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On the Failure of University-Industry Research Collaboration to Stimulate High Quality Research in Japan

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Abstract

Using a panel of 30 Japanese chemical and pharmaceutical companies for the period of 1985 to 1998, we estimate the effects of university-industry research collaboration (UIC) on participating firms' research output. We find, as in other studies in the field, that UIC leads to more research output, in terms of the number of patents obtained. In contrast to the results for the U.S., however, we find no evidence that UIC significantly affects quality adjusted patents, that is, citation weighted patent counts. By looking finely at what part of the quality ladder of patents UIC stimulates, we find that UIC increases only those patents with a small number of citations, thus failing to affect the "average" quality of patents. Discussions of possible reasons for this finding are also offered.

JEL classifications: O32, O38, L65

key words: university-industry research collaboration, patent quality, science and technology policy

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1 Introduction

Numerous studies have found evidence of the positive role of university-industry research collaboration for promoting research productivity of private firms. In a series of work, Zucker, Darby and their collaborators have made a significant contribution to the analysis of the role of prominent scientists for R&D activities of companies in the biotech industry [1]. They show that university-industry research collaboration (henceforth, UIC), more specifically, the involvement of "star scientists" in UIC is a key to firms' good performance (successful start-up and vigorous innovative activities) in the industry. They document this mainly for the U.S. In addition, Zucker and Darby (2001) find similar results for the Japanese biotech industry. Based on a different data set, Odagiri and Kato (1998) also find significant effects of UIC on Japanese biotech firm's innovations [2] .

Most of these researches have used the number of patents as a measure of the performance of firms' R&D activities. Some have weighted patents by the number of citations. Surely, patents with many citations are of greater value than others [3] . In this sense, one can think of the distribution of the "quality" of a firm's patents, that is, the number of patents at each number of citations. This distribution is known to be skewed to the left. A small number of patents attract many citations, while many are not cited at all. Thus, the "average" quality of a firm's patents can be a poor measure of the quality of the firm's research output. As far as we know, none of the existing studies have looked carefully at how UIC affects the distribution of the quality of patents. It is, however, of great interest to know what type of innovations in terms of their quality UIC promotes. In this study we intend to carry out the analysis of this question using data on Japanese chemical and pharmaceutical companies.

More specifically, we investigate the effects of UIC on several percentile points of the cumulative distribution function of patent quality, i.e., the number of patent citations. UIC does not necessarily affect the quality of patents uniformly. The impact may be stronger for research with higher quality, because cutting-edge scientific knowledge may be significant only for very innovative R&Ds. On the other hand, UIC may only generate patents of moderate quality, while

[1] A summary of their research program so far is available in Zucker, Darby, and Armstrong (2002).

[2] Odagiri and Kato use as an indicator of UIC a dichotomous variable which indicates whether a firm has had any collaborative research with university scientists.

[3] Griliches (1990) thoroughly discusses the effectiveness of patent counts as a measure of R&D.

patents of high quality are mainly results of firms' own R&Ds. The objective of the paper is to find out, by using detailed information on firms' R&D activities, which one of these possibilities is closer to reality in the case of Japanese firms.

Such an analysis is also interesting in light of recent changes in Japan's science and technology policy. Legislative measures have been taken in order to encourage UIC since the late 1990s [4] . Although our sample does not cover the period after the change in the government's policy, our results can be used to infer the effectiveness of such a policy change for raising the performance of Japanese companies' R&Ds.

Our sample consists of 30 major chemical and pharmaceutical companies in Japan. We collect detailed information on their patents and collaborations with universities from various sources. Our sample period is determined by data availability and is from the mid-1980s to the latter half of the 1990s. It ends at the time just when science and technology policy in Japan started to encourage UIC and university patenting.

We find that although UIC in the Japanese chemical industry led to increases in the number of patents, it failed to raise the "quality" of patents. In other words, UIC did not lead to increases in the number of patents with many citations; it only succeeded in stimulating patents with only a small number of citations. This result is in sharp contrast with those for the U.S. where authors have found significant effects of UIC on citation weighted patent counts. The result implies that policies aimed at merely promoting UIC may fail to significantly improve the performance of R&D activities of Japanese firms. Policy makers need to think more deeply about why UIC does not lead to major innovations in the industry.

In section 2, we lay out our data and its descriptive properties. Details of data construction are provided in the data appendix. Estimation methods and results are provided in section 3. Implications of the results are also discussed in the section. Section 4 offers concluding remarks.

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[4]The reform of Japan's science and technology policy began with *The Science and Technology Basic Plan* in 1995. One of the aims of this plan is to strengthen the competitiveness of industries by promoting the industry-academia-governmental research cooperation nexus. Following this agenda, a series of laws were legislated in order to encourage the transfer of technology from universities to industries, for example, by encouraging university scientists to develop their research into patents, which is a useful device of technology transfer. Among others, the *Promotion Law of Technology Transfer from Universities, etc.* (TLO Law) was enacted in 1998 and the *Law on Special Measures for Industrial Revitalization* (the Japanese version of the Bayh-Dole Act) was enacted in 1999.

2 Data

Measures of Patent Quality

The value or quality of patents varies widely, even among the patents filed by the same firm in the same year. There are several attempts to evaluate the quality of individual patents [5]. Among them, we adopt the number of citations received as a measure of patent quality. The U.S. patent system requires patent applicants to cite existing patents that technologically relate to their inventions. Trajtenberg (1990) and Harhoff, et al. (1999) show that the number of citations received has high correlation with other variables that measure the value of the inventions. We collect the citation data from NBER patent citation data compiled by Hall, Jaffe, and Trajtenberg (2001).

The distribution of citations received of a firm's patents is significantly skewed to the left, meaning that many patents are of low-quality and that only a small number of patents receive many citations. Figure 1 shows the distribution of citations for one representative firm in our sample in a particular year. The median (3) is much closer to the minimum value (0) than to the maximum value (12). The mean (4) exceeds the median. Furthermore, the maximum varies much with the year of application. For such a skewed distribution, small variations near the maximum can change the mean significantly. Thus, the mean quality of a firm's patents can be a poor measure of the firm's research quality.

Though citation received is a usual measure of patent quality, we need to take care of its measurement problem. The value of one citation may vary with time. More specifically, available citation data is truncated at the end of the sample (1998 for the NBER citation data). Thus, more recent patents tend to receive fewer citations. We deal with this truncation problem in the simplest way by using a fixed-effects specification. Thus, differences in the value of citations are absorbed in year and firm dummies in estimation equations [6] .

Measures of UIC

UIC is measured by the number of articles jointly authored by corporate and university researchers. The data source is Science Citation Index (SCI) as in the preceding literature such

[5] See Schamkerman and Pakes (1986) and Lanjouw (1998), for example.

[6] A more thorough discussion of the measurement problem is provided in Hall, Jaffe, and Trajtenberg (2001).

as Cockburn and Henderson (1998). This database provides detailed information on articles in scientific journals. We count the articles whose authors are affiliated with universities or colleges as well as with our sample firms.

Figure 2 presents the time series pattern of our co-authorship data. The number of co-authorship starts in the mid-1980s at a very low level, about five articles per firm, but then starts a consistent rising trend and reaches a peak of about fifteen articles per firm in 1996. This is followed by a small decline at the end of the sample period. A similar trend is observed for macro-level data. Based on the data of Japanese firms from 13 industries, Pechter and Kakinuma (1999) report that firm-university co-authorship increased from about 800 in 1981 to about 4800 in 1996, but the growth faltered around the mid-1990s. The rising trend during this period is also observed in the ratio of co-authored articles to total, which was 41.5% in 1985 and over 60% in the late 1990s. For Pechter and Kakinuma's data, the ratio is 23.1% in 1981 and 46.4% in 1996. Thus, our sample firms have higher intensity of UICs in their research activity than average.

Table 1 summarizes descriptive statistics of main variables used in the econometric analysis. Details of the construction of the variables are provided in the data appendix.

3 Estimation Method and Results

3.1 Estimation method

Our main goal is to estimate the impact of UICs on firms' research productivity and quality. The sample consists of 30 major companies in the Japanese chemical industry from the mid-1980s to the second half of 1990s.

Our basic estimation equation is:

$$y_{it} = \alpha + \beta \log R_{it} + \gamma \log C_{it} + \delta_i + \lambda_t + \epsilon_{it}. \tag{1}$$

i and t are indices for firm and year, respectively. R is the main input in corporate research activities, i.e., R&D spending. C is UIC measured by the co-authorship data. This is defined as the average number of co-authored articles for three years before t in order to consider a possible gestation lag between UICs and patents. We also include firm effect δ_i and year effect λ_t. ϵ is disturbance that satisfies traditional assumptions.

We consider three types of dependent variable y. The first one is the number of patents granted in the U.S. for firm i but applied in year t, which is often used in conventional estimation of knowledge generating function. Using the U.S. patent data has two advantages over using Japanese patent data. First, the citation data to measure patent quality is available for the U.S. data, but Japanese patent data does not include the comparable information. Second, the Japanese patent system was modified amid our sample period, making the comparison of the data before and after the modification difficult.

The second dependent variable we consider is the number of patents weighted by individual patent's quality, i.e., the number of citations received.

The third one tries to capture finer characteristics of the distribution of the quality of patents. We consider six variables: 40%, 50% (median), 60%, 70%, 80%, and 90% percentile points of the cumulative distribution of patent quality, i.e., citations that firm i's patents filed in year t received. The descriptive statistics of these patent quality measures and the mean values are presented in Table 2 [7] . For example, the mean of the 40% percentile point is 1.74, which means that averaging across firms, 40% of patents have citations less than 1.74, conforming to the usual pattern that the distribution of patent quality is skewed to the left.

Note that estimation of (1) by simple OLS may suffer from simultaneity biases. For example, innovative firms may be able to efficiently conduct joint research projects with universities. If so, the error term, which captures such ability to innovate, correlate with explanatory variables, hence OLS estimates are biased.

To deal with this problem, we adopt an instrumental variable estimation method. The instruments used in this paper are a constant, dummy variables, lagged (endogenous) explanatory variables, and the following three variables: lagged total corporate articles, the current proportion of joint patent application to the total, and the number of prefectures where corporate research

[7] We use the same set of explanatory variables irrespective of the choice of the dependent variable. This can be interpreted as follows. The quantity of inventions (the simple patent count) is determined by $P = f(X)$, where X is the vector of explanatory variables in (1), including year and firm dummies. The patent quality Q is also determined by $Q = g(X)$. The total value of knowledge created by a firm, K, is a function of P and Q, so $K = \phi(f(X), g(X)) = \varphi(X)$. This is exactly the knowledge generation function which Pakes and Griliches (1984) advocate. $f(X)$, $\varphi(X)$, and $g(X)$ correspond to (1) where y is the number of patents, the quality-weighted sum of patents, and quality measures, respectively.

labs locate. The first two of the final three instruments represent the degree to which the firm is oriented toward basic research and cooperative research, respectively. The third tries to capture the geographical proximity of firms to universities. Some preceding studies have suggested the importance of this variable [8, 9] .

3.2 Estimation results

Estimation results of the equation with the simple count of patents as the dependent variable are presented in Table 3. Table 4 shows estimation results based on citation weighted patents. We also check the robustness of the results by replacing R&D spendings by R&D stock, and the UIC variable by its one-year lagged value. We can see that the choice of explanatory variables does not essentially affect the estimation results. In table 3, UIC has a significantly positive impact on the patent counts as does firm's own R&D. However, UIC's coefficient, although positive, is insignificant in Table 4. Thus, citations weighted patents are not influenced by UIC, while they are affected by firms' own R&D.

Table 5 reports the results for the data up to 1993. This is to deal with problems with citation data toward the end of the sample. Because five observations of the dependent variable (total citations that patents in the year received up to 1998) in 1997 take the value of zero, the variable is subject to a $\log 0$ problem [10] . In addition, the truncation bias problem explained above seems more serious than it first appeared. That is, toward the end of the sample, the number of citations is not just fewer than in earlier years, but shows only a small amount of variation across observations. Thus, both high and low quality patents, applied in, say, 1997, receive either 0 or 1 citation by 1998. This means that the data, toward the end of the sample, may not contain much information regarding the quality of patents. Thus, in Table 4 we drop the data after 1994 to mitigate the effects of these problems on estimation results [11] . As can be seen, even for this shorter sample, the results do not change essentially. Among others, the coefficient of the UIC

[8] See, for example, Zucker, Darby, and Brewer (1998).

[9] We tried several alternative definitions of the three instruments, such as the number of universities in the prefectures where corporate research labs locate, instead of the number of the prefectures where corporate research labs locate. The results mentioned below were essentially unchanged.

[10] In table 3 this problem was absent because the simple patent count was positive for all observations. In Table 4 the $\log 0$ problem was taken care of by adding one to all observations.

[11] We also dealt with the $\log 0$ problem of the sample up to 1997 by adding one only for zero-value observations. This modification results in similar estimates to those shown in Table 4.

variable remains positive, but is insignificant [12] .

By comparing the results in Table 3, where y in (1) is simple patent counts, and Table 4 and 5, where y in (1) is the total citations the firms' patent received, we find that the UICs' impact on the "quality" of patents is insignificant (Note that the difference between log of patent counts and log of the total citations is log of the "average" number of citation received). However, as discussed in preceding sections, the distribution of patent quality is very much skewed to the left. The mean value (citations received per patent application) gives little information about the entire distribution. Thus, we examine further the impact of UICs on the quality dimension of firms' R&D activities by using finer parameters of the distribution of patent quality. Table 6 presents the estimation results using six percentile points of the cumulative distribution of patent quality as y in (1). We limit the sample period up to 1993, because the 40% percentile point and median are almost the same across firms after 1994. After 1994, the 40% percentile points are either 0 or 1 for all firms. The same is true for the median except for two firms.

In Table 6, the effects of the UIC variable are in sharp contrast with those of firms' own R&D. The coefficients of UIC are significantly positive for lower percentile points (the 40% percentile point and median) and become smaller in value for higher percentile points. They are insignificant, with only one exception, for the 60% percentile point or higher. In contrast, firms' own R&D significantly improves the quality of higher percentile points (60% percentile point or higher). In case (d) where R&D is defined as a stock variable and one-year lagged UIC is used, UIC turns insignificant for the 40% percentile point. The broader pattern of results in this case, however, is similar to the other three cases in Table 6.

Figure 3 presents a result of an attempt to estimate, using the regression results, the effect of UIC on the distribution of patent quality. It shows two distributions, one, with the level of UIC at its 1987-93 mean, and the other, UIC at its 1997 mean. The latter is 14.36, while the former is 8.40. Thus, the distribution with UIC at its 1997 mean involves a higher level of UIC. As can be seen, the higher level of UIC mainly affects patents with 2 or 3 citations. The number of patents

[12] Zucker, Darby, and Armstrong (2002) use the co-authorship data for the UIC measure and find the significant impact of UICs on the quality-adjusted research outputs, i.e., the total of patent citations. Zucker, Darby, and Armstrong (2002) is different from our analysis in the following three points: (1) they focus on "star" scientists who are prominent in their scientific fields; (2) their sample is limited to biotech industry, where UICs is especially important; and (3) they do not use firms' R&D spendings as an explanatory variable. We think that the third point is a problem. Exclusion of R&D spendings arises omitted variable bias, because it highly correlates with UIC (the correlation coefficient between the two variables is 0.69 in our sample).

in this range increases, while the rest of the distribution is largely unaffected. Of course, this is in Table 6 why the 40 and 50% percentile points are affected, but not the higher percentile points.

Thus, UIC in the Japanese chemical industry stimulates research activities of low to moderate quality, but not those of high quality. As a result, although the number of patents increases with more UIC, citation weighted patents are unaffected because the latter is largely dominated by patents with many citations. High quality patents seem to be results of firms' own R&D activities.

The reform of Japanese science and technology policy since the late 1990s has promoted UIC in order to improve "industrial competitiveness." However, our analysis does not find a convincing piece of evidence that UIC results in industrial innovations of high-quality, at least for the data up to the early 1990s.

4 Conclusion

We have analyzed in detail the role UIC involving major Japanese chemical and pharmaceutical firms play in enhancing their innovation productivity. Our main results show that UIC measured by firm-university co-authorship has a significantly positive impact on the participating companies' innovations measured by simple patent counts. This is consistent with the findings of preceding literature such as Cockburn and Henderson (1998), and Zucker and Darby (2001) among others.

However, the role of UIC is limited. Although UIC significantly stimulates firms' patents of moderate quality, it does not affect the number of patents with many citations. The latter is mainly determined by firms' own R&D efforts. Thus, UIC has not been found to affect the citation weighted patent counts.

Japan's science and technology policy has been under reform since the mid-1990s. One of the reform's primary objectives has been to advance "industrial competitiveness." For this purpose, several policies have been implemented to encourage UICs. However, our findings cast doubts about the effectiveness of such an approach. Policymakers need to investigate more carefully into the reason for the failure of UIC to stimulate high quality R&Ds. There could be several explanations for this. First, for whatever reason, Japanese university researches may intrinsically be of low commercial value. Second, Japanese private firms may lack the infrastructure, for example, researchers with Ph.Ds, to appropriate the potential returns implicit in UIC [13, 14]. Third, as pointed out by Kneller (1999, 2003), Japanese style UIC may lack the incentive scheme to stimulate high quality research. For example, until recently Japanese academic researchers were not allowed to directly share in the commercial returns of UIC they participated.

Such potential reasons for the failure of Japanese UIC to stimulate high quality research suggest some areas for future study. On the question of intrinsic ability of university researchers to produce high quality research, results of Zucker and Darby (2001) that emphasize the role of "star" scientists may be relevant. It may well be that participation of star scientists in UIC is a key to its successful performance. Second, it might be interesting to examine how results may change depending on participating firm's ability to understand and apply research output. There is ample evidence that firms have to build up "absorptive capacity" for exploiting benefits from external knowledge. [15] Thus, for example, collaboration with universities may contribute more to firms' innovation in the technological field where participating firms have accumulated research experience. Finally, given the recent change in Japan's science and technology policy including incentive schemes for academic researchers participating in UIC, it is important to if results similar to ours obtain even with the inclusion of more recent data.

[13] Branstetter and Nakamura (2003) point out that the shortage of in-house Ph.D. level engineers is one reason for Japanese companies' weakness in conducting basic research.

[14] Nihon Keizai Shimbun (2003) argues that Japanese firms lack this ability and point out a few examples where promising research results were not regarded as such by management and were sold to U.S. firms at low prices, who then developed them into major profit sources.

[15] Cohen and Levinthal (1989), among others, presents evidence of this. Kamien and Zang (2000) propose a theoretical model where "absorptive capacity" can influence the formation of research joint ventures.

A Data Appendix

Collaboration in article data

The article data source is Science Citation Index (SCI) compiled by ISI, as in preceding literature including Cockburn and Henderson (1998). We count articles written by corporate researchers with researchers affiliated universities or colleges. The data is confined to "article," that is, does not include other types of publications such as "letter" and "meeting-abstract." Thus, our data is confined to "solid" results of academic research.

R&D spending and R&D stock

The R&D spending data comes from a survey by *Kaisha Shiki Hō*. In the case of missing figures, we fix them up using other data sources such as *Nikkei NEEDS* and *Kagaku Kigyō no Dōkō to Senryaku*. The latter is an annual periodical published by Kagaku Gijutsu Tokkyo Chōsa-kai (Chemical Technology and Patent Survey Group), which collects various information about research activities of major Japanese chemical and pharmaceutical companies. These nominal figures are deflated by R&D deflator for companies, etc., in 1995 yen.

Construction of the R&D stock follows a conventional perpetual inventory method. Calculating the growth rate of each firm's R&D spending (real value), g_R, we define the initial value of R&D stock, RS_0, as

$$RS_0 = \frac{R_0}{g_R + o_R},$$

where o_R is the obsolescence rate of R&D stock derived from *White Paper of Science and Technology* (Science and Technology Agency (1986)), as do Goto and Suzuki (1989). Then, the R&D stock for year t, RS_t, is calculated as

$$RS_t = (1 - o_R)RS_{t-1} + R_t.$$

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Table 1: Descriptive Statistics of Main Variables

variable name	# obs.	mean	s.d.	max	min
# U.S. Patents during 1987-97	330	42.30	32.93	188.00	4.00
# citations received up to 1998 for patents of a firm in a year during 1987-97	330	99.26	106.95	540.00	0.00
R&D flow during 1987-97 (in 1995 mill. yen)	330	17265.77	12929.01	74559.69	2869.96
R&D stock during 1987-97 (in 1995 mill. yen)	330	132828.00	97280.75	501897.47	17273.80
3-year average of # university co-authorship during 1987-97	330	10.58	9.61	50.00	0.00

Table 2: Descriptive Statistics of Patent Quality Variables for 1987-93

variable name	# obs.	mean	s.d.	max	min
average	210	3.82	1.96	13.40	0.66
40% percentile point	210	1.74	1.20	6.00	0.00
50% percentile point (median)	210	2.41	1.45	6.50	0.00
60% percentile point	210	3.28	1.81	11.50	0.00
70% percentile point	210	4.40	2.29	17.00	0.00
80% percentile point	210	6.08	3.24	28.50	1.00
90% percentile point	210	9.45	5.16	40.00	2.00

Table 3: Impacts of University-Industry Collaboration on Patent Counts

eq. No.	(i)	(ii)	(iii)	(iv)
Sample	1987-97	1988-97	1987-97	1988-97
# obs.	330	300	330	300
log R&D flow	0.655	0.703		
	***(0.196)	***(0.206)		
log R&D stock			0.547	0.842
			**(0.265)	***(0.290)
UIC	0.328	0.251	0.315	0.197
	***(0.116)	**(0.117)	**(0.117)	*(0.117)
Adjusted R^2	0.787	0.779	0.785	0.780
UIC measure's One-year lag	N	Y	N	Y

Dependent variable is log of patent counts.
Estimation method is instrumental variable estimation. All estimation equations include unreported year and firm dummies.
Figures in parentheses are standard errors. ***: significant at 1%, **: at 5%, *: at 10%.

Table 4: Impacts of University-Industry Collaboration on Citation Weighted Patents

eq. No.	(i)	(ii)	(iii)	(iv)
Sample	1987-97	1988-97	1987-97	1988-97
# obs.	330	300	330	300
log R&D flow	0.625	0.581		
	**(0.278)	*(0.322)		
log R&D stock			0.705	0.564
			*(0.372)	(0.452)
UIC	0.201	0.048	0.180	0.012
	(0.164)	(0.174)	(0.165)	(0.175)
Adjusted R^2	0.898	0.897	0.899	0.899
UIC measure's One-year lag	N	Y	N	Y

Dependent variable is log of # total citations recieved up to 1998. Figures are added one before taking log.
Estimation method is instrumental variable estimation. All estimation equations include unreported year and firm dummies.
Figures in parentheses are standard errors. ***: significant at 1%, **: at 5%, *: at 10%.

Table 5: Impacts of University-Industry Collaboration on Citation Weighted Patents: Sample up to 1993

eq. No.	(i)	(ii)	(iii)	(iv)
Sample	1987-93	1988-93	1987-93	1988-93
# obs.	210	180	210	180
log R&D flow	1.816	2.238		
	***(0.487)	***(0.661)		
log R&D stock			1.426	1.601
			***(0.528)	**(0.708)
UIC	0.281	0.152	0.323	-0.061
	(0.214)	(0.261)	(0.208)	(0.255)
Adjusted R^2	0.784	0.785	0.797	0.800
UIC measure's One-year lag	N	Y	N	Y

Dependent variable is the same as in Table 4.
Estimation method is instrumental variable estimation. All estimation equations include unreported year and firm dummies.
Figures in parentheses are standard errors. ***: significant at 1%, **: at 5%, *: at 10%.

Table 6: Impacts of University-Industry Collaboration on the Patent Quality Distribution

		40%	50%	60%	70%	80%	90%
a. UIC's one-year lag = N, R&D = flow (1987-93)	log($R\&D$)	0.553	0.478	1.361	1.087	0.909	0.884
		(0.364)	(0.333)	***(0.335)	***(0.360)	***(0.326)	**(0.395)
	UIC	0.345	0.302	0.102	0.017	0.168	0.055
		**(0.160)	**(0.146)	(0.147)	(0.145)	(0.143)	(0.174)
b. UIC's one-year lag = Y, R&D = flow (1988-93)	log($R\&D$)	0.794	0.714	1.994	2.092	1.560	1.259
		(0.502)	(0.465)	***(0.475)	***(0.471)	***(0.460)	***(0.557)
	UIC	0.366	0.380	0.124	-0.071	-0.054	-0.245
		*(0.198)	**(0.183)	(0.187)	(0.186)	(0.181)	(0.220)
c. UIC's one-year lag = N, R&D = stock (1987-93)	log($R\&D$)	0.289	0.174	1.164	0.947	0.741	0.787
		(0.409)	(0.372)	***(0.349)	***(0.354)	**(0.350)	*(0.428)
	UIC	0.363	0.320	0.129	0.038	0.187	0.072
		**(0.161)	**(0.146)	(0.137)	(0.139)	(0.138)	(0.168)
d. UIC's one-year lag = Y, R&D = stock (1988-93)	log($R\&D$)	0.235	0.033	1.773	1.877	1.539	1.606
		(0.555)	(0.510)	***(0.472)	***(0.475)	***(0.478)	***(0.601)
	UIC	0.308	0.327	-0.051	-0.256	-0.207	-0.386
		(0.200)	*(0.184)	(0.170)	(0.171)	(0.172)	*(0.217)

Dependent variables are log values of percentile points indicated on the top row of each column. Figures are added one before taking log.
Estimation method is instrumental variable estimation. All estimation equations include unreported year and firm dummies.
Figures in parentheses are standard errors. ***: significant at 1%, **: at 5%, *: at 10%.

Figure 1. Typical Distribution of Patent Quality
Firm A, 1989

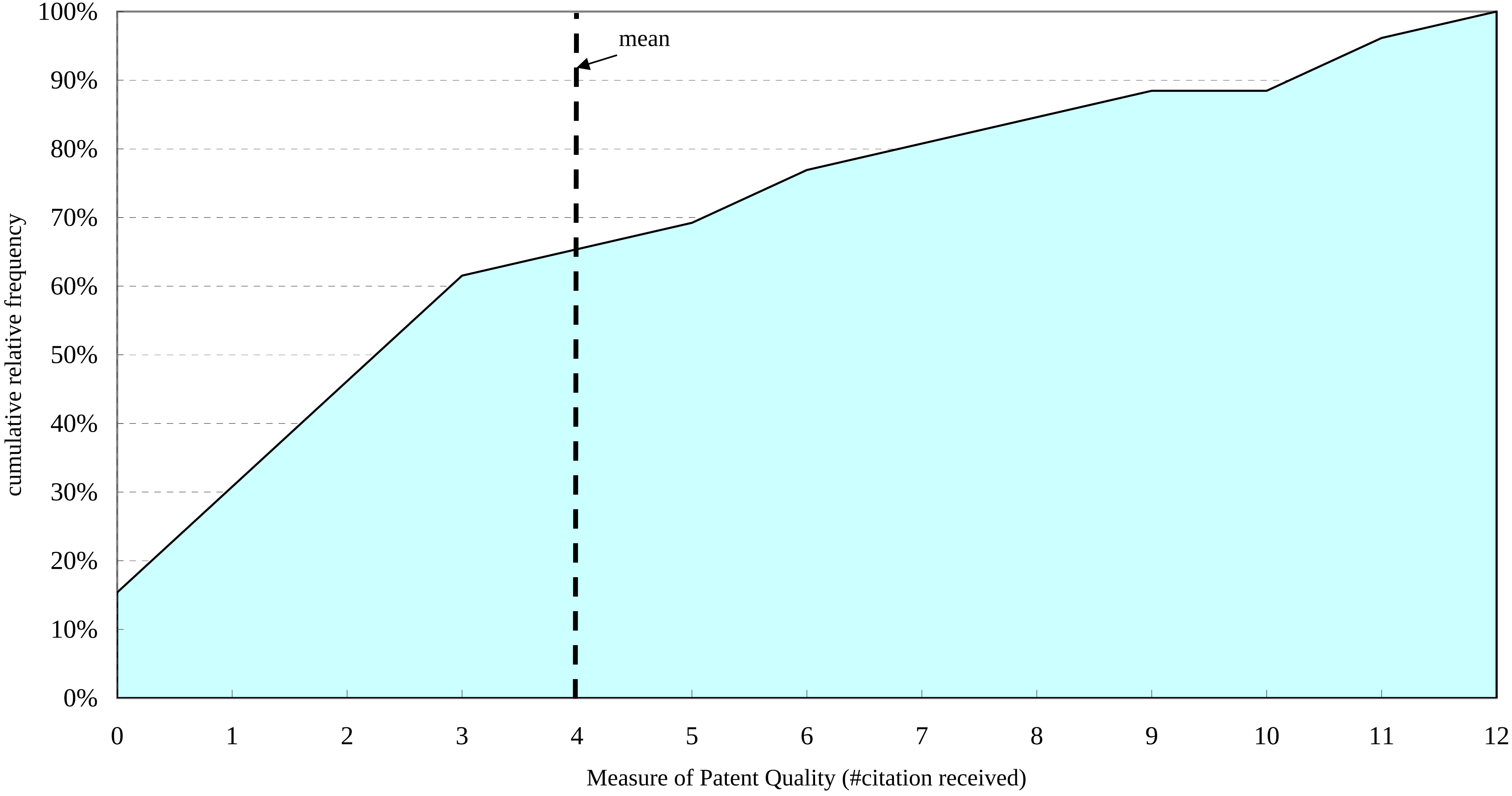


Figure 2. Average Trend of UIC in the Sample

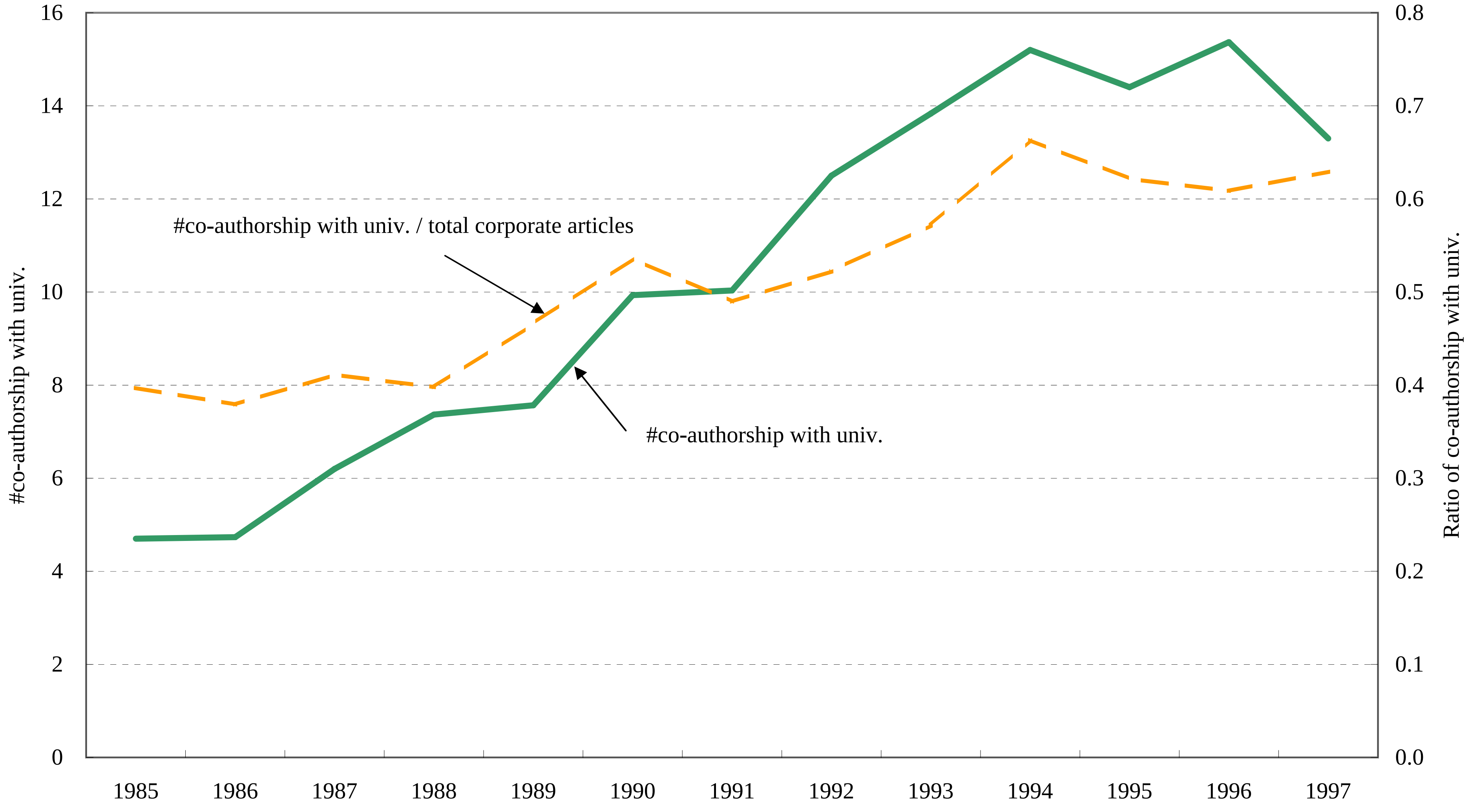
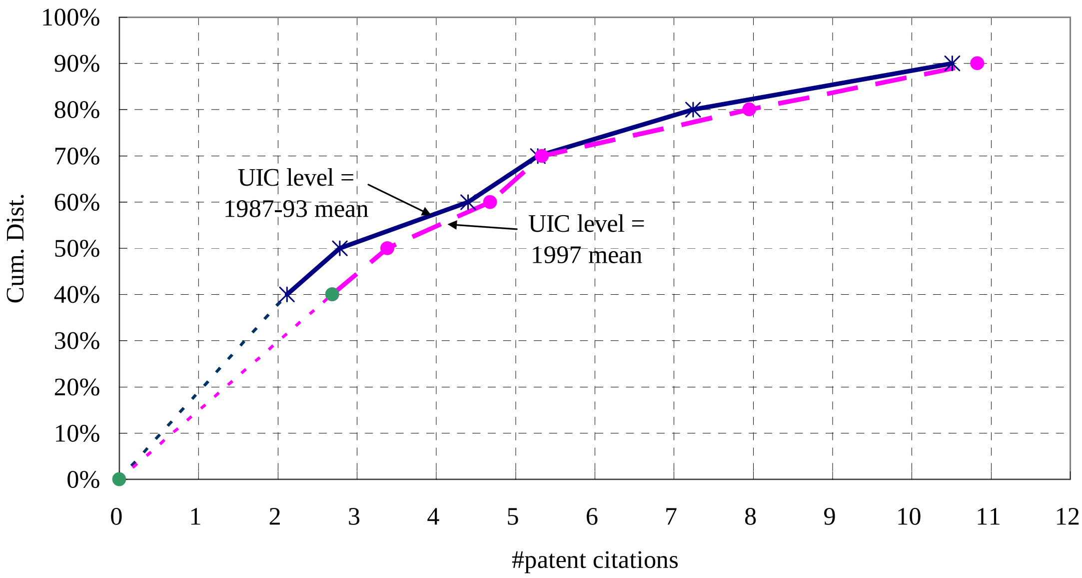


Figure 3. Estimated Effects of UIC on the Distribution of Patent Quality

(a) R&D variable = Flow, UIC lag = 0



(b) R&D variable = Flow, UIC lag = 1

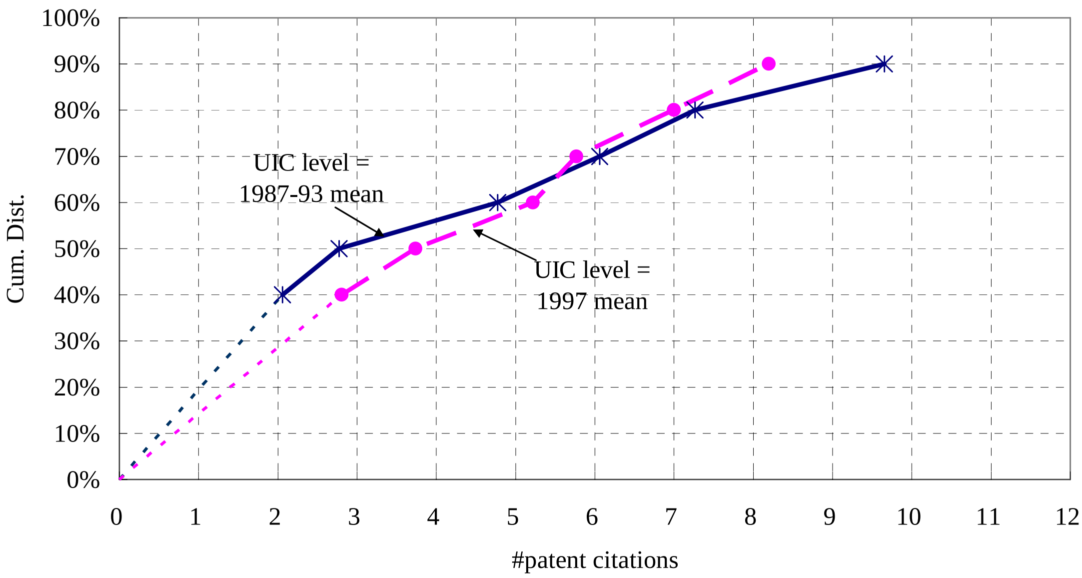
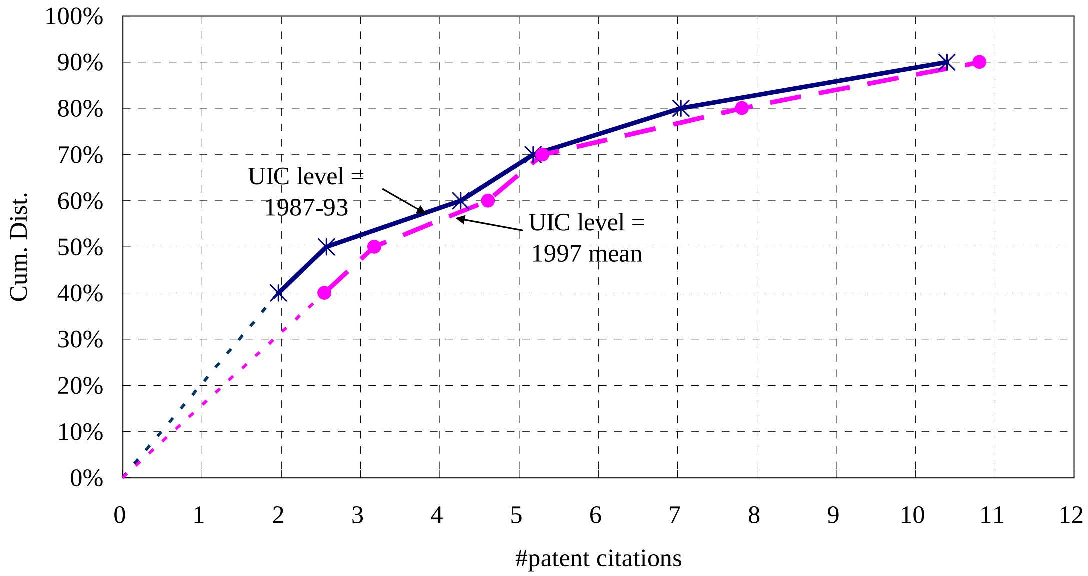
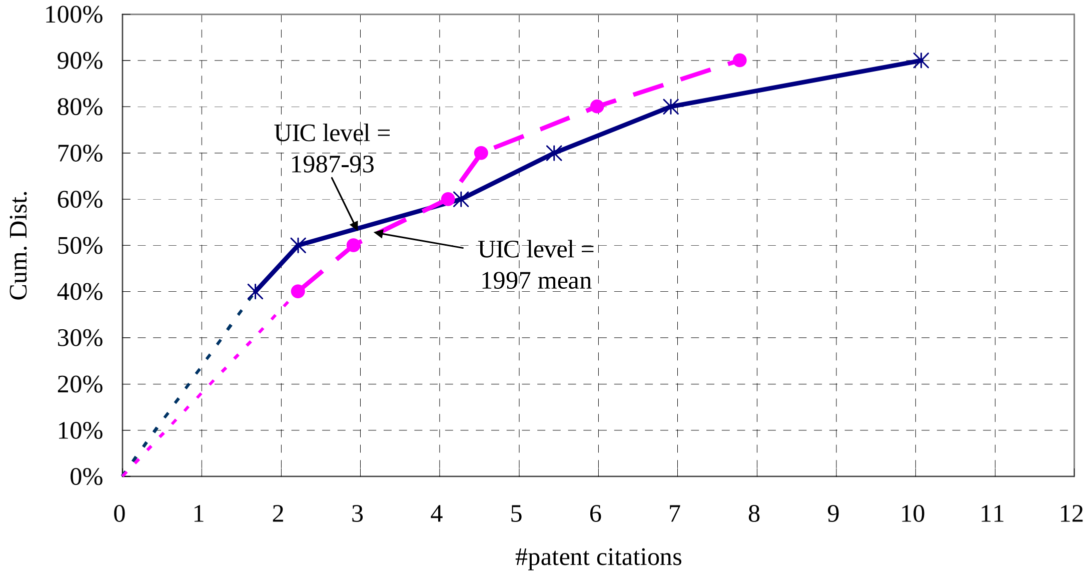


Figure 3. Estimated Effects of UIC on the Distribution of Patent Quality (continued)

(c) R&D variable = Stock, UIC lag = 0



(d) R&D variable = Stock, UIC lag = 1



In all four panels, the level of R&D variable is hold to 1987-93 mean for the two lines.