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Bargaining in Technology Markets: An empirical study of biotechnology alliances

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Bargaining in Technology Markets: An empirical study of biotechnology alliances[1]

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Abstract

We empirically examine the distribution of bargaining power between buyers and sellers on the biotechnology markets by estimating the extracted surplus in alliance agreements, which depends on each party's bargaining power. The results show that buyers have extracted more surplus than sellers. However, these also reveal that the surplus extracted by buyers has been decreasing while that of the sellers has been increasing. We construe that the prices of biotechnologies have been lower than their market value because of the strong bargaining position of buyers, but that sellers' negotiating power may been improving.

Key words: Technology market, biotechnology, alliance, bargaining model
JEL classification: L24, L65

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1. Introduction

The division of innovative labor between biotechnology and pharmaceutical companies has become essential in drug research since the first successful biotechnology products reached the market in the early 1990s.[1] The advancement of biotechnology by universities and public research institutes (PRIs) has significantly contributed to the improved productivity of pharmaceutical R&D in the United States (Cockburn and Henderson, 2001). Dedicated biotechnology companies, generally spin-offs from universities and PRIs, play an important role in this technology transfer process. Europe (Fuchs, 2003) and Japan (Motohashi, 2007) also exhibit changes in the pharmaceutical innovation process from in-house R&D to an open model. A well-functioning market for knowledge assets, where biotechnology and pharmaceutical companies trade technologies in various types of alliance agreements, is now indispensable for the effective R&D management of pharmaceutical companies.

Alliances between biotech and pharmaceutical companies take various forms, including collaborative research, licensing, equity investment, and joint ventures. Baker et al. (2008) compare the governance mechanism of various types of alliances, using a model that takes into account both externality associated with collaboration and ex-post contracting problems and ex-ante ones in the conventional model (Grossman and Hart, 1986; Holmstrom and Milgrom, 1994). They show that all types of alliances do not lead to the first-best solution by the merger of the two parties and that an optimal type of alliance is determined by various parameters and payoff functions. A substantial number of empirical studies analyze the innovative impacts of strategic alliances. Product development of a pharmaceutical company benefits from an alliance with biotech start-ups, particularly when the former has complementary assets (Rothaermel, 2001). Anand and Khanna (2000) reveal the effects on stock market valuations of strategic alliances. However, empirical studies that investigate bargaining alliance contracts are quite rare.

This paper examines the workings of the knowledge market in the biopharmaceutical industry by empirically analyzing the distribution of bargaining power among sellers and buyers

of knowledge assets. With regard to biotechnologies, both groups can possess considerable bargaining power in an alliance contract, and the unbalanced negotiation outcome between the two sides can negatively affect research performance and thus pharmaceutical innovation.

The possession of strong patent rights among sellers, many of which are biotechnology companies, can lead to considerable bargaining clout. Pro-patent policy reforms, such as the establishment of CAFCs and the Bayh Dole Act of 1980, have contributed to the propagation of biotech spin-off firms in the United States (Cockburn et. al, 1999). It should be noted that too strong patent rights may cause the "anti-commons" problem (Heller and Eisenberg, 1998). If the price of research input is too high, many pharmaceutical companies may be discouraged to use them, resulting in the delay of new drugs. The buyers, often pharmaceutical companies, can gain in negotiating power through financial constraints on biotechnology firms (Lerner et al., 2003). Biotechnology products usually require many years of R&D and large investments of capital. Moreover, because of considerable information asymmetries in biotechnology research, it is often difficult for investors to assess its progress. Many research-intensive biotechnology companies have financed themselves through both public equity issues and alliances with pharmaceutical companies. However, given the characteristics of biotechnology research, the amount of capital raised from the public market has been highly variable.[2] Thus, when a biotechnology firm has difficulty in financing a R&D project, pharmaceutical corporations can have large bargaining power as investors. This could cause inefficiency if the latter gained a large part of the control rights in the research project.[3]

We analyze the bargaining outcome in the formation of biotechnology alliances by applying the empirical framework proposed by Kumbhakar and Parmeter (2009a). Although their econometric method does not identify the bargaining power of the respective parties, it does estimate the surplus, which depends on the former, extracted by each in individual alliances. Thus, the approach of Kumbhakar and Parmeter (2009a) is useful in examining the distributions of bargaining power among the buyers and sellers of biotechnologies. Using their empirical framework, we found that buyers tend to extract more surplus than sellers. The results

imply that the contract prices of biotechnologies have been lower than their market value because of the stronger bargaining positions of pharmaceutical firms. However, the findings, after controlling for those firm features that affect bargaining power, also show that the extracted surplus of buyers has been decreasing, and that of sellers slightly increasing. It appears, therefore, that the bargaining positions of sellers may be improving and that contract prices may be approaching the market values of biotechnologies.

The organization of the paper is as follows. Section 2 explains its empirical framework. Section 3 describes the sample data. Section 4 presents the estimation results. The final section discusses the results and offers a conclusion.

2. Empirical framework

Both the seller and the buyer extract surplus from an alliance agreement, but the division of the surplus between them depends on their respective bargaining power. As already indicated, we apply the empirical framework of Kumbhakar and Parmeter (2009a), which is explained below, to examine the effect of bargaining on alliance agreements.[4]

Let the contract price of an alliance agreement, a seller's reservation price, and a buyer's maximum offer be p, $\underline{p}$, and $\overline{p}$, respectively Then, the contract price can be decomposed as follows:

$$p = \underline{p} + \eta\left(\overline{p} - \underline{p}\right), \tag{1}$$

where $0 \le \eta \le 1$ is the bargaining power of the seller.

Next, let $\mu(x) \equiv E(v \mid x)$ denote the expected market value of technologies traded in an alliance agreement, conditional on technology characteristics and alliance types, where v is the unobservable value of traded technologies and x is a vector of that characteristics of the technologies and alliance types. We assume that the value of technologies depends on their types, based on interviews with industry experts from several pharmaceutical companies. The interviewees acknowledged that different types of technologies are traded at diverse contract

prices and also that the important technologies of pharmaceutical companies have been changing over years. By assuming that the contract price depends on alliance types, we examine the interview results in light of the findings of Baker and others (2008). They reveal that the spillover (or externality) from a joint project onto the parent companies is an important factor in determining the form of strategic alliances in biotechnologies. Therefore, the contract price can be different across diverse alliance types.

By construction, $\underline{p} \le \mu(x) \le \overline{p}$. Then, equation (1) is rewritten as

$$p = \mu(x) + \eta\left(\overline{p} - \mu(x)\right) - (1-\eta)\left(\mu(x) - \underline{p}\right). \quad (2)$$

The terms $\left(\overline{p} - \mu(x)\right) \ge 0$ and $\left(\mu(x) - \underline{p}\right) \ge 0$ in equation (2) are a buyer and a seller's expected surplus from the transaction, respectively. In equation (2), the difference between the actual contract price and $\mu(x)$ is determined by each party's bargaining power and the expected surplus. The seller can increase the price by extracting the buyer's surplus $\left(\overline{p} - \mu(x)\right)$, depending on the bargaining power η. Similarly, the buyer can decrease the price by extracting the seller's surplus $\left(\mu(x) - \underline{p}\right)$, depending on the bargaining power $(1-\eta)$. Although η cannot be identified, the surplus extracted by the seller and buyer, $\eta\left(\overline{p} - \mu(x)\right)$ and $(1-\eta)\left(\mu(x) - \underline{p}\right)$, can be interpreted as the result of each party's bargaining on the contract price.

In equation (2), the outcome variable *p* has the lower boundary $\mu(x) - (1-\eta)\left(\mu(x) - \underline{p}\right)$ and the upper boundary $\mu(x) + \eta\left(\overline{p} - \mu(x)\right)$. Then, equation (2) can be rewritten as the regression equation in the format of a two-tier stochastic frontier model:

$$p = x'\delta + w - u + v. \quad (3)$$

The regression part of equation (3), $x'\delta$, corresponds to the market value of traded technologies, $\mu(x)$, where δ is a vector of parameters for the covariates x. In the residual part of equation (3), $\varepsilon \equiv w - u + v$, w corresponds to the buyer's surplus extracted by the seller, $\eta\left(\overline{p} - \mu(x)\right)$,

and u corresponds to the seller's surplus extracted by buyer, $(1-\eta)(\mu(x)-\underline{p})$, where both w and u are nonnegative. Finally, v is the classical error term.

To estimate the parameter set $\theta=\{\delta,\sigma_v,\sigma_u,\sigma_w\}$, it is assumed that (i) w follows an exponential distribution with the mean σ_w, (ii) u follows an exponential distribution with the mean σ_u, (iii) v follows a normal distribution with zero mean and variance σ_v^2, and (iv) the error components are distributed independently of each other and from the covariates x. Based on these distributional assumptions, the pdf of the i-th residual, ε_i, $f(\varepsilon_i)$, is driven as

$$f(\varepsilon_i)=\frac{\exp(\alpha_i)}{\sigma_u+\sigma_w}\Phi(\beta_i)+\frac{\exp(a_i)}{\sigma_u+\sigma_w}\Phi(b_i) \tag{4}$$

where $\alpha_i=\frac{\varepsilon_i}{\sigma_u}+\frac{\sigma_v^2}{2\sigma_u^2}$, $\beta_i=-\frac{\varepsilon_i}{\sigma_v}-\frac{\sigma_v}{\sigma_u}$, $a_i=-\frac{\varepsilon_i}{\sigma_w}+\frac{\sigma_v^2}{2\sigma_w^2}$, and $b_i=\frac{\varepsilon_i}{\sigma_v}-\frac{\sigma_v}{\sigma_w}$ (Φ is the cumulative distribution function of the standard normal variable). Kumbhakar and Parmeter (2009a) explain the derivation of the pdf (4).[5] Then, the estimates of the parameter set $\theta=\{\delta,\sigma_v,\sigma_u,\sigma_w\}$ can be obtained by the maximum likelihood method based on (4). Since the parameters σ_u and σ_v appear in distinct parts of the log likelihood equation, the identification of the two parameters is achievable.

Having estimated the coefficients of equation (3), we calculate the observation-specific expectation of w and u conditional on the total residual ε, $E[w\mid\varepsilon]$ and $E[u\mid\varepsilon]$, which are driven by Kumbhakar and Parmeter (2009a). As explained in section 2, they are estimates of the extracted surplus by a seller and buyer in an alliance agreement. Since the dependent variable is in log form, $E[w\mid\varepsilon]$ and $E[u\mid\varepsilon]$ approximate the rates of increase and decrease of the contract price as a result of the bargaining between the seller and buyer. Then, we further examine the relationship between the extracted surplus, $E[w\mid\varepsilon]$ and $E[u\mid\varepsilon]$, which are proxy variables of the seller and buyer's bargaining power and of the various exogenous factors that are possibly related to each party's bargaining power but not directly related to the

characteristics of the traded technologies and alliance types (the controls of the two-tier stochastic frontier model). This examination is done by regressing $E[w \mid \varepsilon]$ and $E[u \mid \varepsilon]$ on the exogenous variables.[6]

For the exogenous variables, we choose several characteristics of each party, which are explained in detail in the following section, and the year dummies as the variables of macro-economy factors. In using year dummies as the macro-economy factors, we assume that annual changes in governmental policy and market condition affect each party's bargaining power in the individual alliance contract, as explained in our introduction. We do not include year dummies in the estimation of the two-tier stochastic model, based on the conjecture that exogenous factors cause changes in the value of technologies more gradually, such as in periods of five to ten years.

3. The data

All the data for the empirical analysis explained above is taken from RDNA database of Deloitte Recap, a company specializing in the biotechnology industry since 1988.[7] We downloaded 21,451 records of alliances formed from September 1973 to September 2008 from the RDNA database. However, since many alliances in the database lack data for some variables, only part of them are viable in an empirical analysis. To be specific, among the total 21,451 alliance records that we downloaded, only 10,390 alliances contain data for the development stages of traded technologies. In the following, we first define the sample for estimating the two-tier stochastic frontier model and then define the sub-samples for the regression analysis of the extracted surplus by sellers and buyers.

3.1 The variables and sample for the two-tier stochastic frontier model

For the contract price of alliance agreements, the dependent variable of equation (3), we use log of *SIZE* in RDNA, where *SIZE* is deflated by using US GDP deflator. A licensing

agreement consists typically of payments, milestone payments, and royalty fees. The *SIZE* variable is the total amount of payments expressed in the licensing contract, not only in cash but also in equities. In this sense, the royalty payment (designated by a percentage of sales) is not taken into account here. In addition, milestone payments will be paid only when each specific condition is met. Therefore, the *SIZE* may underestimate the total expected value of the contract by missing the royalty, and overestimate it by adding all milestone payments. Therefore, we decided to use this value as the proxy of total value (price) of the licensing contract. Such biases do not exist for other type of alliances, such as research collaborations and joint ventures. Among the total 21,451 alliances, only 7,809 have the data for the *SIZE*.

For the technological characteristics of an alliance agreement, a part of the control variables of equation (3), we use types and development stages of traded technologies in this manner. RDNA classifies technology types into more than fifty. We grouped these into twelve. Appendix, Table 1 presents the correspondence between the RDNA technology types and the integrated twelve types. For the development stages, we use nine stages in RDNA: Discovery, Lead Molecule, Preclinical, Phase I, Phase II, Phase III, Approved, BLD/NDA filed, and Formulation. Several technologies can be traded in an alliance, which can possess several development stages. For the alliances with several technologies, we include all technology dummies but use only the latest stage dummy for the development stages.

For the characteristics of each alliance agreement, that is, the other part of control variables in equation (3), we employ five alliance types created out of the integration of the RDNA's twenty-two alliance types. RDNA originally lists twenty-six, but we excluded the following four: Letter of Intent, Security, Settlement, and Termination, which are ancillary information to alliance types.[8] Appendix, Table 2 presents the correspondence between the RDNA's original alliance types and our integrated variants.

The estimation of the two-tier stochastic frontier model is based on the sample of the alliances containing all the data of the above variables. The sample, however, excludes those with universities, since these may have been in different competitive positions than commercial

organizations.[9] Moreover, only the alliances formed from January 1990 are used, for after that year did pharmaceutical and biotechnology companies develop relationships that commercialized biotechnology products (Audretsch, 2001). All the 21,451 alliance records include data for the year of the contract. The sample is confined to 2,980 alliances. Figure 1 shows the number of alliances and the average *SIZE* in each year, and Table 1 summarizes the data for the technological traits and the alliance types. In both Figure 1 and Table 1, the sample is compared to all the data containing each variable.

Figure 1 Number of alliances and the average SIZE

Table 1 Summary of the sample data for the estimation of two-tier stochastic frontier model

3.2 The variables and sample for the regression of the extracted surplus

As characteristics of a seller and buyer, that is, the control variables in the regression analysis of the extracted surplus, we use (i) regional dummies (US, Europe, Japan, others), (ii) type of business dummies (biotech, drug, others), (iii) public company dummy, and (iv) the number of previous alliances that a firm contracted. As explained in section 2, we also add year dummies as macro-economy factors.

Several factors influence the relative strengths and weakness in a firm's bargaining position. One of the factors is a firm's region, since differences in market conditions and technological levels among regions exist. Variations in the regional locations of sellers can be related to their bargaining power, since regional differences in stock markets may be large for young high-technology companies seeking financing. For example, Pagano et al. (2002) argue that US exchanges tend to be better suited to the needs of high-tech companies, based on statistical analysis of the cross-listing behavior of European and US firms from 1986–1997. In addition, a business type can place financial constraints on a firm. For example, a large pharmaceutical company may be less financially restricted, while a young biotechnology company may operate within strict economic limits. Similarly, the public or private status of a company is related to its

accessibility to the financial market, which bears on its financial constraints.

Finally, we add the number of a firm's previously contracted alliances to capture its experience with such agreements. It is well known that such familiarity is an important factor in the success of alliances, since it allows firms to master the management skills required in the latter (Kale et al. 2002). Rothaermel and Deeds (2006) report that biotechnology firms with such knowledge tend to develop more new products in alliances in comparison to firms without it. Thus, previous alliance experiences of a firm, especially seller, may affect its bargaining power in contracting an alliance.

From the estimation of the two-tier stochastic frontier model, we obtain 2,980 observation-specific estimates of the extracted surplus for both sellers and buyers. However, not all of these alliances contain full data, many lacking information on either the seller or buyer. We use different sub-samples for the regression analysis of $E[w \mid \varepsilon]$ and $E[u \mid \varepsilon]$, the sample sizes of which are 1818 and 1792, respectively.[10] Tables 2 and 3 summarize the sample data for the explanatory variables for the regression of $E[w \mid \varepsilon]$ and $E[u \mid \varepsilon]$, compared to all the data containing each variable.

Table 2 Summary of the sample data for OLS of $E[w \mid \varepsilon]$

Table 3 Summary of the sample data for OLS of $E[u \mid \varepsilon]$

4. Results

4.1 The two-tier stochastic frontier model

Table 4 shows estimates of the two-tier stochastic frontier model (3).

Table 4 Estimates of the two-tiered stochastic frontier model

Since many alliance agreements include several technology and alliance types, we include

all the technology, stage, and alliance type dummy variables, rather than the constant term. We also include the product of technology dummies and 2000 dummies (1 for alliances since the year 2000 and 0 for alliances before this) to capture changes in the value of technologies. For the maximum likelihood estimation of equation (3), the estimated coefficients of OLS with the same control variables are employed as the initial values for the coefficients of the controls. For the variance parameters, these are all set to one.

The results reveal that the development stages are the dominant factors in the determination of the contract price. The coefficients of the development dummies are all larger than those of the technology and alliance dummies. Moreover, later stages tend to be priced higher than earlier stages, which makes sense because the technologies of the former are closer to the market than those of the latter.

Although the effects of technology and alliance dummies are relatively small, differences exist among them. The estimated coefficients of the technology dummies are the technological differences of the 1990s. The estimated coefficients of the products of the technology and 2000 dummies are the differences between the technology dummies' coefficients of the 1990s and those of the 2000s. The results of the Wald test reject the null hypothesis that changes of the 2000 technology dummies are all zero. Among the changes in technological differences, the increases in Monoclonals and Synthetics are remarkable. Among the alliance types, joint ventures tend to be priced higher than others, since the former include alliances concerning marketing. This conjecture is consistent with the finding that technologies in later stages tend to be priced higher.

The variance parameters of the error terms are all statistically significant, and the parameter σ_u is more than two times larger than σ_w. Since σ_u and σ_w are equal to the means of u and w, which follow exponential distributions, it can be implied that on average, buyers tended to have larger bargaining power than sellers did in biotechnology alliances.

4.2 Regression of the extracted surplus

Tables 5 and 6 show estimates of the regression (OLS) of $E[w|\varepsilon]$ and $E[u|\varepsilon]$, the rate of increase, and the decrease in contract price (*SIZE*), respectively. In the following, we refer to $E[w|\varepsilon]$ and $E[u|\varepsilon]$ as the price increase and decrease effects. In both regression results, constant terms correspond to the coefficient of non-listed biotech firms in the US for the year 1990.

Table 5 Estimates of the regression (OLS) of $E[w|\varepsilon]$

Table 6 Estimates of the regression (OLS) of $E[u|\varepsilon]$

After controlling seller/buyer characteristics, the estimated coefficients of the year dummies show that $E[w|\varepsilon]$ has an increasing trend, while $E[u|\varepsilon]$ has the opposite, although the increasing trend of sellers' prices is moderate compared to the decreasing one of buyers (figure 2). It can be conjectured that the bargaining position of sellers may have been improving relative to that of buyers, which could explain the increasing trend in the average *SIZE* observed in Figure 1. A temporary gain in the bargaining power of buyers in the late 1990s may be related to the US biotech start-up boom, when the number of start-ups increased significantly because of advances in genomics, as well as the active venture financing in biotechnology (Motohashi, 2010). The increased choice of technologies for pharmaceuticals may have contributed to the better bargaining position. In contrast, the number of new of biotech startups sharply dropped after the burst of the IT bubble in the early in this century, which led to a drop in buyers' surpluses.

Figure 2 Estimated coefficients for year dummies

For the differences in regions, sellers' price increase effects are lower for Japanese and

other regions' companies than for their US counterparts, while the difference between the latter and European firms is almost zero and statistically insignificant. For buyers, the coefficients of the three regions are inferior to those of US companies. Among them, the coefficient of Japanese firms is the lowest and statistically significant. Regional differences may have existed not only in the bargaining power of sellers, as explained in section 3, but also in that of buyers. It may be harder for Japanese pharmaceuticals to negotiate with US biotech startups because of regional and cultural distances. This finding justifies a regional cluster policy for promoting technology providers (universities and biotech startups) and users (pharmaceutical firms) within proximity of each other.

As for company-type differences, drug firms as sellers have a higher price increase effect than biotechnology companies, which as buyers have a higher price decrease effect than the former. As shown in tables 2 and 3, biotechnology companies are mainly sellers in alliances. We assume that small numbers of successful biotechnology companies may have exerted a greater bargaining power as buyers relative to other firms of the same type than as sellers competing against pharmaceutical companies. On the other hand, since drug companies include many established large pharmaceutical corporations, they also exert significant bargaining power as sellers of biotechnologies.

As explained in section 3, we include a public company dummy because unlisted companies can face financial restrictions. However, the estimated parameters are statistically insignificant in both regressions, perhaps because the sample includes only a small number of unlisted companies. In the two sub-samples, there are only 153 alliances in which unlisted companies were sellers and only 75 in which they were buyers. If the unlisted companies in these alliances mostly consisted of large companies, such as subsidiaries of pharmaceutical firms, they may have been less financially restricted.

Finally, in terms of familiarity, sellers with greater experience have a higher price increase effect, which is consistent with the findings of the previous empirical research explained in section 3. On the other hand, for buyers in the same situation, the price decrease effect becomes

smaller. The number of licensing contracts is correlated with firm size, and a deep pocket firm may make licensing deal with relatively generous conditions. In addition, a buyer's tight interactions with one seller can generate sunk costs, which give rise to switching costs and lock-in problems (Arora et al., 2001). Thus, if buyers with longer experience mainly consisted of those who drew up repeated contracts with the same seller, longer experience would mean a higher sunk cost, which can make the coefficients for buyers negative, as a result of their reduced bargaining power.

5. Conclusion

Because of the success of biotechnology, many new drugs for previously intractable diseases, such as cancer and HIV, are coming to the markets.[11] Not only patients but also investors are delighted to have such drugs, since they command large markets. For example, it is reported that the market for hepatitis C medications could reach four billion to five billion dollars by 2015.[12] For the health of both the human body and the economy, the division of labor between biotechnology and drug companies should be efficient.

In this paper, we investigated the distribution of bargaining power between sellers and buyers of biotechnologies, by estimating the extracted surplus by each party in alliance agreements, which depend on each party's bargaining power. The findings show that the buyers have extracted large surplus from these transactions relative to the sellers. From these results, it can be conjectured that the negotiating force of pharmaceutical companies has been larger than that of their biotechnology counterparts. Therefore, government policies to decrease financial constraints on new biotechnology companies could contribute to an improvement in the efficiency of the biotechnology market.

On the other hand, the results reveal that after controlling various firms' characteristics possibly related to their bargaining power, the extracted surplus by buyers has been decreasing while that of sellers has been increasing. These findings imply that the bargaining position of

biotechnology companies relative to pharmaceutical ones has been improving since 1990. Moreover, the market for biotechnologies might have been growing more efficient, since the findings imply that contract prices were approaching the market values of biotechnologies.

A few factors may explain the increasing bargaining power of sellers. First, their success in developing biotech-based new drugs is attracting more investors and thus improving the financial conditions of biotechnology companies. Second, the trend of the pro-patent policy, which is often criticized for deterring innovation by causing the anti-commons problem, might have contributed to health care innovation by reducing the large bargaining power of pharmaceutical companies relative to their biotechnology counterparts.

We also have found a statistically significant difference in bargaining power of buyers across countries. It is relatively greater for US companies than for those of other regions, particularly Japanese firms. Since most of the sellers in our datasets are US biotech startup companies, this result confirms the importance of the regional proximity of sellers and buyers in the technology market. The relationship between technology spillover and regional proximity in biotechnology innovation has been extensively investigated (Zucker and Darby, 2001; Owen-Smith and Powell, 2004). This study reconfirms these findings, specifically in the process of the deal-making process of licensing contracts.

Appendix

Table 1: Technology types

Integrated tech types	Original tech types in RDNA
1 Genetics	Gene Diagnostics
	Gene Expression
	Gene Sequencing
	Microarrays
	Pharmacogenomics
2 Bioinformatics	Bioinformatics
	Rational Drug Design - Computational
	Rational Drug Design - Synthetics
3 Recombinant DNA	Recombinant DNA
4 Other biotechnology	Carbohydrates
	Cell Therapy - Stem Cells/Factors
	Micropropagation
	Oligonucleodites - Ribozymes
	Oligonucleotide ligands
	Oligonucleotides - Antisense/Triple helix
	Oligonucleotides - Gene Therapy
	Oligonucleotides - Ribozymes
	Proteomics
	Transcription Factors
	Transgenics
5 Monoclonals	Monoclonals
	Monoclonals - Anti-Idiotypes
	Monoclonals - Conjugates
	Monoclonals - Fully human Abs
	Monoclonals - Human Abs
	Monoclonals - Humanized & Fully Human Abs
	Monoclonals - Humanized Abs
	Monoclonals - Transgenic mice
6 Drug related materials	Fusion Proteins
	Fusion proteins
	Natural Product
	Natural product
	Peptides
	Polyclonal Antibodies
	Polyethylene glycol (PEG) products
	Vaccines
7 In-licensed products	In-licensed Products
8 Synthetics	Synthetics
9 Screening	Combinatorial
	Screening
10 Diagnotics	DNA Probes
	Diagnostics

Table 1: Technology types (continued)

Integrated tech types	Original tech types in RDNA
11 DDS	Drug Delivery - Liposomes
	Drug Delivery - Oral
	Drug Delivery - Other
	Drug Delivery - Sustained Release
	Drug Delivery - Transdermal
	Microspheres
12 Others	Adjuvant
	Collagen matrix
	Device
	Formulation
	Generics
	Hyaluronic acid
	Immunoassay
	Immunoglobulin
	Implantable Devices
	PFOB Emulsions
	Phototherapy
	Purines & Pyrimidines
	Research reagents
	Resin Polymers
	Separations
	Service Laboratory

Table 2: Alliance types

Integrated alliance types	RDNA's original alliance types
Acquisition and merger	Acquisition
	Asset Purchase
	Assignment
	Merger
	Warrant
Investment	Equity
	Loan
Joint venture	Co-Market
	Co-Promotion
	Joint Venture
Licenses	Cross-license
	License
	Option
	Sublicense
Unstructured collabolation	Co-Development
	Collaboration
	Development
	Distribution
	Manufacturing
	Marketing
	Research
	Supply

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Table 1 Summary of the sample data for the estimation of two-tier stochastic frontier model

		Sample		All data	
		Number of counts	Percentage	Number of counts	Percentage
Technology	Genetics	258	0.087	1934	0.119
	Bioinformatics	118	0.040	1199	0.074
	Recombinant DNA	209	0.070	889	0.055
	Other biotechnology	387	0.130	2068	0.127
	Monoclonals	274	0.092	1347	0.083
	Drug related components	337	0.113	1785	0.110
	In-licensed products	370	0.124	1117	0.069
	Synthetics	954	0.320	2708	0.166
	Screening	414	0.139	1847	0.113
	Diagnotics	73	0.024	2461	0.151
	DDS	524	0.176	1949	0.120
	Others	256	0.086	2759	0.169
	Number of records	2980		16299	
Stage	Discovery	842	0.283	4401	0.424
	Lead Molecule	240	0.081	1013	0.097
	Preclinical	308	0.103	874	0.084
	Phase I	181	0.061	455	0.044
	Phase II	284	0.095	593	0.057
	Phase III	246	0.083	431	0.041
	Approved	342	0.115	1096	0.105
	BLA/NDA filed	79	0.027	186	0.018
	Formulation	458	0.154	1341	0.129
	Number of records	2980		10390	
Alliance type	Acquisition and merger	489	0.164	4113	0.193
	Investment	939	0.315	2633	0.124
	Joint venture	503	0.169	1374	0.065
	Licenses	2513	0.843	12442	0.584
	Unstructured collabolation	2242	0.752	12503	0.587
	Number of records	2980		21296	

Table 2 Summary of the sample data for OLS of $E[w \mid \varepsilon]$

		Sample		All data	
		Number of counts	Percentage	Number of counts	Percentage
Region	US	1439	0.792	7207	0.711
	Europe	219	0.120	1729	0.171
	Japan	27	0.015	335	0.033
	Others	133	0.073	861	0.085
	Number of records	1818	1	10132	1
Type	Biotech	304	0.167	9067	0.536
	Drug	121	0.067	1451	0.086
	Others	1393	0.766	6407	0.379
	Number of records	1818	1	16925	1
Public	Non-Public firms	153	0.084	1363	0.146
	Public firms	1665	0.916	7951	0.854
	Number of records	1818	1	9314	1

Table 3 Summary of the sample data for OLS of $E[u \mid \varepsilon]$

		Sample		All data	
		Number of counts	Percentage	Number of counts	Percentage
Region	US	1184	0.661	8708	0.671
	Europe	372	0.208	2536	0.195
	Japan	163	0.091	810	0.062
	Others	73	0.041	932	0.072
	Number of records	1792	1	12986	1
Type	Biotech	135	0.075	6462	0.346
	Drug	523	0.292	4504	0.241
	Others	1134	0.633	7734	0.414
	Number of records	1792	1	18700	1
Public	Non-Public firms	75	0.042	961	0.082
	Public firms	1717	0.958	10731	0.918
	Number of records	1792	1	11692	1

Table 4 Estimates of the two-tiered stochastic frontier model

		Coefficient	S.E.
Tech dummy	Genetics	0.345	0.139
	Bioinformatics	-0.049	0.184
	Recombinant DNA	-0.212	0.142
	Other biotechnology	-0.234	0.115
	Monoclonals	-0.370	0.148
	Drug related components	-0.319	0.131
	In-licensed products	-0.568	0.153
	Synthetics	-0.419	0.120
	Screening	-0.017	0.116
	Diagnotics	-0.598	0.208
	DDS	-0.613	0.162
	Others	-0.509	0.138
Tech dummy*	Genetics	-0.480	0.199
2000s dummy	Bioinformatics	0.456	0.283
	Recombinant DNA	0.798	0.211
	Other biotechnology	0.507	0.163
	Monoclonals	1.140	0.181
	Drug related components	0.616	0.168
	In-licensed products	0.289	0.183
	Synthetics	1.235	0.121
	Screening	0.093	0.162
	Diagnotics	0.595	0.379
	DDS	0.716	0.144
	Others	0.316	0.197
Stage dummy	Discovery	1.894	0.170
	Lead Molecule	2.146	0.180
	Preclinical	2.318	0.170
	Phase I	2.556	0.181
	Phase II	2.618	0.173
	Phase III	2.757	0.174
	Approved	2.899	0.173
	BLA/NDA filed	2.414	0.214
	Formulation	2.039	0.190
Type dummy	Acquisition or merger	0.551	0.097
	Investment	0.449	0.063
	Joint venture	0.873	0.076
	License	0.506	0.097
	Unstructured collaboration	0.676	0.074
Error component	σ_v	0.977	0.080
parameter	σ_u	1.204	0.063
	σ_w	0.476	0.090
Tech-changes in 2000s	Wald test statistics	305.040	
	p-value	0.000	

Table 5 Estimates of the regression (OLS) of $E[w|\varepsilon]$

		Coefficient	S. E.
Constant		0.445	0.023
Year	1991	-0.023	0.019
	1992	0.001	0.023
	1993	0.006	0.018
	1994	0.000	0.018
	1995	0.051	0.022
	1996	0.071	0.024
	1997	0.076	0.019
	1998	0.094	0.026
	1999	0.050	0.021
	2000	-0.016	0.017
	2001	0.019	0.023
	2002	0.023	0.021
	2003	0.013	0.019
	2004	0.008	0.019
	2005	0.057	0.023
	2006	0.094	0.026
	2007	0.162	0.028
	2008	0.155	0.049
Region	Europe	0.002	0.017
	Japan	-0.059	0.028
	Others	-0.024	0.012
Party	Drug	0.034	0.027
	Others	-0.010	0.015
Public		-0.023	0.020
Experience		0.002	0.001
R-square		0.893	

Table 6 Estimates of the regression (OLS) of $E[u \mid \varepsilon]$

		Coefficient	S. E.
Constant		1.735	0.214
Year	1991	0.273	0.257
	1992	-0.100	0.231
	1993	-0.179	0.227
	1994	-0.331	0.215
	1995	-0.317	0.218
	1996	-0.537	0.202
	1997	-0.570	0.199
	1998	-0.527	0.205
	1999	-0.399	0.206
	2000	-0.236	0.209
	2001	-0.217	0.209
	2002	-0.034	0.215
	2003	-0.242	0.207
	2004	-0.345	0.202
	2005	-0.379	0.205
	2006	-0.331	0.205
	2007	-0.494	0.206
	2008	-0.561	0.209
Region	Europe	-0.100	0.059
	Japan	-0.296	0.063
	Others	-0.064	0.117
Party	Drug	-0.104	0.088
	Others	0.040	0.085
Public		-0.047	0.092
Experience		-0.004	0.000
R-square		0.683	

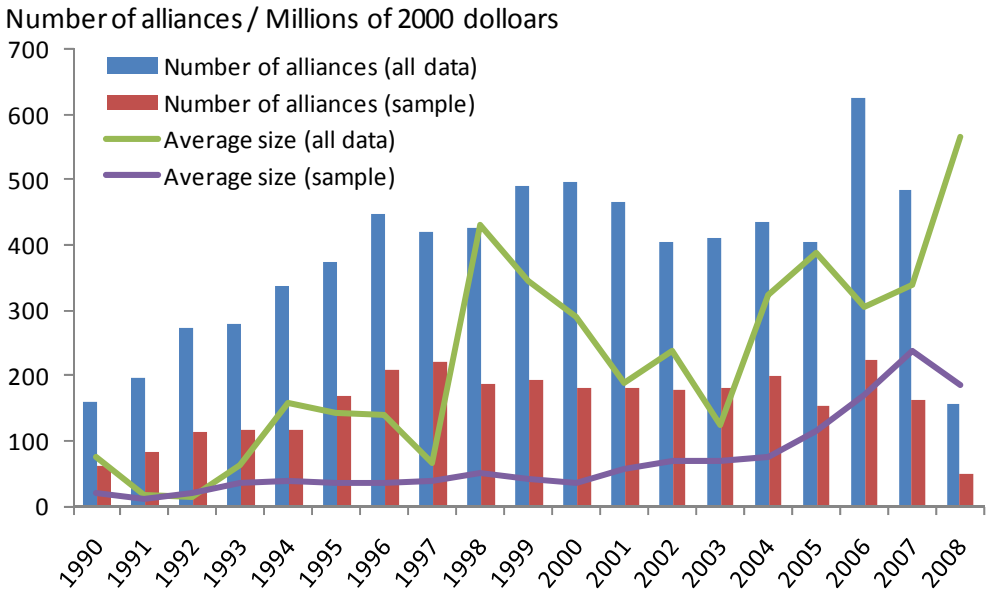

Figure 1 Number of alliances and the average SIZE

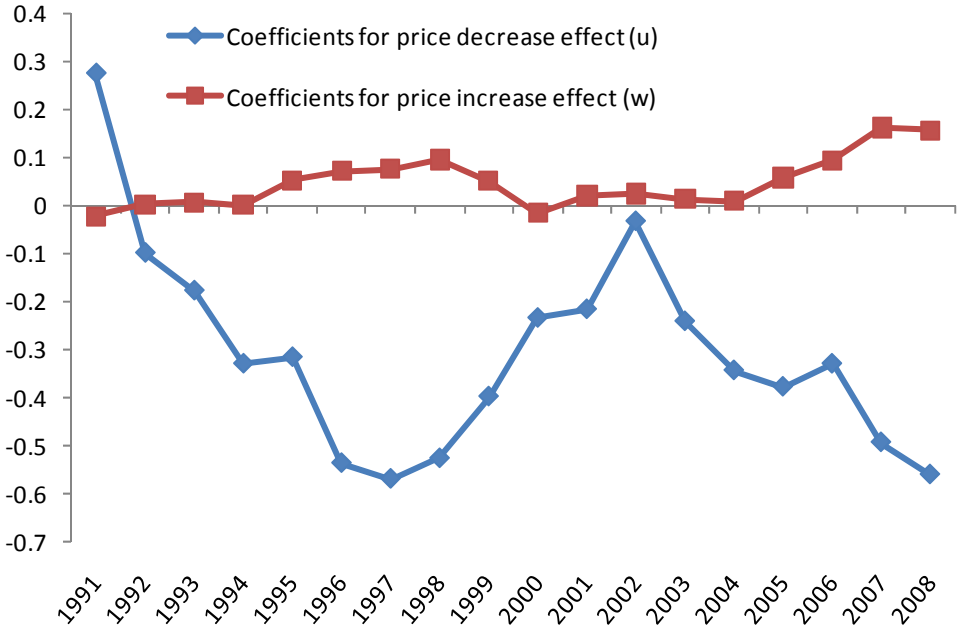

Figure 2 Estimated coefficients for year dummies

[1] For a history of the development of the biotechnology industry, see Audretsch (2001).

[2] See Lerner et al. (2003), Figure 2 (page 418).

[3] See Ibid. for a survey of the theoretical literature on the relationship between external finance and a firm's R&D performance.

[4] Kumbhakar and Parmeter (2009a) applied the framework to examine the relationship between wage dispersion in labor markets and bargaining power in each job match.

[5] This speciation of the two-tier stochastic frontier model is originally proposed by Polachek and Yoon (1987).

[6] The "two-step" estimation, where the stochastic frontier model is first estimated and then the estimated error component is regressed on exogenous variables, has been criticized in that the estimated parameters in the second step are biased (Wang and Schmidt, 2002). See the footnote 10 for the reason that we employ the two-step approach despite the bias problem.

[7] http://www.rdna.com/

[8] In the database, there are several alliance types that are not listed in the help file. Alliances of these unlisted types are also excluded from our dataset.

[9] For example, see Edwards et al. (2003).

[10] The sample size is reduced to 1,053 when the sample includes all the data for both the control variables of the two-tier stochastic frontier model and the exogenous variables related to the error components, which is a main reason that we employ the "two-step" estimation. As Wang and Schmidt (2002) show, it is always desirable to specify the stochastic frontier model so that both the control and exogenous variables are included and estimate it in "one-step." The two-tier stochastic frontier model can be estimated in the one-step, as is done by Kumbhakar and Parmeter (2009b). By using their specification, we tried the one-step estimation with the reduced sample but did not obtain reliable results.

[11] See, for example, "Cancer Drugs: Therapy for Stocks?" by Barney Brodie, *Businessweek*, August 25, 2005.

[12] "Gilead Sciences: High-Performing Pharmaceutical Gilead Science," by Aili McConnon, *Businessweek*, April 6, 2009.