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Residual Income Claimancy, Monitoring, and the R&D Firm: Theory with Application to Biotechs

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This paper models the assignment of residual income claimancy to an R&D manager and applies the model to biotechnology firms. Residual income claimancy provides incentives for the manager to monitor the R&D process. Since the nature of R&D and of monitoring scientific effort is different, our model predicts stark differences in the residual income claimancy of managers and in other aspects of organization for innovative R&D firms like biotechs. In particular, R&D firms are expected to be more owner-managed, more expert-managed, and smaller in size. Cross-sectional data on biotechnology firms is consistent with these implications. Additionally, longitudinal data indicate that as firms alter their focus on biotech research, their organizational structure changes as expected. Our approach suggests a process of firm and industry evolution related to technological maturity and points to the importance of incentives rather than risk sharing in determining organizational form, similar to the original analysis of franchising.

INTRODUCTION

The seminal papers of Alchian and Demsetz (1972) and Jensen and Meckling (1976) on the modern theory of the firm emphasize monitoring and monitoring costs. This paper takes up the question of monitoring by a manager of a firm or establishment. We model the manager as monitoring employees to establish an incentive system. Greater monitoring effort by the manager lowers costs by improving the incentive system for workers. Residual income claimancy by the manager is his/her incentive to monitor.

Our model focuses on the organization of firms involved in R&D. Our prior expectations and the literature indicate that the nature of monitoring is quite different in many advanced technological environments than in other settings. The former requires innovation, creativity, and other intangibles that make monitoring more difficult but more important. The latter is characterized by more routine procedures making monitoring comparatively easier. Owing to this, our model predicts stark differences in the residual income claimancy of managers and in other aspects of organization for R&D firms.

Anecdotal evidence regarding the biotechnology industry supports this. Much biotechnology research apparently is done by small, independent, start-ups with contractual ties to various firms in the pharmaceutical industry (Burrill, 1988; Teece, 1988).[1] This is in contrast to the traditional 'in-house' organization of pharmaceutical research. This change in organization occurred simultaneously with the change in the technology of drug research. This paper provides a model linking the

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two phenomena. Additionally, we provide systematic evidence regarding the organization of the new biotech firms at a point in time and how it evolves over time.

The following section of the paper presents the model. It focuses on the assignment of residual income claimancy to motivate managers to monitor and establish an effective incentive system for researchers. Exogenous characteristics that distinguish innovative R&D firms are built into the model. Our approach is in keeping with other models of assignment of residual income claimancy through its emphasis on incentives, but it is unique in its explicit consideration of monitoring to improve incentives for workers and in its focus on the nature of R&D to generate differences in ownership and other aspects of organization. It is also consistent with the approach of Rubin (1978), who emphasized the importance of incentives over risk sharing in determining residual income claimancy in franchising.

We find that the greater the importance of monitoring the researchers, the greater the residual income claimancy of the R&D manager. Other implications regarding firm size and ownership by experts also are developed. The next section presents the empirical work. We utilize data on firms in the biotechnology industry. Some of these firms are involved in state-of-the-art biotech research and others are not. The first subsection provides a brief overview of biotechnology research and the biotechnology industry. It highlights the nature of the new, biotech research and contrasts it to other settings. The predictions of the model based on this discussion are made concrete. The data also are discussed in this subsection. They are from the 1992, 1995, and 1998 BioScan, a survey of nearly 900 firms involved in biotechnology. Subsequent subsections present the empirical work. Patterns in the data are consistent with the model, though some caveats emerge. Firms that are more focused on the newer, biotechnology research tend to be management owned, have more experts in the field as owner–managers, and are smaller in size. Also, we find that many firms have evolved away from the specialized biotech and, as a result, to larger, less expert-managed, and less management-owned firms. These findings represent the first systematic evidence of the organization of firms in the biotechnology industry.

The last section of the paper summarizes and concludes. We note that the model extends beyond the biotechnology industry. It is capable of explaining what types of new products come from what types of firms and predicts a process of firm and industry evolution that coincides with the maturation of a technology.

A MODEL OF OWNERSHIP AND MONITORING IN AN R&D FIRM

The focus of our model is determining the ownership of residual income claimancy in an environment where R&D is important. Other studies have considered the assignment of residual income claimancy in different settings. Stock ownership by CEOs is examined in numerous studies. See Murphy (1999) for a wide-ranging survey and Jensen and Murphy (1990), Garen (1994), and Aggarwal and Samwick (1999) for empirical studies grounded in a principal-agent framework. The literature also considers the determinants of the ownership concentration of stock by managers, directors, and blockholders. Demsetz and Lehn (1985) is a seminal paper in this area and recent studies are Himmelberg *et al.* (1999) and Demsetz and Villalonga (2001). Other related sets of literature are those on the sharing of residual income between franchisees and franchisors and between landowners and sharecroppers.[2] Bhattacharyya and Lafontaine (1995) discuss both in their paper and Lafontaine (1992) and Wimmer and Garen (1997) are examples of empirical papers on residual income claims in franchising while Allen and Lueck (1993) present empirical work on sharecropping contracts.

Our model considers residual income claimancy for an owner/manager that alters his/her incentives to monitor and set incentives for workers. Certain aspects of our model are related to the work of Holmstrom and Milgrom (1987, 1991), but it is unique in many respects. Holmstrom and Milgrom consider a principal setting incentives for an agent. This is part of our model in that we consider R&D managers establishing incentives for R&D workers. We go beyond this in several ways, though. First, we model monitoring by managers and use of the information from monitoring in setting pay. Second, we consider the manager's incentives to monitor and set an incentive system for workers.

This 'incentives to set incentives' is unique to the literature. Third, we focus on characteristics that are expected to matter for R&D firms, i.e., the creativity and intangibles that are a natural part of research and development activities.

Model Background[3]

Consider a model with three groups: a manufacturing manager, an R&D manager, and research scientist–employees. Managers also may be owners in the sense of holding residual income claimancy. The R&D manager plays an important role in the model. R&D managers presumably have many duties that, for start-up firms, include promoting the firm's capabilities and products and raising outside capital. We concern ourselves with the R&D manager's internal duties, however. These include directing the scientific activity of the firm, monitoring its progress, and hiring and compensating scientists. The monitoring and setting of compensation to induce scientist effort is key in our approach.[4]

The research effort of the R&D unit is combined with inputs from the manufacturer to produce a final product. The manufacturing division does not simply acquire or buy the R&D and put it to use. Both the manufacturing and the R&D units must provide ongoing effort to assure that the end product is produced. Both sides require incentives to induce effort. Owing to the cooperative nature of the efforts to produce the final product, it is difficult to determine the contribution of each side and so is assumed to be non-contractible. Therefore, the managers contract on the division of residual income claimancy on the joint output. This has its tradeoffs: Greater residual income claimancy for the R&D (manufacturing) side creates more incentive for the R&D (manufacturing) manager, but less for the manufacturing (R&D) manager.

Greater residual income claimancy for the manufacturing side is interpreted as being closer to in-house R&D. More residual income claimancy for the R&D side is interpreted as being closer to an independent R&D firm.[5] It is assumed that residual income claimancy is awarded to maximize the value of the joint enterprise. We determine the conditions that the R&D unit will be the major residual income claimant, as apparently has become more commonplace with biotech firms, and also how this evolves over time.

Our model has three layers. The first is the contractual stage where the residual income of the joint product is divided between managers. At the second layer, the R&D manager, based on his/her incentives, decides how carefully to monitor scientists and sets pay. Finally, the scientist–employees set effort according to the incentive structure established by the R&D manager. The model is solved by backward induction. Given a pay structure, scientists decide how much effort to put forth. Given scientist behavior and residual income claimancy, the R&D manager decides how to monitor and set pay. Given manager behavior, the decision on how to allocate residual income is made.

The Scientist's Problem

A modified version of the linear-incentives model is considered.[6] Scientists have CARA utility as $U = -\exp\{-\rho(W - C(e))\}/\rho$, where W is compensation, e is effort, and $C(e) = 1/2Ke^2$ is the utility cost of effort. Scientists produce R of useful research output. Let $R = e + \varepsilon_1$, where ε_1 is random noise with $\varepsilon_1 \sim N(0, \sigma_1^2)$. The manager observes R. Also, through directing and monitoring the research and its progress, we assume that the R&D manager obtains additional information about each scientist. That is, s/he learns not only of useful results the scientist produces but of intangibles about the scientist such as whether the scientist has good ideas, pursues them diligently and systematically, contributes ideas to others, and additional aspects of scientist effort. Denote the manger's observation of scientist effort as S. Assume that it is an imperfect signal of effort so that $S = e + \varepsilon_2$, with $\varepsilon_2 \sim N(0, \sigma_2^2)$ and ε_1 and ε_2 uncorrelated.

The pay to scientists, W, is linear in R and S as $W = b_0 + b_1 R + b_2 S$.

Scientists maximizing utility given the pay function gives effort level as $e^* = (b_1 + b_2)/K$. Substituting this into the utility function and solving for the expected wage, $E(W)$, that meets scientist reservation utility level gives $E(W) = \tau + (b_1 + b_2)/2K + 1/2\rho(b_1^2\sigma_1^2 + b_2^2\sigma_2^2)$, where τ is a constant related to the reservation utility level.

The term σ_2^2 plays an important role in our analysis. Below, we posit that increased monitoring by the manager reduces σ_2^2, i.e., it reduces the noise in the signal of scientist effort. Also, we

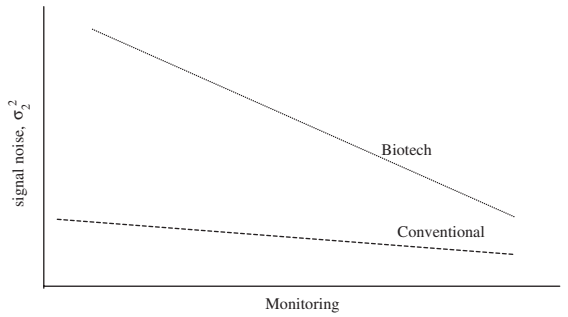

Figure 1. The relationship between the signal noise and monitoring.

argue that this parameter distinguishes innovative research environments, as in biotechs, from more conventional settings. In conventional settings, procedures are well known and more routine, making the signal of effort, S, observed by the manager quite accurate. This is in contrast to high-tech environments such as biotechnology that require mental tasks, idea creation, the production of new knowledge and where there is a substantial uncertainty regarding appropriate methods and processes. Monitoring is especially difficult for a manager in this setting, implying that σ_2^2 is relatively large.

We also argue that the marginal effects of monitoring differ between high-tech and conventional environments. This is illustrated in Figure 1. The figure graphs the relationship between the noise (σ_2^2) in the signal against the extent of monitoring. The dashed line is for conventional settings and the dotted line is for biotechnology environments. In the conventional setting, σ_2^2 is low and it does not fall much with monitoring. Since procedures are routine and it is easy to determine if they are carried out, more intensive monitoring adds little to the accuracy of the manager's information. Roughly speaking, if one initially has nearly complete information, more monitoring has little to add.

In contrast, in the biotech setting, little is routine and it is difficult to determine scientist effort because it involves creativity and innovation in an uncertain environment. Thus, the noise in the manager's signal of scientist effort is higher than in conventional settings. This is shown by the dotted locus in Figure 1. It lies above the dashed locus, indicating that σ_2^2 is higher. However, in the biotech setting, more careful oversight of the research process adds a lot to the manager's knowledge of scientist effort. This is shown by the steeper slope of the locus for biotechs.

The R&D Manager's Problem

Choosing the pay structure. One internal duty of the R&D manager is to utilize his/her information gleaned about scientists from monitoring the research process to set compensation policy. This involves setting the parameters b_1 and b_2 of the pay function. Thus, given scientist behavior, the manager's residual income share, and signal accuracy, the R&D manager's problem is to set the pay structure to maximize his/her expected income. Let the expected value of output, q, be a function of the useful research output, R, and manufacturing input, M, so that $q = q(R, M)$.[7] Assume that the manager is risk neutral and receives the share α of net income $q(R, M) - E(W)$. Also, let the expected value of output be $E[q(R, M)] = a_1 e + a_2 M$ so the manager chooses the compensation method (b_1 and b_2) to maximize his/her share of net income given by[8] $B = \alpha(a_1 e + a_2 M - E(W))$. The optimizing solutions for b_1 and b_2 are $b_1 = a_1\sigma_2^2/(\sigma_1^2 + \sigma_2^2 + K\rho\sigma_1^2\sigma_2^2)$ and $b_2 = a_1\sigma_1^2/(\sigma_1^2 + \sigma_2^2 + K\rho\sigma_1^2\sigma_2^2)$.

The value of both b_1 and b_2 are greater the higher is a_1.[9] The parameter a_1 denotes the marginal value of research in producing the final output. This parameter is another that distinguishes innovative, R&D firms from conventional ones. Naturally, a_1 is higher for the R&D firms, reflecting the greater importance of research in this type of firm.

Choosing monitoring intensity. The other internal duty of the R&D manager that we focus on is the choice of his/her effort in monitoring the research process and the scientists. The intensity of monitoring depends on the manager's incentives. Thus, the manager's incentives for effort determine effort and the incentives established for scientists.

The manager engages in monitoring effort, m, and increases in m make the signal, S, more accurate. Let $\sigma_2^2 = t(m)$, with $t' < 0$. Assume this function is linear so that $t = C_0 - C_1 m$. Manager utility is $U = \alpha(a_1 e + a_2 M - E(W)) - H(m)$, where $H(m)$ is the cost of monitoring effort. The manager chooses m to maximize utility which yields the first-order condition: $1/2\alpha\rho b_2^2 C_1 — H'(m) = 0$. The first term is the marginal benefit; better monitoring reduces the cost of hiring workers and the

manager gets the share α. The second term is the marginal cost of monitoring. The effect of the R&D manager's share of residual income (α) on monitoring effort is

$$\frac{\partial m}{\partial \alpha} = \frac{-0.5\rho b_2^2 C_1}{D} > 0,$$

where $D<0$ is the second-order condition. As the R&D manager's share of net income increases, s/he reaps more of the benefits of monitoring and so monitoring effort increases.

Above we argued that R&D intense firms are characterized by a greater marginal value of research in producing the final product and a greater marginal effect of monitoring in improving the accuracy of the signal of effort, i.e., larger values for a_1 and C_1. Both a_1 and C_1 increase the magnitude of $\partial m/\partial \alpha$: C_1 does so directly and a_1 does because it makes b_2 larger.[10]

Determining Residual Income Claimancy

Given all of the above, residual income claimancy is determined. The R&D and manufacturing managers contract over α to maximize expected joint returns given by $V = a_1 e^* + a_2 M^* - H(m^*) - G(M^*)$, recognizing that α raises the R&D division's incentives but lowers the manufacturing divisions. The first-order condition, with some simplification is

$$(1-\alpha)\frac{\partial N^*}{\partial m}\frac{\partial m}{\partial \alpha} + \alpha a_2 \frac{\partial M}{\partial \alpha} = 0.$$

The first term is the marginal benefit of α due to α increasing monitoring by the R&D unit and raising V. The cost is the second term: a higher α reduces the manufacturing unit's incentives.

The marginal benefit of α rises with $\partial m/\partial \alpha$, i.e., the amount of monitoring induced by a larger α. The term $\partial m/\partial \alpha$ is greater if a_1 or C_1 are larger.[11] Larger values of these parameters are characteristic of R&D intense firms, thus our model implies that for firms that emphasize R&D, the manager holds more residual income claimancy and so the R&D unit is more like an independent firm.

Other Implications

Employment[12]. We incorporate employment of the R&D unit into the model as follows. Modify expected output level, q, so that $q = a_1 eL + a_2 M$, where L is number of scientist–employees of the R&D unit. This modification does not change the scientist's choice of effort nor the choice of the pay structure (b_1 and b_2).

The R&D manager chooses both monitoring effort and employment, m and L. Monitoring effort is now spread over L workers so is less effective. To capture this, assume that $\sigma_2^2 = t(m, L)$, with $t_m < 0$, $t_L > 0$, and $t_{mL} > 0$. Greater employment worsens the accuracy of the signal of effort for a given m and it reduces the marginal effectiveness of m in improving the signal. It is straightforward to show that m increases with α as in the simpler model. The effect of α on employment is somewhat more complicated, though under plausible conditions L falls with α. This is because the greater monitoring associated with a higher α raises the marginal cost of employment.[13] Since α is higher for research firms, they are likely to have less employment.

The character of managers. Recall that $\sigma_2^2 = t = C_0 - C_1 m$. Let C_0 be an inverse measure of the manager's monitoring talent and assume managers differ in C_0. A higher C_0 implies greater monitoring noise and less talent in monitoring. Consider how V is affected by C_0:

$$\frac{\partial V}{\partial C_0} = \frac{\partial N}{\partial C_0} - H_m \frac{\partial m}{\partial C_0} = \frac{-a_1^2 K \rho \sigma_1^4}{(\sigma_1^2 + \sigma_2^2 + K\sigma_1^2\sigma_2^2)^2 K^2} < 0.$$

The negative value of $\partial V/\partial C_0$ implies that a greater joint return is achieved with a lower C_0, i.e., a better manager raises value. The magnitude of this effect is larger the larger is a_1; the value of the R&D firm is increased the most by a better manager. Therefore, these firms will outbid traditional firms for better monitors.[14] It is plausible that scientist-managers have lower $C_0 s$ because they are more knowledgeable about the research than non-scientist–managers. Therefore, we expect that scientists are over-represented among management in firms that emphasize R&D research.

Dynamics. Firms may evolve over time in their research and non-research emphasis. Also, the technology used by firms may mature and become more routine. While our model is static, it can predict firm and industry dynamics based on these considerations. We predict that, as a firm's R&D technology changes and matures and/or it takes on different tasks, its organizational structure will evolve. For example, if a firm moves toward more routine activities or it acquires more non-R&D

activities, one expects a_1 and C_1 to fall. These imply a lower α, more employment, and fewer scientist–managers. If a firm's technology matures to become more routine, we expect similar changes. This type of evolution of firm ownership and firm size linked to technological maturity is consistent with our model.

EMPIRICAL EXAMINATION OF BIOTECHNOLOGY

Background, Data, and an Overview of Biotechnology Research

We apply our analysis to firms in the biotechnology/pharmaceutical industry. Not all firms in this industry are involved in state-of-the-art biotechnology research. Some have agreements to manufacture products developed by biotechnology research. Others have licensing agreements to market and distribute biotechnology products. Firms in this industry may be specialized in biotech research, do exclusively manufacturing or marketing of biotech products, or some combination of the three.

Also, some firms in the industry may do more traditional pharmaceutical research. Conventional pharmaceutical innovation is largely an experimental process (Schwartzman, 1976). It involves systematic and extensive chemical modification of basic compounds to create new molecules that are subsequently screened in clinical trials. The process is referred to as chemical screening (Gambardella, 1995). Extensive chemical screening to develop new drugs via manipulation of basic compounds was at one time the predominant mode of innovation in this sector. This type of research usually was conducted within the laboratories of large research-based corporations.

The recent development of genetic engineering techniques and rapid advancements in molecular biology changed many of the methods of innovation and pharmaceutical research and spawned the biotechnology industry. The commercial potential of biotechnology has been vastly expanded by a set of techniques that allows researchers to manipulate the genetic structures of microorganisms and other biological production processes. Instead of the old chemical screening methods, much of the industry now employs such approaches as r-DNA and monoclonal antibodies techniques and a host of newer technologies to discover new drugs by carefully designing the chemical structure of the drug to achieve the desired effect (Dawson *et al.*, 1996).

The nature of the technology and the process of innovation are quite different for new, biotechnology research than traditional pharmaceutical research. The latter relies on more routine, incremental methods while the former emphasizes the creative application of new ideas and technologies to 'design' discoveries. We argue that the biotechnology research firm, and not the traditional pharmaceutical firm, is like the R&D intense firm in our model. In our empirical work, we contrast the former type of firm to other firms.

The primary data sources for the empirical work are the 1992, 1995, and 1998 BioScan. BioScan is a commercial data source covering biotechnology firms as well as pharmaceutical, chemical, and other major companies that have in-house biotechnology research groups or agreements with biotechnology companies. There is a wide range of firms in the data, from small firms with as few as five employees to large firms such as NEC with more than 100 000 employees. Thus, the data provide current, factual information for firms involved in biotechnology.

For inclusion in BioScan, there must be some connection to the biotechnology industry, though it may be through an agreement or contract with a biotech. Thus, firms engaged in research, manufacturing, or marketing of pharmaceuticals that have nothing to do with biotechnology are excluded. It is not entirely clear how this may bias our empirical findings. The specialized sample may reduce variation in firm characteristics and cause our estimated effects to be more muted than they truly are. However, the relatively narrow sample may mean that we miss effects occurring among a larger set of firms, causing bias in our estimates.

The information in BioScan is gathered from a variety of sources, including direct communications with the companies, newspapers, magazines, and journals, annual reports, Securities and Exchange Commission (SEC) filings, and investment reports. The data includes information regarding the firms' managerial team, employment, business strategies, research or production progress, and facilities. Where possible, we supplement these data with more detailed information on the ownership of firms from Compact D/SEC.

Information provided in Compact D/SEC is from SEC filings.

A key to our empirical analysis is determining the nature of the firm's research activities. Using the information from BioScan on the firm's activities, three main categories of firms are created—'new' R&D, manufacturing, and marketing.[15] R&D is considered 'new' if it involves advanced medicinal applications, such as MAbs, r-DNA techniques, protein syntheses, vaccine development, anti-viral and cancer treatment, or gene therapy. Our model predicts that this type of firm has more management ownership, less employment, and more scientist–managers. Other R&D activities are considered traditional R&D and are excluded from the R&D category. Based on this classification of R&D and other activities, seven mutually exclusive dummy variables are generated. They are:

R&D only—the firm only having 'new' R&D activity.
Manufacturing only—the firm only involved in manufacturing of pharmaceutical products.
Marketing only—the firm with only marketing activities, e.g., licensing and distribution agreements.
RD&Mfg—the firm with both R&D and manufacturing activities, but no marketing.
RD&Mkt—the firm with both R&D and marketing, but no manufacturing.
Mfg&Mkt—the firm with both manufacturing and marketing, but no R&D.
Conglomerate—the firm with all three activities.

BioScan has information on the ownership of the residual income of the firms. We use the following variables:[16]

Private—a dummy variable equal to 1 if the firm is privately held, zero otherwise,
Diffused owner—a dummy variable equal to 1 if it is a publicly traded firm with no owner having more than a 10% share of ownership, zero otherwise.

Unfortunately, these are not direct measures of management ownership. It is desirable to have precise measures of ownership. However, privately held firms usually have ownership concentrated in managers and the opposite for diffusely owned firms and these variables are available for a wider sample of firms.

We obtain more accurate measures of ownership by management from Compact D/SEC. We use:

Insiders' share—the percent of stock held by firm insiders.
Individual owners' share—the percent of stock held by non-institutional owners with a greater than 5% stake plus the percent held by insiders.

However, observations are lost with these data because Compact D/SEC includes only publicly traded firms and so has fewer firms than BioScan. Several other variables from BioScan are collected. They are as follows. Employment is the total number of employees of the firm. Scientists is the total count of PhDs, MDs, and PharmDs of the firm per 100 employees. The key scientists variable is number of scientists that appear in the key personnel field in BioScan per 100 employees. Key personnel are the company's chief officers (e.g., CEO, CFO, and COO), vice presidents, founders, and managers of divisions. Year founded is the year the firm began operation. Venture capitalist (VC) involvement is a binary variable indicating whether a venture capital firm is involved with the company. There are fewer observations for these variables because of non-reporting.

Data Overview

Table 1 presents the means of the variables discussed above for each sample year. The first three columns are for all firms in the data. Every firm is not observed in each sample year. The last three columns show means for the subset of firms that are in the data continuously. The continuously sampled firms, based on their 1992 characteristics, are somewhat less research focused, are more likely to have manufacturing operations or be in the conglomerate category, are more apt to have diffused ownership, and were founded earlier. These suggest, unsurprisingly, that firms not lost from the sample due to attrition are somewhat better established. Despite the attrition, the cross-sectional means for each year show similar patterns for the entire sample as for the subsample of firms observed in all years. Also, the longitudinal pattern of firm transitions over time is seen more clearly in the continuously observed firms because it is not confounded by movements of firms into and out of the data.

Table 1. Means, All Firms and Firms in All Sample Years

	All observations			'92, '95, and '98 Firms		
	1992	1995	1998	1992	1995	1998
Categories of firm[a]						
R&D only	0.258	0.032	0.091	0.212	0.022	0.015
Manufacturing only	0.027	0.004	0.015	0.022	0.007	0.000
Marketing only	0.015	0.057	0.061	0.022	0.044	0.029
RD & Mfg	0.130	0.231	0.136	0.153	0.270	0.153
RD & Mkt	0.158	0.300	0.284	0.109	0.307	0.270
Mfg & Mkt	0.136	0.024	0.011	0.161	0.015	0.007
Conglomerate	0.276	0.352	0.402	0.321	0.336	0.526
Ownership and other firm variables[a]						
Private[b]	0.394	0.352	0.492	0.394	0.263	0.212
Diffused owner[b]	0.318	0.462	0.375	0.379	0.562	0.562
VC involvement	0.382	0.315	0.201	0.377	0.321	0.197
Year founded	1977.0	1976.0	1978.4	1976.1	1976.1	1976.1
Sample size	330	247	264	137	137	137
Other variables with fewer observations						
Ownership concentration[a]						
Insiders' share	18.48	15.80	9.98	23.59	15.34	11.74
Indiv. owners' share	44.63	31.46	39.19	42.20	31.43	37.30
Sample size	147	76	90	78	58	73
Labor force[a]						
Employment	4781.9	4382.2	3330.4	4500.5	5183.8	5210.1
Scientists/100 Emp.	41.36	23.58	25.61	48.38	24.17	20.83
Key scientists/100 Emp.	7.69	3.72	4.86	6.02	3.33	3.04
Sample size	308	239	257	131	134	133

Source: 1992, 1995, and 1998 BioScan and Compact D/SEC.
[a] Precise definitions are in the text.
[b] The private and diffused owner percentages do not sum to one. The two missing categories are: an owner having more than 10% ownership and a wholly owned subsidiary.

Consider the means for 1992 for the continuously sampled firms. Over one-fifth of firms are specialized in only R&D activities. This is our indicator of firms with newer types of research activities and are expected to have more management ownership, less employment, and more scientist-managers than firms with less focus on R&D. A large fraction of the firms are privately held; over 39%. Also, in the Compact D/SEC subsample, there is a large amount of management ownership. Insiders own over 23% and large, individual owners control over 42%.[17] There also is considerable venture capitalist backing; about 38% of firms in 1992 had involvement by a venture capital firm.

Changes in the means for the continuously sampled firms gives a rough look at the longitudinal experiences of firms. There is a substantial reduction in the number of firms that are R&D only; from 21.2% in 1992, to 2.2% in 1995, then to 1.5% in 1998. This does not imply, though, that these firms are dropping all R&D activity. Substantial increases by 1995 of firms that are R&D and manufacturing and R&D and marketing indicate that many integrated into manufacturing or marketing. The decline in these categories for 1998 and an increase in the conglomerate category imply that many firms integrated further.

Along with this pattern of change comes a reduction in the number of firms privately held, a rise in the number of diffusely held firms, reduced insider and individual ownership, and reduced venture capitalist involvement. For example, the fraction of firms privately held falls from 39.4% in 1992 to 26.3% in 1995 and to 21.2% in 1998. Also,

Table 2. Summary Information on Firm Transitions, 1992, 1995, and 1998 BioScan

Panel A: Transition type definitions.

Transition type 1: an R&D firm becoming more integrated.
Transition type 2: an integrated R&D firm de-integrating to become more R&D focused (reverse of type 1).
Transition type 3: a non-R&D firm integrating into R&D.
Transition type 4: an integrated R&D firm de-integrating by dropping R&D (reverse of type 3).
Transition type 5: an R&D only firm becoming a non-R&D firm.
Transition type 6: a non-R&D firm becoming an R&D only firm (reverse of type 5).
Transition type 7: non-transition and other changes not involving R&D.

Panel B: Illustration of transitions; entries are transition type

Starting category	Ending category						
	R&D Only	Mfg. Only	Mkt. Only	RD & Mfg.	RD & Mkt.	Mfg. & Mkt.	Conglom.
R&D Only	7	5	5	1	1	5	1
Mfg. Only	6	7	7	3	3	7	3
Mkt. Only	6	7	7	3	3	7	3
RD & Mfg.	2	4	4	7	7	4	1
RD & Mkt.	2	4	4	7	7	4	1
Mfg. & Mkt.	6	7	7	3	3	7	3
Conglom.	2	4	4	2	2	4	7

Panel C: Number and Type of Transitions

	1992–1995	1995–1998
Transition type 1	52	37
Transition type 2	27	13
Transition type 3	27	4
Transition type 4	8	3
Transition type 5	3	0
Transition type 6	0	1
Transition type 7	66	136
Total	183	194

firm employment increases while the fraction of scientists and key scientists approximately halves. These trends are consistent, in the context of our model, with the movement of firms away from exclusive focus on R&D and illustrate the model's usefulness in understanding firm and industry evolution.

Table 2 provides more information regarding the longitudinal experiences of firms. Table 1 shows a large movement of firms out of specializing in R&D to R&D and manufacturing or marketing by 1995, then to all three by 1998. Table 2 examines two sets of 3-year firm transitions; 1992–1995 and 1995–1998.[18] We classify each firm by its change in category and then later examine how its organizational structure changed in response. There are seven categories of firm types, implying 43 transition types; 42 possible changes in firm category and non-transition. Many of these transition cells are empty, so all transitions are aggregated into seven types. They are summarized below and shown in detail in Table 2:

Transition type 1: an R&D firm becoming more integrated.
Transition type 2: an integrated R&D firm de-integrating to become more R&D focused (reverse of transition type 1).
Transition type 3: a non-R&D firm integrating into R&D.
Transition type 4: an integrated R&D firm de-integrating by dropping R&D (reverse of transition type 3).
Transition type 5: an R&D only firm becoming a non-R&D firm.
Transition type 6: a non-R&D firm becoming an R&D only firm (reverse of transition type 5.
Transition type 7: non-transition and other changes not involving R&D.

Panel B of Table 2 illustrates the transition-type definitions. For example, transition type 1 corresponds to an R&D-only firm integrating into manufacturing, marketing, or both and an R&D and manufacturing firm or an R&D and marketing firm integrating to a conglomerate. These are indicated by the numeral 1 in the table. Transition type 2 is the reverse of transition type 1, indicated by the numeral 2. Remaining types are shown similarly and are defined verbally above (and in panel A).

Panel C of Table 2 shows the number and type of transitions for each 3-year period. Even with the aggregated transition categories, there are some small cell sizes. The most common transition is type 1; an R&D firm becoming more integrated either to manufacturing or marketing or to both. This is consistent with the means in Table 1. Although this is the predominant change, there are a substantial number of the opposite transitions (type 2) where an integrated R&D firm de-integrates to become more R&D focused. A non-R&D firm integrating into R&D (type 3) between 1992 and 1995 also is a frequent transition. There are many type 7 observations in both periods, though more in the later period. Type 7 is non-transition, so this is not surprising. By 1995, many firms may have reached a stable state and are less likely to make another transition.

Evidence on Ownership: Cross-Sectional and Longitudinal

This subsection presents more detailed evidence on ownership patterns. Table 3 shows a more detailed look at the ownership structure of the industry. The entries show the percent of privately held and diffused-owner firms for each firm category by year. Recall that privately held is a proxy for management ownership and diffused ownership is an inverse proxy. Column (1) indicates that, in 1992, 71.78% of firms with only R&D activities are privately held and column (2) shows that only 14.12% have diffused ownership.[19] In contrast, the conglomerate firm is least likely to be privately held in 1992; only 14.29% are privately held. The conglomerate has the highest percentage diffusely held; 47.25%. Also, firms without any R&D activity are much less likely to be privately held. For example, in 1992, only 22.22% of manufacturing only firms and 20.0% of manufacturing and marketing firms are privately held. Columns (3)–(6) show the figures for 1995 and 1998. Very similar patterns emerge.

A more rigorous examination of the cross-sectional variation of ownership type is undertaken in Table 4. Column (1) presents logit estimates of the probability of being privately held. Column (2) does likewise for the probability of being diffusely held. The 1992 cross-section is used. The covariates are the seven mutually exclusive firm categories (conglomerate is the omitted category), employment, the year of firm founding, and the venture capitalist involvement dummy. The last three control for the effect that firm size, firm age, and venture capitalists may have on the financial structure of the firm.[20] Firms without employment data are dropped, resulting in very small cell sizes for the manufacturing only (eight firms) and marketing only (four firms) categories. These observations are dropped.

The findings of Table 4 are consistent with Table 3. The R&D-only variable has a positive and significant effect on the probability of being privately held and is the largest in magnitude of all the firm categories. Also, the coefficients on

Table 3. Percent of Ownership Type for Each Firm Category

Firm category	1992 Observations		1995 Observations		1998 Observations	
	(1) Privately held	(2) Diffused owner	(3) Privately held	(4) Diffused owner	(5) Privately held	(6) Diffused owner
R&D only	71.78	14.12	87.50	12.50	87.50	8.33
Manufacturing only	22.22	33.33	0.00	1.00	1.00	6.25
Marketing only	60.00	00.00	71.43	21.43	87.50	50.00
RD & manufacturing	41.86	32.56	19.30	64.91	33.33	50.00
RD & marketing	46.15	25.00	59.46	18.92	72.00	16.00
Manufacturing & Marketing	20.00	44.44	16.67	33.33	33.33	66.67
Conglomerate	14.29	47.25	16.09	64.37	22.64	60.38
Sample size	330	330	247	247	264	264

Source: 1992, 1995, and 1998 BioScan.

Table 4. Logit Estimates of Ownership Type and OLS Estimates of Ownership Concentration, 1992 BioScan and Compact D/SEC[a]

	Logit estimates		OLS/selectivity estimates			
	(1)	(2)	(3)	(4)	(5)	(6)
	Privately held	Diffused owners	Indiv. owners' share	Indiv. owners' share	Insiders' share	Insiders' share
R&D only	1.905	−1.403	19.657	16.152	4.833	3.721
	(4.08)	(3.44)	(2.38)	(1.40)	(0.94)	(0.63)
RD & manufacturing	0.8779	−0.7026	12.839	9.950	0.5107	−1.283
	(1.75)	(1.59)	(1.26)	(0.67)	(0.08)	(0.19)
RD & marketing	0.9681	−0.7080	6.412	2.682	3.603	1.967
	(1.93)	(1.57)	(0.63)	(0.19)	(0.57)	(0.31)
Manufacturing & marketing	−0.0071	−0.2118	13.302	12.814	2.882	2.677
	(0.01)	(0.50)	(1.59)	(0.95)	(0.56)	(0.44)
Employment[b]	−0.0040	0.00005	−0.0005	−0.0003	−0.00027	−0.00011
	(2.62)	(2.96)	(3.94)	(0.43)	(3.24)	(0.34)
Year founded	0.0359	−0.0043	−0.1440	−0.2487	−0.1077	−0.1551
	(1.47)	(0.48)	(0.87)	(0.70)	(1.04)	(0.97)
VC Involvement	0.6214	−0.1042	−2.000	−2.247	−3.727	−3.738
	(1.92)	(0.36)	(0.33)	(0.25)	(1.00)	(0.92)
Inverse Mills' Ratio	—	—	—	78.839	—	35.376
				(1.28)		(1.28)
Sample size	272	272	133	133	133	133
Log Likelihood	−123.90	−149.26	—	—	—	—
R^2	—	—	0.179	—	0.1071	—

Source: 1992 BioScan and Compact D/SEC.
[a] Absolute valued of *t*-statistics are in the parentheses.
[b] Employment is measured in the thousands.

RD & Manufacturing and RD & Marketing are positive and large in magnitude, with the latter being statistically significant. These findings indicate that the greater the focus of the firm on R&D, the more likely it is privately held. This holds with employment, year founded, and venture capital backing held constant. Thus, our results do not arise simply because R&D firms are smaller, younger, or more venture capital backed than average. Not surprisingly, employment has a negative effect, year founded has a positive effect, and venture capitalist involvement has a positive effect.

These results are reinforced by those of column (2). The R&D only firms are least likely to have diffused ownership, followed by the RD & marketing and the RD & manufacturing, though the latter two effects are marginally significant.[21] Since privately held firms are more heavily management owned than those diffusely owned, the findings support our model.

Columns (3)–(6) of Table 4 examine the more precise measures of ownership concentration from the Compact D/SEC data. These measures are treated as dependent variables in regressions with the same covariates as previously. Unfortunately, there is tradeoff regarding use of these data; the sample size is considerably smaller because the data are available only for public firms on Compact D/SEC. In comparing the means of this subsample to the entire sample for 1992, we find that there is a smaller proportion of R&D-intense firms, more conglomerates, more with diffused ownership, greater average employment, and a higher mean age. The subsample is of somewhat larger, less purely research firms.

Table 4 presents both OLS estimates and estimates corrected for the selectivity bias generated by the missing data. Columns (3) and (5) are the OLS estimates for ownership by large, individual owners and for insider ownership, respectively. Columns (4) and (6) include the inverse Mills' ratio to correct for selectivity bias. The OLS estimates of column (3) show that all firm categories have greater ownership by large, individual owners than conglomerates and the same holds with inside ownership in column (5), though statistical significance is weak for most of the latter effects. The first row of columns (3) and (5) indicate that, all else constant, large, individual owners have a 19.66% larger stake in R&D-only

firms than in conglomerates and insiders have a 4.83% larger stake. These are the largest shares of all the firm categories. Again, these hold with employment, year founded, and venture capitalist involvement held constant.[22]

Regarding the selectivity corrected estimates in columns (4) and (6), the results are similar in the sense that all firm categories have greater ownership by large, individual owners and insiders than conglomerates. However, the selectivity terms reduce the magnitude and significance of the effects, most likely because of collinearity with variables already in the equations.[23] Taken together, the findings are consistent with our approach but because of weak statistical significant in several cases, we can claim only cautious support.

The fact that the means in Table 3 and the multivariate analysis in Table 4 generally provide the same message lends support to our model. Firms with a greater R&D focus are more likely to be privately held and have a higher concentration of ownership among insiders and large, individual owners. This coincides with the idea that the research firm needs more ownership concentration among managers to motivate monitoring effort. Broadly speaking, this evidence squares with other empirical research on the assignment of residual income claimancy in that it illustrates the importance of agency issues. Demsetz and Lehn (1985) and Himmelberg *et al*. (1999) show that the ownership concentration of large corporations is influenced by the opportunity for moral hazard and Lafontaine (1992) and others find that incentive issues affect the assignment of residual income claimancy in franchising.

Now consider the longitudinal evidence regarding firm ownership. A longitudinal analysis essentially examines changes over time for each firm. As a firm's R&D technology changes and matures and/or it takes on different tasks, our model predicts that its organizational structure evolves. The firms in our sample do undergo substantial change during the 1992–1998 period. Tables 1 and 2 show that there is a large movement of firms out of specializing in R&D to R&D and manufacturing or marketing or to all three. We predict that these changes are accompanied by less residual income claimancy by management, larger firms, and fewer scientists in key positions. This subsection examines changes in residual income claimancy, as proxied by changes in the privately held and diffusely held dummies and by individual and insider ownership.

Consider the seven transitions types outlined above an in Table 2. Our main focus is on the type 1 and type 2 transitions compared to the non-transitions. The main reason for this is that predictions are clearest for type 1 and type 2 transitions. The former represents an R&D-only firm becoming less focused on new R&D and the latter is the reverse. Our model predicts that the type 1 transition is accompanied by less managerial ownership and the opposite for type 2 transitions.[24] Also, sample sizes are large enough for these transitions to give some confidence in the results.[25]

Table 5 presents the means in changes for firms making selected transitions from 1992 to 1995. When compared to non-transition firms (type 7) or all firms, the type 1 transition firms are much more likely to cease being privately held, more likely to become diffusely held, have a larger reduction in ownership by large, individual shareholders or insiders, and are more likely to have venture capitalist involvement before the transition in

Table 5. Mean Changes in Ownership Characteristics, by Selected Transition Types, 1992–1995

	Type 1: R&D only becoming integrated	Type 2: More R&D focus	Type 7: Non-transition	All
Cease privately held	0.404	0.148	0.136	0.208
Become privately held	0.019	0.111	0.061	0.055
Cease diffusely held	0.019	0.148	0.061	0.060
Become diffusely held	0.442	0.148	0.152	0.251
Chg. in indiv. owners' share[a]	−28.6	8.8	−16.8	−19.8
Chg. in insiders' share[a]	−13.2	−12.5	−4.8	−9.0
1992 VC involvement	0.420	0.385	0.365	0.383
Sample size	52	27	66	183

Source: 1992 and 1995 BisoScan and Compact D/SEC.
[a] Sample size is smaller for observations involving shareholdings.

1992. The reverse tends to be true of the type 2 transition firms. For example, 40.4% of type 1 transitions are accompanied by the firm ceasing privately held, compared to 14.8% for type 2 transitions and 20.8% for all firms. Similarly, 44.2% of type 1 transitions occur with the firm becoming diffusely held, compared to 25.1% for the whole sample and 14.8% for type 2 transitions. Related findings occur with the 1995–1998 transitions.

Table 6 reports a multivariate analysis of changes in whether the firm is privately held and whether it is diffusely held. Panel A is for 1992–1995 and panel B for 1995–1998. In each panel, the first two columns show multinomial logit estimates of the probability of three outcomes: ceasing privately held, becoming privately held, and no change in whether privately held. The latter is the base category.[26] Columns (3) and (4) show a similar multinomial logit for ceasing diffusely held, becoming diffusely held, and no change in whether diffusely held. The covariates in each logit are the transition categories, with non-transition being the omitted category, the percentage change in firm employment, year founded, and initial venture capitalist involvement. Owing to the interest in the type 1 and type 2 transitions only those coefficients are reported.[27]

For both 1992–1995 and 1995–1998, the type 1 transition is associated with a larger and statistically significant probability of ceasing privately held and becoming diffusely held relative to non-transition firms. This occurs with employment changes, year founded, and initial venture capital backing held constant, so is not driven simply by increasing firm size or firm age or venture capitalist involvement. One expects that the type 2 transition is more likely to be associated with becoming privately held and ceasing diffusely held. However, panel A shows no statistically significant results for this variable. Oddly, panel B indicates that it is positively associated with this but also with the reverse. Large changes in employment increase the probability of ceasing privately held

Table 6. Multinomial Logit Estimation of Probabilities of: Cease Being Privately Held, Becoming Privately Held, Cease Being Diffusely Held, and Becoming Diffusely Held[a,b]

	(1) Cease priv. held	(2) Become priv. held	(3) Cease diffusely held	(4) Become diffusely held
Panel A: 1992–1995				
Type 1: R&D only becoming integrated	1.190	−1.355	−1.074	1.152
	(2.33)	(1.15)	(0.93)	(2.43)
Type 2: more R&D focus	−0.0624	0.4312	0.9168	−0.2622
	(0.08)	(0.49)	(1.18)	(0.36)
Pct. change in employment	0.0067	−0.0307	0.0008	−0.0051
	(0.48)	(0.21)	(0.03)	(0.35)
Year founded	0.0614	0.1960	0.0668	0.0330
	(1.59)	(2.10)	(1.14)	(1.64)
1992 VC involvement	0.9459	−0.7615	0.6241	0.8361
	(2.21)	(0.86)	(0.91)	(2.11)
Log likelihood	−94.003	−94.003	−110.879	−110.879
Sample size	162	162	162	162
Panel B: 1995–1998				
Type 1: R&D only becoming integrated	2.831	0.9346	0.2610	2.353
	(2.46)	(0.69)	(0.29)	(2.39)
Type 2: more R&D focus	2.673	2.676	1.955	3.541
	(1.74)	(1.79)	(2.06)	(3.01)
Pct. change in employment	0.1154	−3.615	0.0073	0.0252
	(1.76)	(2.61)	(0.10)	(0.44)
Year founded	0.0023	−0.0079	0.0176	−0.0217
	(0.10)	(0.30)	(0.59)	(1.88)
1995 VC involvement	0.4538	−6.245	−0.3578	0.0938
	(0.51)	(0.00)	(0.48)	(0.11)
Log likelihood	−34.387	−34.387	−62.462	−62.462
Sample size	175	175	175	175

Source: 1992, 1995, and 1998 BioScan.
[a] Dummy variables for type 3 and type 4 transitions also are included as covariates. The left-out category is non-transition.
[b] Absolute value of *t*-ratios are in parenthesis.

and reduce the likelihood of becoming privately held for 1995–1998, but have little effect elsewhere. Initial venture capitalist involvement increases the likelihood of ceasing to be privately held and of becoming diffusely held for 1992–1995 but there is little effect for 1995–1998.

A multivariate analysis of changes in shareholdings is not done, though the means in Table 5 suggest that they move in the expected direction. The sample size is too small to place much confidence in results with these variables.

Generally, our findings are as expected regarding changes in type of ownership. Firms becoming less R&D focused alter their ownership structure away from management ownership. This, combined with the cross-sectional evidence, is supportive of our model. However, our support is cautious because our proxies for management ownership are somewhat crude and the more precise measures are only for a limited sample.

Evidence on Employment and Changes in Employment

Panel A of Table 7 investigates the cross-sectional relationship between firm size and R&D. Our model predicts a negative association. Data from 1992 is used, though the findings for 1995 and 1998 are similar. Column (1) shows mean employment by firm category. In column (2), the number of employees is used as the dependent variable in an OLS regression. The independent variables are the five firm category dummies used in Table 4, with conglomerate the excluded category, along with

Table 7

Panel A: 1992 Employment by Category

	(1) Employment means	(2) Employment regression[a]
R&D only	102.81	−9280.22
		(3.38)
RD & manufacturing	1799.77	−8042.58
		(2.44)
RD & marketing	125.29	−9065.90
		(2.70)
Manufacturing & marketing	12346.78	1599.13
		(0.49)
Conglomerate	11012.32	—
Year founded	—	−210.07
		(3.50)
VC involvement	—	1211.08
		(0.58)
Sample size	272	272
R^2	—	0.114

Panel B: Percentage Change in Employment

	(1) Means, 1992–1995	(2) Regression, 1992–1995	(3) Regression, 1995–1998
Type 1: R&D only integrating	2.72	1.596	3.183
		(0.80)	(4.59)
Type 2: more R&D focus	0.594	−0.3288	1.784
		(0.12)	(1.41)
Type 7: non-transition	1.32	0.5564	0.4808
		(0.31)	(1.24)
All firms	2.42	—	—
Year founded	—	0.0270	(0.0143)
		(0.54)	(1.14)
Initial VC involvement	—	2.285	–0.8666
		(1.14)	(1.41)
Sample size	162	162	231
R^2	—	0.030	0.129

Source: 1992, 1995 and 1998 BioScan.
[a] Absolute value of *t*-ratios in parenthesis.

year founded and the venture capitalist dummy. Column (1) shows that R&D-only firms are the smallest, with an average of 102.81 employees. The conglomerates and manufacturing & marketing firms are the largest, with average employment 12 346.78 and 11 012.32, respectively. All categories aside from these two are much smaller. The employment regression in column (2) indicates this clearly. This regression includes year founded to control for the possibility that newer firms are smaller. The negative coefficient on this variable shows that this is the case. Venture capitalist involvement also is controlled for. The R&D-only firm is estimated to be the smallest, though the RD & marketing firm is nearly as small. All else constant, both have over 9000 fewer employees than the conglomerate.

Our longitudinal analysis considers the percentage change in employment for firms. One expects that firms that move away from specializing in R&D become larger and experience the most growth in employment. Panel B of Table 7 examines growth in employment by transition type. Column (1) shows mean percentage growth in employment for 1992–1995. Employment growth was remarkably large for firms in this industry during this time; the mean was a 242% increase. Type 1 firms show an even larger growth; 272%. Non-transition firm grew 132%, but type 2 transitions had less growth at 59.4%. While there was tremendous growth for firms during this time period, firms moving to a greater R&D focus grew relatively less while the opposite is true for firms moving away from a strictly R&D focus. The difference in growth rates of type 1 and type 2 firms is statistically significant, but other differences are not.

Columns (2) and (3) of panel B show the results of regressions of the percentage change in employment on the transition types, with year founded and venture capitalist involvement as control variables. Column (2) is for 1992–1995 and column (3) for 1995–1998. In both cases, the type 1 transition shows the greatest employment growth. This is as expected, though the effect in column (2) is not statistically significant. For 1992–1995, the type 2 transition shows the lowest employment growth, but not for 1995–1998. Neither finding is statistically significant, though. Thus, while the basic pattern of findings is consistent with our model, statistical significant is weak in many cases. We can only claim cautious support.

The Character of Managers: Scientists as Key Personnel

Our model also predicts that R&D firms' owner-managers are disproportionately scientists and that as the firm moves away from R&D intensity its ownership/management become less scientist intense. Unfortunately, an exact measure of the proportion of owner-managers who are scientists is not available. We use the number of the firm's key personnel who are scientists reported by the firm as a proxy for scientists who are owner-managers. We refer to this variable as key scientists. Key personnel are the company's chief officers (e.g., CEO, CFO, and COO), vice presidents, founders, and managers of divisions. These individuals are more likely to hold stock in their firms or be compensated based on firm performance. More scientist representation in this group thus represents greater residual income claimancy by scientists. A more precise measure is desirable and our proxy is likely to suffer from considerable measurement error, but is the best available measure we have. The findings should be interpreted with caution in this light.

Table 8 examines the total scientist and key scientist intensities for firms in the 1992 sample, which is similar to the other years. Columns (1) and (2) give the means of total scientists and key scientists per 100 employees. Column (1) shows that, not surprisingly, the R&D-only firms are very scientist intense, with 62 scientists per one hundred employees. Column (2) indicates that the R&D-only firm have the most key scientists per 100 employees at 11.37. Other types of firms with R&D activity also tend to have more scientists in key positions.

We wish to know whether scientists are disproportionately in key positions in R&D firms, though. Random promotion to key positions implies that having more scientists results in more key scientists. A disproportionately high number of scientists in key positions in the R&D firm is more in keeping with the implications of the model. To examine this, the determinants of the number of key scientists are estimated holding total scientists constant. Again, firm categories are the regressors with conglomerate the excluded category. We also hold constant year founded and venture capitalist involvement.

Columns (3) and (4) present the findings. In column (3), the ratio of key scientists to total

Table 8. Means of Total and Key Scientists, by Firm Category, and Determinants of Key Scientists, 1992 BioScan

	(1) Total scientists	(2) Key scientists	(3) Key sci./total sci.[a]	(4) Key scientists[a]
R&D only	62.00	11.37	0.1562	6.625
			(2.61)	(4.15)
RD & manufacturing	39.35	7.86	0.1099	3.838
			(1.43)	(1.89)
RD & marketing	26.48	7.95	0.1024	4.553
			(1.32)	(2.24)
Manufacturing & marketing	26.62	3.64	0.0942	0.5669
			(1.19)	(0.27)
Conglomerate	34.19	3.38	—	—
Scientists per 100 Employees	—	—	—	0.0272
				(3.52)
Year founded	—	—	0.0021	0.0496
			(1.53)	(1.32)
VC Involvement	—	—	−0.0013	2.056
			(0.03)	(1.65)
Sample size	213	213	213	213
R^2	—	—	0.056	0.193

Source: 1992 BioScan.
[a] Absolute value of *t*-ratios in parenthesis.

Table 9. Mean Changes in Total Scientists and Key Scientists, By Selected Transition Type, 1992–1995

	(1) Chg. in total scientists	(2) Chg. in key scientists
Type 1: R&D only becoming integrated	−28.52	−3.46
Type 2: more R&D focus	−9.06	−1.02
Type 7: non-transition	−10.23	−3.46
All	−20.19	3.36
Sample size	169	143

Source: 1992 and 1995 BioScan.

scientists is used as the dependent variable. It shows that the R&D firm has the highest intensity of scientists in key positions. Key scientists relative to total scientists is over 15 percentage points higher in this firm category than the conglomerate category. This result is statistically significant and is with year founded and venture capitalist involvement held constant. The magnitude is about the same as that from comparing the mean for R&D-only firms to conglomerates. In the R&D-only firm, 38.5% of the scientists in are in key positions compared to about 20% for the conglomerates. Other firm categories involving R&D also have more key scientists relative to total scientists, but statistical significance is not as strong.

Column (4) presents the results with number of key scientists as the dependent variable with total scientists as a regressor. It shows similar results. The R&D-only firm has the largest coefficient, followed by the RD & marketing and the RD & manufacturing firms and all are significant. Holding total scientists constant, the R&D only firm has over six more scientists in key positions.

Somewhat similar findings hold for changes in the number of scientists and key scientists. Referring to Table 9, for the entire sample, there is a drop in the number of scientists and key scientists per 100 employees. This decline is largest for the type 1 transitions and smallest for type 2. However, statistical significance for differences across types is low. Those changing to less R&D focus seem to become relatively less scientist and key scientist intense but this result is not robust.[28]

CONCLUSION

This study focuses on determination of the incentives of a manager to monitor the R&D process. Our maintained hypothesis is that monitoring is quite different in technologically advanced R&D environments than in other settings in that it is more difficult but more important. In our model of managerial incentives, this implies important differences in the organization of firms that specialize in R&D. First, residual income claimancy tends to be concentrated in the hands of managers for R&D intensive firms. Second, to facilitate monitoring accuracy, firm size tends to be small. Third, owner-managers are disproportionately likely to be scientists in the R&D-oriented firms since they improve monitoring accuracy.

Data from the mid-1990s on the biotechnology industry are generally consistent with the model. At any point in time, firms with greater focus on the newer, biotech R&D are more likely to be privately held and have more ownership by insiders. This holds even for a given level of employment. The number of employees is, on average, lower for R&D-only firms. Additionally, they have more scientists in key, managerial positions per scientist-employee.

During the 1992–1998 period, firms in the sample change substantially. On average, they become less focused on R&D and initially integrate into manufacturing or marketing, then to both. As predicted by our model, these changes were accompanied by less managerial ownership. Firms also grew during this time, but the multivariate analysis shows that the reduction in managerial ownership is at least partly attributable to the decline in R&D focus, not just to the increase in firm size. Along with the reduction in management ownership and growth in employment came a reduction in scientists in managerial positions.

Although our cross-sectional and longitudinal findings are broadly consistent with each other and the model, some caveats are in order. The first is that proxy variables are used in several instances which do not exactly coincide with concepts in the model. Second, there are small sample sizes for some of the firm transition cells in the longitudinal analysis. Third, statistical significance is low for some of the findings.

While the empirical work pertains to a single industry, the ideas apply more generally. Our findings suggest a possible natural evolution of the innovative firm and industry. For a new technology, small, owner-managed firm are expected to dominate. As the technology matures and becomes more routine, there is less need for the high level of residual income claimancy of the R&D manager. R&D moves in-house into large, diffusely held companies. Thus, we predict a process of firm and industry evolution that coincides with the maturation of the technology.

Consider another possible implication. Casual observation indicates that many new products come from small, owner-managed firms while many others come from large, diffusely owned companies. This paper suggests which types of new products are generated by which types of firms. We predict that products requiring newer technologies with less routine procedures and/or more intangible, difficult-to-monitor worker input are more likely to appear from small, owner-managed and expert-managed firms.

Finally, note that risk plays a minor role in our analysis. R&D probably is more risky than average and so risk considerations alone imply that these activities take place in diffusely held companies that are owned primarily by diversified stockholders. Incentive considerations imply the opposite and apparently dominate in the biotechnology industry, as in the analogous case of incentives versus risk sharing in franchising (Rubin, 1978).

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NOTES

1. For further discussion of the linkages of biotech firms to other firms, see Arora and Gambardella (1990), Pisano (1991) and Powell *et al.* (1996). For economic analysis of contractual ties among these firms, see Chang (1998), Mayer and Nickerson (1998), and Lerner and Merges (1998). Also, for a treatment of vertical integration and control rights to an innovation, see Aghion and Tirole (1994).
2. See Rubin (1978) for the original application to franchising.
3. Much of this and other modeling sections are drawn from Chang (1998).

4. The manufacturing manager's job may have analogous duties but is not modeled.
5. The R&D unit with 100% residual income claimancy is an independent firm that receives 100% of royalties from the innovation. This is not forward vertical integration by the R&D division because the manufacturer may produce or purchase many other components not involving the R&D unit.
6. Linear-incentive models are common in the literature and originally justified by Holmstrom and Milgrom (1987). Any non-linear incentive system gives odd incentives to alter effort in non-optimal ways. For example, a bonus that is paid if a quota is attained gives no incentive if the quota is unreachable, a strong incentive just below the quota, and no incentive once the quota is reached. For this reason, and its analytical tractability, linear-incentive models are used in the literature and here.
7. Let M be determined by the actions of the manager of manufacturing.
8. This assumes that monitoring and compensation practices of both managers are non-contractible between managers. A Nash game also is assumed, where managers act taking the other's behavior as given.
9. Each b_i also is declining in its own variance, σ_i^2, and increasing in the other variance, σ_j^2.
10. The parameters a_1 and C_1 also increase the level of m.
11. The marginal benefit of α also is higher the greater is $\partial N^*/\partial m$, which also increases with a_1 and C_1.
12. In a different approach, Holmstrom (1989) models employment in an R&D firm based on the assignment of tasks to employees.
13. To obtain $\partial L/\partial \alpha < 0$, this effect must outweigh the effect of a higher m has on lowering $E(W)$ and raising L.
14. This can occur via a lumpsum transfer between the two parties.
15. Not all firms in BioScan are used because very limited information is provided for some firms. Specifically, if more than two major fields in the main entry section (the major fields include the agreements, employees, business strategies, research and development, and facilities) are missing from BioScan, the companies are excluded. Pure agricultural-oriented firms also are excluded from the data set, as are foreign (non-US) firms, unless they are listed with Securities and Exchange Commission.
16. Two additional categories of ownership are a publicly traded firm with a single owner having a 10% or greater share and a wholly owned subsidiary. We use the categories in the text as the clearest indicators of ownership concentration. They are used are dependent variables so leaving out the other two variables does not affect the analysis.
17. The sample that has data for these latter two variables is smaller. This is discussed in more detail below.
18. This gives us a larger sample size than the group of firms sampled all 3 years.
19. These ownership concentration categories are not exhaustive, so the percentages do not add to 100.
20. Pagano *et al.* (1998) find that firm size affects the decision to go public. Lerner (1995) shows that experienced venture capital backing and a higher IPO stock index makes firms more likely to go public. We are able to control for firm size and venture capital backing and the stock index is constant across firms in the sample.
21. We find similar results with the 1995 and 1998 cross-sections and so report only the 1992 results.
22. Similar finding emerge from the 1995 and 1998 cross-sections so are not reported.
23. Identification of the coefficient on the inverse Mills' ratio is an issue in selectivity models. Here, the probit underlying the selectivity term is a function of firm age and firm employment.
24. Type 3 transitions have unclear predictions as there is less focus on a firm's initial tasks but more on R&D. Similar arguments apply to type 4 transitions.
25. Above it was noted that firms that survived for all three time periods are somewhat different than those lost due to attrition. Similar comments apply to the two-period survivors, though not quite to the same degree. If survivors differ on an unobservable trait, cross-sectional analysis with survivors may be biased. However, if the unobservable trait is fixed for each firm, it differences out when examining changes and should not bias the longitudinal findings.
26. Multinominal logit is used as there are three possible outcomes for the change in privately held status.
27. Also, type 5 and type 6 transition categories are dropped because they have so few observations.
28. Multivariate analysis shows a similar conclusion so is not reported.

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