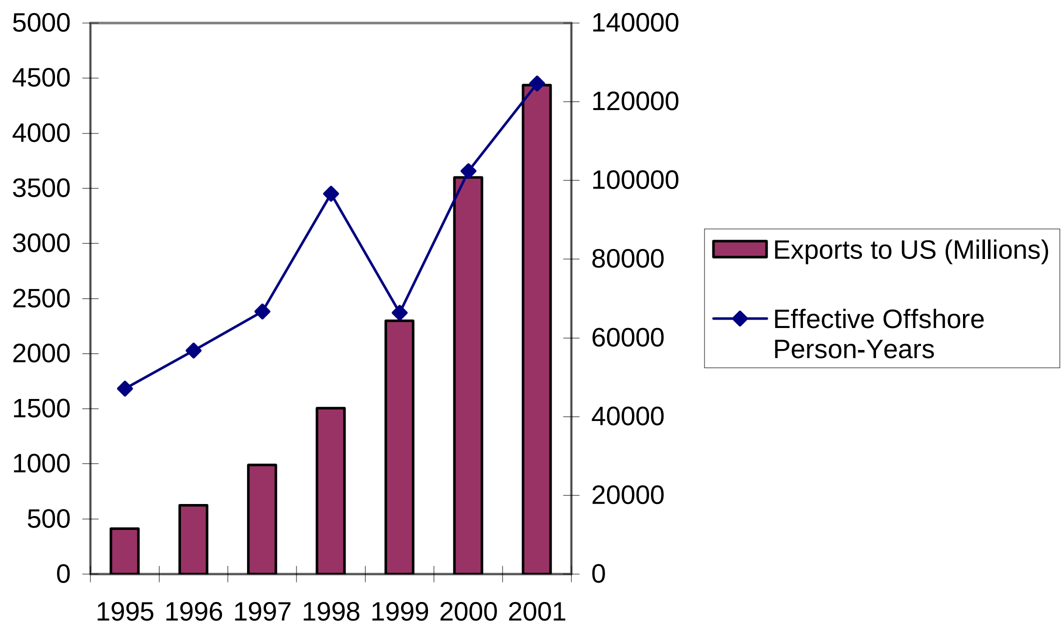


Figure 9 provides a different take on the resource constraint, by looking at offshoring of software development by the United States to India. Using data from NASSCOM on the annual levels of Indian software exports and their breakdown across regions, we compute a total amount of software exports to the U.S. which is, of course, a significant underestimate of total U.S. software offshoring in all locations. Using data on average revenue per employee, we can convert these export flows into "effective offshore labor units" – this crude calculation suggests that by 2001, more than 120,000 Indian software workers were employed full time on software development projects for U.S. customers.[39] Similar statistics for Japanese software offshoring do not appear to exist for the late 1990s, but even by 2005, after many years of rapid growth, the available data suggest that Japanese firms were importing no more than 15,000 person-years and the level of imports was on the order of U.S. $1 billon or less.[40] Accounting for the level of software offshoring in the U.S. and Japan would significantly increase the resource gap implied by Figure 8.

Given these magnitudes, it seems possible that imports of workers and, more recently, software outsourcing may have been a critical source of advantage for U.S. based firms. It is possible that relatively few of these imported experts may have been software architects of the highest order, capable of undertaking transformative innovation. However, creating, testing, and implementing software for IT product innovation required both fundamental innovators (akin to architects) and programmers undertaking more routine and standardized kinds of software engineering (akin to skilled construction workers). America's ability to tap into an increasingly abundant (and increasingly foreign) supply of the latter may have raised the productivity of the former and enabled American firms to outproduce their rivals. It is possible to write down a

[39] See Athreye (2005). Wages rose substantially between 1997 and 1998 – so much so that the "implied labor units" actually fell between these years. Note that NASSCOM's "export" data often include revenue derived from projects to which Indian employees working in the U.S. on H-1B visas have contributed. We have attempted to correct for this in the data.

[40] See Kojima and Kojima (2007). These authors also use survey data and direct interviews to analyze the reasons for relatively low levels of software offshoring. Language and cultural barriers were identified as an important constraints limiting Japanese offshoring, especially to India. Japanese offshoring has focused much more on China, which has a much smaller and less well developed software offshoring sector than India.

simple model of IT innovation that has these features, and we hope to include such a model in future drafts of this paper.

An alternative hypothesis posits that Japanese firms did not suffer from a labor resource constraint. Instead, Japan's relative decline in innovative productivity was driven by a managerial failure to recognize and adapt to fundamental change. Several strands of literature have explored this problem and proposed explanations for why it could occur. The literature on learning and innovation has argued that the ability of a firm to recognize the value of external information, assimilate it, and apply it to commercial ends is critically dependent on previous investments in that sector. For instance, Cohen and Levinthal (1990) argue that lack of investment in a sector of expertise may foreclose the future development in it. Our data suggest that, relative to American firms, Japanese IT firms have invested fewer resources in software innovation. Following a software-intensive technology shift, this mechanism would lead to vicious circle where the Japanese have lower absorptive capacity for software knowledge, thus produce fewer software inventions, which in turn again diminishes their absorptive capacity. This idea is similar to the notion of technological lock-in by historical reasons (Arthur, 1989) and learning myopia (Levinthal and March, 1993).

A related strand of management literature has focused on how managerial mindsets affect the (in)ability of firms to make strategic shifts. The key assertion is that managers develop mindsets, formed through years of experience, which in turn guide their decisions (Prahalad and Bettis, 1986). However, when the environment changes, these mindsets may prevent managers from responding to the change (Bettis and Hitt, 1995). The problem is more severe when managers have less experience in diverse settings. Japanese institutions, such as the lifetime employment system, imply that Japanese IT firms are more likely than US IT firms to be led by seasoned technocrats who have risen through the ranks. In contrast, US IT firms are more likely to be led by managers with business backgrounds and diverse experience. If this results in US firms' managers having systematically more flexible managerial mindsets, this could again explain the inability of the Japanese to make the required strategic innovation shift.

Initial Evidence for Distinguishing Between Possible Hypotheses

While our current data does not enable us to rule out any of the proposed explanations, we can obtain an initial insight by exploring data on patenting behavior of Japanese and US IT firms. The identification strategy we follow is based on the fact that the two possible explanations yield different predictions regarding what types of innovative activities Japanese firms should undertake in Japan and abroad. If they are constrained by their software knowledge pool at home, then Japanese firms will have the incentive to tap into foreign knowledge pools by setting up software intensive R&D facilities abroad. Thus, if we observe that innovative efforts of Japanese firms are markedly more software intensive when done outside Japan, this would suggest the existence of the software knowledge/labor constraint in Japan.

We classified USPTO granted patents assigned to the Japanese firms in our sample on the basis of where they were invented – *Japan, United States, or elsewhere (rest).* Then, we compared the shares of software, IT, and other patents in different invention locations. The results of this exercise are reported in Tables XI-XIV of the Appendix. What we observe is consistent with the constraint hypothesis. The share of software patents in total patents invented in Japan and assigned to the Japanese firms in our sample is 6%. However, the share of software patents in total patents invented in the US and assigned to the Japanese firms is significantly higher – 33%. Similarly, software patents represent 24% of total patents invented in other parts of the world. This suggests Japanese firms are disproportionally likely to engage in software innovation abroad. In addition, comparing citation behavior of non-software IT patents belonging to Japanese firms in our sample, we see that US invented patents are more likely to cite software innovation than those invented in Japan. We also conducted the exercise separately by sector – electronics, semiconductors, IT hardware - and see that increasing propensity to conduct software innovation abroad holds for all of them, but is strongest in IT hardware.

This does not rule out managerial myopia insofar as Japanese firms that recognize the importance of using software knowledge are also willing and able to invest in software related innovation activities abroad. It does imply that conducting software intensive research in Japan is more difficult than doing so elsewhere, consistent with a software resource constraint in Japan.

V. Conclusions, Implications and Next Steps

In this paper, we document the existence of a software-biased shift in the nature of the innovation process in information technology. Using data on the citation patterns of IT patents, we show that IT inventions increasingly rely on software knowledge. In addition, we provide initial evidence of its economic importance by studying how the innovation performance of IT firms in the United States and Japan was affected by this shift. Using a panel of large publicly listed IT firms, we show that Japanese firms produce significantly fewer software inventions and rely less on software knowledge in innovation production than their US counterparts. We present evidence consistent with the hypothesis that this difference has resulted in a deterioration in the relative performance of Japanese firms, and show that this effect is more pronounced in software intensive sectors. Finally, we provide suggestive evidence, consistent with a constrained supply of software knowledge and skills in Japan being a key factor in explaining the relatively weaker performance of Japanese IT firms in the 1990s. However, a full investigation of the connections between labor market constraints and our results is beyond the scope of this paper.

Our findings highlight important interconnections between firm competencies, technical change, and innovation performance, and they contribute to a growing literature that explores linkages between factor endowments, technological change, and industry performance (e.g. Acemoglu, 2002; Dudley and Moenius, 2007). Our results also point to some questions that are now the focus of ongoing research. The most important of these is the mechanism that lies behind our main results. Did American firms' access to a substantially larger pool of software engineering labor play an important role in their ability to outperform their Japanese rivals as the software-intensity of IT innovation rose? Or was the divergence driven by the superior organizational competence of American firms, or other institutional factors? Determining the answer to this question could have important implications for policies in Japan and elsewhere that are aimed at promoting the advancement of the IT sector. To the extent that the labor constraint story holds, institutional reforms in Japan that fail to open Japanese labor markets to highly skilled immigrants could leave Japanese firms at a disadvantage even in the longer run. Likewise, these results could inform the heated debate in the U.S. over the H-1B visa program. U.S. IT executives have long argued for generous H-1B visa caps, maintaining that liberal immigration was key to the competitiveness of American industry. This claim deserves further scrutiny.

References

Acemoglu, D. 2002. "Technical Change, Inequality, and the Labor Market", Journal of Economic Literature, Vol. 40(1), pp.7-72.

Alcácer, J. and Gittelman, M. 2006. "Patent Citations as a Measure of Knowledge Flows: The Influence of Examiner Citations", The Review of Economics and Statistics, Vol. 83(4), pp.774-779.

Allan, A. et al. 2001. "2001 Roadmap for Semiconductors", Vol. 35(1), pp.42-53.

Allison, J.R. and Tiller, E. 2003. "The Business Method Patent Myth", Working Paper.

Allison, J.R., Dunn, A., and Mann, R.J. 2006. "Patents and Business Models for Software Firms", The University of Texas School of Law Research Paper No. 77.

Anchordoguy, M. 2000. “Japan’s Software Industry: A Failure of Institutions”, Research Policy, Vol. 29, pp.391-408.
Arora, A. and Gambardella, A. 1994. “The Changing Technology of Technological Change: General and Abstract Knowledge and the Division of Innovative Labor”, Research Policy, Vol. 23(5), pp.523-532.
Arora, A., Drev, M., Forman, C., and Alpman, M.D. 2007. “A Note on the Classification of Software Patents”, Research Note.
Arrison, T. et al (Eds.). 1992. “Japan’s Growing Technological Capability – Implications for the U.S. Economy”, Washington, D.C.: National Academy Press.
Arrison, T. and Caldwell Harris, M. 1992. “Japan’s Growing Technological Capability and Implications for the U.S. Economy – An Overview”, in Arrison, T. et al (Eds.), “Japan’s Growing Technological Capability – Implications for the U.S. Economy”, Washington, D.C.: National Academy Press.
Arthur, W.B. 1989. “Competing Technologies, Increasing Returns, and Lock-in By Historical Events”, The Economic Journal, Vol. 99, pp.116-131.
Athreye, S. 2005. “The Indian Software Industry,” in Arora, A. and A. Gambardella (Ed.), From Underdogs to Tigers: The Rise and Growth of the Software Industry in Brazil, China, India, Ireland, and Israel, Oxford, Oxford University Press.
Baba, Y., Takai, S., and Mizuta, Y. 1996. “The User-Driven Evolution of the Japanese Software Industry: The Case of Customized Software for Mainframes.”, In Mowery, D. (Ed.), The International Computer Software Industry. New York, NY: Oxford University Press.
Belderbos, R. 2001. “Overseas Innovation by Japanese Firms: An Analysis of Patent and Subsidiary Data. Research Policy, Vol. 30(2), pp. 313-332.
Belderbos, R., K. Fukao, H. Kwon 2006. “Intellectual Property Rights Protection and the Location of Research and Development Activities by Multinaitonal Firms,” Hi-Stat Discussion Paper no. 167, Hitotsubashi University Research Unit for Statistical Analysis in the Social Sciences.
Bessen, J. and Hunt, R. 2007. “An Empirical Look at Software Patents”, Journal of Economics & Management Strategy, Vol.6(1), pp.157-189.
Bettis, R. and Hitt, M. 1993. “The New Competitive Landscape”, Strategic Management Journal, Vol. 16, pp.7-19.
Bloom, N. and Van Reenen, J. 2002. “Patents, Real Options and Firm Performance”, The Economic Journal, Vol. 112, pp.97-116.
Branstetter, L. 2001. “Are Knowledge Spillovers International or Intranational in Scope? Microeconomic Evidence from the U.S. and Japan”, Journal of International Economics, Vol. 53, pp.53-79.
Branstetter, L. and Ogura, Y. 2005. “Is Academic Science Driving a Surge in Industrial Innovation? Evidence from Patent Citations”, NBER Working Paper 11561.
Branstetter, L. and Nakamura, Y. 2003. “Has Japan’s Innovation Capacity Declined?” in Kashap, A., Blomstrom, M., Corbett, J., Hayashi, F., (Eds.), Structural Impediments to Growth in Japan, Chicago, University of Chicago Press and NBER.
Branstetter, L. 2006. “Is Foreign Direct Investment a Channel of Knowledge Spillovers? Evidence from Japan’s FDI in the U.S.,” Journal of International Economics, Vol. 53, pp. 53-79.
Brock, G.W. 1975. “The U.S. Computer Industry”, Cambridge, Ma: Ballinger.

Brynjolfsson, E. 1993. "The Productivity Paradox of Information Technology", Communications of the ACM, Vol. 36(12), pp.67-77.
Burnham, B. 2007. "What's Next?", Union Square Ventures Website. (http://www.unionsquareventures.com/2007/01/whats_next.html, April 21st 2008).
Buzzachi, L., Colombo, M.G., and Mariotti, S. 1995. "Technological Regimes and Innovation in Services: The Case of The Italian Banking Industry", Research Policy, Vol. 24, pp.151-168.
Caballero, R. and Jaffe, A. 1993. "How High are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth", NBER Macroeconomics Annual, Vol. 8, pp.15-74.
Cantwell, J. 1992. "Japan's Industrial Competitiveness and the Technological Capability of Leading Japanese Firms", in Arrison, T. et al (Eds.), "Japan's Growing Technological Capability – Implications for the U.S. Economy", Washington, D.C.: National Academy Press.
Chuma, H. and Hashimoto, N. 2007. "Moore's Law, Increasing Complexities, and the Limits of Organization: Modern Implications of the Japanese DRAM Era," working paper, Hitotsubashi University.
Cockburn, I. and Griliches, Z. 1988. "Industry Effects and Appropriability Measures in the Stock Market's Valuation of R&D and Patents.", The American Economic Review, Vol. 78, pp.419-423.
Cohen, W.M. and Levinthal, D.A. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation", Administrative Science Quarterly, Vol. 35(1), pp.128-152.
Cottrell, T. 1996. "Standards and the Arrested Development of Japan's Microcomputer Software Industry.", In Mowery, D. (Ed.), The International Computer Software Industry. New York, NY: Oxford University Press.
Cusumano, M. 1991. "Japan's Software Factories: A Challenge to US Management", New York, NY: Oxford University Press.
D'Costa, A., 2007. "Adjusting to Globalization: Japan and the Mobility of Asian Technical Talent," Asia Research Institute Working Paper no. 97, National University of Singapore.
De Micheli, G. and Gupta, R.K. 1997. "Hardware/Software Co-Design", Proceedings of the IEEE, Vol. 85(3), 349-365.
Dudley, L. and Moenius, J. 2007. "The Great Realignment: How Factor-Biased Innovation Reshaped Comparative Advantage in the U.S. and Japan, 1970-1992", Japan and the World Economy, Vol. 19, pp.112-132.
Duguet, E. and MacGarvie, M. 2005. "How Well Do Patent Citations Measure Flows of Technology? Evidence From French Innovation Surveys", Economics of Innovation and New Technology, Vol. 14(5), pp.375-393.
"Pricing and Apps Will Drive PDA Growth", Express Computer, December 23rd 2002.
Finan, W. and Williams, C., 1992. "Implications of Japan's 'Soft Crisis': Forcing New Directions for Japanese Electronics Companies," in Arrison, T. et al (Eds.), "Japan's Growing Technological Capability – Implications for the U.S. Economy", Washington, D.C.: National Academy Press.
Fransman, M. 1995. "Japan's Computer and Communications Industry: The Evolution of Industrial Giants and Global Competitiveness", Oxford, UK: Oxford University Press.
Galambos, L. and Sturchio, J.L. 1998. "Pharmaceutical Firms and the Transition of Biotechnology: A Study in Strategic Innovation", The Business History Review, Vol. 72(2), pp.250-278.

Gelijns, A.C. and Rosenberg, N. 1995. “The Changing Nature of Medical Technology Development”, in Rosenberg, N. and Gelijns, A.C. (Eds.), “Sources of Medical Technology: Universities and Industry”, Institute of Medicine Press.
Gore, T. 1998. “OMI – Developments in Processor Cores and Peripherals”, in Roger, J.Y. (Ed). “Technologies for the Information Society: Developments and Opportunities”, IOS Press.
Goto, A. 2000. “Japan’s National Innovation System: Current Status and Problems,” Oxford Review of Economic Policy, Vol. 16, pp. 103-113.
Goto, A. and Odagiri, H., (Eds), 2003. Science-Based Industries (in Japanese), Tokyo, NTT Publishing Co., Ltd.
Graff, B., Lormans, M., and Toetenel, H. 2003. “Embedded Software Engineering: The State of the Practice”, IEEE Software, Nov/Dec Edition, pp.61-69.
Graham, S. and Mowery, D. 2003. “Intellectual Property Protection in the U.S. Software Industry” in Cohen, W. and Merrill, S.A.: Patents in the Knowledge-Based Economy.
Griliches, Z. 1981. “Market Value, R&D, and Patents”, Economic Letters, Vol. 7, pp.183-187.
Griliches, Z. and Mairesse, J. 1984. “Productivity and R&D at the Firm Level”, in Griliches, Z. (Ed.), “R&D, Patents, and Productivity”, Chicago, IL: The University of Chicago Press and NBER.
Griliches, Z. 1990. “Patent Statistics as Economic Indicators: A Survey Part I”, NBER Working Paper 3301.
Griliches, Z. and Schmookler, J. 1963. “Inventing and Maximizing”, The American Economic Review, Vol. 53(4), pp.725-729.
Hall, B. 1993. “The Stock Market’s Valuation of R&D Investment During the 1980’s.” AEA Papers and Proceedings, May 1993, pp.259-264.
Hall, B. and Vopel, K. 1997. “Innovation, Market Share, and Market Value.” University of California at Berkeley Working Paper.
Hall, B. 2000. “Innovation and Market Value”. In Barrell. R., Mason, G., and O’Mahoney, M. (Eds.) “Productivity, Innovation, and Economic Performance”, Cambridge, UK: Cambridge University Press.
Hall, B. and Kim, D. 2000. “Valuing Intangible Assets: The Stock Market Value of R&D Revised”, University of California at Berkeley Working Paper.
Hall, B., Jaffe, A., and Trajtenberg, M. 2001. “The NBER Patent Citations Data File: Lessons, Insights, and Methodological Tools”, NBER Working Paper No. 8498.
Hall, B. and MacGarvie, M. 2006. “The Private Value of Software Patents”, UC Berkeley Working Paper.
Hall, B. and Oriani, R. 2006. “Does the Market Value R&D Investment by European Firms? Evidence from a Panel of Manufacturing Firms in France, Germany, and Italy”, International Journal of Industrial Organization, Vol. 24(5), pp.971-993.
Hamada, Y. 1996. Venture Capital in Japan: Strategic Investment for the Future. (in Japanese) Tokyo, Nikkei Shimbun Press.
Hausman, J., Hall, B., and Griliches, Z. 1984. “Econometric Models for Count Data with an Application to the Patents – R&D Relationship”, NBER Technical Working Paper No. 17.
Hayashi, F. and Inoue, T. 1991. “The Relation Between Firm Growth and Q with Multiple Capital Goods: Theory and Evidence from Panel Data on Japanese Firms”, Vol. 59(3), pp.731-753.

Hoshi, T., Kashyap, A., and Scharfstein, D. 1991. "Corporate Structure, Liquidity, and Investment: Evidence from Japanese Industrial Groups", The Quarterly Journal of Economics, Vol. 106(1), pp.33-60.
Hunt, J. and Gauthier-Loiselle, M. 2008. "How Much Does Immigration Boost Innovation," NBER Working Paper no. 14312.
Ikeda, Nobuo, 2003. "The Pitfalls of the 'Digital Appliances Bubble'," online column, Research Institute of Economy, Trade and Industry, accessed on the internet at http://www.rieti.go.jp/en/columns/a01_0112.html.
Jaffe, A., Trajtenberg, M., and Henderson, R. 1993. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations", The Quarterly Journal of Economics, Vol. 108(3), pp.577-598.
Jaffe, A. and Trajtenberg, M. 1996. "Flows of Knowledge from Universities and Federal Labs: Modeling the Flow of Patent Citations over Time and across Institutional and Geographic Boundaries", NBER Working Paper No. 5712.
Jaffe, A., Trajtenberg, M., and Fogarty, M.S. 2000. "Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors", The American Economic Review, Vol. 90(2), pp. 215-218.
Jaffe, A. and Trajtenberg, M. 2002. "Patents, Citations, and Innovations: A Window on the Knowledge Economy", Boston: MIT Press.
JETRO, 2007. "Japanese Video Game Industry," Industrial Report, Japanese Economy Division.
Jorgenson, D. and Nomura, K., 2007. "The Industry Origins of the U.S.-Japan Productivity Gap," Economic Systems Research, Vol. 19(3), pp. 315-342.
Kerr, W. and Lincoln, W. 2008. "The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention." HBS Working Paper.
Kirkegaard, J. 2005. "Outsourcing and Skill Imports: Foreign High-Skilled Workers on H-1B and L-1 Visas in the United States," Peterson Institute for International Economics Working Paper 05-15.
Kojima, S. and Kojima, M., 2007. "Making IT Offshoring Work for the Japanese Industries," in Meyer, B. and Joseph, M. (Eds.), SEAFOOD (Software Engineering for Offshore and Outsourced Development) 2007 Conference Proceedings, LNCS 4716, pp. 67-82.
Kurokawa, T., and Hayashi, S., 2008, "The ICT Human Resources as a Crisis for Japan," (in Japanese), research draft.
Levinthal, D.A. and March, J.G. 1993. "The Myopia of Learning", Strategic Management Journal, Vol. 14(52), pp.95-112.
Lowell, B. Lindsay. 2000. "H-1B Temporary Workers: Estimating the Population," The Center for Comparative Immigration Studies, UCSD, Working Paper 12.
Mairesse, J. and Hall, B. 1996. "Estimating the Productivity of Research and Development: An Exploration of GMM Methods Using Data on French and United States Manufacturing Firms." NBER Working Paper 5501.
Mansfield, E. 1988. "The Speed and Cost of Industrial Innovation in Japan and the United States: External vs. Internal Technology", Management Science, Vol. 34(10), pp.1157-1168.
March, J. and Simon, H. 1958. "Organizations", New York, NY: Wiley Publishers.
McGill, M. and Slocum, J. 1994. "The Smarter Organization: How to Build a Company that Learns, Unlearns, and Adapts to Capitalize on Marketplace Needs", New York, NY: Wiley Publishers.

Merges, R.P. 2006. “Patents, Entry, and Growth in the Software Industry”, University of California at Berkeley School of Law Working Paper Series.
Ministry of Internal Affairs and Communications (MIC), Government of Japan, 2008, “Research Report on High-Level ICT Human Resource Development,” (in Japanese), MIC website.
Minetaki, K. and Motohashi, K. 2009. “The Subcontracting Structure of the Software Industry: Empirical Analysis of Innovation Productivity” (in Japanese), RIETI Discussion Paper 09-J-002
Mowery, D., Oxley, J., and Silverman, B. 1996. “Strategic Alliances and Interfirm Knowledge Transfer”, Strategic Management Journal, Vol. 17(4), pp.77-91.
Nagaoka, S. 2007. “Assessing the R&D Management of a Firm in Terms of Speed and Science Linkage: Evidence from the U.S. Patents,” Journal of Economics, Management, and Strategy, Vol. 16(1), pp. 129-156.
Odagiri, H. and Yasuda, H. 1997. “Overseas R&D Activities of Japanese Firms,” in Goto, A. and Odagiri, H. (Eds.), Innovation in Japan, Oxford, Clarendon Press.
Pakes, A. and Griliches, Z. 1984. “Patent and R&D at the Firm Level: A First Look”, NBER Working Paper No. 561.
Pakes, A. and Griliches, Z. 1984. “Estimating Distributed Lags in Short Panels with Application to the Specification of Depreciation Patterns and Capital Stock Constructs”, Review of Economic Studies, Vol. 51(2), pp.243–262.
Perfect, S. and Wiles, K. 1994. “Alternative Constructions of Tobin’s Q: An Empirical Comparison”, Journal of Empirical Finance, pp.313-341.
Prahalad, C. and Bettis, R. 1986. “The Dominant Logic: A New Linkage Between Diversity and Performance”, Strategic Management Journal, Vol. 7(6), pp.485-501.
Singh, J. 2005. “Collaborative Networks as Determinants of Knowledge Diffusion Patterns”, Management Science, Vol. 51(5), pp.756-770.
Tanaka, T. 2003. “The Software Industry,” in Goto, A. and Odagiri, H., (Eds), 2003. Science-Based Industries (in Japanese), Tokyo, NTT Publishing Co., Ltd.
Yamaguchi, E. 2003. “The Semiconductor Device Industry,” in Goto, A. and Odagiri, H., (Eds), 2003. Science-Based Industries (in Japanese), Tokyo, NTT Publishing Co., Ltd.

Table I: Citation Function Results

	Full Sample		Citations to Software Patents Only	
Citing Grant Year	Coefficient	Std. Error	Coefficient	Std. Error
1993	0.1364 ***	0.0432	0.2345 ***	0.0533
1994	0.3248 ***	0.0500	0.4157 ***	0.0640
1995	0.6339 ***	0.0609	0.8949 ***	0.0771
1996	1.1426 ***	0.0769	1.7482 ***	0.0954
1997	1.4741 ***	0.0942	2.2345 ***	0.1345
1998	1.9031 ***	0.1123	2.7757 ***	0.1572
1999	2.2265 ***	0.1372	3.2193 ***	0.1635
2000	2.3847 ***	0.1622	3.4400 ***	0.1971
2001	2.8789 ***	0.1978	3.7422 ***	0.2304
2002	3.3690 ***	.	3.98453 ***	.
Cited Grant Year				
1981	-0.6114 ***	0.0184	-0.6314 ***	0.0191
1982	-0.7758 ***	0.0119	-0.7851 ***	0.0127
…	…	…	…	…
2000	-0.9977 ***	0.0004	-0.9981 ***	0.0003
2001	-0.9988 ***	0.0005	-0.9990 ***	0.0005
Citing Patent From Japan	-0.3358 ***	0.0220	-0.3916 ***	0.0231
Cited Software Patent	1.3483 ***	0.0484	n/a	n/a
Citing Patent From Japan X Cited Software Patent	-0.9225 ***	0.0590	n/a	n/a
Obsolescence	0.3824 ***	0.0053	0.3978 ***	0.0062
Diffusion	0.0002 ***	0.0000	0.0003 ***	0.0000
Adj R-Squared	0.8526		0.6460	
Number of Obs.	804		402	

Table II: Software Intensity by Sector, Firms in Tobin's Q Regression Sample, 1993-1999

		Share of Software Patents		Share of Citations to Software Patents	
Industry	No. of Firms	Mean	St. Deviation	Mean	St. Deviation
Electronics	68	0.0139 (**/**)	0.0183	0.1650 (**/**)	0.1528
Semiconductors	56	0.1452 (**/**)	0.1684	0.2691(**/*)	0.2099
IT Hardware	99	0.2320 (**/**)	0.2200	0.3316 (**/*)	0.2100

** - Test for equality of means rejected at 5% level for a pair of industries, * - Test for equality of means rejected at 10% level for a pair of industries

(/) - First term in bracket represents the upper pair, second term in bracket represents the lower pair

Table III: Software Patent Shares by Sector and Firm Origin, Tobin's Q Regression Sample, 1983-1999

	US Firms			Japanese Firms		
Industry	No. of Firms	Mean	St. Deviation	No. of Firms	Mean	St. Deviation
Electronics	16	0.0248(**/**)	0.0261	52	0.0106 (*/**)	0.0137
Semiconductors	43	0.1820 (**/**)	0.1749	13	0.0234 (*/**)	0.0450
IT Hardware	76	0.2822 (**/**)	0.2277	23	0.0663 (**/**)	0.0387

** - Test for equality of means rejected at 5% level for a pair of industries, * - Test for equality of means rejected at 10% level for a pair of industries

(/) - First term in bracket represents the upper pair, second term in bracket represents the lower pair

Table III-2: Share of Citations to Software by Non-Software IT Patents by Sector and Firm Origin, Tobin's Q Regression Sample, 1983-1999

	US Firms			Japanese Firms		
Industry	No. of Firms	Mean	St. Deviation	No. of Firms	Mean	St. Deviation
Electronics	16	0.1160 (**/**)	0.1231	52	0.1800 (/**)	0.1589
Semiconductors	43	0.3089 (**/)	0.2118	13	0.1374 (/**)	0.1434
IT Hardware	76	0.3378 (**/)	0.2260	23	0.3109 (**/**)	0.1476

** - Test for equality of means rejected at 5% level for a pair of industries, * - Test for equality of means rejected at 10% level for a pair of industries

(/) - First term in bracket represents the upper pair, second term in bracket represents the lower pair

Table IV: Tobin's Q Regression Results - By Period

	Entire Sample		1983-1988		1989-1993		1994-1999	
lnQ	NLS		NLS		NLS		NLS	
RD/Assets	**0.1721**		**-0.5772**		**-0.1905**		**0.1972**	
	(0.0489)	***	(0.0655)	***	(0.0566)	***	(0.0594)	***
RD/Assets * Japan	**-0.1625**		**0.5819**		**0.2078**		**-0.2099**	
	(0.0494)	***	(0.0654)	***	(0.0611)	***	(0.0617)	***
lnSales	0.0380		0.0498		0.0475		0.3236	
	(0.0016)	***	(0.0019)	***	(0.0027)	***	(0.0022)	***
N	2973		913		888		1172	
R-squared	0.4889		0.6051		0.5171		0.4925	

Industry controls, time controls, and other dummy variables not reported

Table IV-2: Tobin's Q Regression Results - By Period - Software Intensity

	Entire Sample		1983-1988		1989-1993		1994-1999	
lnQ	NLS		NLS		NLS		NLS	
RD/Assets	**0.0619**		**-0.3478**		**-0.1834**		**0.0848**	
	(0.0440)		(0.1019)	***	(0.0689)	***	(0.0524)	
RD/Assets * Japan	**0.0514**		**0.3375**		**0.3289**		**-0.0042**	
	(0.0643)		(0.1023)	***	(0.0934)	***	(0.0922)	
RD/Assets * Sof.Intensity	**0.2568**		**-0.0498**		**0.3557**		**0.1671**	
	(0.1233)	**	(0.0816)		(0.2259)		(0.1681)	
N	2973		913		888		1172	
R-squared	0.5108		0.6154		0.5304		0.4991	

Industry controls, time controls, and other level and dummy variables not reported

Appendix A

Table V: Patent Production Function Results: Entire Sample and By Sector

	Entire Sample			Electronics			Semiconductors			IT Hardware		
	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE
Log R&D	0.8300	0.1865	0.0124	1.0778	0.6272	0.2364	0.6294	0.1393	0.0330	0.7564	0.1286	0.0183
	(0.0452)	(0.2159)	(0.2178)	(0.0711)	(0.0515)	(0.0649)	(0.0814)	(0.0393)	(0.0369)	(0.0758)	(0.0301)	(0.0299)
Time 1989-1993	0.5256	0.5409	0.5388	0.0578	0.1209	0.1771	0.4726	0.6685	0.7089	0.6885	0.6516	0.6342
	(0.1312)	(0.0684)	(0.0624)	(0.1611)	(0.1314)	(0.1252)	(0.2566)	(0.1486)	(0.1282)	(0.1718)	(0.0907)	(0.0834)
Time 1994-1999	1.0674	1.3098	1.3752	-0.3737	-0.2725	-0.1716	1.3183	1.9250	2.1288	1.2491	1.3759	1.4005
	(0.1704)	(0.0665)	(0.0612)	(0.2574)	(0.1305)	(0.1249)	(0.3015)	(0.1422)	(0.1241)	(0.2083)	(0.0883)	(0.0819)
Japan Dummy	0.4003	0.4853	n.a.	-0.5425	-1.2094	n.a.	0.2269	0.3428	n.a.	0.9121	1.7556	n.a.
	(0.1974)	(0.1814)		(0.2600)	(0.2796)		(0.3511)	(0.3336)		(0.3239)	(0.2869)	
Japan * Time 1989-1993	-0.6963	-0.2654	-0.1614	-0.3780	-0.1123	0.0072	-0.2529	-1.0391	-0.0492	-0.7936	-0.2734	-0.1812
	(0.1515)	(0.0943)	(0.0861)	(0.1941)	(0.1479)	(0.1415)	(0.3583)	(0.2621)	(0.2264)	(0.2038)	(0.1472)	(0.1353)
Japan * Time 1994-1999	-1.0023	-0.7146	-0.6435	0.2891	0.5941	0.7105	-1.1184	-1.1435	-1.1602	-1.0569	-0.7088	-0.6333
	(0.2003)	(0.0946)	(0.0869)	(0.2884)	(0.1490)	(0.1431)	(0.5263)	(0.2498)	(0.2173)	(0.2767)	(0.1491)	(0.1377)
Electronics	-0.9619	0.8915	n.a.									
	(0.2402)	(0.2064)										
Semiconductors	-1.1759	0.6300	n.a.									
	(0.2258)	(0.2145)										
IT Hardware	-1.1356	0.5599	n.a.									
	(0.2443)	(0.1938)										
_cons	n.a.	n.a.	2.5148	-0.9807	0.9164	1.5926	-0.4581	0.5473	1.7714	-1.0538	1.0991	2.9155
			(0.0972)	(0.3612)	(0.3284)	(0.2433)	(0.2985)	(0.2386)	(0.1657)	(0.3462)	(0.1978)	(0.1540)

Table VI: Tobin's Q Regressions - US and Japan - Comparing Time Trends

	Entire Sample				US				Japan	
lnQ	FE		NLS		FE		NLS		FE	NLS
RD/Assets	**0.0175**		**0.1242**	***	**-1.2380**		**-0.1531**		**0.0072**	**0.0105**
	(0.0094)	*	(0.0322)		(0.1771)	***	(0.1791)		(0.0087)	(0.0071)
RD/Assets * Year_1989-1993	**0.0084**		**-0.0629**	*	**-0.3799**		**-0.4052**		**0.0059**	**0.0072**
	(0.0246)		(0.0385)		(0.0920)	***	(0.0711)	***	(0.0234)	(0.0306)
RD/Assets * Year_1994-1999	**0.01256**		**-0.0726**	*	**1.2647**		**0.2194**		**-0.0026**	**-0.0008**
	(0.0111)		(0.0428)		(0.1771)	***	(0.1838)		(0.0275)	(0.0250)
N	2973		2973		1529		1529		1444	1444
R-squared	0.1129		0.5180		0.2207		0.5883		0.2888	0.7532

Firm size coefficient, Industry controls, and other controls not reported

Table VII: Total Sample Period Tobin's Q Regression - Logarithmic Approximation FE and NLS - US and Japanese Firms - Electronics

lnQ	US FE		Japan FE		US NLLS		Japan NLLS	
RD/Assets	**1.1709**		**0.0178**		**1.5170**		**0.0114**	
	(0.3692)	***	(0.0097)	*	(0.6332)	**	(0.0078)	
RD/Assets * Time 1989-1993	**-0.7581**		**-0.0056**		**-0.5278**		**0.0000**	
	(0.1792)	***	(0.0244)		(0.2101)	**	(0.0345)	
RD/Assets * Time 1994-1999	**-0.2068**		**0.0207**		**-1.6333**		**0.0093**	
	(0.3045)		(0.0294)		(0.6450)	**	(0.0286)	
N	209		865		209		865	
R-squared	0.3936		0.3510		0.5828		0.7598	

Firm size, time dummies, and other controls not reported

Table VIII: Total Sample Period Tobin's Q Regression - Logarithmic Approximation FE and NLS - US and Japanese Firms - Semiconductors

	US		Japan		US		Japan	
lnQ	FE		FE		NLLS		NLLS	
RD/Assets	**-1.4462**		**0.0061**		**0.3945**		**-0.0148**	
	(0.3001)	***	(0.0294)		(0.3757)		(0.0193)	
RD/Assets * Time 1989-1993	**-0.5272**		**0.0609**		**-0.6778**		**0.1805**	
	(0.1596)	***	(0.2403)		(0.1473)	***	(0.1903)	
RD/Assets * Time 1994-1999	**1.4761**		**-0.1022**		**-0.1831**		**-0.3690**	
	(0.3001)	***	(0.2663)		(0.3957)		(0.1451)	**
N	468		209		468		209	
R-squared	0.3831		0.1276		0.6615		0.7696	

Firm size, time dummies, and other controls not reported

Table IX Total Sample Period Tobin's Q Regression - Logarithmic Approximation FE and NLS - US and Japanese Firms - IT Hardware

	US		Japan		US		Japan	
lnQ	FE		FE		NLLS		NLLS	
RD/Assets	**-1.6589**		**-0.0742**		**0.6943**	**	**0.2306**	
	(0.2633)	***	(0.1185)		(0.3546)		(0.1253)	*
RD/Assets * Time 1989-1993	**0.2243**		**-0.1399**		**0.2566**	***	**-0.1201**	
	(0.1553)		(0.1475)		(0.0946)		(0.1761)	
RD/Assets * Time 1994-1999	**1.0624**	***	**-0.0154**		**1.2291**	***	**-0.1962**	
	(0.2725)		(0.1469)		(0.3558)		(0.1754)	
N	852		370		852		370	
R-squared	0.1798		0.2604		0.5607		0.7524	

Firm size, time dummies, and other controls not reported

Table X: Tobin's Q Regressions Summary - Share of Software Patents

TOTAL

lnQ	below median		above median		25 percentile or lower		75th percentile or higher	
RD/Assets - US	**-0.2975**	***	**0.1107**	*	**0.1059**		**0.1689**	**
RD/Assets- Japan	**0.0499**	***	**0.0482**		**0.0155**		**-0.1519**	**

ELECTRONICS

lnQ	below median		above median		25 percentile or lower		75th percentile or higher	
RD/Assets - US	**0.1012**		**0.0200**		**0.9330**	***	**-0.0989**	*
RD/Assets- Japan	**0.1677**		**0.0058**		**0.2112**	**	**-0.1863**	

Table X: Tobin's Q Regressions Summary - Share of Software Patents (contd.)

SEMICONDUCTORS

lnQ	below median		above median		25 percentile or lower	75th percentile or higher
RD/Assets - US	**-0.4071**	***	**0.3880**		**-0.2349**	**0.8945** ***
RD/Assets- Japan	**0.0562**	***	**0.2246**		**0.0163**	**0.6957** **

IT HARDWARE

lnQ	below median		above median		25 percentile or lower	75th percentile or higher
RD/Assets - US	**(n/a)**		**-0.3662**	***	**-0.4499** ***	**-0.3327** ***
RD/Assets- Japan	**(n/a)**		**0.2175**	***	**-0.4599** ***	**0.0825** ***

Table XI: Distribution of Patents Held By Japanese Firms by Innovation Origin – Entire Sample

CITATION PATTERNS (citation counts)

PATENT COUNTS

Invented in Japan

citing patent class	Cited Patent Class: other	IT	software	Total	
other	426,152	40,199	6,358	**472,709**	50.25
IT	85,663	262,811	46,791	**395,265**	42.02
software	11,936	34,144	26,575	**72,655**	7.72
Total	**523,751**	**337,154**	**79,724**	**940,629**	
	55.68	35.84	8.48		
composition of citations for IT patents	22%	66%	12%		
composition of citations for software patents	16%	47%	37%		

	Freq.	Percent	Cum.
other	72,503	50	50.44
IT	62,326	43	93.8
software	8,914	6	100
Total	143,743	100	

Invented in the US

citing patent class	Cited Patent Class: other	IT	software	Total	
other	9,998	1,257	436	**11,691**	33.97
IT	2,699	5,126	1,595	**9,420**	27.37
software	1,976	5,064	6,264	**13,304**	38.66
Total	**14,673**	**11,447**	**8,295**	**34,415**	
	42.64	33.26	24.10		
composition of citations for IT patents	29%	54%	17%		
composition of citations for software patents	15%	38%	47%		

	Freq.	Percent	Cum.
other	977	36	35.54
IT	858	31	66.75
software	914	33	100
Total	2,749	100	

Invented elsewhere

citing patent class	Cited Patent Class: other	IT	software	Total	
other	1,115	141	28	**1,284**	22.30
IT	319	960	286	**1,565**	27.17
software	267	1,494	1,149	**2,910**	50.53
Total	**1,701**	**2,595**	**1,463**	**5,759**	
	29.54	45.06	25.40		
composition of citations for IT patents	20%	61%	18%		
composition of citations for software patents	9%	51%	39%		

	Freq.	Percent	Cum.
other	230	36	35.99
IT	258	40	76.37
software	151	24	100
Total	639	100	

Table XII: Distribution of Patents Held By Japanese Firms by Innovation Origin – Electronics

CITATION PATTERNS (citation counts)

PATENT COUNTS

Invented in Japan

citing patent class	Cited Patent Class: other	IT	software	Total	
other	162,555	10,097	1,714	**174,366**	66.58
IT	19,487	52,322	6,959	**78,768**	30.08
software	1,855	4,203	2,692	**8,750**	3.34
Total	**183,897**	**66,622**	**11,365**	**261,884**	
	70.22	25.44	4.34		
composition of citations for IT patents	25%	66%	9%		
composition of citations for software patents	21%	48%	31%		

	Freq.	Percent	Cum.
other	28,574	66	65.84
IT	13,573	31	97.12
software	1,252	3	100
Total	43,399	99.99	

Invented in the US

citing patent class	Cited Patent Class: other	IT	software	Total	
other	3,720	199	28	**3,947**	79.27
IT	275	459	34	**768**	15.42
software	64	137	63	**264**	5.30
Total	**4,059**	**795**	**125**	**4,979**	
	81.52	15.97	2.51		
composition of citations for IT patents	36%	60%	4%		
composition of citations for software patents	24%	52%	24%		

	Freq.	Percent	Cum.
other	251	77	76.99
IT	50	15	92.33
software	25	8	100
Total	326	100	

Invented elsewhere

citing patent class	Cited Patent Class: other	IT	software	Total	
other	103	4	0	**107**	76.43
IT	6	23	4	**33**	23.57
software	0	0	0	**0**	0.00
Total	**109**	**27**	**4**	**140**	
	77.86	19.29	2.86		
composition of citations for IT patents	18%	70%	12%		
composition of citations for software patents	#DIV/0!	#DIV/0!	#DIV/0!		

	Freq.	Percent	Cum.
other	24	67	66.67
IT	12	33	100
software	0	0	
Total	36	100	

Table XIII: Distribution of Patents Held By Japanese Firms by Innovation Origin – Semiconductors

CITATION PATTERNS (citation counts)

PATENT COUNTS

Invented in Japan

citing patent class	Cited Patent Class: other	IT	software	Total	
other	14,360	1,654	160	**16,174**	47.97
IT	3,673	11,473	1,100	**16,246**	48.18
software	242	721	334	**1,297**	3.85
Total	**18,275**	**13,848**	**1,594**	**33,717**	
	54.20	41.07	4.73		

	other	IT	software
composition of citations for IT patents	23%	71%	7%
composition of citations for software patents	19%	56%	26%

	Freq.	Percent	Cum.
other	2,605	45	45.2
IT	2,943	51	96.27
software	215	4	100
Total	5,763	100	

Invented in the US

citing patent class	Cited Patent Class: other	IT	software	Total	
other	95	7	0	**102**	14.78
IT	145	275	28	**448**	64.93
software	7	79	54	**140**	20.29
Total	**247**	**361**	**82**	**690**	
	35.80	52.32	11.88		

	other	IT	software
composition of citations for IT patents	32%	61%	6%
composition of citations for software patents	5%	56%	39%

	Freq.	Percent	Cum.
other	14	25	25.45
IT	28	51	76.36
software	13	24	100
Total	55	100	

Invented elsewhere

citing patent class	Cited Patent Class: other	IT	software	Total	
other	34	3	0	**37**	90.24
IT	0	4	0	**4**	9.76
software	0	0	0	**0**	0.00
Total	**34**	**7**	**0**	**41**	
	82.93	17.07	0.00		

	other	IT	software
composition of citations for IT patents	0%	100%	0%
composition of citations for software patents	0%	0%	0%

	Freq.	Percent	Cum.
other	6	86	85.71
IT	1	14	100
software	0	0	
Total	7	100	

Table XIV: Distribution of Patents Held By Japanese Firms by Innovation Origin – IT Hardware

CITATION PATTERNS (citation counts)

PATENT COUNTS

Invented in Japan

citing patent class	Cited Patent Class: other	IT	software	Total	
other	249,237	28,448	4,484	**282,169**	43.76
IT	62,478	198,882	38,720	**300,080**	46.53
software	9,839	29,220	23,549	**62,608**	9.71
Total	**321,554**	**256,550**	**66,753**	**644,857**	
	49.86	39.78	10.35		
composition of citations for IT patents	21%	66%	13%		
composition of citations for software patents	16%	47%	38%		

	Freq.	Percent	Cum.
other	41,324	44	43.7
IT	45,788	48	92.12
software	7,447	8	100
Total	94,559	100	

Invented in the US

citing patent class	Cited Patent Class: other	IT	software	Total	
other	6,183	1,051	408	**7,642**	26.58
IT	2,279	4,392	1,533	**8,204**	28.54
software	1,905	4,848	6,147	**12,900**	44.88
Total	**10,367**	**10,291**	**8,088**	**28,746**	
	36.06	35.80	28.14		
composition of citations for IT patents	28%	54%	19%		
composition of citations for software patents	15%	38%	48%		

	Freq.	Percent	Cum.
other	712	30	30.07
IT	780	33	63.01
software	876	37	100
Total	2,368	100	

Invented elsewhere

citing patent class	Cited Patent Class: other	IT	software	Total	
other	978	134	28	**1,140**	20.44
IT	313	933	282	**1,528**	27.39
software	267	1,494	1,149	**2,910**	52.17
Total	**1,558**	**2,561**	**1,459**	**5,578**	
	27.93	45.91	26.16		
composition of citations for IT patents	20%	61%	18%		
composition of citations for software patents	9%	51%	39%		

	Freq.	Percent	Cum.
other	200	34	33.56
IT	245	41	74.66
software	151	25	100
Total	596	100	

Appendix B

A Simple Model of Skill Complementarity in IT Innovation (Version 1, 2-Level CES)

In this section we present a very simple model of IT innovation in which we embed a particular kind of skill complementarity. To create new IT innovations (I), firms must employ hardware engineers (H) and software engineers (S). The highly labor intensive nature of software development requires contributions from very high skilled software architects (S_H) and lower skilled "code warriors," (S_L), who actually create, test, and maintain the subroutines and program modules scripted out by the architects. These two kinds of software engineers are complements. The productivity of the highly skilled architects, S_H, is enhanced by hiring larger numbers of code warriors and vice versa. To build this complementarity into our innovation production function in a simple way, we start with a two-level CES production function of the following nature:[41]

$$I_{it} = A[aS_{it}^{\rho} + (1-a)H_{it}^{\rho}]^{1/\rho} \text{ where } (\rho \leq 1) \qquad \text{(A-1)}$$

and

$$S_{it} = [b(S_{Hit}^{\theta} + (1-b)S_{Lit}^{\theta}] \text{ where } (\theta \leq 1) \qquad \text{(A-2)}$$

For notational simplicity, the coefficients a and b are represented as stable over time, but could, in principle vary. Complementarity between high-skilled and low-skilled software workers requires that $\rho > \theta$; in other words, the direct elasticity of substitution between H and S must exceed the direct elasticity of substitution within the "nest" between S_H and S_L.

[41] We follow Fallon and Layard (1975), Goldin and Katz (1996), Sanders and Weel (2000), and many others in using the 2-level CES as a mathematical formulation of this complementarity. An extensive literature uses this and other closely related functional forms to examine the hypothesis of complementarity between physical capital and worker skill. Our notation is closely related to Fallon and Layard (1975)

Note that, in this formulation, the increasing tendency of IT innovation to draw upon software advances (and less so upon hardware advances) can be represented by an increase over time in the a parameter. This is mathematically isomorphic to the way that many researchers in the labor and trade literatures have attempted to model the impact of skill-biased technical change. Profit maximization, taking factor prices as given, yields the result that relative factor payments in equilibrium will be:

$$\omega = \frac{W_H}{W_S} = \left[\frac{(1-a)}{a}\right]^{\rho}\left[\frac{H}{S}\right]^{\rho-1} \qquad \text{(A-3)}$$

In this simple case, Hicks-neutral technical progress in IT innovation can be defined as an increase in productivity that leaves relative factor prices stable for a given employment ratio; or equivalently leaves the factor employment ratio stable for a given wage ratio. From A-3, it follows that technical change in IT innovation is Hicks neutral so long as a does not change. The "changing nature of technical change" in IT is biased against hardware engineers (and toward software engineers) if a increases. Software-biased technical change could show show up empirically either as a relative wage change when controlling for supply shifts or as an employment-ratio change when controlling for relative wage shifts.

But the fact that we represent S as a composite of two different kinds of software engineers complicates the analysis somewhat. If Japanese and U.S. firms have approximately similar access to high-skilled software architects but very different levels of access to lower-skilled code warriors, then this could directly impact the optimal response of these two groups of to a common shift in a, in ways that we will illustrate below.

Given our representation, we can express the Hicks (1970) elasticity of complementarity for a constant returns production function as

$$c_{ij} = \frac{1}{v_j}\frac{\partial \log f_i}{\partial \log X_j} \qquad \text{(A-4)}$$

where v_j is the share of the jth factor in output, and $\partial \log f_i / \partial \log X_j$ indicates the proportional effect on the marginal product of the *i*th factor of a change in quantity of the *j*th factor, holding all other input quantities constant. This implies that

$$c_{S_H S_L} = \frac{1}{v_{S_L}} \cdot \frac{f_{S_H S_L}}{f_{S_H}} \cdot S_L \qquad \text{(A-5)\_}$$

which, in the case of our two-level CES function, can be expressed as

$$c_{S_H S_L} = 1 - \rho + \frac{1}{v_S}(\rho - \theta) \qquad \text{(A-6)}$$

and this implies that an increase in the quantity of S_L will raise the marginal product of S_H, and it will do so by more than it raises the marginal product of H. The Hicks elasticity of complementarity between S_L and H can be shown to be

$$c_{HS_L} = c_{S_H H} = 1 - \rho \qquad \text{(A-7)}$$

and this will be strictly less than the expression defined in (A-6) so long as $\rho > \theta$, which is true by assumption. We can also define the Allen elasticity of substitution used by Griliches (1969), which gives the impact of a factor price change on optimal factor quantities. In general, the Allen elasticity of substitution is

$$\sigma_{ij} = \frac{1}{v_j} \cdot \frac{\partial \log X_i}{\partial \log p_j} \qquad \text{(A-8)}$$

and in our 2-level CES, this corresponds to

$$\sigma_{S_H S_L} = \frac{1}{1-\rho} + \frac{1}{v_S}\left(\frac{1}{1-\theta} - \frac{1}{1-\rho}\right) \qquad \text{(A-9)}$$

while

$$\sigma_{HS_L} = \sigma_{S_H H} = \frac{1}{1-\rho} \qquad \text{(A-10)}$$

This implies that a decrease the price of S_L will tend to raise the optimal quantity of S_H, so long as $\rho > \theta$, which is true by assumption.

With these basic mathematics as background and foundation, here is the story we believe unfolded in the late 1980s and, especially, the 1990s. IT innovation became more software intensive. That is, a increased rapidly and sharply. The optimal response for IT firms in all countries was to respond by hiring more software engineers relative to hardware engineers. U.S.-based firms were able to tap into a fairly elastic supply of lower-skilled code warriors by importing increasingly large numbers of (disproportionately Indian) software engineers under the H-1B visa program and by outsourcing an increasing fraction of software development to offshore workers. This prevented the price of lower-skilled software engineers from rising. In fact, a true quality-adjusted index of lower-skilled software services might have actually declined for American firms as Indian software enterprises ramped up their ability to serve the U.S. market. In any case, the cost of lower-skilled software engineers remained much lower for U.S.-based firms than for Japanese firms. This raised the marginal product of higher skilled software engineers for U.S. firms while labor constraints in Japan –

the limited availability and relatively high prices of low-skilled software workers – lowered the marginal product of higher-skilled software workers from the perspective of Japan-based firms.

In the presence of the labor constraint they faced, the optimal response of Japanese firms was to invest in relatively fewer software engineers than their U.S counterparts. This, however, limited their innovative output relative to their U.S. counterparts and helped bring about the decline in relative performance documented in the text of the paper.