GOING SOFT: HOW THE RISE OF SOFTWARE-BASED INNOVATION LED TO THE DECLINE OF JAPAN'S IT INDUSTRY AND THE RESURGENCE OF SILICON VALLEY

Ashish Arora, Lee G. Branstetter, and Matej Drev*

Abstract—This paper documents a systematic shift in the nature of innovation in information technology (IT) toward increasing dependence on software. Using a broad panel of U.S. and Japanese publicly listed IT firms in the period 1983 to 2004, we show that this change in the nature of IT innovation had differential effects on the performance of the IT industries in the United States and Japan, resulting in U.S. firms increasingly outperforming their Japanese counterparts, particularly in more software-intensive sectors. We provide suggestive evidence that human resource constraints played a role in preventing Japanese firms from adapting to the documented shift in IT innovation.

I. Introduction

THE surge of innovation in information technology (IT) is one of the great economic developments of the past two decades. This period also coincides with the unexpected resurgence of the IT sector in the United States, belying the gloomy predictions about this industry popular in the late 1980s and early 1990s (Cantwell, 1992; Arrison & Harris, 1992). In this paper, we argue that these two developments are closely related.

We present evidence that the IT innovation process is increasingly software intensive: 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 see substantial differences across IT subsectors in the degree to which innovation is software intensive. We exploit these differences to sharpen our empirical analysis.

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 the United States and Japan for the period 1983 to 2004 show that U.S. IT firms have started to outperform their Japanese counterparts as measured by both the productivity of their innovative activities and the stock market valuation of their R&D.[1]

The timing and the concentration of this improvement in relative performance appear 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 subsectors in which the software intensity of innovation is the highest. Finally, much of the measured difference in financial performance disappears when we separately control for the software intensity of IT innovation at the firm level.

Why were U.S. firms better able to take advantage of the rising software intensity of IT innovation? Bloom, Sadun, and Van Reenen (2012) argue that superior American management allows U.S. multinationals to derive a greater productivity boost out of a given level of IT investment than their European rivals. In the context of our study, we find evidence that the openness of America's labor market to foreign software engineers may have played a key role in alleviating for American firms what was likely to have been a global shortage of skilled software engineers during the 1990s. When Japanese firms undertake R&D and product development in the United States, it appears to be much more software intensive than similar activity undertaken in Japan. These results highlight the importance of local factor market conditions in shaping the geography of innovation.

This paper is structured as follows. Section II documents the existence of a shift in the technological trajectory of IT, section III empirically explores its implications for the innovation performance of U.S. and Japanese IT firms, and 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 suggestions for future work.

Received for publication July 27, 2010. Revision accepted for publication February 2, 2012.

* Arora: Fuqua School of Business, Duke University, and NBER; Branstetter: Carnegie Mellon University and NBER; Drev: Carnegie Mellon University.

This paper is based on work supported by the U.S. National Science Foundation under grant no. 0830233 and FCT (the Portuguese National Science Foundation) under grant CMU-PT/Etech/0042/2009. We also received financial support from the Software Industry Center at Carnegie Mellon University and benefited from the research assistance of Kanako Hotta of UCSD. We acknowledge with gratitude useful comments from Hiroyuki Chuma, Anthony D'Costa, Kyoji Fukao, Shane Greenstein, Susumu Hayashi, Takao Kato, Toshiaki Kurokawa, Mark Kryder, Koji Nomura, Robert Cole, Jeffrey Smith, David Weinstein, and participants in the 2009 Spring Meeting of the NBER Productivity Program, the 2009 NBER Japan Project Conference, and the September 2009 Meeting of the Japan Economic Seminar at Columbia University.

A supplemental appendix is available online at http://www.mitpressjournals.org/doi/suppl/10.1162/REST_a_00286.

[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 divergence in productivity. For an earlier study of changing Japanese innovative performance using patent and R&D date, See Branstetter and Nakamura 2003).

The Review of Economics and Statistics, July 2013, 95(3): 757–775

II. The 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 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 et al. (2003) further argue that software will increase in importance 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 industries (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 that software has become more important in IT. In the next section, we validate this assertion formally, using data on citation patterns of IT patents.

III. Measuring the Shift in the Technology of Technological Change in IT

A. *Approach*

If innovation in IT truly has come to rely more heavily on software, then we should observe that more recent cohorts of IT patents cite software technologies with increasing intensity, and this should be the case even when we control for the changes over time in the volume of IT and software patenting. We therefore 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. Though subject to a variety of limitations, patent citations are frequently used to measure knowledge flows (Griliches, 1990; Jaffe & Trajtenberg, 2002). Following Caballero and Jaffe (1993) and Jaffe and Trajtenberg (1996, 2002), we use a citation function model in which we model the probability that a particular patent, p, applied for in year t, will cite a particular patent, P, 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 & Trajtenberg, 2002). The probability, $\Pr(p,P)$, is a function of the attributes of the citing patent p and the the cited patent P, $\alpha(p, P)$ and the time lag between them $(t - \mathrm{T})$:

$$\Pr(p,P) = \alpha(p,P) \times \exp(-\beta_1(t-T) \times (1-\exp(-\beta_2(t-T)). \quad (1)$$

We sort all potentially citing patents and all potentially cited patents into cells corresponding to the attributes of patents. The attributes of the citing patents comprise the citing patent's grant year, its geographic location, and its technological field (IT, software). The attributes of the cited patents are the cited patent's grant year, its geographic location, and its technological field. Thus, the expected number of citations from a particular group of citing patents to a particular group of cited patents can be expressed as

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

where the dependent variable measures the number of citations made by patents with grant year (a), geographic location (b), and technological field (c) to patents with 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, and n_{abc} and n_{def} are the number of patents in the respective categories. Rewriting equation (2) gives us the Jaffe–Trajtenberg (2002) version of the citation function, expressing the average number of citations from one category patent to another:

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

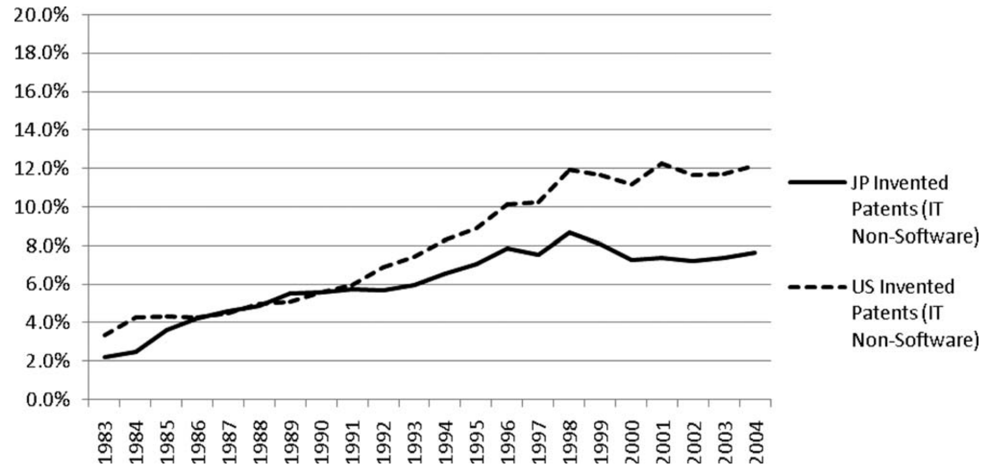
Adding an error term, we can estimate this equation using the nonlinear least squares estimator. The estimated equation thus becomes

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

In estimating equation (4), we adjust for heteroskedasticity by weighting the observations by the square root of the

[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.

FIGURE 1.—SOFTWARE INTENSITY OF NON-SOFTWARE IT PATENTS
FRACTION OF IT PATENT CITATIONS MADE TO SOFTWARE PATENTS



product of potentially cited patents and potentially citing patents corresponding to the cell, that is,

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

B. *Data*

We use patents granted by the U.S. Patent and Trademark Office (USPTO) between 1983 and 2004. We use the geographic location of the first inventor to determine the "nationality" of the patent. We identify IT patents, broadly defined, using a classification system based on USPTO classes, developed by Hall, Jaffe, and Trajtenberg (2001). They classified each patent into 36 technological subcategories. We applied their system and identified IT patents as those belonging to any of the following categories: computers and communications, electrical devices, or semiconductor devices. We obtained these data from the most recent version of the NBER patent data set, which covers patents granted through the end of 2006.

Next, we identified software-related patents, which is a challenge in itself. There have been three significant efforts to define software patents. Graham and Mowery (2003) defined software patents as the intersection of those falling within a narrow range of International Patent Classification (IPC) classes and those belonging to packaged software firms. This created a sample that omitted large numbers of software patents, according to Allison and Mann (2007).

The second effort was that of Bessen and Hunt (2007), who defined 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 and used a keyword search method instead. They identified a small set of patents that adhered to their definition and then used a machine learning algorithm to identify similar patents in the patent population, using a series of keywords in the patent title and abstract. Arora et al. (2007) used a similar approach that connects the Graham-Mowery and Bessen-Hunt definitions.[3]

We used a combination of broad keyword-based and patent class strategies to identify software patents. First, we generated a set of patents, granted after January 1, 1983, and before December 31, 2004, 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 to 2006. This produced a data set consisting of 106,379 patents.

These data are potentially affected by a number of biases. Not all inventions are patented, and special issues are raised by changes in the patentability of software over the course of our sample period, making it all the more important 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 the U.S. patents of Japanese firms are a reasonably accurate proxy of their inventive activity (Branstetter, 2001; Nagaoka, 2007). This is particularly true in IT, given the importance of the U.S. market in the various components of the global IT industry.

C. *Results*

Figure 1 shows trends over time in the fraction of total (non-software) IT patents' citations going to software patents. While the trends for both Japanese and U.S. firms rise significantly over the 1990s and then level off a bit in

[3] Allison and Mann (2007) 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 more accurate, this method is inherently subjective and not scalable.

TABLE 1.—CITATION FUNCTION RESULTS

	Full Sample		Citations to Software Patents Only	
	Coefficient	SE	Coefficient	SE
Citing grant year				
1991	0.4549**	0.1760	0.5013***	0.1662
1992	0.6572***	0.1783	0.7418***	0.1716
1993	0.7317***	0.1683	0.8482***	0.1645
1994	1.0131***	0.1750	1.2010***	0.1752
1995	1.2123***	0.1717	1.4509***	0.1742
1996	1.5258***	0.1722	1.8499***	0.1779
1997	1.5966***	0.1548	1.9673***	0.1619
1998	1.7073***	0.1378	2.1389***	0.1462
1999	1.6623***	0.1156	2.1203***	0.1239
2000	1.5740***	0.0960	2.0478***	0.1039
2001	2.1979***	0.0966	2.8943***	0.1072
2002	2.3529***	0.0915	3.1451***	0.1029
2003	2.3546***	.	3.1691***	.
Cited grant year				
1990	−0.0958***	0.0197	−0.1078***	0.0174
1991	−0.3330***	0.0191	−0.3621***	0.0165
...	...	...	...	...
2001	−0.8881***	0.0157	−0.9138***	0.0112
2002	−0.9167***	0.0191	−0.9367***	0.0137
Citing patent type				
Computer hardware and software	1.0414***	0.0398	1.1936***	0.0403
Computer peripherals	0.4806***	0.0345	0.5443***	0.0339
Information storage	0.3778***	0.0324	0.4296***	0.0317
Other computer and communication	2.3707***	0.0652	2.7084***	0.0674
Electrical devices	−0.8256***	0.0209	−0.9188***	0.0192
Semiconductors	−0.6657***	0.0199	−0.7863***	0.0186
Other				
Citing from Japan	−0.3078***	0.0313	−0.6298***	0.0059
Cited software patent	9.4217***	0.2573	n/a	n/a
Citing from Japan × Cited Software	−6.2592***	0.1981	n/a	n/a
Obsolescence	0.3252***	0.0095	0.3398***	0.0087
Diffusion	3.61e-06***	4.79e-07	3.56e-04***	4.27e-06
Adjusted R^2	0.9232		0.9674	
Number of observations	2,940		1,470	

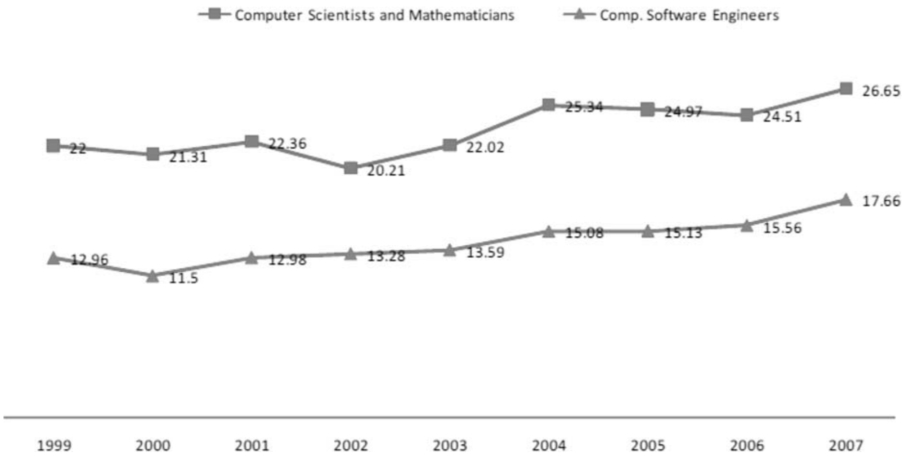
The data for regression estimations presented in this table are drawn from the CASSIS patent database maintained by the U.S. Patent and Trademark Office and from the NBER Patent Data Project database. Regression specifications are estimated in STATA using the nonlinear least squares algorithm. The dependent variable is an empirical measure of the probability a citing patent of a given type cites a cited patent of a given type. All presented coefficients are relative to base categories. They are the following: citing patent grant year = 1990, cited patent grant year = 1989, citing patent type = "Communications," cited patent category = "non-software" (only applicable to column I), citing patent geography = "Japan." Patent origin is defined using all inventors listed on the patent document.

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 of interest. However, this analysis does not take into account a variety of other factors; thus, we turn next to parametric analysis.

The unit of analysis in table 1 is an ordered pair of citing and cited patent classes. Our regression model is multiplicative, so a coefficient of 1 indicates no change relative to the base category. Our coefficients are reported as deviations from 1. The cited software patent dummy, large, positive, and statistically significant, indicates that IT patents in the 1990s are 9.42 times more likely to cite software patents than prior IT patents, controlling for the sizes of available IT and software patent pools. The second specification in table 1 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 1991 to 2003. An IT patent granted in 1996 is 1.85 times more likely to cite a software patent than an IT patent granted in 1990. Furthermore, an IT patent granted in 2003 is almost 3.2 times more likely to cite a software patent than that granted in 1990. Comparing the citing grant year coefficients in the left-hand column of table 1, obtained from the full sample, to the citing grant year coefficients in the right-hand column, obtained from citations to software patents only, shows that the tendency of IT patents to cite software patents increases over time, suggesting that software patents are becoming increasingly important for IT innovation. In table 1, 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 31% less likely to cite other IT patents than non-Japanese IT patents. However, they are also much 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 more recent years of our sample, we esti-

FIGURE 2.—TRENDS IN SOFTWARE ENGINEERING EMPLOYMENT
(PERCENT OF TOTAL EMPLOYMENT IN COMPUTER AND PERIPHERAL EQUIPMENT MANUFACTURING)



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

mated the propensity of U.S. IT patents to cite software patents generated outside the United States 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. Finally, concerned that this result might be observed at least partially due to traditionally stronger university-industry ties in the United States,[4] we also estimated a version of the citations function in which we excluded all university-assigned patents and those citing them. We found our results to be robust to this as well.

The U.S. Bureau of Labor Statistics data on U.S. employment by occupation and industry from 1999 to 2007 reveal trends consistent with a rising importance of software in IT innovation.[5] 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. Although we do not provide the additional figures for reasons of space, we have also seen similar trends in other IT subsectors. The share is highest in computers and peripherals, lowest in audio and visual equipment manufacturing, and at intermediate levels in semiconductors. Interestingly, the relative share of software engineers in total employment across subsectors appears to accord with patent citation-based measures of software intensity.

IV. Comparing U.S. and Japanese Firm-Level Innovation Performance in IT

Our citation function results suggest that there has been a shift in the nature of technical change within IT: invention has become much more software intensive. Our results also suggest that U.S. firms have more actively incorporated software into their inventive activity than have Japanese firms. If this is true, then it is reasonable to expect that changes in the relative performance of Japanese and American firms may be related to the software intensity of the industry segments in which they operate. In segments of IT where innovation has become most reliant on software, we should expect to see American firms improve their innovative performance relative to Japanese firms. In segments of IT where innovation does not draw heavily on software, we would expect less of an American resurgence. As we shall see, two very different measures of relative performance show exactly this pattern.

We use two of the most commonly employed empirical approaches to compare firm-level innovation performance of U.S. 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).

A. *Patent Production Function*

This approach builds on Pakes and Griliches (1984) and Hausman, Hall, and Griliches (1984). 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

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

In equation (6), P_{it} are patents taken out by firm i in period t, R_{it} are research and development expenditures, JP_i

[4] See Goto (2000) and Nagaoka (2007) for a more detailed discussion.
[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.

indicates if the firm is Japanese, and Φ represents sector-specific technological opportunity and patenting propensity differences D across c different innovation sectors as specified in equation (7). Substituting equation (7) into (6), taking logs of both sides, and expressing the sample analog we obtain

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

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 equation (9) to contain a firm-specific component, ξ_i, which accounts for the intraindustry firm-specific unobserved heterogeneity, and an i.i.d. random disturbance, u_{it}. The presence of the firm-specific error component suggests using random- or fixed-effects 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.

B. *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 Hall, 2000, for a detailed review, see also table 3). 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.[6] We follow the literature, which assumes that the different assets enter into the equation additively:

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

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 standard practice in the literature (Hall & Oriani, 2006), we assume constant returns to scale ($\sigma = 1$). Then, by taking natural logs on both sides of equation (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:

$$\ln Q_{it} = \ln\left(\frac{V_{it}}{A_{it}}\right) = \ln q_t + \ln\left[1 + \beta \times \left(\frac{K_{it}}{A_{it}}\right)\right]. \tag{12}$$

Following Hall and Kim (2000) and others, we estimate a version of equation (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 equation (12) with fixed effects.

C. *Data and Variables*

Sample. Our sample consists of large publicly traded IT companies in the United States and Japan, observed from 1983 to 2004.[7] We obtained the sample of U.S. firms from historical lists of constituents of Standard & Poor's (S&P) U.S. 500 and S&P 400 indices. The resulting set of firms was refined using Standard & Poor's Global Industry Classification Standard (GICS) classification so that only firms appearing in "electronics," "semiconductors," "IT hardware," and "IT software and services" categories remained in the sample.[8] This initial set of approximately 290 firms was narrowed further as follows: (a) only firms with least ten patents in between 1983 and 2004 were retained, (b) U.S. firms in "IT software and services" were removed to achieve compatibility, and (c) only firms for which at least three consecutive years of R&D investment and sales data were available were kept in the sample.[9] This yielded an unbalanced panel of 133 US IT firms.

The initial sample of 154 large, publicly traded Japanese IT firms derived from the Development Bank of Japan (DBJ) database[10] was supplemented by an additional 34 firms included in Standard & Poor's Japan 500 index as of January 1, 2003, that belong to either "electronics," "semiconductors," "IT hardware," or "IT software and services."[11]

We winnowed the sample by dropping all firms without at least ten patents in the observed period, dropping Nippon Telephone and Telegraph, and dropping all firms that did not have at least three consecutive years of R&D investment and positive output data. This produced a final sample of 77 Japanese IT firms.

Collectively, the Japanese and U.S. firms in our sample accounted for over 70% of total U.S. IT patenting by Japanese and U.S. firms, respectively, in the late 1990s and early

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

[7] We use the NBER Patent Database, which currently incorporates all patents granted through 2006. Since our empirical specifications use patents dated by the date of application, and since patents can take more than two years to work their way through the USPTO evaluation process, we are currently unable to extend our data past 2004.

[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.

[10] We thank the Columbia Business School Center on the Japanese Economy and Business for these data.

[11] January 1, 2003, was the date of creation of this index.

Table 2.—Software Intensity by Sector, 1983–2004

A. Firm-Level Software Intensity

	Share of Software Patents			Share of Citations to Software Patents		
Industry	Number of Observations	Mean	SD	Number of Observations	Mean	SD
Electronics	65	0.0387 (***/***)	0.0808	65	0.0544 (*/***)	0.0654
Semiconductors	53	0.1069 (***/***)	0.1246	53	0.0768 (*/***)	0.0837
IT hardware	92	0.1974 (***/***)	0.1681	92	0.1428 (***/***)	0.1109

B. Patent-Level Software Intensity

	Share of Software Patents			Share of Citations to Software Patents		
Industry	Number of Observations	Mean	SD	Number of Observations	Mean	SD
Electronics	67,775	0.0476 (***/***)	0.2130	23,452	0.0532 (***/***)	0.1429
Semiconductors	83,609	0.0995 (***/***)	0.2994	48,214	0.0742 (***/***)	0.1678
IT Hardware	25,1422	0.1439 (***/***)	0.3510	126,339	0.1127 (***/***)	0.2092

This table compares measures of software intensity of firms in our sample that belong to different subsectors. The data used to construct measures of software intensity come from the CASSIS patent database maintained by the U.S. Patent and Trademark Office and from the NBER Patent Data Project database. The unit of observation for descriptive statistics and statistical tests presented in panel A is a firm. The share of software patents for each firm is computed as the number of software patents granted to a firm in the sample period divided by the total number of patents granted to that firm in the sample period. The share of citations to software patents for each firm is calculated as the number of citations directed to software patents generated by the firm's non-software IT patent portfolio divided by the total number of citations generated by the firm's non-software IT patent portfolio. The tests for differences in means across sectors are performed using one-sided t-tests and are reported in the brackets next to the value of the mean. The difference is significant at *** 0.01, ** 0.05, and * 0.1. The first series of asterisks in any given bracket represents the results of a one-sided t-test for differences of means using the sector in question and the sector listed in the row above, while the second series of asterisks represents the results of a one-sided t test using the sector in question and the sector listed in the row below. For sectors listed in the first row, the first series of asterisks refers to a comparison with the sector listed in row immediately below, while the second series of asterisks refer to a comparison with the sector listed in the final row. An identical system applies to the interpretation of asterisks for sectors listed in the final row. The unit of observation for descriptive statistics and statistical tests presented in panel B is a patent. The share of software patents for each sector is computed as the number of software patents granted to all firms belonging to that sector in the sample period divided by the total number of patents granted to firms in that sector in the sample period. The share of citations to software patents for each sector is calculated as the number of citations directed to software patents generated by all firms' non-software IT patent portfolios divided by the total number of citations generated all firms' non-software IT patent portfolio. The tests for differences in means across sectors are performed using one-sided t tests and are reported in the brackets next to the value of the mean. The difference significant at ***0.01, **0.05, and *0.1. The first series of asterisks in any given bracket represents the results of a one-sided t test for differences of means using the sector in question and the sector listed in the row above, while the second series of asterisks represents the results of a one-sided t test using the sector in question and the sector listed in the row below. For sectors listed in the first row, the first series of asterisks refers to a comparison with the sector listed in row immediately below, while the second series of asterisks refers to a comparison with the sector listed in the final row. An identical system applies to the interpretation of asterisks for sectors listed in the final row.

2000s, confirming that we are capturing a large majority of private sector innovative activity in this domain.[12]

Locating firms in software intensity space. To explore how innovation performance differentials between U.S. and Japanese firms vary with software intensity, we classify firms into industry segments. GICS provided us with a classification of U.S. 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 data from Japan's Standard Industrial Classification (JSIC), supplemented by data from 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, averaged across firms in an industry category. Second, we calculate the fraction of citations to software patents by non-software IT patents, averaged across firms in a sample category. Table 2 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. Table 3 calculates 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 applies to the country-specific subsamples as well.[13] Japanese firms are disproportionately located in less software-intensive sectors, and within those sectors, are less software-intensive than their U.S. counterparts.

Taking the assignment of firms to the different IT industries as given, we test whether U.S. firms outperform Japanese firms and whether this performance gap is more marked in IT industries that are more software intensive.[14]

Construction of variables. *Patent counts*—Patent data for our sample of firms were collected from the updated NBER patent data set containing patents granted by the end of 2006. Compustat firm identifiers were matched with assignee codes based on the matching as constructed and available on the NBER's Patent Data Project website.[15] The matching algorithm for Japanese firms was based on a

[12] Figuring out what fraction of total IT production is accounted for by our firms is harder because of the far-reaching globalization of IT production by the late 1990s. According to the OECD, the top ten IT U.S. firms in our sample in 1999 had global revenues greater than the entire amount of IT production in the United States in that year. The picture is similar for our Japanese firms, which have also taken increasing advantage of opportunities to offshore production.

[13] Depending on the measure, tests of equality are not always statistically significant when we disaggregate them by country of origin. When Japanese software intensity is measured by citations to software in non-software patents, electronics is (insignificantly) more software intensive than semiconductors.

[14] Our main results are robust to using firm-level software intensity assignments instead of industry classifications.

[15] Downloaded from https://sites.google.com/site/patentdataproject/.

TABLE 3.—SOFTWARE INTENSITY BY SECTOR AND FIRM ORIGIN, 1983–2004

A. Software Patent Shares by Sector and Firm Origin

	U.S. Firms			Japanese Firms		
Industry	Number of Observations	Mean	SD	Number of Observations	Mean	SD
Unit of observation is a firm:						
Electronics	22	0.0806 (*/***)	0.1425	43	0.0173 (/***)	0.0195
Semiconductors	41	0.1341 (*/***)	0.1292	12	0.0138 (/***)	0.0213
IT hardware	70	0.2411 (***/***)	0.1699	22	0.0585 (***/***)	0.0329
Unit of observation is a patent:						
Electronics	38,902	0.0647 (***/***)	0.2460	28873	0.0247 (***/***)	0.1551
Semiconductors	56,833	0.1324 (***/***)	0.3389	26776	0.0298 (***/***)	0.1700
IT hardware	104,998	0.2337 (***/***)	0.4232	146424	0.0795 (***/***)	0.2705

B. Share of Citations to Software by Non-Software IT Patents by Sector and Firm Origin

	U.S. Firms			Japanese Firms		
Industry	Number of Observations	Mean	SD	Number of Observations	Mean	SD
Unit of observation is a firm:						
Electronics	22	0.0761 (/***)	0.0921	43	0.0435 (/***)	0.0452
Semiconductors	41	0.0895 (/***)	0.0884	12	0.0286 (/***)	0.0334
IT Hardware	70	0.1647 (***/***)	0.1173	22	0.0738 (***/***)	0.0384
Unit of observation is a patent:						
Electronics	12,915	0.0617 (***/***)	0.1504	10,537	0.0430 (***/***)	0.1325
Semiconductors	36,389	0.0797 (***/***)	0.1726	11,825	0.0572 (***/***)	0.1507
IT Hardware	53,706	0.1466 (***/***)	0.2326	72,633	0.0877 (***/***)	0.1862

This table compares measures of software intensity of firms in our sample that belong to different subsectors, separately for those firms based in Japan and those based in the United States. The data used to construct measures of software intensity come from the CASSIS patent database maintained by the U.S. Patent and Trademark Office and from the NBER Patent Data Project database. The unit of observation for descriptive statistics and statistical tests presented in the upper panel is a firm, while it is a patent in the lower panel. For details about the construction of software intensity measures, consult table 2. The tests for differences in means across sectors are performed using one-sided *t* tests and are reported in the brackets next to the value of the mean. The difference is significant at ***0.01, **0.05, *0.1. The first series of asterisks in any given bracket represents the results of a one-sided *t* test for differences of means using the sector in question and the sector listed in the row above, while the second series of asterisks represents the results of a one-sided *t* test using the sector in question and the sector listed in the row below. For sectors listed in the first row, the first series of asterisks refers to a comparison with the sector listed in row immediately below, while the second series refers to a comparison with the sector listed in the final row. An identical system applies to the interpretation of asterisks for sectors listed in the final row.

Tokyo Stock Exchange (TSE) code – assignee code concordance previously used in Branstetter (2001), but was manually updated by matching strings of firm names and strings of assignee names as reported by the USPTO.

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 was collected from annual volumes of the Kaisha Shiki Ho survey.[16] We deflated R&D expenditures following Griliches (1984), and constructed a separate R&D deflator for U.S. and Japanese firms that weigh 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, 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.[17]

R&D stocks—We calculated R&D capital stocks from R&D expenditure flows using the perpetual inventory method, with a 15% depreciation rate.[18] We used five presample years of R&D expenditures to calculate the initial stocks.[19]

Market value of the firm: The market value of a firm equals the sum of market value of its equity and market value of its debt (Perfect & Wiles, 1994). The 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 U.S. 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 mean of the two to obtain share price for each firm-year combination. In addition, preferred capital data were not available for Japanese firms, which should not create problems as long as preferred capital does not systematically vary with time and across technology sectors. For the market value of debt, we used total long-term debt and debt in current liabilities. For

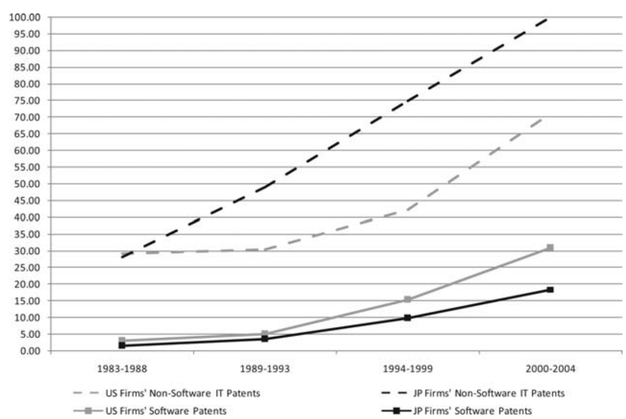
[16] *Kaisha Shiki Ho* (Japan Company Handbooks) is an annual survey of Japanese firms, published by the Japanese equivalent of Dow Jones & Company, Toyo Keizai. We thank Kanako Hotta for assistance in obtaining these data from the collections at the School of International Relations and Pacific Studies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

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

[18] See Griliches and Mairesse (1984) and Hall and Oriani (2006) for a detailed description and discussion of this methodology. We used several depreciation rates between 10% and 30%, with little change in the results.

[19] When the expenditure data were not available, we used the first five 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.

FIGURE 3.—AVERAGE NUMBER OF NON-SOFTWARE IT AND SOFTWARE PATENTS PER FIRM



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.[20]

Replacement cost of assets—The replacement cost of the firm's assets is the deflated year-end book values of total assets, where the deflator is a country-specific capital goods deflator obtained from the Bureau of Labor Statistics and the Statistics Bureau of Japan, respectively.[21]

D. *Patent Production Function Results*

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

Table 4 reports the estimates of the patent production functions of U.S. and Japanese IT firms. Our first key result is presented in figure 4, which plots the pooled OLS average difference in log patent production per dollar of R&D, between Japanese and U.S. firms in our sample through time, controlling for time and sector dummies. We see that R&D spending by Japanese firms was 70% more productive than that of their U.S. counterparts during 1983–1988, but became less and less productive from 1989–1993 onward. This trend accelerated in the 1990s and early 2000s, with Japanese IT firms producing 20% fewer patents, controlling for the level of R&D spending, than their U.S. counterparts in the period 2000 to 2004.

Figure 5 reports Japan-U.S. differences in patent output controlling for R&D input by IT sector. In electronics, previously shown to be the least software intensive and where average software intensity is similar between U.S. and Japanese firms, Japanese firms were less productive in patent production in the 1980s and early 1990s, but were catching up to their US counterparts in the mid- to late 1990s and early 2000s.[22] In semiconductors and IT hardware, which have significantly higher software intensity than electronics and where the average software intensity of U.S. firms is greater than of Japanese firms, Japanese firms exhibited higher productivity in the mid-1980s, started losing their advantage by the turn of the 1990s, and started to lag behind their U.S. counterparts in the middle to the end of early 2000s.[23]

Most of the results in table 4 are statistically significant at the 5% level and become more statistically significant in more recent time periods. In addition, the results are robust to changes in estimation techniques and measures. Random effects and fixed effects estimates are similar, suggesting that our results are not driven by unobserved firm-specific research productivity or patent propensity differences. The dependent variable in these estimations is the log of total patents applied for by firm i in year t. Unreported estimations show that the results are very similar if we use instead the log of IT patents, or the log of IT patents excluding software patents, or if we weight patents by subsequent citations or by the number of claims.

E. *Accounting for Alternative Hypotheses*

Collapse of the Japanese bubble economy at the end of the 1980s. The shift in relative performance parallels the slowdown in the Japanese domestic economy at the end of the 1980s. This domestic slowdown could have led to lower levels of R&D expenditure by Japanese firms. However, a simple recession-induced decline in R&D investment cannot explain our results. We are estimating the productivity of R&D in producing patents rather than the number of patents produced. If Japanese firms sought cost savings by eliminating marginal R&D projects, measured productivity should be higher, not lower. Budget pressures could also have led Japanese firms to change their patent propensity, filing fewer but higher-quality patents outside Japan. However, estimates using citation-weighted patents yield results

[20] Perfect and Wiles (1994) suggest that the measurement error in using book value of debt is modest.

[21] Perfect and Wiles (1994) note that different calculation methodologies result in different absolute replacement cost values but do not seem to bias coefficients on R&D capital.

[22] In the middle of the first decade of the twenty-first century, 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 (2007), warned of imminent commoditization of these new products, a prediction that has been borne out in the latter years of the decade.

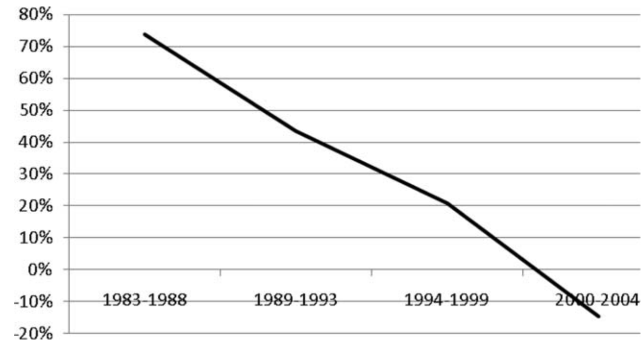
[23] An earlier version of the paper used data that ended in the late 1990s, raising the possibility that our results were driven by the late 1990s IT bubble. Extension of our data into the first decade of the new century shows that this is not the case. We thank an anonymous referee for pushing us to extend these data. See Chuma and Hashimoto (2007) for an alternative discussion of the difficulties of the Japanese semiconductor industry.

TABLE 4.—PATENT PRODUCTION FUNCTION REGRESSIONS, JAPANESE INDICATOR AND TIME TRENDS, ENTIRE SAMPLE AND BY SECTOR, 1983–2004

	Entire Sample			Electronics			Semiconductors			IT Hardware		
	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE	OLS	RE	FE
Log R&D	0.9814	0.7429	0.6682	0.9456	0.6944	0.6208	0.9725	0.8241	0.6761	0.9541	0.6865	0.6186
	(0.0392)***	(0.0463)***	(0.0542)***	(0.0762)**	(0.0465)***	(0.0672)***	(0.0907)***	(0.1019)***	(0.1205)***	(0.0582)***	(0.0718)***	(0.0817)***
1989–1993	0.0066	0.1056	0.1237	0.1132	0.2701	0.3049	0.1310	0.1312	0.1378	0.0029	0.0983	0.1136
	(0.0765)	(0.0668)	(0.0680)*	(0.1771)	(0.0982)***	(0.0995)***	(0.1660)	(0.1411)	(0.1420)	(0.0954)	(0.0937)	(0.0969)
1994–1999	0.1151	0.4168	0.4942	−0.2141	0.0723	0.1328	0.2525	0.6259	0.8167	0.2313	0.4461	0.5067
	(0.1269)	(0.1142)***	(0.1174)***	(0.3336)	(0.3504)	(0.3598)	(0.2278)	(0.1931)***	(0.2002)***	(0.1677)	(0.1380)***	(0.1414)***
2000–2004	0.5053	1.0171	1.1456	−0.1647	0.3258	0.4280	0.3877	1.0983	1.4642	0.9636	1.1928	1.2684
	(0.1381)***	(0.1230)***	(0.1294)***	(0.2629)	(0.2137)	(0.2235)*	(0.2581)	(0.2317)***	(0.2553)***	(0.1954)***	(0.1718)***	(0.1752)***
Japan dummy	0.7363	0.8482	NA	−0.0607	−0.1600	NA	0.5806	0.7832	NA	1.2059	1.5392	NA
	(0.1796)***	(0.1922)***		(0.2692)	(0.3053)		(0.3523)	(0.3951)**		(0.2835)***	(0.2843)***	
Japan × 1989–1993	−0.3033	−0.1823	−0.1584	−0.5258	−0.4881	−0.4850	−0.1639	0.0697	0.1415	−0.1511	−0.0052	0.0230
	(0.1116)***	(0.0984)*	(0.0994)	(0.2069)**	(0.1341)***	(0.1345)***	(0.2761)	(0.2772)	(0.2795)	(0.1702)	(0.1451)	(0.1456)
Japan × 1994–1999	−0.5294	−0.5037	−0.5111	−0.3492	−0.2176	−0.2118	−0.4814	−0.5691	−0.5924	−0.3786	−0.4228	−0.4283
	(0.1713)***	(0.1435)***	(0.1451)***	(0.3706)	(0.3584)	(0.3666)	(0.4434)	(0.4132)	(0.4172)	(0.2414)	(0.2086)**	(0.2100)**
Japan × 2000–2004	−0.8835	−1.0319	−1.0758	−0.3181	−0.4322	−0.4551	−0.6613	−1.0342	−1.1847	−1.0342	−0.9954	−1.0056
	(0.1884)***	(0.1740)***	(0.1759)***	(0.3145)	(0.2392)*	(0.2407)*	(0.5045)	(0.5781)*	(0.6008)*	(0.2905)***	(0.2771)***	(0.2781)***

The asterisks that are listed next to coefficients reported in the table denote statistical significance in the following manner: (***) represents significance at the 0.01 level, (**) at 0.05, and (*) at 0.1. The firm-level R&D expenditure data for regression estimations presented in this table were obtained from Compustat and annual volumes of the Kaisha Shiki Ho survey for U.S. and Japanese firms, respectively. Patent data come from the CASSIS patent database maintained by the U.S. Patent and Trademark office and from the NBER Patent Data Project database. The data represent an unbalanced panel of large, publicly traded U.S. and Japanese IT firms active in the sample period, 1983–2004. The dependent variable is the log of the number of total patents granted in a given year. The Japan dummy equals 1 when a firm is based in Japan. Regression specifications are estimated in STATA using ordinary least squares, random effects, and fixed effects algorithms. Robust and cluster-corrected standard errors are reported in brackets. For detailed information about the specification, sample selection, and variable construction, consult the text. For brevity, only coefficients on variables of interest are reported, while coefficients on some of the control variables may be omitted. Detailed estimation results are available from the authors by request.

FIGURE 4.—AVERAGE JAPAN-U.S. R&D PRODUCTIVITY DIFFERENCES, ENTIRE SAMPLE



Based on results from table 4. Reported are pooled OLS estimation coefficients.

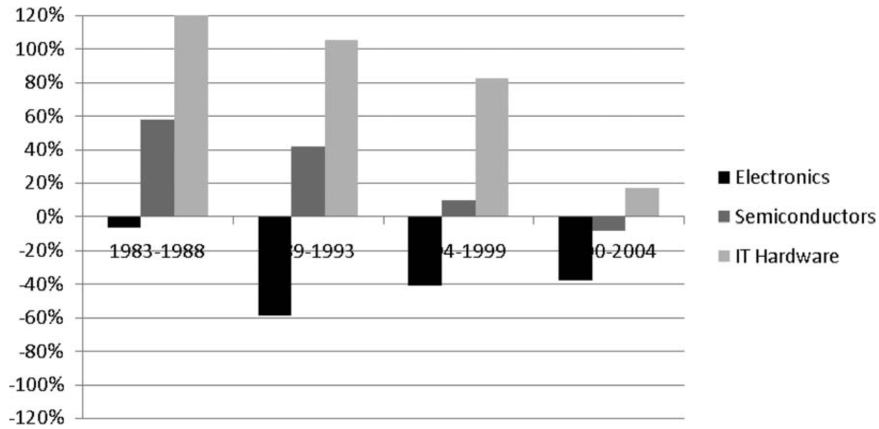
similar to those reported above. More fundamentally, no simple story about a post-bubble slowdown in the domestic economy can explain the observed pattern, wherein the relative decline in productivity is greater in more software-intensive segments.

Appreciation of the yen after 1985. The yen appreciated sharply in the mid-1980s and remained much stronger through the mid- to late 1990s.[24] These exchange rate shifts lowered the international competitiveness of Japan-based manufacturing. However, we do not think that exchange rate shifts are driving our results. All the segments of the Japanese IT industry confronted the same yen-dollar exchange rate, yet the relative innovative performance of the different segments varied in ways that are difficult to explain based on exchange rate considerations alone. For example, the Japanese electronics sector is arguably the one most likely to be affected by an appreciating currency; electronics had a much larger "commodity" share in total output, as compared to semiconductors and hardware. However, it is electronics in which Japan's relative performance strengthened the most.

Strong venture capital in the United States, weak venture capital in Japan. Kortum and Lerner (2001) provide evidence of the strong role played by venture capital–backed firms in the acceleration of innovation in the United States in the 1990s. Recent Japanese scholarship (Hamada, 1996; Goto, 2000; Goto & Odagiri, 2003) stresses the relative weakness of venture capital in Japan as an impediment to the growth of science-based industries. While it is certainly true that new firms adept at software-based innovation entered the market in the mid- to late 1990s, often with backing from venture capitalists, our results do not depend on their inclusion in the sample. For instance, we get similar results if we remove all U.S. firms that went public after the Netscape IPO, widely regarded as the start of the VC-fueled boom in the United States.

[24] See Jorgenson and Nomura (2005) and Hamada and Okada (2009) for a discussion of the impact of exchange rate movements on Japanese industry and the overall economy.

FIGURE 5.—AVERAGE JAPAN-U.S. PRODUCTIVITY DIFFERENCES, BY SOFTWARE INTENSITY SECTOR



Based on results from table 4. of Appendix A. Reported are selected pooled OLS estimation coefficients.

Strong university-industry linkages in the United States, weak linkages in Japan. Goto (2000), Nagaoka (2007), and many others have suggested that weaker Japanese universities and weaker mechanisms for university-industry technology transfer impede growth in Japan's science-based industries. We acknowledge the importance of these linkages. However, if university-generated inventions were an important element in the transformation of the U.S. IT sector, then corporate patents citing these university-generated inventions should be especially important in generating our empirical results. We delete all university-owned inventions and all corporate patents citing university-owned inventions from our data; the results do not change.

Technology standards and market dominance Japanese scholars such as Tanaka (2003) have suggested that the increasing dominance of U.S. IT firms since the 1990s is driven largely by U.S. ownership of key technology standards in the industry. Though owning a major technology standard may be beneficial, we can delete from our sample all U.S firms that could plausibly be described as owners of a major IT technology standard without altering our results. The most (in)famous standard owner, Microsoft, is never included in the sample: we do not include firms from the packaged software industry, because there are very few publicly traded Japanese firms in that segment.[25] If we were to include the packaged software firms such as Oracle and Google, the productivity differences would be even more favorable to the United States.

The same arguments may apply to the decline of one of Japan's important technology standards. Throughout the 1980s, the Japanese firm NEC dominated the sales of personal computers in Japan. NEC pioneered the development of a PC capable of handling Japan's complex written language. The popularity of the NEC standard created a virtuous cycle in which Japanese software firms and game developers focused their efforts on NEC-compatible products, reinforcing NEC's market dominance. In 1991, a consortium led by IBM Japan introduced DOS/V, an operating system that allowed IBM-compatible PCs to handle the Japanese language without any additional IT hardware.[26]

The introduction of this software ended NEC's market dominance and allowed a new group of firms to gain market share. The firm most obviously affected by DOS/V is NEC, and our results are robust to the exclusion of NEC. Insofar as the introduction of DOS/V reduced R&D by other Japanese IT firms by shrinking their markets, this may be reflected in our Tobin's q results. However, to the extent that this market compression induced firms to reduce R&D spending, they should have cut the marginal projects first, suggesting, if anything, an increase in R&D productivity rather than the decrease that we see in the data.

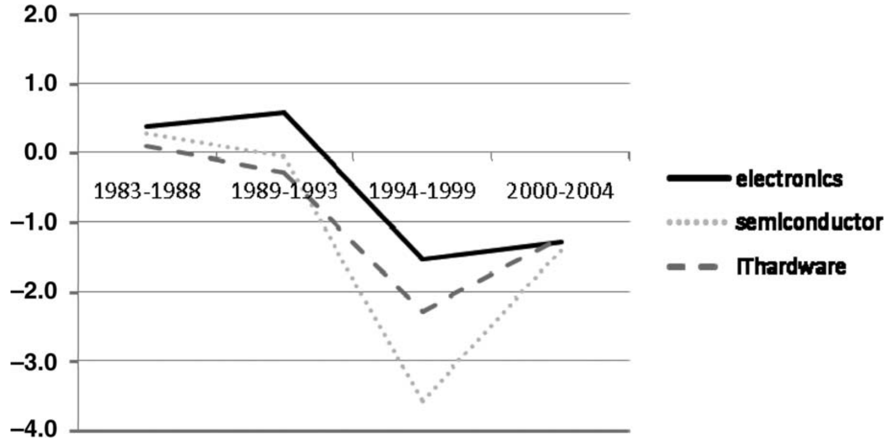
F. *Results Based on Private Returns to R&D*

We begin by plotting the average difference in Tobin's Q between our sample of U.S. and Japanese firms through time, shown in figure 6. We observe that Japanese firms, on average, had higher q values than U.S. firms in the mid-1980s and early 1990s. These differences diminished with the bursting of the Japanese economic bubble at the dawn of the 1990s, and Japanese q values lagged throughout the 1990s, especially in semiconductors and, to a lesser extent, in IT hardware, before recovering somewhat in the early 2000s with the bursting of the U.S. stock market bubble. Thus, trends in average Tobin's q values generally parallel those in patent production.

[25] Toward the end of the 1990s, a small number of publicly listed firms, such as Softbank, that we could classify as software firms appeared on the Tokyo Stock Exchange. Motohashi (2009) uses a different data set to explore productivity trends in the Japanese software industry but does not attempt an international comparison.

[26] We thank an anonymous referee for stressing the importance of this event. Jorgenson and Nomura (2005) discuss this event and show that the pace of IT price declines in Japan accelerates after the introduction of DOS/V.

FIGURE 6.—AVERAGE DIFFERENCE IN A RAW MEASURE OF TOBIN'S Q, BY SECTOR



Tobin's q as calculated in the database, averaged across sector. Calculated as U.S. average subtracted from JP average.

TABLE 5.—TOBIN'S Q REGRESSIONS

A. Tobin's q Regressions by Period, 1983–2004

lnQ	Entire Sample NLS	1983–1988 NLS	1989–1993 NLS	1994–1999 NLS	2000–2004 NLS
RD/Assets	0.1087	0.0158	−0.0564	0.2196	−0.0579
	(0.0415)***	(0.1451)	(0.0812)	(0.0897)**	(0.0495)
RD/Assets × Japan	−0.1327	0.0008	0.0250	−0.2844	−0.2916
	(0.0556)**	(0.1516)	(0.1129)	(0.1310)**	(0.1408)**
lnSales	0.0356	0.0198	0.0309	0.0995	0.0966
	(0.0039)***	(0.0069)***	(0.0062)***	(0.0059)***	(0.0050)***
Number of Observations	3,571	825	833	1,082	831
R^2	0.2986	0.2763	0.2429	0.4414	0.4049

B. Tobin's Q regressions by period, Including Firm-Level Software Intensity, 1983–2004

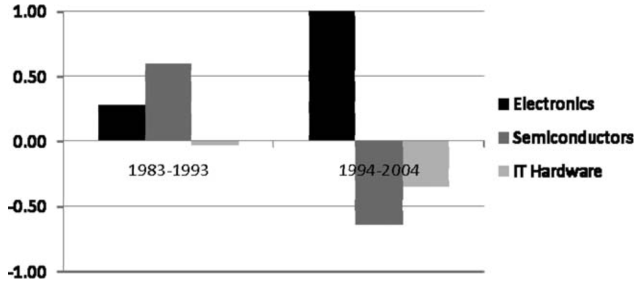
lnQ	Entire Sample NLS	1983–1988 NLS	1989–1993 NLS	1994–1999 NLS	2000–2004 NLS
RD/Assets	−0.2342	−0.2302	−0.2020	−0.1580	−0.2412
	(0.0553)***	(0.1554)	(0.0945)**	(0.1189)	(0.0820)***
RD/Assets × Japan	0.1992	0.2227	0.1615	0.0779	−0.1365
	(0.0651)***	(0.1593)	(0.1208)	(0.1483)	(0.1478)
RD/Assets × Sof. Int.	0.9752	2.4214	0.7938	0.9375	0.7052
	(0.1844)***	(0.6740)***	(0.3688)**	(0.3365)***	(0.2968)**
lnSales	0.0419	0.0135	0.0305	0.1093	0.0995
	(0.0039)***	(0.0070)*	(0.0062)***	(0.0061)***	(0.0049)***
Number of Observations	3571	825	833	1082	831
R^2	0.3052	0.2884	0.2465	0.4452	0.4089

The data for regression estimations presented in this table were obtained from Compustat and the Development Bank of Japan for U.S. and Japanese firms, respectively. R&D expenditure data for Japanese firms come from annual volumes of the Kaisha Shiki Ho survey. The data represent an unbalanced panel of large publicly traded U.S. and Japanese IT firms active in the sample period, 1983–2004. As a consequence of using an unbalanced panel, total number of observations used in regression estimations can vary between time periods. Regression specifications are estimated in STATA using the nonlinear least squares algorithm. The dependent value is the log of Tobin's q, calculated as the ratio of the firm's market value to the replacement value of its total assets. RD/Assets are calculated as the ratio of the stock of firm's accumulated R&D expenditures, calculated using the perpetual inventory method, to the replacement value of the firm's total assets. The Japan dummy equals 1 if the firm is based in Japan. Standard errors are reported in brackets. For detailed information about the specification, sample selection, and variable construction, consult the text. Statistical significance at ***0.01, **0.05, and *0.1. For brevity, only coefficients on variables of interest are reported, while coefficients on some of the control variables may be omitted. Detailed estimation results are available from the authors by request.

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 5 reports estimates of equation (12) by period using nonlinear least squares. It shows that the shadow price of R&D/assets for U.S. firms was close to 0 and not statistically significant in most periods but rose to positive and statistically significant levels by the mid- to late 1990s. On the other hand, the coefficient on R&D/assets for Japanese firms has not followed this trend. It hovered just above 0 in the 1980s but dropped significantly by the mid-1990s and early 2000s. In these periods, it was much lower than that of U.S. firms, with the difference statistically significant at the 5% level. This is consistent with what we observed when plotting the values of Tobin's Q through time, except that we do not observe much of a positive pullback for Japanese firms in the early and mid-2000s.

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 5 also reports the results of a regression in which we add a variable representing the interaction between firm-level

FIGURE 7.—AVERAGE DIFFERENCE IN PRIVATE RETURNS TO R&D, BY SECTOR



Shadow values of R&D as estimated by OLS/FE in table 6. Calculated as U.S. average subtracted from JP average.

software intensity and R&D/assets.[27] This additional regressor significantly alters our results. The R&D/assets coefficient for U.S. firms is lower than before, while the differences between U.S. and Japanese firms disappear and, in some periods, reverse with the inclusion of an indicator of firm-level software intensity. These results support the view that the relative increase in U.S. performance is related to software intensity.

Figure 7 compares private returns to R&D for Japanese and U.S. firms by IT sector, graphically summarizing the results of table 6. As with patent productivity, we find that results differ by sector. In electronics, the least software-intensive sector, the Japanese firms started off with a small advantage in the 1980s, before increasing it substantially by the mid-1990s. The reverse is true in IT hardware, the most software-intensive sector. We report detailed regression results in tables 6 and 7.[28] These tables report the results of parallel specifications; table 6 incorporates firm fixed effects into a linear model, while table 7 presents results from a nonlinear least squares specification that does not include firm fixed effects.

We conducted several robustness checks. We first estimated versions of equation (12) using NLS and FE estimators, where we directly estimated time trends for private returns to R&D separately for U.S. and Japanese firms. Table 8 shows that the direction of the trends remains unperturbed. Private returns to R&D for Japanese firms linger, as before, around 0, and show a slight negative trend over time, while private returns to R&D for US firms show a marked and statistically significant positive trend. Table 6 reports estimates of a linear approximation using firm fixed effects; table 7 reports estimates obtained using nonlinear least squares. Again, we observe that the signs of the coefficients remain qualitatively unchanged in these alternative specifications.

As in the previous section, we consider our results alongside alternative explanations. We estimated versions of equation (12) by excluding VC-backed entrants from our sample and found little qualitative change in our results. Similarly, we reestimated our regressions by excluding firms that owned major technological standards during the sample period (as well as to the exclusion of NTT), and again found little change in our results.

In order to directly test the robustness of our results to changes in industry group assignment of firms, we estimated a linearized version of the regression where we assigned firms in our sample into groups of the same sizes as those suggested by the industry classification, but based on both firm-level shares of software patents and firm-level shares of citations directed toward software patents. We found our results to be qualitatively robust to this exercise that allowed us to estimate the regressions without imposing possibly restrictive assumptions about firm industry assignments. Finally, we estimated a version where we split U.S. and Japanese firms into quartiles according to the firm-level share of software patents in total patents. We observe that U.S. firms' private returns to R&D increase with software intensity, while they fall in the case of Japanese firms. Interestingly, we also observe that U.S. firms' 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.

Our paper is focused on innovation in the IT sector and the market returns to IT innovation in that sector rather than IT production. However, our findings are consistent with reported industry-level productivity trends. Specifically, Jorgenson and Nomura (2007) show that in both computers and electronic components, an initially more productive Japanese industry is sharply overtaken by its U.S. counterpart in TFP over the course of the 1990s.[29]

IV. Discussion

This paper documents three facts. First, IT innovation has become more software intensive. Second, Japanese firms rely less on software knowledge in IT hardware invention than their U.S. counterparts (and produce significantly fewer software inventions). Third, the innovation performance of Japanese IT firms is increasingly lagging behind, particularly in software-intensive sectors. Together they point to a link between the changing technology of technical change in IT and an inability of Japanese firms to respond adequately to the shift.[30]

[27] We obtain qualitatively similar results if we also include the level of firm-level software intensity in this specification.

[28] In unreported estimates, we obtain similar results if we divide our sample into the following periods:1983–1988, 1989–1993, 1994–1999, and 2000–2004.

[29] Interestingly, Jorgenson and Nomura find quite different trends in the communications equipment industry. The firms in our sample include many major Japanese manufacturers of communications equipment, but as one of many lines of business. Given our data, we cannot separately analyze the communications equipment business units of IT firms.

[30] As we were writing this paper, we became aware of the work of Cole (2006) and Cole and Fushimi (2011), who use narrative history and interviews with practitioners to suggest that the changing fortunes of the U.S. and Japanese IT industries are linked to the superior ability of American firms to exploit software advances in their new product development. Our quantitative analysis is broadly consistent with their interview-based description.

TABLE 6.—TOBIN'S Q REGRESSIONS, BY INDUSTRY AND TIME PERIOD, FIXED EFFECTS, 1983–2004

	Electronics		Semiconductors		IT Hardware	
lnQ	1983–1993	1994–2004	1983–1993	1994–2004	1983–1993	1994–2004
RD/Assets	−0.3464	−1.1880	−0.7058	0.0609	−0.3933	−0.2278
	(0.3059)	(0.3865)***	(0.1752)***	(0.0017)***	(0.3095)	(0.1496)
RD/Assets × Japan	0.2789	1.1019	0.6043	−0.6449	−0.0335	−0.3502
	(0.3040)	(0.4283)**	(0.1966)***	(0.9356)	(0.5447)	(0.4091)
Number of observations	603	638	349	530	706	745
R^2	0.1158	0.1030	0.0286	0.0796	0.0966	0.1089

The data for regression estimations presented in this table were obtained from Compustat and the Development Bank of Japan for U.S. and Japanese firms, respectively. R&D expenditure data for Japanese firms come from annual volumes of the Kaisha Shiki Ho survey. The data represent an unbalanced panel of large publicly traded U.S. and Japanese IT firms active in the sample period, 1983–2004. As a consequence of using an unbalanced panel, total number of observations used in regression estimations can vary between time periods. Regression specifications are estimated in STATA using the fixed effects algorithm. The dependent value is the log of Tobin's q, calculated as the ratio of the firm's market value to the replacement value of its total assets. RD/Assets is calculated as the ratio of the stock of the firm's accumulated R&D expenditures, calculated using the perpetual inventory method, to the replacement value of the firm's total assets. The Japan dummy equals 1 if the firm is based in Japan. Robust and cluster-corrected standard errors are reported in brackets. For detailed information about the specification, sample selection, and variable construction, consult the main text. Statistically significant at ***0.01 level, **0.05, and *0.1. For brevity, only coefficients on variables of interest are reported, while coefficients on some of the control variables may be omitted. Detailed estimation results are available from the authors by request.

TABLE 7.—TOBIN'S Q REGRESSIONS, BY INDUSTRY AND TIME PERIOD, NLS, 1983–2004

	Electronics		Semiconductors		IT Hardware	
lnQ	1983–1993	1994–2004	1983–1993	1994–2004	1983–1993	1994–2004
RD/Assets	−0.0804	0.3760	−0.2752	0.2919	−0.1399	−0.1412
	(0.1216)	(0.1995)*	(0.0904)***	(0.1098)***	(0.1019)	(0.0429)***
RD/Assets × Japan	0.1070	−0.3838	0.1239	−1.5693	−0.3292	−0.3107
	(0.1271)	(0.2147)*	(0.1287)	(0.2756)***	(0.3255)	(0.2500)
Number of observations	603	638	349	530	706	745
R^2	0.4826	0.2414	0.2416	0.6240	0.1431	0.3760

The data for regression estimations presented in this table were obtained from Compustat and the Development Bank of Japan for U.S. and Japanese firms, respectively. R&D expenditure data for Japanese firms come from annual volumes of the Kaisha Shiki Ho survey. The data represent an unbalanced panel of large publicly traded U.S. and Japanese IT firms active in the sample period, 1983–2004. As a consequence of using an unbalanced panel, total number of observations used in regression estimations can vary between time periods. Regression specifications are estimated in STATA using the nonlinear least squares algorithm. The dependent value is the log of Tobin's q, which is calculated as the ratio of the firm's market value to the replacement value of its total assets. RD/Assets is calculated as the ratio of the stock of firm's accumulated R&D expenditures, calculated using the perpetual inventory method, to the replacement value of the firm's total assets. The Japan dummy equals 1 if the firm is based in Japan. Standard errors are reported in brackets. For detailed information about the specification, sample selection, and variable construction, see the main text. Statistically significant at *** 0.01 level, ** 0.05, and * 0.1. For brevity, only coefficients on variables of interest are reported, while coefficients on some of the control variables may be omitted. Detailed estimation results are available from the authors by request.

TABLE 8.—TOBIN'S Q REGRESSIONS, COMPARING TIME TRENDS, BY COUNTRY, 1983–2004

	Entire Sample		United States		Japan	
lnQ	FE	NLLS	FE	NLLS	FE	NLLS
RD/Assets	−0.0814	−0.0167	−1.1304	−0.5120	−0.0273	0.0115
	(0.1257)	(0.0442)	(0.2753)***	(0.1310)***	(0.0497)	(0.0352)
RD/Assets × 1989–93	−0.3011	−0.1369	0.6919	0.1800	−0.1295	−0.0209
	(0.1016)***	(0.0552)**	(0.2890)**	(0.1447)	(0.0421)***	(0.0768)
RD/Assets × 1994–99	0.1375	0.1309	1.1809	0.5798	−0.1191	−0.0086
	(0.1262)	(0.0700)*	(0.2753)***	(0.1390)***	(0.0563)**	(0.0795)
RD/Assets × 2000–04	0.0611	−0.0396	0.9727	0.3475	−0.1678	−0.0897
	(0.1460)	(0.0663)	(0.2932)***	(0.1366)**	(0.2461)	(0.1303)
Number of observations	3,571	3,571	1,978	1,978	1,593	1,593

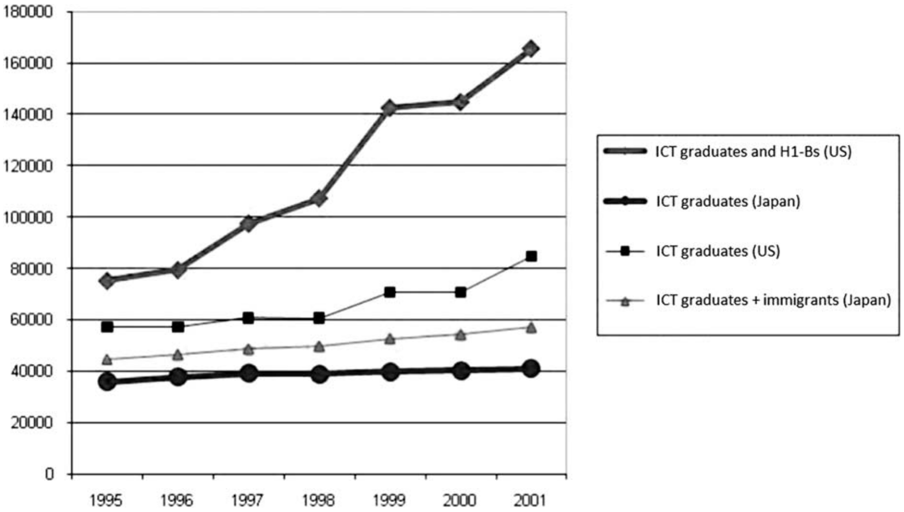
The data for regression estimations presented in this table were obtained from Compustat and the Development Bank of Japan for U.S. and Japanese firms, respectively. R&D expenditure data for Japanese firms come from annual volumes of the Kaisha Shiki Ho survey. The data represent an unbalanced panel of large publicly traded U.S. and Japanese IT firms active in the sample period, 1983 to 2004. The regression estimation results presented in this table are analogous to those presented in tables IV and IV-2, except that they include a direct estimation of the time trends. Regression specifications are estimated in STATA. A linearized version of the specification is estimated using the fixed effects algorithm, while a nonlinear version of the specification is estimated using the nonlinear least squares algorithm. The dependent value is the log of Tobin's q, calculated as the ratio of the firm's market value to the replacement value of its total assets. RD/Assets is calculated as the ratio of the stock of firm's accumulated R&D expenditures, calculated using the perpetual inventory method, to the replacement value of the firm's total assets. Standard errors are reported in brackets. Robust and cluster-corrected standard errors are reported for specifications estimated using the fixed effects algorithm. For detailed information about the specification, sample selection, and variable construction, see the main text. Statistical significance at ***0.01, **0.05, and *0.1. For brevity, only coefficients on variables of interest are reported, while coefficients on some of the control variables may be omitted. Detailed estimation results are available from the authors by request.

What prevented Japanese firms from using software advances as effectively as U.S. firms? There are at least two explanations. The first is a resource constraint argument: U.S.-based firms have access to a much larger pool of software engineers than do their Japanese counterparts. Japanese firms have not yet been able to 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.

Many studies have pointed out the persistent shortages of software engineers in Japan, dating back to the 1970s and 1980s.[31] This longstanding weakness did not prevent Japanese firms from acquiring a strong market position in IT in the 1980s (Arrison et al., 1992), but it may have become more

[31] Finan and Williams (1992) and Cusumano (1991, 2005) discuss the scarcity of software engineers, as do Fransman (1995), the Japanese Ministry of Internal Affairs and Communications (2005), and Kurokawa and Hayashi (2008).

FIGURE 8.—ICT HUMAN RESOURCES IN THE UNITED STATES AND JAPAN
ICT GRADUATES AND H1-B IMMIGRANTS ENTERING COMPUTER-RELATED PROFESSIONS, 1995–2001



important as IT hardware product development became steadily more software intensive.[32] The level of local human capital might not be a constraint if knowledge flowed freely across countries. However, tapping into foreign knowledge pools can be difficult (Jaffe, Trajtenberg, & Henderson 1993), especially for Japanese firms.[33] Belderbos (2001), Odagiri and Yasuda (1997), and Belderbos, Fukao, and Kwon (2006) document the relatively limited extent of Japanese R&D activity outside Japan during the period under consideration. Japan's relatively restrictive immigration laws and its long history as an ethnically homogeneous society mitigate against large-scale importation of skilled labor.[34]

The available data make it difficult to precisely quantify the differences in software human resources between the United States and Japan, but the gap between the two is clearly large. Figure 8 presents data from several sources comparing the flows of new (potential) domestic IT workers during the crucial years from the mid-1990s through the early 2000s.[35] Due to differences in reporting conventions, we aggregate over IT software- and hardware-related disciplines to produce a count of total IT bachelors', masters', and Ph.D.-level graduates for both countries. We use data reported by Lowell (2000) and Kirkegaard (2005) to estimate the number of temporary workers joining the U.S. labor force in "computer-related fields" under the auspices of an H-1B visa. In figure 8, we assume that half of all foreign workers newly admitted to Japan as "researchers," "engineers," or "intracompany transferees" are employed as IT workers in Japan—a far larger fraction than plausibly holds true in reality.[36]

Arora, Branstetter, and Drev (2010) describe these data (and their shortcomings) in greater detail.[37] Despite these caveats, the picture painted by figure 8 is quite striking: the flow into the domestic IT labor pool grew much faster in the United States compared to Japan. In 1995, the inflows into the domestic IT labor pool in the United States were about 68% greater than those in Japan. By 2001, the inflows in the United States were nearly three times bigger than those in Japan, with the difference being driven largely by H-1Bs. In some of the latter years of the sample period, the United States was importing more IT specialists per year than it was graduating from all IT-related bachelors', masters', and doctoral programs combined. Of course, firms are not confined to their domestic labor pool. Accounting for

[32] Some Japanese firms, most notably in video games, have maintained a strong international market positions in software-intensive segments of IT. However, video game 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 on.

[33] Branstetter (2006) finds a positive but limited impact of U.S. R&D centers on the research productivity of Japanese firms' home R&D operations. Anchordoguy (2000) argues that tapping into foreign pools of software knowledge was especially difficult for Japanese firms, given language barriers and differences in labor market practices.

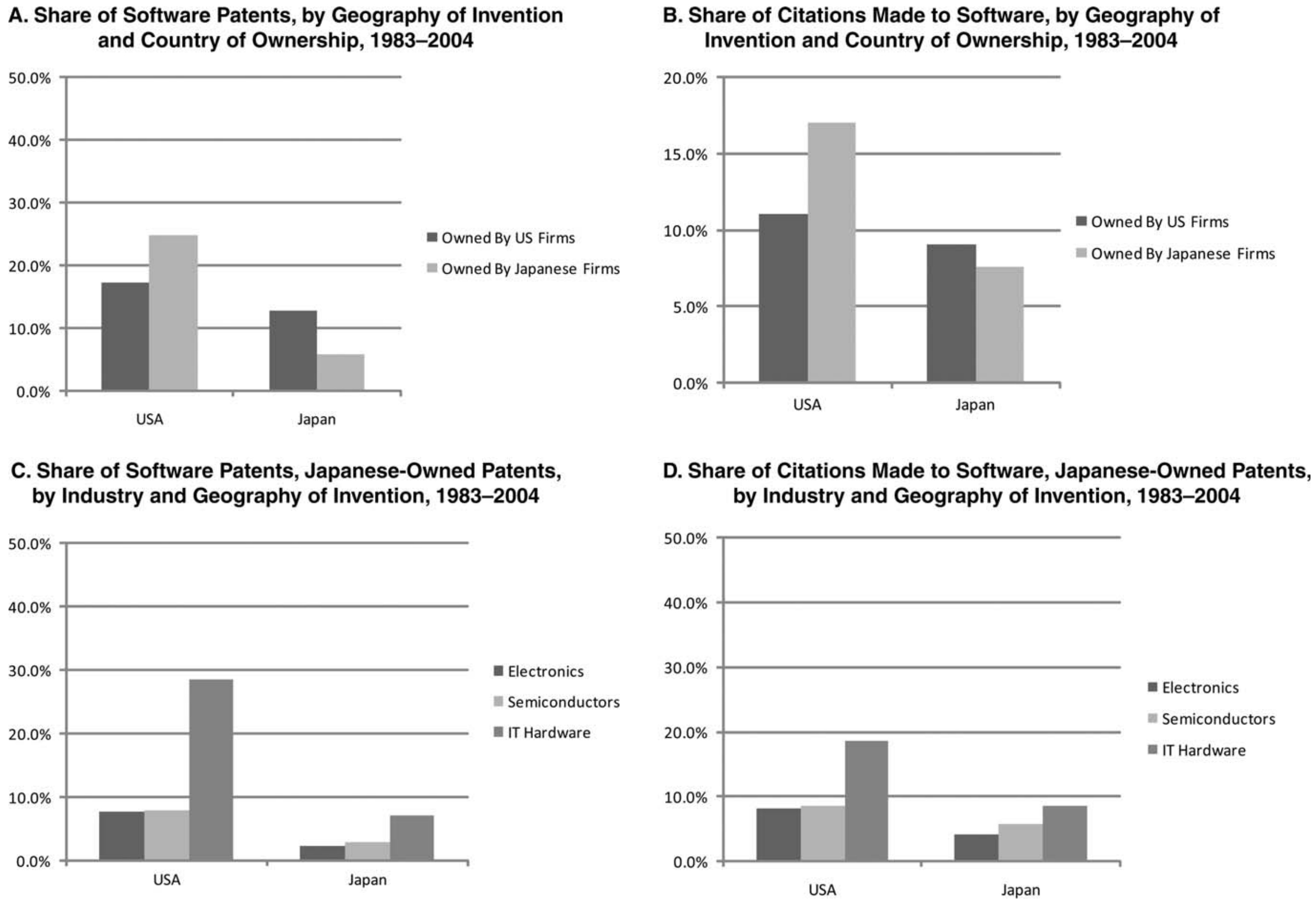
[34] Kojima and Kojima (2007) examine the available data on Japanese offshoring of software development to other countries. While the data are highly problematic, they suggest a very low level of offshoring relative to the United States—as low as 5% to 10% of the U.S. level—even by the middle of the first decade of the new century.

[35] U.S. data are from the NSF's SESTAT survey (http://www.nsf.gov/statistics/recentgrads/) and the annual Survey of Earned Doctorates http://www.nsf.gov/statistics/doctorates/. Data for Japan are taken from the Japanese Ministry of Education, Sports, and Welfare's Basic School Survey. We thank Kyoji Fukao of Hitotsubashi University and Takao Kato of Colgate University, and Anthony D'Costa of Copenhagen Business School for helping us identify and obtain the Japanese data sources used in this paper.

[36] Japanese statistics track newly registered foreign workers across a number of broad categories including "researchers," "engineers," and "intracompany transferees." These data are reported annually in the *Shutsu Nyukoku Kanri Toukei Nenpo* (Annual Report of Statistics on Legal Migrants), published by the Japanese Ministry of Justice.

[37] Only a fraction of IT graduates 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 (potential) new entrants to the IT workforce, not the total stocks of workers available for employment in the sector.

FIGURE 9.—SOFTWARE INTENSITY OF PATENTING



This figure compares a measure of firm-level software intensity of patenting for the firms in our sample by the geographical region of their origin and the geographical region of invention. The data used to construct measures of software intensity come from the CASSIS patent database maintained by the U.S. Patent and Trademark Office and the NBER Patent Data Project database. Geography of invention is determined using geographical locations of all inventors listed on the patent document. *T* tests for differences in means across geographical groups show that differences are statistically significant at the 0.01 level in the case of all group pairs. (A) The software intensity variable is calculated as the share of software patents in total patents granted in the sample period, 1983–2004, averaged across all firms belonging to a given region of origin—region of invention combination. (B) The software intensity of citations variable is calculated as the share of citations made to software patents in total citations made by all patents granted to a firm in our sample period, 1983–2004, averaged across all firms belonging to a given region of origin–region of invention combination. (C) The software intensity measure used in (A), based on the share of software patents in total patents, is calculated separately for Japanese firms in the three subsectors of information technology. (D) The software intensity measure used in (B), based on patent citations, is calculated separately for Japanese firms in the three subsectors of information technology. T-tests for differences in means across geographical groups show that differences are statistically significant at the 0.01 level in the case of all group pairs except in the case of "electronics," and "semiconductors" where the region of invention is the United States.

the level of software offshoring in the United States and Japan is even harder, but the available data suggest that consideration of software offshoring would significantly increase the resource gap implied by figure 8 (Arora et al., 2010).

In other words, imports of workers and software offshoring may have been a critical source of advantage for U.S.-based firms. 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 innovation requires both fundamental innovators and programmers undertaking more routine and standardized kinds of software engineering. 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 outpace their rivals (Hunt & Gauthier-Loiselle, 2010; Kerr & Lincoln, 2010). Arora et al. (2010) present a simple model in which a more abundant supply of software engineers capable of routine coding and testing raises the productivity of highly skilled software innovators and shows how it could imply results for the relative research productivity of Japanese and U.S. IT firms that are similar to those documented in this paper.

An alternative hypothesis posits that Japan's relative decline in innovative productivity was driven by the failure of Japanese IT managers to appreciate and respond to the rising importance of software in IT product development. A stream of the recent management literature has focused on how managerial mind-sets, formed through years of experience, affect the (in)ability of firms to make strategic shifts when firm environments change (Bettis & Hitt, 1995). In the economics literature, Nick Bloom, John Van Reenen, and their coauthors have shown that persistent performance differences across firms based in different countries could be driven by differences in management practices (Bloom et al., 2012; Bloom & Van Reenen, 2007, 2010). The papers also show that multinationals tend to bring their management practices, both good and bad, with them when they set up subsidiaries abroad.

These 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 human resources at home, then Japanese firms will have the incentive to tap into foreign knowledge and expertise by setting up software-intensive R&D facilities abroad. But if differences in relative performance are because Japanese managers downplay or ignore the importance of software, then the research output of Japanese overseas subsidiaries also ought to be less software intensive than that of their American counterparts.

Because Japanese and U.S. firms conduct IT R&D (and generate patents associated with that activity) at home and in the other country, we can submit these two hypotheses to a test. What we observe is consistent with the resource constraint hypothesis. The share of software patents in total patents invented in Japan by Japanese parent firms in our sample is 6%, as reported in figure 9A. However, the share of software patents in total patents invented in the United States by Japanese firms is significantly higher, at 24%. This surpasses even the share of software patents in total patents invented in the United States by U.S.-based IT firms, which is approximately 17%. This suggests that Japanese firms are disproportionally likely to engage in software innovation abroad. In addition, as shown in figure 9B, patents invented in the United States by the subsidiaries of Japanese firms are far more likely to cite software innovation than those invented in Japan, and they are even more likely to cite software than the comparable patents of U.S.-based firms. As reported in figures 9C and 9D, these patterns hold when we focus on individual sectors—electronics, semiconductors, IT hardware—but are strongest in IT hardware. It is almost as if Japanese firms are trying to work around the constraints in their home market by choosing a very software-intensive style of innovation in the United States, where the resources exist to support it.

Bloom et al. (2012) present a compelling case that superior American firm management practices may be important in explaining why American firms deploy IT more effectively than their foreign rivals. In this paper, we find evidence that human resource constraints may be important in explaining the success of American firms in creating new IT products. In general, the role of international differences in access to human resources and the interaction of these differences with local management practices would appear to be an interesting and fruitful area for further research.

V. Conclusions, Implications, and Next Steps

In this paper, we document the existence of a software-biased shift in the innovation process in information technology. Although widely acknowledged in the computer and software engineering literature, this shift has received very little prior attention from economists or management scholars.[38] We provide evidence on the economic importance of this shift by studying how it affected the innovation performance of IT firms in the United States and Japan. We show that this shift has resulted in a deterioration of the relative innovation performance of Japanese firms, and we find that this effect is more pronounced in software-intensive sectors. This pattern of relative deterioration and its concentration in software-intensive sectors is robust to controls for the different levels of development of venture capital and formal mechanisms for university-industry technology transfer in the two countries and to controls for disproportionately American ownership of key technology standards. Our findings thus provide a largely new explanation for the precipitous global decline of one of Japan's once leading industrial sectors, another development that has received relatively little attention from mainstream economists.

Finally, we provide evidence that suggests that a constrained supply of software knowledge and skills in Japan might explain the relatively weaker innovation performance of Japanese IT firms in the 1990s. These findings are particularly interesting in light of a growing literature that explores linkages between factor endowments, technological change, and industry performance (Acemoglu, 2002; Dudley & Moenius, 2007), and may provide a useful complement to the growing literature that links the superior performance of American firms in some contexts to superior management practices (Bloom & Van Reenen, 2010).

[38] The growing literature on software patents has examined the impact of software patentability on R&D and the impact of software patents on venture firm financing, but it has not yet addressed the impact of software technology on innovation elsewhere in IT. See Bessen and Hunt (2007), Hall and MacGarvie (2010), and Cockburn and MacGarvie (2009).

REFERENCES

Acemoglu, Daron, "Technical Change, Inequality, and the Labor Market," *Journal of Economic Literature* 40:1 (2002), 7–72.

Allan, A., D. Edenfeld, W. H. Joyner, A. B. Kahng, M. Rodgers, and Y. Zorian, "2001 Roadmap for Semiconductors," *Computer* 35:1 (2001), 42–53.

Allison, John R., and Ronald J. Mann, "The Disputed Quality of Software Patents," *Washington University Law Review* 85 (2007), 297–342.

Anchordoguy, Marie, "Japan's Software Industry: A Failure of Institutions," *Research Policy* 29:3 (2000), 391–408.

Arora, Ashish, Lee. G. Branstetter, and Matej Drev, "Going Soft: How the Rise of Software Based Innovation Led to the Decline of Japan's IT Industry and the Resurgence of Silicon Valley," NBER working paper 16156 (2010).

Arora, Ashish, Matej Drev, Chris Forman, and Mustafa D. Alpman, "A Note on the Classification of Software Patents," Unpublished research note (2007).

Arrison, Thomas S., C. Fred Bergsten, Edward M. Graham, and Martha Harris (eds.), *Japan's Growing Technological Capability: Implications for the U.S. Economy* (Washington, DC: National Academy Press, 1992).

Arrison, Thomas S., and Martha Caldwell Harris, "Japan's Growing Technological Capability and Implications for the U.S. Economy—An Overview," in Thomas S. Arrison C. Fred Bergsten, Edward M. Graham, and Martha Harris (eds.), *Japan's Growing Technological Capability: Implications for the U.S. Economy* (Washington, D.C.: National Academy Press, 1992).

Belderbos, Rene, "Overseas Innovation by Japanese Firms: An Analysis of Patent and Subsidiary Data," *Research Policy* 30:2 (2001), 313–332.

Belderbos, Rene, Kyoji Fukao, and Hyeog Ug Kwon, "Intellectual Property Rights Protection and the Location of Research and Development Activities by Multinational Firms," Hi Stat discussion paper series d 06–167, Institute of Economic Research, Hitotsubashi University (2006).

Bessen, James, and Robert M. Hunt, "An Empirical Look at Software Patents," *Journal of Economics and Management Strategy* 6:1 (2007), 157–189.

Bettis, Richard A., and Michael A. Hitt, "The New Competitive Landscape," *Strategic Management Journal* 16:S1 (1995), 7–19.

Bloom, Nick, and John Van Reenen, "Measuring and Explaining Management Practices across Firms and Countries," *Quarterly Journal of Economics* 122:4 (2007), 1351–1408.

——— "Why Do Management Practices Differ across Firms and Countries?" *Journal of Economic Perspectives* 24:1 (2010), 203–224.

Bloom, Nick, Raffaella Sadun, and John Van Reenen, "Americans Do I.T. Better: US Multinationals and the Productivity Miracle," *American Economic Review* 102:1 (2012), 167–201.

Branstetter, Lee G., "Are Knowledge Spillovers International or Intranational in Scope? Microeconomic Evidence from the U.S. and Japan," *Journal of International Economics* 53:1 (2001), 53–79.

——— "Is Foreign Direct Investment a Channel of Knowledge Spillovers? Evidence from Japan's FDI in the United States," *Journal of International Economics* 68:2 (2006), 53–79.

Branstetter, Lee G., and Yoshiaki Nakamura, "Is Japan's Innovation Capacity in Decline?" in Anil Kashyap, Magnus Blomstrom, Jennifer Corbett, and Fumio Hayashi (eds.), *Structural Impediments to Growth in Japan* (Chicago: University of Chicago Press and NBER, 2003).

Burnham, Brad, "What's Next?" Union Square Ventures [computer file] (2007). http://www.unionsquareventures.com/2007/01/whats_next.html.

Caballero, Ricardo J., and Adam B. Jaffe, "How High Are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth," *NBER Macroeconomics Annual* 8 (1993), 15–74.

Cantwell, John, "Japan's Industrial Competitiveness and the Technological Capability of Leading Japanese Firms," in Thomas S. Arrison, C. Fred Bergsten, Edward M. Graham, and Martha Caldwell (eds.), *Japan's Growing Technological Capability: Implications for the U.S. Economy* (Washington, DC: National Academies Press, 1992).

Chuma, Hiroyuki, and Norikazu Hashimoto, "Moore's Law, Increasing Complexities, and the Limits of Organization: Modern Implications of the Japanese DRAM Era," in Hiroyuki Itami, Ken Kusunoki, Tsuyoshi Numagami, and Akire Takeishi (eds.), *Dynamics of Knowledge, Corporate Systems, and Innovation* (New York: Springer, 2007).

Cockburn, Iain M., and Megan J. MacGarvie, "Patents, Thickets, and the Financing of Early-Stage Firms: Evidence from the Software Industry," *Journal of Economics and Management Strategy* 18:3 (2009), 729–773.

Cole, Robert E., "Software's Hidden Challenges," in D. Hugh Whittaker, and Robert E. Cole (eds.), *Recovering from Success: Innovation and Technology Management in Japan* (London: Oxford University Press, 2006).

Cole, Robert E., and Shinya Fushimi, "The Japanese Enterprise Software Industry," in Hiroaki Miyoshi, and Yoshifumi Nakata (eds.), *Have Japanese Firms Changed?* (London: Palgrave Macmillan, 2011).

Cusumano, Michael A., *Japan's Software Factories: A Challenge to U.S. Management* (New York: Oxford University Press, 1991).

——— "The Puzzle of Japanese Software," *Communications of the ACM* 48:7 (2005), 25–27.

De Micheli, Giovanni, and Rajesh K. Gupta, "Hardware/Software Co-Design," *Proceedings of the IEEE* 85:3 (1997), 349–365.

Dudley, Leonard, and Johannes Moenius, "The Great Realignment: How Factor-Biased Innovation Reshaped Comparative Advantage in the U.S. and Japan, 1970–1992," *Japan and the World Economy* 19:1 (2007), 112–132.

Express Computer, "Pricing and Apps Will Drive PDA Growth" (December 23 2002).

Finan, William F., and Carl Williams, "Implications of Japan's 'Soft Crisis': Forcing New Directions for Japanese Electronics Companies," in Thomas L. Arrison, C. Fred Bergston, Edward M. Graham, and Martha Harns (eds.), *Japan's Growing Technological Capability: Implications for the U.S. Economy* (Washington, DC: National Academy Press, 1992).

Fransman, Martin, *Japan's Computer and Communications Industry: The Evolution of Industrial Giants and Global Competitiveness* (Oxford: Oxford University Press, 1995).

Gore, Tony, "OMI: Developments in Processor Cores and Peripherals," in Jean-Yves Roger, (ed.), *Technologies for the Information Society: Developments and Opportunities* (San Francisco: IOS Press, 1998).

Goto, Akira, "Japan's National Innovation System: Current Status and Problems," *Oxford Review of Economic Policy* 16:2 (2000), 103–113.

Goto, Akira, and Hiroyuki Odagiri, (eds.), *Science-Based Industries* (Tokyo: NTT Publishing, 2003).

Graff, Bas, Marco Lormans, and Hans Toetenel, "Embedded Software Engineering: The State of the Practice," *IEEE Software* 20:6 (2003), 61–69.

Graham, Stuart J. H., and David D. Mowery, "Intellectual Property Protection in the U.S. Software Industry," in Wesley M. Cohen, and Stephen Merrill (eds.), *Patents in the Knowledge-Based Economy* (Washington DC: National Academies Press, 2003).

Griliches, Zvi, "Market Value, R&D, and Patents," *Economic Letters* 7:2 (1981), 183–187.

——— "Comment (on Mansfield)," in Zvi Griliches, ed., *R&D, Patents, and Productivity* (Chicago: University of Chicago Press, 1984), pp. 148–149.

——— "Patent Statistics as Economic Indicators: A Survey Part I," NBER working paper 3301 (1990).

Griliches, Zvi, and Jacques Mairesse, "Productivity and R&D at the Firm Level," in Zvi Griliches, (ed.), *R&D, Patents, and Productivity* (Chicago: University of Chicago Press and NBER, 1984).

Hall, Bronwyn H., "Innovation and Market Value," in Ray Barrell, Geoff Mason, and Mary O'Mahoney (eds.), *Productivity, Innovation, and Economic Performance* (Cambridge: Cambridge University Press, 2000).

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg, "The NBER Patent Citations Data File: Lessons, Insights, and Methodological Tools," NBER working paper 8498 (2001).

Hall, Bronwyn H., and Daehwan Kim, "Valuing Intangible Assets: The Stock Market Value of R&D Revised," University of California at Berkeley working paper (2000).

Hall, Bronwyn H., and Megan J. MacGarvie, "The Private Value of Software Patents," *Research Policy* 39:7 (2010), 994–1009.

Hall, Bronwyn H., and Raffaele Oriani, "Does the Market value R.D Investment by Europeon Firms? Evidence from a panel of manufacturing Firms in France, Germany, and Italy," *International Journal of Industrial Organization* (2006), 971–973.

Hamada, Yasuyuki, *Venture Capital in Japan: Strategic Investment for the Future* (Tokyo: Nikkei Shimbun Press, 1996).

Hamada, Koichi, and Yasushi Okada, "Monetary and International Factors behind Japan's Lost Decade," *Journal of the Japanese and International Economies*, 23:2 (2009), 200–219.

Hausman, Jerry A., Bronwyn H. Hall, and Zvi Griliches, "Econometric Models for Count Data with an Application to the Patents: R&D Relationship," NBER technical working paper 17 (1984).

Hunt, Jennifer, and Marjolaine Gauthier-Loiselle, "How Much Does Immigration Boost Innovation," *American Economic Journal* 2:2 (2010), 31–56.

Ikeda, Nubuo, "The Pitfalls of the Digital Appliance Bubble," Research Institute of Economy, Trade, and Industry (2007). http://www.rietio.go.jp/en/columns/c01_0112.html.

Jaffe, Adam B., and Manuel Trajtenberg, "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 5712 (1996).

——— *Patents, Citations, and Innovations: A Window on the Knowledge Economy* (Cambridge, MA : MIT Press, 2002).

Jaffe, Adam B., Manuel Trajtenberg, and Rebecca Henderson, "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations," *Quarterly Journal of Economics* 108:3 (1993), 577–598.

Japanese Ministry of Justice, *Annual Report on Statistics of Legal Migrants*, (various issues).

Jorgenson, Dale W., and Koji Nomura, "The Industry Origins of Japanese Economic Growth," *Journal of the Japanese and International Economies* 19:4 (2005), 482–542.

——— "The Industry Origins of the U.S.-Japan Productivity Gap," *Economic Systems Research* 19:3 (2007), 315–342.

Kerr, William R., and William F. Lincoln, "The Supply Side of Innovation: H-1B Visa Reforms and U.S. Ethnic Invention," *Journal of Labor Economics* 28 (2010), 473–508.

Kirkegaard, Jacob F., "Outsourcing and Skill Imports: Foreign High-Skilled Workers on H-1B and L-1 Visas in the United States," Institute for International Economics working paper 05-15 (2005).

Kojima, Sakura, and Makoto Kojima, "Making IT Offshoring Work for the Japanese Industries" (pp. 67–82) in Bertrand Meyer, & Mathai Joseph (eds.), *SEAFOOD (Software Engineering for Offshore and Outsourced Development) Conference Proceedings*, LNCS 4716 (New York: Springer, 2007).

Kortum, Samuel, and Josh Lerner, "Assessing the Contribution of Venture Capital to Innovation," *RAND Journal of Economics* 31:4 (2001), 674–692.

Kurokawa, Toshiaki, and Susumu Hayashi, "Japan's Critical Issues on IT Human Resource," *Science and Technology Trends Quarterly Review* 30 (2008) 23–40.

Lowell, Lindsay B., "H-1B Temporary Workers: Estimating the Population," Center for Comparative Immigration Studies working paper 12 (2000).

Ministry of Internal Affairs and Communications (MIC), Government of Japan, "Research Report on High-Level ICT Human Resource Development" (2005). http://www.soumu.go.jp/main-sosiki/joho_tsusin/eng/Releases/Newslatter/V0118/V0118-11/V0118-11.pdf.

Motohashi, Kazuyuki, "Software Patent and Its Impact on Software Innovation in Japan," Research Institute of Economy, Trade, and Industry discussion paper 09038 (2009).

Nagaoka, Sadao, "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* 16:1 (2007), 129–156.

Odagiri, Hiroyuki, and Hideto Yasuda, "Overseas R&D Activities of Japanese Firms," in Akira Goto, and Hiroyuki Odagiri (eds.), *Innovation in Japan* (Oxford: Clarendon Press, 1997).

Pakes, Ariel, and Zvi Griliches, "Patent and R&D at the Firm Level: A First Look," NBER working paper 561 (1984).

Perfect, Steven B., and Kenneth W. Wiles, "Alternative Constructions of Tobin's Q: An Empirical Comparison," *Journal of Empirical Finance* 1:3–4 (1994), 313–341.

Tanaka, Tatsuo, "The Software Industry," in Akira Goto, and Hiroyuki Odagiri (eds.), *Science-Based Industries* (Tokyo: NTT Publishing, 2003).