The Great Realignment: How the Changing Technology of Technological Change in Information Technology Affected the US and Japanese IT Industry, 1983-1999

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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

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 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.

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 tend to emerge 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 even the design of hardware products requires extensive software expertise. Gore (1998) argues that even peripherals are marked by the increasing emphasis on the software component of the solution, bringing together hardware and software into an integrated environment. 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 (Griliches, 1990; Jaffe and Trajtenberg, 2002; Trajtenberg, Schiff and Melamed, 2006), and although problems in using citaitons to measure knowledge flows have been identified (Alcácer and Gittelman, 2006), they are still the richest and most readily available micro level measure of innovation.

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, especially in the presence of changing patentability regimes, and (b) tracking patent counts does not tell us much about the connections between different types of IT innovation. The first problem is particularly severe in our case because of large changes in the patentability regime for software patents in the time period of interest.

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. [1]

The citation function has been pioneered in the work of Caballero and Jaffe (1993) and Jaffe and Trajtenberg (1996, 2002). Jaffe (1996) and Branstetter and Ogura (2005) successfully applied it to examining knowledge linkages between academic science and industrial innovation, Singh (2005) estimated citation functions to study collaborative networks as determinants of knowledge diffusion patterns, while Caballero and Jaffe (1993) used them to explore the rates of knowledge diffusion and obsolescence.

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:

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

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[1]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:

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

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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:

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

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

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

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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

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

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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.[2] 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.[3]

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

[2] 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.
[3] 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.[4]

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). 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.

[4]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.

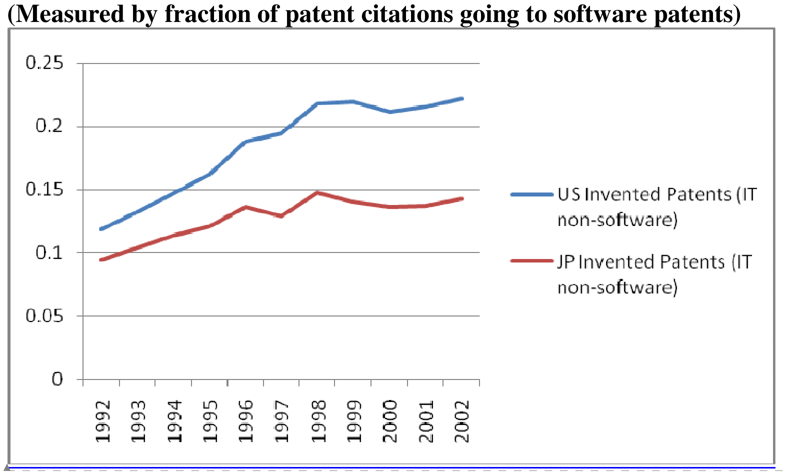
Results

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. It 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 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.

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



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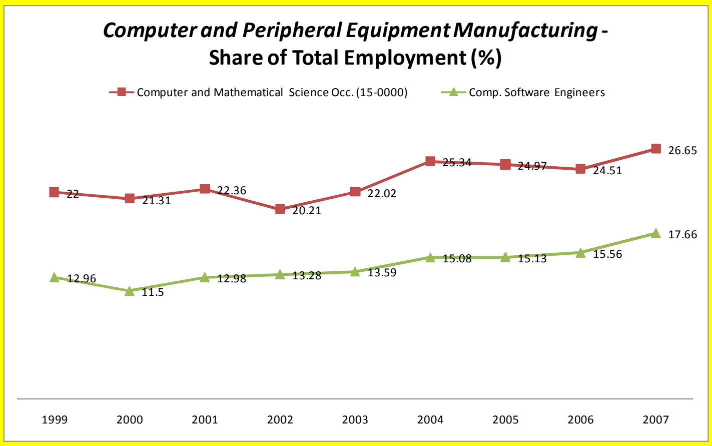
The results from the two specifications in Table I portray an interesting picture: software innovation is (increasingly) important for IT innovation broadly defined, and this appears to be especially true in the U.S. If this is true, then we might expect to see supporting evidence in patterns of employment 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[5] 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

[5] 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.

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.

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

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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.

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

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where

$$\phi_{it} = e^{\sum_c \delta_c D_c} \tag{7}$$

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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:

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

Field Code Changed

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

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

Field Code Changed

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).[6] In this approach, efficient capital markets are assumed, so that the market value 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:

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

Field Code Changed

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[7]. The functional form of f is not known, and we follow the literature, which assumes that the different assets enter additively..:

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

Field Code Changed

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:

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

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[6] See Hall (2000) for a detailed review.
[7] The construction of variables is explained in greater detail in subsequent sections.

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.

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[8] 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,[9] 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.

[8] GICS, the Global Industry Classification System, is constructed and managed by Moody's in collaboration with Compustat.

[9] NTT is the only Japanese firms in "IT services and software" in our sample.

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.[10] 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[11], and that were listed as belonging to either "electronics", "semiconductors", "IT 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[12] 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, which was as the only "IT Software and Services" firm, 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

[10] We thank the Columbia Business School Center on the Japanese Economy and Business for these data.
[11] January 1st, 2003 was the date of creation of this index.
[12] 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.

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.

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.[13] 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

[13] 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.

innovation than their foreign counterparts.[14] 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.

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.[15] 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-

[14] This is true in five out of six cases, although the measured differences are not always statistically significant.
[15] Downloaded from the following link: http://elsa.berkeley.edu/~bhhall/bhdata.html (12/15/2007)

producing employees,[16] 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 Hall, 1996; Hall, 1993).[17] We used 5 pre-sample years of R&D expenditures to calculate the initial stocks.[18]

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,

[16] We obtained these data from the Bureau of Labor Statistics and Statistics Bureau of Japan, respectively.
[17] 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..
[18] 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.

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.[19]

Replacement Cost of Assets: The replacement cost of the firm's assets is the deflated year-end book values of total assets.[20] 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.

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[19] 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.

20 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

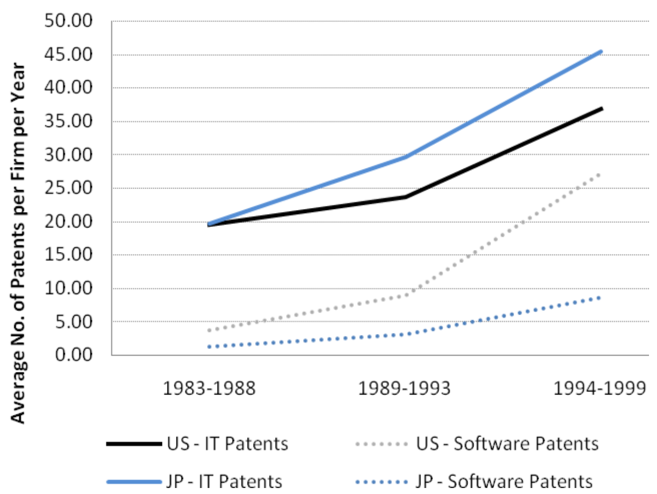
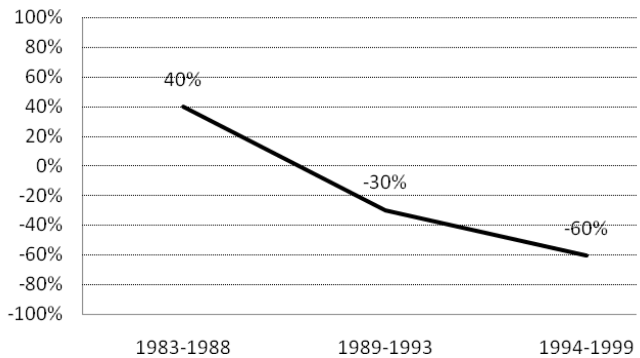


Table V in the Appendix reports the estimates of the patent production functions of Japanese and US IT firms. Our first key result is presented in Figure 4 below, which plots the pooled OLS average difference in log patent production per dollar of R&D, between Japanese and US firms in our sample through time, controlling for time and sector dummies,.[21] 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.

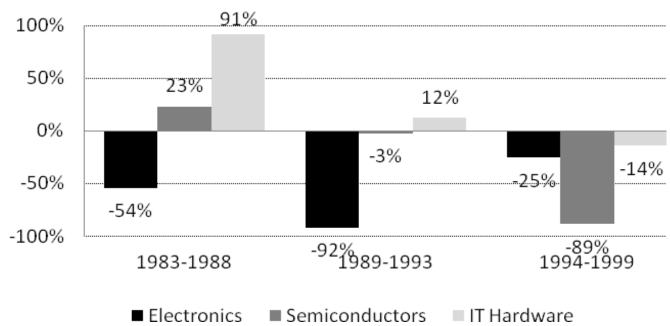
[21] Detailed results are found in Table IV in the Appendix.

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. On the other hand, in semiconductors and IT hardware, 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.[22]

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

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

Our empirical approach does, however, suffer from other possibly serious 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. If the few large Japanese semiconductor firms that we capture in the sample are systematically less productive in research than smaller or privately held Japanese semiconductor firms that we do not observe in our sample, then US-Japan productivity difference estimators might be upward biased. However, 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.

Another limitation is that we are unable to compare the research productivity of US and Japanese software firms, which is the sector where we could expect differences to be most pronounced. However, the lack of Japanese software firms is itself suggestive; if we were to such firms, the productivity differences would likely be favorable to US firms.[23]

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 ferociously 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.

[23] 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.

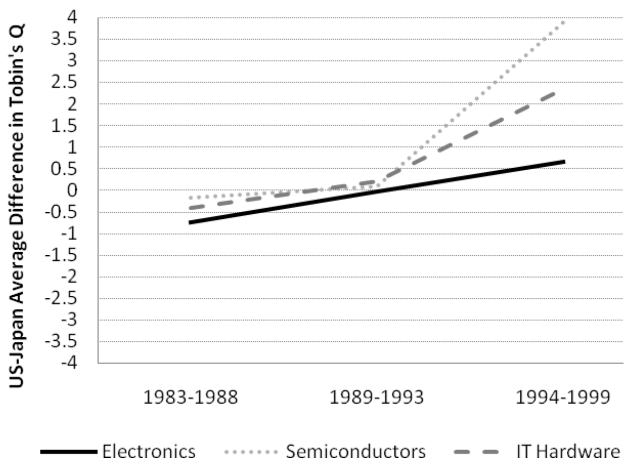
Private Returns to R&D

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.

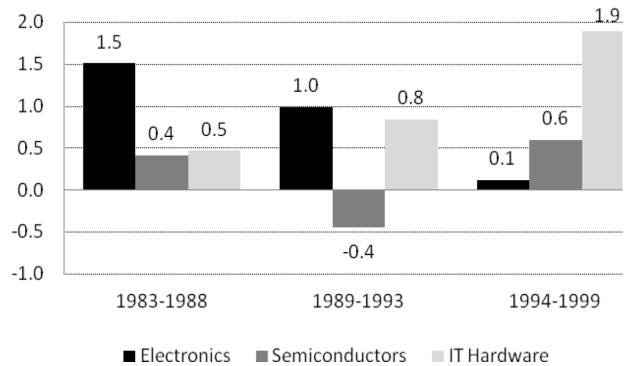
Figure 6: Average Difference in Tobin's Q, By Sector



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 that U.S. firms have superior access to software knowledge, and software professionals. The first explanation posits that the software related knowledge pool is constrained in Japan, whereas the same is not true in the US, and it also presumes that Japanese IT firms cannot overcome this disadvantage by tapping into foreign knowledge pools.

Japan's weakness in software has been widely recognized in the literature.[24] Anchordoguy (2000) argues that Japan has historically lagged the United States in systems and application software. Cusumano (1991), in his book, showed how Japan's electronics and hardware companies, at least partially due to the lack of availability of skilled software labor, took a factory approach to software, focusing on cost minimization, software reuse, bug minimization, and other techniques in order to increase productivity of their inadequately skilled and scarce software labor. Other studies, citing reasons as diverse as the Japanese language, lack of creativity of Japanese workers, and weak university computer science education, all reach the same conclusion of weak software competence of Japanese firms, weak software skills of Japanese software workers, and inadequate supply of highly skilled software labor in Japan (e.g., Fransman, 1995; Baba et al, 1996).

Further, it is widely acknowledged that tapping into distant knowledge pools is difficult, particularly across national boundaries (Jaffe, Trajtenberg, and Henderson 1993; Thompson and Fox-Kean 2005). 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.

Finally, 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

[24] Exceptions to this are the video game industry, some parts of the robotics industry, and Japan's indigenous cellular phone industry.

activities intensive in factors they are abundant with, a phenomenon they dub “factor-biased technical change”.

It is also possible that Japanese firms are simply less efficient in taking advantage of the access to software knowledge that they possess. 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 (IT). Using data on 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 poor performance of Japanese IT firms in the 1990s.

Our findings highlight important interconnections between firm competencies, technical change, and innovation performance. At an aggregate level, they contribute to a growing literature in international economics that explores linkages between factor endowments, technological change, and industry performance (e.g. Acemoglu, 2002; Dudley and Moenius, 2007). Furthermore, the policy implications of our findings are also potentially significant. Can Japan build up software skill and enhance its software related knowledge pools to augment Japanese IT firms' ability to compete in a software-intensive innovation environment? Could measures such as setting up more software intensive R&D facilities in the US or attracting Ph.D. level software skilled talent to Japan be taken to provide Japanese IT firms with a channel through which they can more effectively tap into foreign software knowledge pools? Answering these questions will require a model linking factor endowments, the "technology of technical change", and firm behavior. Empirically, it would require data on the knowledge and skill endowments available to firms, and the estimation of their impact on firm performance.

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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

lnQ	Entire Sample NLS		1983-1988 NLS		1989-1993 NLS		1994-1999 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

lnQ	Entire Sample NLS		1983-1988 NLS		1989-1993 NLS		1994-1999 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

Field Code Changed

Appendix

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

	US		Japan		US		Japan
lnQ	FE		FE		NLLS		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

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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		
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		
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		
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	