Valuing Biopharmaceutical Alliances; Decisions for New Product Development in the Pharmaceutical Industry; The Effects of Corporate Downsizing on Women

by

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Abstract

This thesis presents two empirical essays, which examine the organization of research and development in the pharmaceutical industry and a third essay that examines the effects of corporate downsizing on the growing number of women in the labor force.

Chapter 2 begins by evaluating strategic alliances undertaken in the pharmaceutical industry. The analysis estimates equity market reaction to the announcements of these partnerships and determines how partner and transaction characteristics affect this reaction. The results indicate that these partnerships have created significant shareholder value. Additionally, there is significant heterogeneity across alliances. Equity participation is correlated with a higher level of value creation. Alliances undertaken for the purposes of developing or marketing products that target complex diseases create less shareholder value. Finally, R&D firms that have been previously performing well do not gain as much as their more poorly performing counterparts.

Chapter 3 examines the organization of new product development. Using a unique dataset of approved drug products, the empirical analyses include firm characteristics and new drug characteristics in limited dependent variable estimation of the firm decision over how to organize its R&D. The results show that a firm's research expertise as measured by patent stock is correlated with less integrated development, and that a firm's development expertise as measured by previously approved drugs, is correlated with integrated development. Additionally, firms with new products designed for complex diseases bring them to market through in-house resources.

The final chapter employs a comprehensive dataset on downsized and non-downsized workers to complete a series of estimations that show a convergence in the downsizing experiences of men and women in the probability of displacement and wage loss due to downsizing. In addition to this convergence, the analysis finds that the experiences of men and women have maintained persistent dissimilarities. Specifically, the probability of leaving the labor force, of finding part-time reemployment, and the duration of unemployment following displacement continues to be significantly higher for downsized women. Finally, the probability of reemployment is significantly lower for downsized women. Interestingly, marital status accounts for a significant proportion of these findings.

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Chapter 1

Introduction

In 1984, the U.S. Congress passed legislation referred to as the Drug Price Competition and Patent Term Restoration Act of 1984. Lawmakers designed this legislation to accomplish two purposes. First, this law significantly reduced the regulatory requirements for drug manufacturers introducing generic products for the purpose of enhancing drug price competition. The legislation accomplished this in Title I by simply requiring manufacturers to show that their products were chemically equivalent to previously approved products rather than complete costly clinical trials with their products. Second, the Act allowed for a new patented drug product to receive an extension on its patent term since innovators were unable to profit from their new products until FDA regulatory review was completed. The two components of this legislation were expected to have offsetting effects upon the incentives for innovation within the industry. Researchers and policy makers expected the increased price competition to reduce incentives for R&D and for the patent term restoration to increase incentives for R&D in the drug industry. On balance observers anticipated a neutral effect upon the research-intensive firms within the industry (see Grabowski and Vernon, 1986).

Proximate to the passage of this legislation, another significant development expected to effect research and development in the drug industry began to gain momentum. The advance of biotechnology as a viable method for new drug development was confirmed by the approval of several substantial drug products. Researchers expected this change in the environment to increase innovative

competition among firms in the industry as entrants from the field of biotechnology pushed for market share.

These two events have arguably been the most significant to effect the drug industry over the past fifteen years. In conjunction with several other regulatory changes and the internationalization of pharmaceutical markets, firms in the industry have had to adjust their R&D strategies to meet the significantly different conditions in the marketplace. By R&D strategy, we refer to the notion described in Nelson and Winter (1977:52), "a conditional probability distribution of innovations (or innovation characteristics) given certain conditions facing the organization" and "a particular set of heuristics regarding R&D project selection."

The next two chapters of this thesis focus on recent changes in pharmaceutical firm R&D strategies. These strategies have evolved in response to the changing regulatory and technological environment over the past fifteen years. The reason we focus on the pharmaceutical industry is that considering multiple industries for the purpose of evaluating alternative R&D strategies is not empirically feasible.[1] Additionally, the drug industry is one in which the decisions that determine how new product development proceeds are particularly important for the performance and survival and firms within the industry.

One of the increasingly favored R&D strategies pursued by biotechnology and pharmaceutical firms has been the construction of interfirm alliances. Since these alliances have only become particularly common in the last few years, detailed industry-specific empirical work has lagged the theoretical literature on this topic. Chapter 2 aims

[1] Nelson and Winter (1977:47) note ". . . the institutional structure for innovation often is quite complex within an economic sector, and varies significantly between economic sectors."

to partially fill this gap by evaluating over one hundred alliances in the biopharmaceutical industry over the last three years, 1995-97. The analysis employs an event study methodology to determine the level of value creation resulting from this recent alliance activity in relation to other related transactions within the drug industry and across other industries. A cross-sectional analysis based on predictions from principal agent theory and transaction cost economics considers which partner firm and alliance characteristics are the most significant in determining the level of value creation.

The results from the event study methodology demonstrate that on average the strategy of alliance creation creates significant value for the R&D firms. Value creation for the much larger client firms, however, is not detectable with the event study methodology. The cross-sectional analysis indicates that equity participation is particularly important for the success of these alliances. This finding is consistent with principal agent theory that suggests that such organizational structures must retain strong incentives for both partners to effectively achieve development objectives. Another important finding in the cross-sectional analysis is that alliances covering complex diseases tend to create significantly less value than the average alliance. This result is consistent with a transaction cost economics interpretation of alliances. Also, prior performance on the part of the R&D firm is negatively correlated with the value resulting from the alliance. Finally, interaction terms that attempt to capture the relationship between the importance of equity linkages and alliance characteristics associated with higher transaction costs indicate that in addition to retaining partner

incentives, equity participation may also serve to offset higher transaction costs for some alliances.

Chapter 3 considers the decisions of pharmaceutical firms for new product development more broadly. The analysis examines a unique dataset of over 300 approved drug products over the period 1985-96 (subsequent to the passage of the 1984 Drug Act) to determine the drug and firm characteristics that are most closely associated with firm development decisions. In this analysis, firm development decisions are taken by discovering firms that are identified through the 1984 Drug Act requirement for patent numbers on new drug applications (NDAs). The chapter estimates a variety of limited dependent variable models with the development choice defined as varying degrees of integration serving as the dependent variable. The estimation results demonstrate that a discovering firm's patent stock, previous drug approvals, and the complexity of the disease that the new drug product is designed to cure, are significantly correlated with the level of integration characterizing the development decision. For this sample of approved products, development decisions were made on average in the middle to late 1980s. The majority of approved drug products as recent as 1996 came to market through in-house means confirming how recent the shift to non-integrated development discussed in Chapter 2 has been.

In contrast to the previous two chapters, Chapter 4 considers another firm strategy that has received significant attention in the 1990s, corporate downsizing. In particular, this chapter examines the effects of corporate downsizing on that portion of the labor force that has received relatively little consideration in the literature to date, women workers. The analysis in this chapter finds that corporate downsizing over the period

1981-95 has effected women quite differently than it has men. In particular, after controlling for demographic, occupational, and industry characteristics, women have experienced a lower level or reemployment, higher levels of reemployment in part-time positions and incidence of leaving the labor force, and a longer duration of unemployment following downsizing. These results appear to be significantly correlated with the marital status of downsized women.

Chapter 2

Valuing Biopharmaceutical Alliances

Strategic alliances among firms in the biopharmaceutical industry (pharmaceutical and biotechnology firms) have increased significantly over the past decade, and particularly over the last three years. This paper applies an event study analysis to 123 alliances in this industry over the last three years, to determine the magnitude of the value creation resulting from these alliances. This paper also completes a cross-sectional analysis using partner characteristics and alliance characteristics to determine some of the potential sources for this value creation. We find that the R&D partner firms in these alliances experience significant positive cumulative abnormal returns of 4.4%. We also find that equity participation is associated with more valuable alliances and that alliances involving complex diseases result in lower value creation. R&D partner firms that had yielded low returns prior to an alliance experience a significant positive effect as a result of the alliance announcement. The result of lower value creation for complex disease alliances is consistent with higher transactions costs involved in completing such alliances. Unlike a previous study that considers alliances across twenty different industries, our analysis finds that research and marketing alliances within the biopharmaceutical industry are equally valuable.

2.1 Introduction

The widely respected chief of research at Roche Holdings, Jurgen Drews, made the following recent pronouncement regarding alliances in the pharmaceutical industry:

> It will be necessary for the pharmaceutical company wishing to develop drugs rapidly from the Human Genome project to form alliances with many partners---in

both biotechnology and academia---to carry out this process as efficiently and as effectively as possible.[2]

Strategic alliances have become increasingly common in several research-intensive industries, including the telecommunications industry, the computer hardware and software industry, and the pharmaceutical and biotechnology industries (or biopharmaceutical industry). Table 1 lists the ten US firms engaged in the greatest number of alliances from 1990-96. Three of these top ten firms (Bristol-Myers Squibb, Eli Lilly, and Merck) are well-established pharmaceutical firms.[3] Combined over this seven-year period, they have participated in a total of 278 alliances, with many of these alliances occurring over the past three years. A number of recent books published primarily for business students and professionals have lauded the significant benefits of these alliances for their participants.[4] Management guru Drucker (1995) describes the growing importance of alliances generally as the "greatest change in corporate structure—and in the way business is being conducted." Interestingly, though alliances have existed for several decades in Corporate America, they have not become a significant feature of the business landscape until rather recently. The growth in the value and number of alliances entered into by companies in all industries in the last decade has been tremendous. The pharmaceutical and biotechnology industries have

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[2] Drews (1996:1518).

[3] Theil (1997) notes that "Eli Lilly & Co., an elder statesman of the pharmaceutical industry, has been showing an almost youthful enthusiasm for dealmaking this year. Indianapolis' favorite son has formed 19 R&D collaborations so far in 1997 [over the first seven months of the year], a huge increase from the seven agreements for 1996 (three of which were mere renewals)."

[4] Brandenburger and Nalebuff (1996) have recently published a business strategy text that incorporates cooperative agreements as a viable strategy. Preiss (1996) provides an overview of the importance of strategic alliances in today's business environment. Gomes-Casseres (1996) describes a revolutionary move towards alliances for a majority of research-focused firms that has significantly affected the competitive environment. He employs a primarily case-based analysis to carefully examine alliances of large computer firms from the US, Europe, and Japan.

been a particularly good example of this trend, as indicated in Figure 1.[5] By considering the total number of alliance transactions involving pharmaceutical or biotech therapeutic firms over the period 1986-94 we observe that combined, the number of alliances has grown from 166 in 1986 to 492 and 427 in 1993 and 1994, respectively.[6] This contrasts with the fairly level trend for merger and acquisition transactions in the pharmaceutical and biotechnology industries over the same time period (although these transactions have also increased in frequency over the past 18 months).

Because this movement toward strategic alliances and cooperative agreements is comparatively recent, there has been limited empirical research on the impact of these agreements upon firm value within the context of the current industry structure.[7] This contrasts sharply with the wealth of theoretical research on the topic and the several papers investigating "collaborative behavior" generally. In this study, we propose to partially fill this gap in our knowledge about the economic value of these alliances by applying event study estimation to three categories of alliances undertaken by biotechnology firms over the past three years. After confirming that alliances enhance firm value in this industry, we apply cross-sectional analyses to determine the sources of value creation.

The remainder of this paper is organized into five sections. Section II reviews the relevant literature. Section III discusses our sample selection and summarizes the data that we employ in our analysis. Section IV explains our methodology and Section V

[5] See also Lerner and Merges (1997: Table 2, p. 34).
[6] These aggregate numbers are compiled in Windhover's Information, Inc. (1996).
[7] Particularly noteworthy exceptions are Chan, et al. (1997) and Lerner and Merges (1997), which we discuss in detail in Section 2.

presents and discusses our results. The final section provides our conclusions and recommendations for future research.

2.2 Survey of the Literature

The theoretical literature on strategic alliances is vast and arguably extends back to Arrow (1962), who considers the economic decision to license technology in a manner directly related to the formation of strategic alliances within the context of today's pharmaceutical and biotechnology industries.[8] More recently, Parkhe (1993) provides a good example of an analysis of alliances using a game theoretic framework. In this paper, Parkhe identifies three important attributes of alliances that could logically affect alliance performance. The first attribute is the pattern of payoffs that each of the partners can expect from the alliance. The central importance of payoffs for alliances stems from the requirement that if the net payoff from entering an alliance is not higher than the next best alternative, the profit-maximizing firm has no incentive to undertake the alliance. Additionally, the expected payoffs for an alliance will fluctuate in response to changes in the environment that may alter the pattern of payoffs for each of the respective alliance partners. Two significant regulatory changes that have occurred recently that may affect the payoffs to alliances (and new drug development in the U.S. generally) are a significant reduction in the approval time for NDAs (New Drug Applications) and the allowance of direct-to-consumer (DTC) marketing. The reduction in the length of the drug development process, which is documented in GAO (1995, 1996), has reduced overall development costs. This reduction should decrease the economies of scale in new drug research and development allowing for a greater

degree of specialization in the less scale-intensive biotechnology-oriented research. This greater specialization should lead to greater returns for more recent alliances that facilitate this specialization. The new marketing guidelines that facilitate DTC marketing, which includes television advertising, should increase the economies to scale in the marketing of new drug products, thereby increasing incentives for specialized research firms to participate in marketing alliances with larger established drug firms.[9] These fluctuations in expected payoffs may directly affect the optimal structure of alliances.

The second attribute of alliance structure that Parkhe refers to as the "shadow of the future" represents the "bond between the future benefits a firm anticipates and its present actions." In other words, when firms anticipate repeated future interactions they are more likely to cooperate in the present.[10] This is related to the third attribute of alliances that Parkhe emphasizes, "the extent to which the parties perceive each other as behaving opportunistically." He identified partner reputation and the previous alliance history of the respective partners as important attributes that affect the propensity for opportunistic behavior. Parkhe then shows how all of these alliance structural attributes may in turn affect alliance performance.

To determine the relationship between alliance structure and performance, Parkhe (1993) uses a survey mailed to firm executives involved in managing strategic alliances to measure structure and performance. His empirical findings indicate a weak relationship between alliance performance and his measures of payoffs, a strong

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[8] Lerner and Merges (1997) also identify Arrow's seminal paper as the antecedent of the relevant theoretical literature.

[9] See Food and Drug Administration (1997) for a summary of the new industry guidelines for DTC advertising.

[10] Game theorists have proven that "iteration improves the prospects for cooperation by encouraging strategies of reciprocity." Parkhe (1993: 799) Parkhe further identifies behavioral transparency, frequency

positive relationship between alliance performance and transparent behaviors and frequent interaction, and a strong negative relationship with factors associated with an increased propensity for opportunistic behavior.[11] In sum, Parkhe demonstrates that the attributes of a given alliance structure appear to be related to the performance of that alliance.

Other papers that provide additional context for our analysis include Oxley (1997) and Tucci (1996). Similar to Parkhe (1993), these two studies examine the attributes of a variety of alliances (including partner characteristics and collaborative behavior) and hypothesize how these different alliance attributes might affect alliance and firm outcomes. Oxley focuses on the different governance properties of alliances as they relate to appropriability hazards. In particular, she hypothesizes that partner firms choose among alliance types (unilateral contract or simple license, versus a bilateral contract or cross-license, versus an equity joint venture) according to the level of transaction costs. These transaction costs are proportional to the "appropriability hazards" implied by the type of technology transfer which the firms are attempting to conduct through their alliance. Oxley examines 165 alliances between U.S.-based manufacturing firms over the period 1980-89. She concludes, "firm-level effects do not have statistically significant effects," and infers that this result is consistent with transaction cost theory, which emphasizes the "attributes of the transaction (i.e., the project), and not those of the firm as a whole" for determining the preferred mode of governance for the alliance.

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of interaction, and long time horizons as important elements that can promote cooperation by strengthening the "shadow of the future."

[11] Parkhe suggests that his counterintuitive result of a weak relationship between payoffs and alliance structure may be due to measurement error of payoffs in his empirical analysis.

Instead of U.S. alliances, Tucci (1996) addresses international technology alliances (his dataset consists of surveys from 125 European R&D managers). He attempts to answer the question "to what extent do partner characteristics and collaborative behavior influence performance outcomes of strategic technology alliances?" Specifically, he identifies market overlap between the partners as a negative influence on alliance outcomes, and technical and social overlap between the partners as positive influences. His measure for alliance outcomes derives from an Internet survey conducted among European technology firms. His conclusions indicate that "it is very difficult to successfully manage horizontal technology alliances . . . (Tucci, 1996: 29)."

Pisano (1989) has conducted a related analysis. Pisano (1989: 109) examines "the motives for using partial equity investments in collaborative relationships." Employing the transaction cost approach of institutional economics he concludes "partial ownership [through direct equity participation] has advantages in collaboration where parties must make transaction-specific investments under conditions of uncertainty Pisano (1989: 114)." This result, like Oxley (1997), is consistent with transaction cost theory.

The performance data that these authors employ generally derive from self-reported survey data or subjective observations of alliance outcomes. Additionally, rather than focusing on quantitative measures of alliance outcomes, these previous studies have focused on alliance governance (Oxley (1997) and Pisano (1989)). One recent study, however, conducts an objective empirical analysis of strategic alliances. Chan et al. (1997) [hereafter CKKM] investigate share price responses to the announcement of 345 strategic alliances over the period 1983-92 in a variety of industries.[12] One of their

[12] For a distribution of industry affiliation for each of the alliances included in their analysis, see Table 2 on p. 207. Their sample covers 20 distinct industries, with the vast majority of the sample classified within the

important findings is that "establishing strategic relationships creates significant value for the shareholders of the partnering firms (CKKM: 209)." In comparison to McConnell and Nantell (1985) [hereafter M&N], who find a 1.10% excess return for small firms and 0.63% for larger firms involved in joint ventures, CKKM find an excess return of 2.22% for smaller firms and a statistically insignificant 0.19% for larger firms involved in strategic alliances. Both CKKM and M&N conclude that the creation of strategic alliances and joint ventures, respectively, are responsible for significant wealth gains. Additionally, both CKKM and M&N convert their findings into dollar values, estimating average gains of $8.9 million and $8.1 million for the smaller and larger firms, respectively, in strategic alliances and $4.5 million and $6.6 million for the small and large firms involved in joint ventures.[13] To determine the possible sources of these gains, CKKM investigate cross-sectional differences in excess returns and find that in general, horizontal alliances (those between firms in the same SIC class) result in significantly higher abnormal returns than non-horizontal alliances.[14] Additionally, alliances that were formed for the purpose of transferring or "pooling complementary technological knowledge and skills" tended to result in greater value creation.[15]

Due to the significant heterogeneity of the CKKM sample, however, the sources of value creation are difficult to identify.[16] In an analysis of biotechnology collaborations,

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"Computers, information technology, and software" industry. This single industry category represents close to 60% of their entire sample.

[13] Note that the M&N sample contains 136 joint ventures over the period 1972-79, while the CKKM sample contains 345 strategic alliances over the period 1983-92, so that corrections for inflation would make the wealth gains for each group of transactions very nearly equal in absolute terms.

[14] It is interesting to note that this result contrasts with the Berg and Friedman (1981) analysis of domestic joint ventures which finds that horizontal joint ventures actually result in a reduction in the rates of return for the participant firms.

[15] See the discussion in (CKKM, 1997:213) and Table 4 on page 221.

[16] CKK M does find that for horizontal alliances (involving partner firms in similar industries), "more value accrues when the alliance involves the transfer or pooling of technical knowledge than with nontechnical

Lerner and Merges (1997:2) [L&M] empirically examine "how control rights are assigned in one particular environment: agreements to research and develop new products and processes between biotechnology firms and either pharmaceutical or larger biotechnology companies." In their analysis, they test the validity of the model presented by Aghion and Tirole (1994) which predicts that the allocation of property rights in alliances will depend on two factors. These two factors are the extent to which underinvestment by either or both of the parties jeopardize the success of the project and the relative bargaining power of the two parties (L&M: 2). L&M use three case studies and the database maintained by Recombinant Capital, which contains detailed information about partnerships between biotechnology companies and universities, research centers, other biotechnology firms, and pharmaceutical firms.[17] The two primary results from their analysis are: 1) There is a statistically significant negative relationship between the number of control rights allocated to the larger firm and the financial strength of the smaller firm and 2) Alliances in the early stages of a project tend to allocate more, not fewer, control rights to the firm financing the R&D (L&M: 23,25). They conclude that their first result is consistent with the Aghion and Tirole (1994) model, but that their second result is not easily interpretable within the context of that model. These results are relevant for the analysis of this paper, because they suggest important factors that might affect the wealth gains from alliance formation in the biotechnology industry.

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alliances." This result is consistent with the findings of Berg and Friedman (1980) for joint ventures facilitating technological knowledge transfers.

[17] The three case studies which L&M include in their analysis are: 1) The 1978 alliance between ALZA and Ciba-Geigy which ceded significant control over ALZA's research projects to Ciba-Geigy, 2) The ImmuLogic Pharmaceutical Corporation alliance with Marion Merrell Dow in 1991, and 3) The highly successful Repligen Corporation and Eli Lilly alliance completed in May 1992.

In this study, we combine the predictions of earlier papers about the relationship between alliance structure and firm performance with the quantitative firm performance measures employed in CKKM. In addition, we add alliance partner characteristics, and alliance partner performance prior to alliance participation to a focused analysis of the biopharmaceutical industry. Because of our single industry focus, we are able to examine several structure-performance-partner characteristic relationships within alliances, which have not been previously considered. Table 2 provides a summary of the relevant empirical research to place our analysis in context.

2.3 Data

The sample for this paper derives from the Recombinant Capital (ReCap) compilation of alliances among pharmaceutical and biotechnology firms over the relatively recent period June 1995 through June 1997.[18] The definition for alliances we use is: "any governance structure involving an incomplete contract between separate firms and in which each partner has limited control (Gomes-Casseres, 1996:34)."[19] Our alliances all consist of two firms.[20] One firm (generally a larger pharmaceutical or biotechnology firm) is considered the client partner, while the other firm (generally a smaller biotechnology firm focused on discovery efforts) is classified as the R&D partner. The dates for our dataset were selected to homogenize our observations as much as possible and to allow for a valid comparison of the major categories of biotech alliances that we identify

[18] See http:\\www.recap.com\.

[19] Alternatively, Parkhe (1991: 581) proposes the following description of strategic alliances, "relatively enduring interfirm cooperative arrangements, involving flows and linkages that utilize resources and/or governance structures from autonomous organizations, for the joint accomplishment of individual goals linked to the corporate mission of each sponsoring firm."

[20] Multifirm alliances are of separate interest and are discussed by Gomes-Casseres (1996) within the context of the computer hardware industry. A brief perusal of the available data suggests that the vast

in our analysis. In particular, we employ the following categories for the alliances in our dataset: 1) research agreements, 2) development agreements, and 3) marketing agreements. These categories account for only a subset of the thirty-one categories employed by ReCap, but they capture the majority of partnerships, which we would classify as strategic alliances as opposed to acquisitions, asset purchases, or joint ventures.[21]

We obtained the initial data on these various alliances from the Recombinant Capital (ReCap) database of strategic alliances.[22] We have employed detailed descriptions of firm operations from industry newsletters such as *Biotechnology* and *BioNature* and, when available, annual reports to confirm our categorization of the alliances. Additionally, we have obtained publicly released statements which are referenced in the ReCap database to confirm the precise announcement dates for each of our alliances. When these statements were not available through ReCap, we obtained them from other published press reports. All of these company press releases were corroborated with publicly available press reports from the financial press, such as the *Wall Street Journal*. The stock-return data employed in the event studies is derived from the CRSP tapes. In our cross-sectional analysis, we employ data available from SEC-filings and the COMPUSTAT database. This data includes revenues, total assets, number of employees, and R&D expenses to measure firm size (in addition to firm market

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majority (> 80%) of alliances in the biopharmaceutical industry are of the two partner variety, although this has changed recently. We plan to address this special category in a future study.

[21] The ReCap database provides a comprehensive compilation of a variety of transactions relevant for the biotechnology and pharmaceutical industries. They include acquisitions, asset purchases, joint ventures, as well as agreements completed between companies and universities. Since our focus is upon strategic alliances, we excluded a majority of the transactions, which we could not classify as multifirm agreements. Future research should analyze in greater detail variations across the various forms of partnership across categories to include acquisitions and joint ventures.

capitalization) and firm commitment to R&D. From these sources, we are able to compile a comprehensive picture of the biotechnology and pharmaceutical firms involved in strategic alliances.

Since our period of analysis is focused on the three-year period 1995-97, several of the firms in our sample have been involved in multiple alliances. For the 123 alliances in our sample, we would have 246 possible participants, if all of our alliances consisted of unique firms. In fact, we have 135 firms in our sample, with the mean number of alliances per firm at just fewer than two. The three firms with the most alliances in our sample, with ten apiece, are Genentech, SmithKline Beecham, and Schering-Plough. Eighty-eight of the firms in our sample are represented with only one alliance in the sample.

Our sample of alliances was reduced from the universe of total alliances for several reasons. The first criterion to confirm with transactions derived from Recap is the type of transaction. Starting with all recorded transactions from January 1, 1995, through July 30, 1997, we begin with approximately 1,400 observations. Half of these observations, however, are non-alliance agreements, such as asset purchases, acquisitions, joint ventures, etc. An additional 200 observations are transactions concluded with university or other nonprofit research organizations. These observations were also eliminated from our sample. In many cases, one or both of the firms were not publicly traded. Since foreign firms must deal with different legal requirements we omit them as well, so as not to complicate the data gathering for now.[23] Two final criteria that we employ to restrict

[22] For a detailed introduction to this and related databases constructed by Recombinant Capital see the following web site: www.recap.com.

[23] We plan on returning to this issue in a subsequent paper focusing on a comparative analysis of domestic versus international biopharmaceutical alliances.

our sample are 1) when significant additional events affect partner companies concurrent with the alliance announcement, 2) insufficient trading days. The criteria for our sample and the approximate number of observations that were eliminated for the various reasons are given in Table 3. Table 4 lists the 123 alliances in our final sample.

For our cross-sectional analysis we model the share price response as a function of firm and alliance characteristics. In particular, we employ the following equation: Δfirm i's share price of R&D firms in the sample = f (client firm size, R&D firm size, client firm R&D intensity, client firm profitability, R&D firm profitability, license indicator, equity indicator, complex disease indicator, early stage indicator, alliance type indicator, year indicator, and four interaction terms). As with any such analysis, the firms and the alliances that we examine are quite heterogeneous. We have attempted to minimize this heterogeneity by focusing on research-intensive pharmaceutical and biotechnology firms.

The first variables that we include in our model are measures of size for the partner firms. These are market capitalization, total assets, and net sales.[24] Firm size variables have been included in previous analyses as control variables. For our analysis of the source of value creation, as exhibited by share price response, we control for the size of the alliance partners since larger firms may exhibit a smaller percentage reaction to the transaction announcement than the smaller partner firms simply because of their greater size. Additionally, firm size may be correlated with alliance value directly for a variety of reasons. Larger firm size, for example, may be positively correlated with a firm's ability to appropriate gains from the product development that may result from a

research or development alliance. Such a correlation would result in higher cumulative abnormal returns for larger client firms.

The second firm-specific variable that we include in our analysis, is R&D intensity. Following CKKM, alliances created for the purpose of exploiting complementarities in research and new product development may on average create more value than other alliances. Such alliances should benefit by having more research-intensive partner firms. Cohen and Levinthal (1989) provide one justification for this reasoning. They demonstrate that for firms to extract value from innovations completed external to their own R&D activities they must possess "absorptive capacity." This is the ability to exploit unfamiliar technology. Within this context, such ability might be relevant for the client firm. Higher R&D-intensity for the client firm may therefore be positively correlated with value creation as a result of this capability.

The third firm variable that we include is a measure of firm performance. Since we have sales variables up to several years prior to each of our alliance announcements, we can determine performance characteristics of the partner firms such as sales growth prior to alliance participation. We have also included net income and total stock returns for each of the partner firms during the one-year period prior to the thirty days before the alliance announcement as alternative firm performance measures. Partner performance measures prior to an alliance are possibly relevant to an alliance outcome for two reasons. First, if a partner firm has been performing well prior to an alliance announcement then it may be the case that its negotiating leverage over alliance provisions is strengthened. This may be correlated with a stronger positive response to

[24] To prevent the alliances from influencing the market capitalization of each of the participating firms, which we use for the second part of our analysis, we take the market capitalization of each firm 30 days

an alliance announcement. By contrast, strong prior performance may also indicate that an alliance may be unnecessary for the realization of good future performance, so that a negative response may follow an alliance announcement. Consistent with this view is the perception that a well-performing firm that announces an alliance may be signaling a previously concealed weakness.[25] Note also that from the perspective of the R&D firm, prior strong client firm performance may also serve to reduce the gains from an alliance transaction to the R&D firm due to the client firm's enhanced bargaining position vis-à-vis the R&D firm. There are thus several empirical possibilities that may result from our cross-sectional analysis with regard to prior partner firm performance. The three possibilities are: 1) it may serve to enhance the overall market valuation of the research being undertaken by the partner firms, 2) it may serve to extract greater gain for the client firm at the expense of the R&D firm, thereby diminishing the beneficial response for the R&D firm which may in turn lead to a lower assessment of the alliance, or 3) the alliance may be perceived as a signal of previously unrevealed weaknesses on the part of the R&D firm, at least when it comes to attracting the necessary capital and/or resources for conducting independent R&D. On balance, stronger client firm performance may lead to lower value creation and stronger R&D firm performance may lead to either higher or lower value creation. Whether either is the case, however, is an empirical question.

The alliance-specific variables include indicator variables for whether the alliance includes equity participation (*equity)*, involves a licensing agreement *(license)*, a product to treat a complex disease (*complex disease*), is made at the early stage of R&D (*early*

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prior to each of the event windows.

stage), or involves a research (*research*) or marketing and development (*marketing agreement*).[26] As demonstrated by Pisano (1989), equity linkages serve to align partner incentives when alliances are characterized by uncertainty and transaction-specific capital. The alliances that we consider in our analysis most likely contain significant levels of both uncertainty and transaction-specific capital, and should therefore benefit from equity participation among alliance partners. Improved partner incentive alignment due to equity linkages may in turn result in greater value creation. This reasoning leads us to the expectation that equity participation among alliance partners will be positively correlated with the level of value creation resulting from the alliance.

The next alliance attribute that we control for and for which we have complete sample representation is an indicator of a license provision within the alliance. This provision is important from a property rights perspective. Partner firms involved in drug alliances are often times involved in complex technology transfer. Given this complexity, it may be the case that when firms are able to agree on a license provision, that the technology being transferred is sufficiently well specified to allow a greater degree of explicit contracting. These more explicit contracts might assign some of the relevant property rights, which could serve as a positive signal to external observers of the structure of the alliance. Alliances with licensing provisions may therefore, exhibit greater value creation than alliances that do not contain such provisions.

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[25] This line of thinking is consistent with the findings by Mohanram and Nanda (1996), which conclude "Firms enter into joint ventures when their performance is deteriorating."

[26] In addition to these alliance attributes we also have the size of the deal, which represents up-front payments made by the client firm to the R&D firm at the beginning of the alliance. This deal size variable, however, is only available for 55 of our 123 alliances due to the common industry practice of redacting this information from their publicly available announcements and filings. Because of its sparse availability we did not include it in our final analysis.

The next two alliance attribute variables that we include in our model, are an indicator for complex diseases and an indicator for early stage alliances. Including these two attributes in our model is consistent with the predictions of the transaction cost literature for contracts involving technology transfer. The more difficult it is to define the technology that a new alliance is designed to develop, the higher will be the transaction costs for completing the alliance.[27] In particular, the contractibility of alliances involving complex diseases is most likely lower than alliances designed to address less complex diseases.[28] As shown in Nelson and Winter (1977) the greater the level of uncertainty affecting a process, the more difficult it will be to write contracts to effectively govern that process. Arguably, alliances over complex diseases feature higher levels of uncertainty. As such, alliances involving complex disease categories may be associated with lower value creation.

Similarly, alliances involving early stage research or products should also correlate with lower net value creation due to the higher transactional costs and greater uncertainty which are inherent in such alliances. According to L&M, "Since most biotechnology firms have expertise in early-stage research, we anticipate that many more control rights would flow to them in the early stages of the project." This suggests that for alliances consummated for early stage research projects, the abnormal returns accruing to the R&D firm should be higher, ceteris paribus. Interestingly, L&M find that early-stage alliances are characterized by a greater degree of control rights allocated to the sponsoring or client partner firm. An alternative interpretation of this result is that

[27] See Williamson (1985: 292-294). In particular, see his discussion on page 293 explaining that "Attempts to transfer technology by contract can break down because of the 'paradox of information.'"

early-stage projects are characterized by greater risk. To adequately compensate the investor for this greater risk, the R&D firms most forgo a greater proportion of their claims to the future revenue streams from the research project.[29] Myers and Howe (1996) estimate the risk of cancellation as particularly high for the early stages of new drug research. They attribute the high cost of capital for biotechnology firms, as observed by their higher market betas, to this higher risk.[30] From a cost-of-capital perspective, then, earlier stage alliances may result in lower abnormal returns for the R&D partners.

The final attribute of alliances that we consider in our analysis is the type of agreement. According to CKKM, greater value accrues to technical alliances that involve technology transfer, as opposed to nontechnical alliances such as marketing alliances.[31] Hagedoorn and Schakenraad (1994) define this technical alliance category as follows, "Strategic technology partnering is the establishment of cooperative agreements aimed at joint innovative efforts or technology transfer that can have a lasting effect on the product-market positioning of participating companies." In this light, given the importance of new product development for drug firms, we might expect that greater value should accrue to alliances focused on research and development (the

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[28] Note that we group diseases such as AIDS, cancer, central nervous system afflictions (excluding depression), and cardiovascular illnesses into a complex disease category. Other diseases that deal with ophthalmic, dermatological or metabolic afflictions fall into the noncomplex disease category.

[29] Note that we classify alliances for products that have not completed Phase II clinical trials or earlier as early-stage alliances. This includes alliances created for the purposes of new product discovery, lead molecule formulation, pre-clinical trials, or the completion of Phase I trials.

[30] In a related research paper, Myers and Shyam-Sunder (1996) estimate that biotechnology firms have a 33% higher cost-of-capital relative to the larger pharmaceutical firms. See Tables 10-4 and 10-5 on pp. 223 and 228.

[31] In particular, they find that for horizontal alliances, technical alliances involving the transfer or pooling of technology, abnormal returns average 3.54% versus 1.00% for nontechnical or marketing alliances. See Table 4. They are not, however able to "distinguish between the value contributions of alliances based on whether the transaction involves more versus less transaction-specific knowledge (CKKM : 213)."

creation of new products) over marketing alliances (the distribution of new products or creating demand for new products).

From another perspective, however, marketing is a particularly important activity for the pharmaceutical industry. To confirm the importance of marketing in this industry we collected data to compute the advertising to sales ratios for the top fourteen firms in the pharmaceutical industry in terms of market capitalization over the years 1991-96.[32] For the fifty-nine firm-years of data that we collected, we compared R&D-to-sales ratios versus advertising-to-sales ratios and found that for fourteen of the firm-years (25% of the sample) the advertising-to-sales ratio actually exceeded the R&D-to-sales ratio. This empirical finding suggests that marketing is a very important activity among the top pharmaceutical firms. Marketing alliances, therefore, may not be significantly less valuable than research and development alliances for this industry. We test these contradictory predictions in our cross-sectional analysis by including controls for each of our three alliance categories.

We also include several interaction terms in our analysis. In particular, the interaction between research and development agreements and equity participation, the interaction between marketing agreements and licensing, the interaction between early stage agreements and equity participation, and the interaction between complex diseases and equity and licensing. The justification for our interaction term between our equity indicator and our indicators for research and development alliances comes from the conventional industry wisdom that equity participation is relatively more important for alliances involving more complex activities such as research and development to align

partner incentives.[33] Similar reasoning applies to early stage and complex disease alliances. We may therefore expect that research and development alliances, and early stage and complex disease alliances with equity participation will create greater value than the same types of alliances without equity participation. Licenses are more important for facilitating technology transfer in later stage alliances such as marketing alliances. Marketing alliances formalized with licensing agreements, therefore, may be more effective than such alliances without licensing provisions.

The final variable we include in our analysis is a control for the year of the alliance, *year97*. Given the history of alliances in this industry over the past decade, it may be that case that substantial learning has occurred with regard to the most appropriate manner to complete these complicated transactions. If this has been the case, then more recent alliances may be more valuable. We use an indicator variable showing our most recent alliances in 1997.[34] We summarize our data and the expected effects of our variables upon alliance value creation in Table 5. We now turn to our specific methodology.

2.4 Methodology

We proceed in two parts. First, we determine the level of value creation attributable to the creation of the alliances we examine. In this analysis, we employ an event study model patterned after MacKinlay (1997). We use the following market model to predict the expected return for a firm in our dataset:

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[32] The fourteen firms are: Abbott Laboratories, American Home Products Corp, Bristol Myers Squibb, Glaxo Wellcome PLC, Hoechst Marion Roussel, Johnson & Johnson, Eli Lilly, Merck, Pfizer, Pharmacia & Upjohn, Rhone-Poulenc Rorer, Schering-Plough, SmithKline Beecham, PLC, and Warner-Lambert Co.
[33] Pisano (1989) also strongly supports the inclusion of such an interaction term.

$$E[R_{it}] = \alpha_i + \beta_i(M_t) + \varepsilon_{it}$$

where R_{it} is the rate of return for security i at time t and M_t represents the market return at time t (such as the NASDAQ composite index or the CRSP Value-Weighted Index).[35] This model gives us a predicted rate of return, $\hat{R}_{it}$, to compare to the rate of return which actually obtains for our sample firms, R_{it}. This allows us to compute abnormal returns $AR_{it} = R_{it} - \hat{R}_{it}$ that result from the creation of each of the alliances in our sample. We apply this model to our sample of 123 alliances. This provides us with a sample of abnormal return estimates, which we aggregate over several different event windows (3-day, 11-day, and 21-day) to arrive at cumulative abnormal return estimates for both partnering firms and a combined cumulative abnormal return for each alliance.[36] We estimate our model using a variety of market indices, but conclude that the CRSP Value-weighted index is the preferred market index.[37] In the second part, we employ these cumulative abnormal returns in a cross-sectional analysis so that we may identify the most important factors that influence the level of value creation attributable to alliance creation in this industry. In particular, we investigate which firm and alliance characteristics are the most important in determining cumulative abnormal returns. The primary specification for this analysis is:

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[34] Using a dummy variable for 1997 alliances almost bisects our sample. Our 1997 alliances comprise close to 44% of our sample.

[35] All returns in our estimation are net of the risk-free rate of return as represented by the three-month U.S. Treasury Bill.

[36] Note that we also used the following asymmetric event windows (-20, +5), (-10, +3), (-5, +1) obtaining similar results.

[37] In particular, we estimated our CAPM equation using the industry index by itself, the market index by itself, and both indices combined, and attained the highest adjusted R-square by using the market index by itself.

$$CAR_i = \alpha_i + \beta_1 MktCap\ R\&D + \beta_2 (MktCap\ R\&D)^2 + \beta_3 MktCap\ Client + \beta_4 (MktCap\ Client)^2 + \beta_5 R\&D\ Intensity\text{-}Client + \beta_6 Total\ Return\ Client + \beta_7 Total\ Return\ R\&D + \beta_8 Equity + \beta_9 License + \beta_{10} Early\ Stage + \beta_{11} Complex + \beta_{12} Research + \beta_{13} Development + \beta_{14} MktCap\ Client * Research + [in\ alternative\ specifications]\ \beta_{15} Equity * Research\ or\ \beta_{16} License * Research + \beta_{17} Year\ '97 + \varepsilon_i$$

where i = R&D firm, client firm

MtkCap R&D = the capitalization of the R&D firm to include a quadratic term[38]

MktCap Client = the capitalization of the Client firm to include a quadratic term

R&D Intensity Client = the R&D intensity of the Client firm

Total Return Client = the total stock return for the Client firm prior to the alliance announcement[39]

Total Return R&D Firm = the total stock return for the R&D firm prior to the alliance announcement

Equity = an indicator for alliances which include equity participation by the Client firm

License = an indicator for alliances which include a license of technology

Early Stage = an indicator for alliances involving research or products earlier than Phase II

Complex = an indicator for alliances involving a complex disease

Research = an indicator for research alliances

Development = an indicator for development alliances[40]

Interaction Terms = include interaction between client market capitalization * research agreement, equity indicator * research agreement, license indicator * research agreement in separate specifications

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[38] Alternative measures that we also include in our analysis are net sales and total assets.
[39] Alternative measures for firm performance that we also include are net income and sales growth.
[40] Note that the indicator for marketing alliances is omitted, so that the interpretation of our coefficient estimates for the research and development alliance indicators will be in relation to marketing alliances.

Year '97 = indicator for alliances announced in 1997, roughly 44% of the sample. We report the results for the various specifications in the next section and discuss their implications.

2.5 Results

The first set of results we obtain involve our estimated cumulative abnormal returns for the R&D and client firms. As indicated above, we consider three possible event windows to ensure that we are not mismeasuring the abnormal returns due to our events of interest, in this case alliance announcements. The data suggest that a narrower event window is more appropriate for our sample, because unlike in large mergers and acquisitions, there appears to be little or no leakage prior to our event announcements. Additionally, since pharmaceutical and biotechnology firms tend to make announcements that materially affect their value at frequent intervals a shorter window is necessary to minimize the noise from unrelated announcements.[41] Table 6A shows our results for our R&D firms and our client firms across the three event windows. As indicated for the R&D firms in our sample, the three-day event window yields the most conclusive results. Value creation (or cumulative abnormal returns, CAR) for these firms averages 4.4% over the event window. [42] For the client firms, the results indicate an average .37% CAR. When we aggregate our observations across all 123 alliances, we obtain very strong t-statistics for the R&D firms, 10.04 using the three-

[41] Ravenscraft and Long (1997) observe that "Announcements concerning new drug discoveries, regulatory changes, legal matters, alliances and individual drug cash flow projections are common." This suggests that the best measure of stock market reaction requires "fairly narrow windows." See page 14.
[42] The 5% and 10% trimmed means for the R&D firms' CAR are also statistically significant at 3.5% and 3.1%, respectively.

day event window and an insignificant t-statistic for the client firms of only 1.25. Due to the relatively skewed distribution of CARs, we also report the median values in Table 6B, of 2.3% for the R&D firms and .14% for the client firms. In sum, the R&D firms do very well in these alliances in percentage terms while we cannot draw substantive conclusions regarding the benefit to the client firms.

Our results in dollar value terms are slightly different due the significant size asymmetry between the client and R&D firms. The dollar value gains for our R&D firms average $21.4 million (with a median value of $4.2 million). The dollar value gains for our much larger client firms average $149.4 million (with a median value of $3.5 million). The combined dollar gain for our alliances average $170.8 million (with a median value of ($10.1 million). We must caveat these results, however, with the fact that only R&D firm gains are statistically significant.

These results are generally consistent with CKKM and M&N in several ways. The smaller partner experiences the greater and statistically significant percentage gains, while the larger partner experiences an insignificant but possibly equivalent or larger dollar gain. Our resulting value gains appear to have a greater variance than either the CKKM or M&N analyses and appear to be slightly more asymmetric. This may be due to our sample's greater size asymmetry. In CKKM's strategic alliance analysis, the larger partners are ten times larger while in M&N's joint venture analysis; the multiple is only five. Our market capitalization ratio of client to R&D firms is twenty to one.[43] This asymmetry in market capitalization may be related to our asymmetry in value creation

[43] Note also that although the mean for the market capitalization for our R&D firms is $1.35 billion, this represents a very skewed distribution. The median market capitalization is only $181 million.

for R&D firms versus client firms. Table 7 summarizes the findings of the three related industry-specific analyses along with our results.[44]

An interesting contrast between our findings and the M&N and CKKM findings is the greater value creation that results from the transactions in our sample. Our dollar-value creation amounts are on average greater than the CKKM findings on strategic alliances across twenty different industries (adjusting for inflation), and also greater than the M&N findings across several industries. This finding is consistent with the claim by CKKM that horizontal, technical alliances provide significant opportunities for value creation, since the alliances in our analysis are clearly horizontal, technical alliances. Unfortunately, the imprecise estimates of effects for client firms, which are not statistically distinguishable from zero, precludes any further analysis of the distribution of wealth gains from alliances between R&D and client firms.

The second stage of analysis models the heterogeneity of returns across firms and alliances. As Figure 2 demonstrates, the averages mask considerable variation in the estimated abnormal returns around alliance announcement dates. Table 8 presents results from the cross-sectional analysis of alliance returns for the R&D firms. We estimate variants of the cross-sectional equation specified in the previous section and present the results in this table. Note that our dependent variable for this analysis is the CAR for the R&D firm.[45] The remainder of this section focuses on the CAR for our R&D firms as the dependent variable.

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[44] We believe that the analysis recently conducted by Ravenscraft and Long (1997) of 65 pharmaceutical mergers is also relevant here for perspective, because it represents another related category of transactions within the same industry. They find CARs of 13.31% and –2.12% for their targets and bidders, leading to a combined dollar value creation of $289 million.

[45] We have performed the same exercise for the returns to client firms, but not surprisingly, find little explanatory power for the model.

Model one includes a quadratic for the market capitalization of the R&D firm and the client firm. Model two includes only the firm market capitalization of the R&D firm. In a variety of specifications employing market capitalization along with alternative measures of firm size such as total net sales, total assets, and R&D expenditures for *both* the R&D and client firms, we never encounter even a marginally significant coefficient.[46] Our results for models one and two are presented in the first two columns of Table 8. These results are consistent with Oxley (1997), who also finds that firm characteristics have insignificant effects upon alliance governance choice.

Unlike the partner firm characteristics, several of the alliance attribute measures are significant in our cross-sectional analysis. Our equity, complex disease, and time trend indictor variables all enter significantly and with the expected sign for each of initial model specifications. Alliances that include equity participation average seven percentage points greater returns (standard error, two percentage points) than alliances without equity participation. Whether this reflects the fact that firms choose to take equity participation in the alliances with the greatest expected value, or a causal effect of equity participation on expected success is beyond the scope of this paper. Our coefficient estimates for our license indicators are essentially zero. This result fails to provide support for our hypothesis that licenses are important for facilitating technology transfer in these alliances.

In addition to our equity indicator estimates, the coefficient estimates for our complex disease indicator enters negatively at close to -.06. This result is consistent with our reasoning above for alliances involving complex diseases. The difficulties associated

[46] In particular, all coefficient estimates are close to zero with relatively large standard errors.

with coordinating separate company efforts to address the more difficult targets is reflected in lower value creation for these alliances.

The early stage indicator enters negatively as hypothesized with a point estimate of -.04, but is not quite statistically significant in our first two specifications with an average p-value of just over .10. Our research alliance indicator enters positively at .04, but is not statistically significant. Our indicator for development agreements enters positively at .03, but is also not statistically significant. These results are inconsistent with CKKM's finding that research and development alliances provide significantly greater opportunities for value creation than comparable marketing alliances, but because of the industry-specific nature of our sample these results are not surprising results. Specifically, biotech firms engage in intensive specialization and large drug firms place significant emphasis upon marketing. Given the apparent importance of marketing in our industry of analysis, it may very well be the case that marketing alliances in the industry are just as important for revenue generation as research and development alliances, unlike in other industries.

In Model 3, we add total return for the R&D and client firms to our specification. The client firm return is insignificant, but the R&D firm return enters with a negative coefficient of -.03 and is statistically significant at the 1% level. Adding this variable also increases the explanatory power of our overall model as suggested by the increased adjusted R-square. None of our other performance measures such as sales growth or net income yields significant coefficients. This result suggests that an R&D firm that is experiencing strong total returns prior to an alliance event will receive lower gains from an alliance announcement than an R&D firm that had been experiencing weak total

returns. If we recall our argument about research project or new product value signaling, this result makes sense. The alliance announcement serves as a more positive signal for previously weak performers than it does for firms that are already doing well without the alliance.

In model 4 we add three interaction terms, R&D alliance*equity, early stage*equity, and complex disease*equity. All three terms enter significantly. Research and development alliances that include equity participation create greater value than such alliances, which do not include equity participation. Our other two interaction terms enter negatively suggesting that early stage and complex disease alliances with equity participation create significantly less value than other alliances involving equity participation. In model 5 we consider an interaction term between our marketing alliances indicator and the license indicator and find no discernible effect.

In the final model presented in Table 8, we drop the irrelevant firm characteristics. With alliance characteristics alone, the return to the R&D firm, and our equity interaction terms, we are able to achieve significant explanatory power as suggested by our adjusted R-square of .24.

Based on our part two cross-sectional analysis we can draw the following conclusions: 1) Equity participation is a significant feature of strategic alliances in the biopharmaceutical industry characterizing alliances resulting in the greatest value creation. 2) Licensing provisions are not as important as one might expect for technical alliances. These two results are robust to model specification. 3) It is more difficult to realize positive value creation for alliances targeting complex diseases. In fact, partners completing complex disease alliances realize significantly less value than partners

involved in noncomplex disease alliances. 4) Research and development alliances do not appear to yield significantly greater value creation relative to marketing alliances in this industry. 5) The market capitalization of neither the client firm nor the R&D firm appears to significantly affect the realization of gains by the R&D firm.

2.6 Conclusions and Recommendations for Future Research

From the first part of our analysis we draw the following conclusions: 1) Alliances between pharmaceutical and biotechnology firms create significant value for the R&D firm. We cannot, however, discern any significant value creation for the client firm, as evidenced by our event study analysis of 123 alliances. 2) In particular, R&D firms experience a higher percentage gain, averaging 4.40%, while client firms gain on average a statistically insignificant .39%. 3) In dollar terms, the R&D firms experience a mean level of value creation of $18 million. 4) In absolute terms, the total value gains from alliances in this industry are significantly larger than the average gains for the alliances considered in CKKM, which is consistent with their proposition that horizontal, technical alliances provide the best opportunities for value creation.

From the second part of our analysis, alliance characteristics appear to be much more important than firm characteristics for explaining the value gains that accrue to the R&D firms involved in the biopharmaceutical alliances. In particular, we find corroboration for Pisano's (1989) results regarding the importance of equity for R&D alliances. Also, consistent with the general predictions of CKKM, it may be the case that because the alliances in our sample are horizontal, technical alliances, they create value that on average exceeds the value gain of the CKKM sample of alliances. We also find results consistent with Lerner and Merges (1997) regarding early stage

alliances, in that R&D firms do not benefit as clearly from such alliances as their client firm partners. More importantly we confirm the importance of equity participation versus licensing provisions for alliances. We recommend that for future research, careful analyses of more homogeneous samples of alliances such as the one we examine here, will allow us to more clearly examine the sources of value creation from these increasingly prevalent interfirm transactions.

Table 1. Ten U.S. Companies with the Most Alliances from 1990-96

Company	Alliances	Annualized Shareholder Return (%)
Dow Chemical	142	5.4
Intel	130	32.6
Ford	127	16.2
Oracle	111	77.8
Westinghouse	107	-15.7
Bristol-Myers Squibb	***98***	**6.9**
Bell Atlantic	98	3.5
Eli Lilly	**94**	**3.8**
MCI	88	7.5
Merck	***86***	**16.8**

Source: Alliance Analyst (1997).

Table 2. Summary of Previous Empirical Research on Alliances

Author	Focus of Analysis	Data Sample	Key Variables	Measures of Performance	Conclusions
Parkhe (1993)	Alliance Structure => Performance	111 U.S.-based alliances in four two-digit SICs 1983-88	Payoffs, Perception of Opportunistic Behavior, and Shadow of the Future (behavioral transparency, frequency of interaction, and/or length of time horizon)	Survey assessment of how well the alliance "fulfilled strategic needs"	1. Payoffs are not that important. 2. Perception of opportunistic behavior is significant. 3. "Shadow of the future is significant.
Oxley (1997)	Appropriability Hazards => Alliance Structure	165 U.S.-based manufacturing alliances across all manufacturing industries, 1980-89	Horizontal technology transfer alliances are categorized as unilateral contractual agreements (licensing), bilateral contractual agreements (cross licensing & technology sharing), and equity-based alliances. These categories are related to the potential for appropriability hazards.	Level of hierarchy in the alliance or structure of the alliance	Greater potential for appropriability hazards leads to more hierarchical alliance structures.
Tucci (1996)	Partner Characteristics => Alliance Performance	121 European-based alliances in five industries related to information technology	Performance is correlated with measures of market, technical, and social overlap between the alliance partners.	Survey assessment of how well the alliance met each partners' goals	1. Market overlap negatively affects alliance performance. 2. Social overlap is weakly positively correlated. 3. Technical overlap and performance are not strongly linked.
Pisano (1989)	Equity Arrangements Key for R&D Alliances	195 U.S. and Foreign Biotech Alliances	Collaborative arrangements that involve R&D and broad scope have a higher probability of equity participation	The likelihood of equity participation	Complex collaborations in biotechnology involve equity participation.
Chan, et al. (1997)	Alliance Structure => Performance	345 strategic alliances in twenty industries, 1983-92	Horizontal and technical structures of alliances are correlated with alliance performance.	The abnormal returns in response to alliances	Abnormal returns are positively correlated with horizontally structured and technical alliances.

Table 3. Alliance Dataset Inclusion Criteria

Reason Excluded	*Transactions Excluded*	*Total*
Initial observations (all transactions from 1/1/95-7/30/97)[1]	-----	1400
Transactions Classified as Non-alliance Agreements	700	700
Observations With University or other Nonprofit Research Organization	500	200
Limit Firm1 significant news 15 days prior to event[3]	26	174
Limit Firm2 no significant news 15 days prior to event[3]	17	157
Firm1 Publicly traded 90 days prior to event[4]	12	145
Firm1 Publicly traded 90 days post event[4]	1	144
Firm2 Publicly traded 90 days prior to event[4]	18	126
Firm2 Publicly traded 90 days post event[4]	3	**123**

1-Recombinant Capital's database as of 3/31/97 (www.recap.com)
2-Sloan Research database (risk.mit.edu:8080)
3-Dow Jones News Retrieval Service using: *The Wall Street Journal, Investors Business Daily, & BioWorld*
4-Initial date of trading based on information provided by the CRSP database. Actual event date determined using Dow Jones sources: *The Wall Street Journal, Investors Business Daily, & BioWorld*

Table 4. Alliance Transactions

No.	Client Firm	R&D Firm	date
1	Genentech Inc	Scios Inc	01/04/95
2	Genentech Inc	Alkermes Inc	01/10/95
3	Roberts Pharmaceutical Corp	Columbia Laboratories Inc	01/10/95
4	Genentech Inc	I D E C Pharmaceuticals Corp	03/17/95
5	Enzo Biochem	Xoma Corp	05/08/95
6	Neorx Corp	Genzyme Transgenics Corp	05/17/95
7	Lilly Eli & Co	Scherer Rp Corp	05/17/95
8	Dura Pharmaceuticals Inc	Colorado Medtech Inc	06/22/95
9	Sheffield Medical Techs Inc	Hemagen Diagnostics Inc	12/21/95
10	Abbott Labs	Cytel Corp	01/02/96
11	Hycor Biomedical Inc	Novitron International Inc	01/04/96
12	Cantab Pharmaceuticals	Ribi Immunochem Resh Inc	01/04/96
13	Hoffmann-La Roche	Genentech	01/18/96
14	Smithkline Beecham Plc	Penederm Inc	01/24/96
15	Syncor International Corp De	Cypros Pharmaceutical Corp	02/02/96
16	Bristol Myers Squibb Co	Cephalon Inc	02/21/96
17	Baxter International Inc	Inhale Therapeutic Systems	03/05/96
18	Glaxo Wellcome Plc	Quidel Corp	03/07/96
19	Teva Pharmaceutical Inds Ltd	Advanced Polymer Systems Inc	03/12/96
20	Teva Pharmaceutical Inds Ltd	Cortecs International Ltd	03/21/96
21	Mallinckrodt Inc New	Immunomedics Inc	04/09/96
22	Genentech Inc	Xoma Corp	04/22/96
23	Genentech Inc	Xoma Corp	05/13/96
24	Abbott	Sonus Pharmaceuticals	05/15/96
25	Monsanto Company(Searle)	Cocensys Inc	05/21/96
26	Novo Nordisk A S	Scios Inc	05/30/96
27	Glaxo Wellcome Plc	Smithkline Beecham Plc	06/06/96
28	Rhone Poulenc Rorer Inc	Guilford Pharmaceuticals Inc	06/14/96
29	Zeneca Group Plc	Incyte Pharmaceuticals Inc	06/17/96
30	Medtronic Inc	Regeneron Pharmaceuticals	06/27/96
31	Schering AG	Incyte Pharmaceuticals	07/08/96
32	Procter & Gamble	Advanced Polymer Systems	07/09/96
33	Bayer	Immune Response	07/09/96
34	Merck	Genome Therapeutics	07/10/96
35	SmithKline	Cantab Pharmaceuticals	07/18/96
36	Sequus	Sheffield Medical Technologies	07/19/96
37	C R Bard	Cytogen	08/01/96
38	Roche Molecular Systems	NeXstar	08/02/96
39	Schering-Plough	Biogen	08/08/96
40	Pharmacia	Gilead	08/08/96
41	Abbott	North American Vaccine	08/15/96
42	Neoprobe	Biomira	08/19/96
43	Pharmacia	Miravant	08/28/96
44	Texas Biotechnology	Structural Bioinformatics	09/05/96
45	Roche Molecular Systems	Perkin-Elmer	09/10/96
46	Chiron	Genetics Institute	09/25/96

Table 4. Alliance Transactions

No.	Client Firm	R&D Firm	date
47	Genentech	Genetics Institute	09/25/96
48	Schering-Plough	Sequus	09/25/96
49	Hoffmann-La Roche	Gilead	09/30/96
50	Nextran	Cytel	10/01/96
51	Janssen	Elan	10/07/96
52	Allergan	Sugen	10/08/96
53	Regeneron	Pharmacopeia	10/10/96
54	Bristol-Myers Squibb	Cortecs	10/21/96
55	Hoffmann-La Roche	Protein Design Labs	10/28/96
56	Medicis Pharmaceutical	Advanced Polymer Systems	10/29/96
57	Merck	Scherer R.P.	11/01/96
58	Bayer	Quidel	11/05/96
59	Merck	Axys Pharmaceuticals	11/14/96
60	SmithKline	Molecular Dynamics	11/19/96
61	Bayer	Fuisz Technologies	11/25/96
62	Genentech	Cyto Therapeutics	11/26/96
63	Wyeth-Ayerst	Neurogen	11/26/96
64	Astra AB	Fuisz Technologies	12/09/96
65	Procter & Gamble	Regeneron	12/12/96
66	Lilly	Incyte Pharmaceuticals	12/18/96
67	Knoll	Intercardia	12/19/96
68	Schering-Plough	Genome Therapeutics	12/23/96
69	Abbott	La Jolla Pharmaceutical	12/23/96
70	Schering-Plough	Corvas International	01/08/97
71	Roche Bioscience	Affymetrix	01/09/97
72	Boston Scientific	Cardio Genesis	01/22/97
73	Wyeth-Ayerst	Biomatrix	02/10/97
74	SmithKline	Magainin	02/13/97
75	Alza	Alkermes	02/13/97
76	SmithKline	Cadus Pharmaceutical	02/27/97
77	Lilly	Emisphere Technologies	02/27/97
78	SmithKline	Penederm	04/08/97
79	SmithKline	Alza	04/14/97
80	Amerisource HealthCorp	Cholestech	04/16/97
81	SmithKline	Medi-Ject	04/16/97
82	Agouron	Nastech Pharmaceutical	04/21/97
83	Procter & Gamble	Regeneron	05/13/97
84	BioChem Pharma	NeoPharm	05/14/97
85	Zeneca	Molecular Dynamics, Nycomed Amersham	05/15/97
86	NABI	Baxter	05/21/97
87	Genentech	Dura Pharmaceuticals	05/29/97
88	Abbott	Scios	05/29/97
89	International Murex Technologies	Genelabs	06/01/97
90	SchererRP	Advanced Polymer Systems	06/18/97
91	Novartis	Incyte Pharmaceuticals	06/19/97
92	MatrixMedicalBV	Osteotech	06/30/97
93	OSIPharmaceuticals	Xenometrix	07/01/97
94	Wyeth-Ayerst	ArQule	07/10/97

Table 4. Alliance Transactions

No.	Client Firm	R&D Firm	date
95	Schering-Plough	Alliance Pharmaceutical	07/21/97
96	Abbott	Genset	07/28/97
97	US Surgical	Seragen	08/01/97
98	Schering-Plough	Aphton	08/03/97
99	Bristol-Myers Squibb	Genzyme Transgenics	08/09/97
100	Abbott	Procept	08/13/97
101	Roche Molecular Systems	Visible Genetics	08/20/97
102	Chiron	Molecular Dynamics	08/22/97
103	IDEC Pharmaceuticals	Protein Design Labs	09/09/97
104	Bristol-Myers Squibb	Genome Therapeutics	09/16/97
105	Alza	IVAX	09/18/97
106	SmithKline	Aradigm	10/01/97
107	Alza	Alkermes	10/06/97
108	Glaxo	Quidel	10/06/97
109	Novartis	BioTransplant	10/07/97
110	Novartis	Tcell Sciences	10/15/97
111	Neurocrine Biosciences	SIBIA	10/22/97
112	Repligen	Tcell Sciences	10/30/97
113	Faulding	Gensia Sicor	11/05/97
114	Schering-Plough	Zonagen	11/17/97
115	TexasBiotechnology	Pharmacopeia	11/20/97
116	Novartis	Titan Pharmaceuticals	11/20/97
117	Amgen	SangStat	12/02/97
118	Merck	Biogen	12/03/97
119	Procter & Gamble	TheraTech	12/03/97
120	Genentech	Alteon	12/04/97
121	Schering-Plough	Sepracor	12/08/97
122	Novartis	Affymetrix	12/11/97
123	Rhone-Poulenc Rorer	Incyte Pharmaceuticals	12/22/97

Table 5. Summary Statistics for Variables

Variable Name	Mean	Standard Deviation	Predicted Sign for Effect on Alliance Value
Partner Firm Attributes:			
Market Cap of Client Firm	$22.9 Bn	$25.8 Bn	+
Market Cap of R&D Firm	$1.35 Bn[47]	$5.33 Bn	+
Combined Market Cap	$24.2 Bn	$26.4 Bn	+
Net Sales of Client Firm	$8.7 Bn	$9.6 Bn	+
Net Sales of R&D Firm	$452 Mn	$2.1 Bn	+
Total Assets of Client Firm	$11 Bn	$11.9 Bn	+
Total Assets of R&D Firm	$683 Bn	$3.0 Bn	+
R&D, Client	$857 Mn	$782 Mn	+
R&D/Sales, Client[48]	.49	1.55	+
R&D/Sales, R&D Firm	3.76	14.2	+
Net Income, Client Firm	$1.1 Bn	$1.1 Bn	+
Net Income, R&D Firm	$44.6 Mn	$273 Mn	+
Total Stock Return, Client	.30	.60	-
Total Stock Return, R&D	.37	.89	+
Alliance Attributes:			
License Indicator	.76	.43	+++
Equity Indicator	.22	.41	+++
Complex Disease Indicator	.26	.44	---
Early Stage Indicator	.43	.50	---
Type of Alliance: Research, Development, Marketing	.23, .24, .53	****	Research>Development> Marketing
Size of Deal (available for 56 of 123 alliances)	$42 Mn	$39 Mn	+++
Indicator for More Recent Alliances (Year = 1997)	.435	.497	+
Interaction Terms:			
Equity * Res & Dev Agmts	.171	.378	+
Equity * Early Stage	.114	.319	+
Equity * Complex Disease	.073	.261	+
License * Marketing	.155	.363	+
Number of Observations	123	****	****

+ denotes expected positive correlation; - denotes expected negative correlation.

[47] The mean market capitalization for the significantly smaller R&D firms in our sample does not effectively convey the significant skewness in the distribution for this variable among the R&D firms. The median market capitalization for our R&D firms is much smaller at only $181 million.

Table 6A. Average and Cumulative Abnormal Returns for 123 Alliances.

Event Window	R&D Firm Means/ Medians	R&D Firm Max/Min	Proportion of Positive ARs/Significant ARs	Client Firm	Proportion of Positive ARs/Significant ARs
3 Day	.044/.023	.525/-.277	67%/13%	.0037	55%/6%
11 Day	.036/.019	.571/-.330	55%/9%	-.0049	47%/3%
21 Day	.027/.006	.587/-.463	51%/8%[49]	.0020	45%/6%
3 Day Aggregate t-statistic	10.04**	-----	-----	1.25	-----
11 Day Aggregate t-statistic	8.23**	-----	-----	-1.66	-----
21 Day Aggregate t-statistic	6.06**	-----	-----	0.67	-----

** Denotes $p < .05$.

Table 6B. Dollar Value Gains for R&D, Client Firms, and Alliances as a Whole.

(in millions of 1996 $s)

	Mean	Standard Deviation	Maximum	Minimum	Number > 0	Proportion>0
R&D Firm Gain	21.4	93	927	-125	82	67%
Client Firm Gain	149.4	1304	11,845	-3,024	67	55%
Total Alliance Gain	170.8	1257	11,918	-3,056	71	58%

Table 7. CARs & Mean Dollar Value CARs in Comparison to Related Studies

Study	Smaller Partner (% CAR/$ CAR)	Larger Partner (% CAR/$ CAR)
CKKM (1997)	2.22%/$8.9 Mn**	0.19%/$8.1 Mn
M&N (1985)	1.10%/$4.5 Mn**	0.63%/$6.6 Mn**
Ravenscraft & Long (1997)	13.31%/$320 Mn**	-2.12%/-$40 Mn
Rodriguez (1998)	**4.40%/$18 Mn****	0.36%/$131 Mn

** Denotes $p < .05$.

[48] Note that in addition to R&D/Sales ratios, we also employed alternative measures for research intensity such as R&D/Total Assets and R&D/Market Value ratios. These alternative measures for research intensity are particularly useful for biotech firms that have zero sales and high R&D.

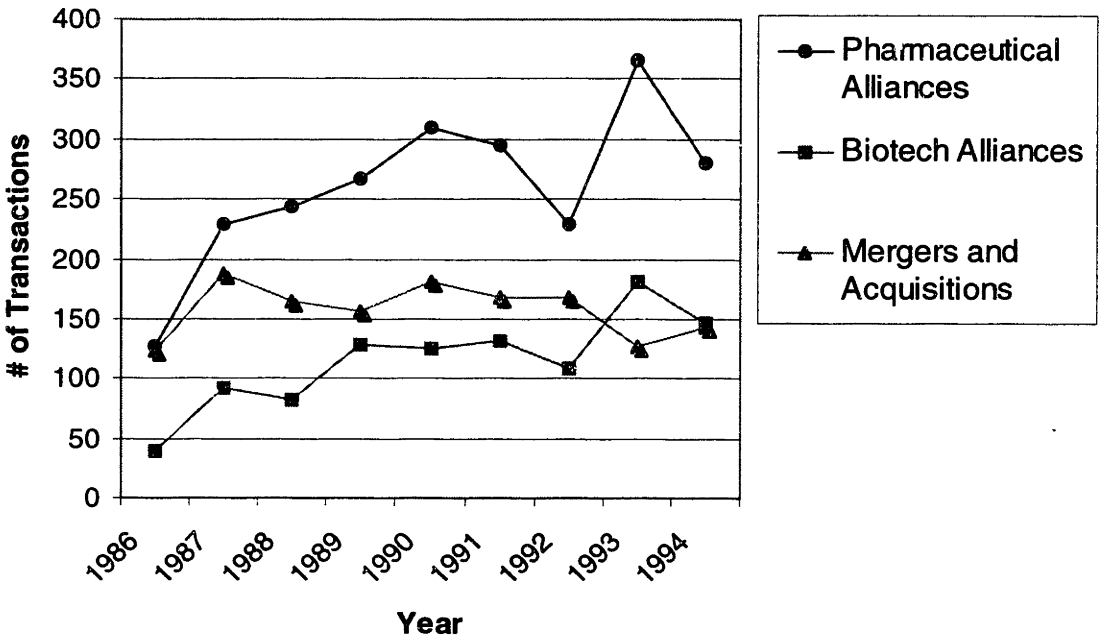
[49] Note that even though only 51% of the observations exhibit positive abnormal returns over the 21-day event window, the positive observations are much larger on average than the negative observations. The graph in Figure 2 provides a perspective on this. There are 30 observations with cumulative abnormal returns greater than 10%, while only 2 observations with cumulative abnormal returns less than –10%. So leaving out a couple of outliers on the positive side does not change our results appreciably.

Table 8. Cross-Sectional Results for CAR of R&D Firm.
(t-statistics in parentheses)

Model :	1	2	3	4	5	6
Constant Term	0.0312	0.0213	0.0446	0.0247	0.0444	0.0155
	(0.99)	(0.73)	(1.50)	(0.86)	(1.28)	(0.65)
R&D Firm Size	0.0000	0.0000	0.0000	0.0000		
	(-0.22)	(-0.53)	(-0.64)	(-0.53)		
R&D Firm Size^2	0.0000	0.0000	0.0000	0.0000		
	(0.14)	(0.47)	(0.53)	(0.34)		
Client Size	0.0000			0.0000		
	(-0.67)			(-0.79)		
Client Size^2	0.0000			0.0000		
	(0.26)			(0.32)		
Client R&D	-0.0022	0.0000	-0.0002	-0.0022		
	(-0.31)	(0.00)	(-0.03)	(-0.70)		
Equity	0.0723	0.0725	0.0695	0.0787	0.0742	0.0884
	(2.86)**	(2.89)**	(2.84)**	(1.65)**	(3.19)**	(2.03)**
License	0.0069	0.0043	0.0104	0.0279	0.0170	0.0263
	(0.27)	(0.17)	(0.42)	(1.18)	(0.57)	(1.17)
Early Stage	-0.0384	-0.0407	-0.0342	-0.0093	-0.0281	-0.0342
	(-1.54)	(-1.65)	(-1.40)	(-0.38)	(-1.22)	(-1.36)
Complex Disease	-0.0601	-0.0566	-0.0554	-0.0217	-0.0556	-0.0207
	(-2.47)**	(-2.34)**	(-2.36)**	(-0.85)	(-2.48)**	(-0.82)
Research Alliance	0.0472	0.0422	0.0204	-0.0061	0.0027	0.0204
	(1.26)	(1.13)	(0.55)	(-0.17)	(0.05)	(0.68)
Development	0.0288	0.0258	0.0139	-0.0088	-0.0035	0.0139
	(1.04)	(0.94)	(0.51)	(-0.31)	(-0.08)	(0.53)
Year = 1997	0.0349	0.0366	0.0265	0.0197	0.0275	0.0196
	(1.62)	(1.73)*	(1.27)	(1.03)	(1.39)	(1.04)
Return Client			-0.0105			-0.0105
			(-0.66)			(-1.25)
Return R&D Firm			-0.030	-0.0251	-0.0301	-0.0243
			(-2.62)**	(-2.29)**	(-2.69)**	(-2.29)**
R&D Alliance*Equity				0.0951		0.0875
				(1.68)*		(1.78)*
Early Stage*Equity				-0.0830		-0.0920
				(-1.72)*		(-2.23)**
Complex Disease*Equity				-0.1284		-0.1297
				(-2.62)**		(-2.70)**
Marketing Alliance * License					-0.0176	
					(-0.35)	
Adj. R-square	0.082	.087	.135	.219	.155	.238
# obs	112	112	112	112	112	112

* denotes significance at the 10% level.
** denotes significance at the 5 % level.

Figure 1. Alliances and Merger and Acquisition Activity in the Pharmaceutical Industry



Source: *Windhover's Pharmaceutical Strategic Alliances* (1996).
* Note that the pharmaceutical alliances category represents the number of alliance transactions involving conventional drug products, and the biotech alliances trend represents the number of alliance transactions involving drug product derived from biotechnology. The mergers and acquisitions category represents all such transactions involving pharmaceutical and biotechnology firms involved in the research and development of new drug products.

Figure 2. Histogram of CARs for R&D Firms.

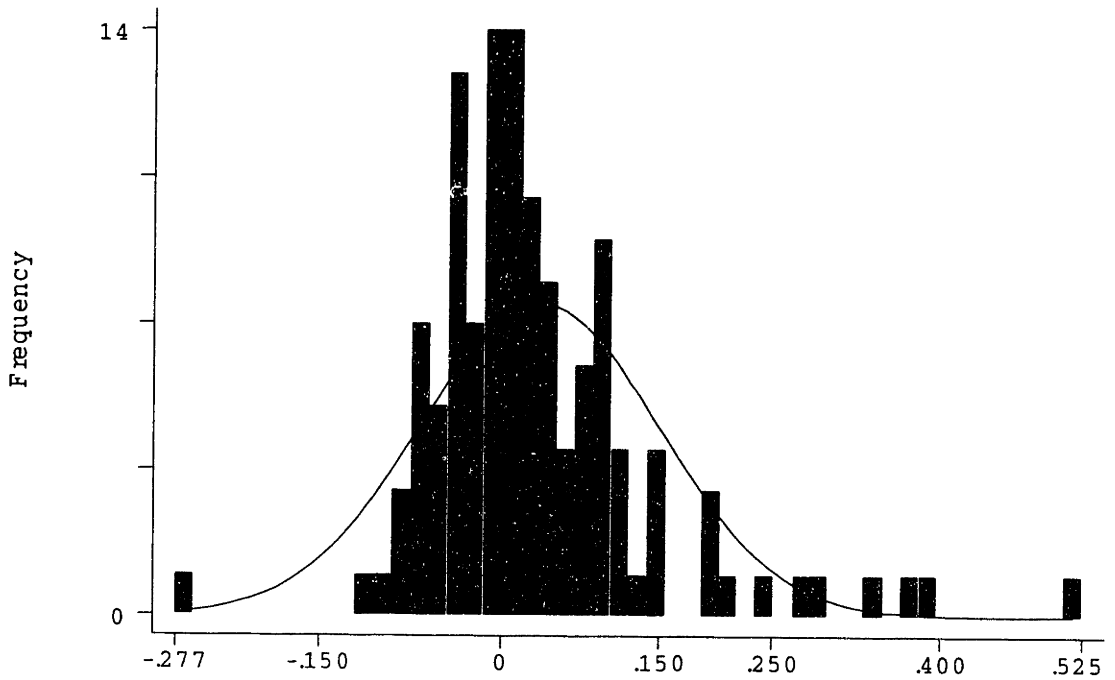
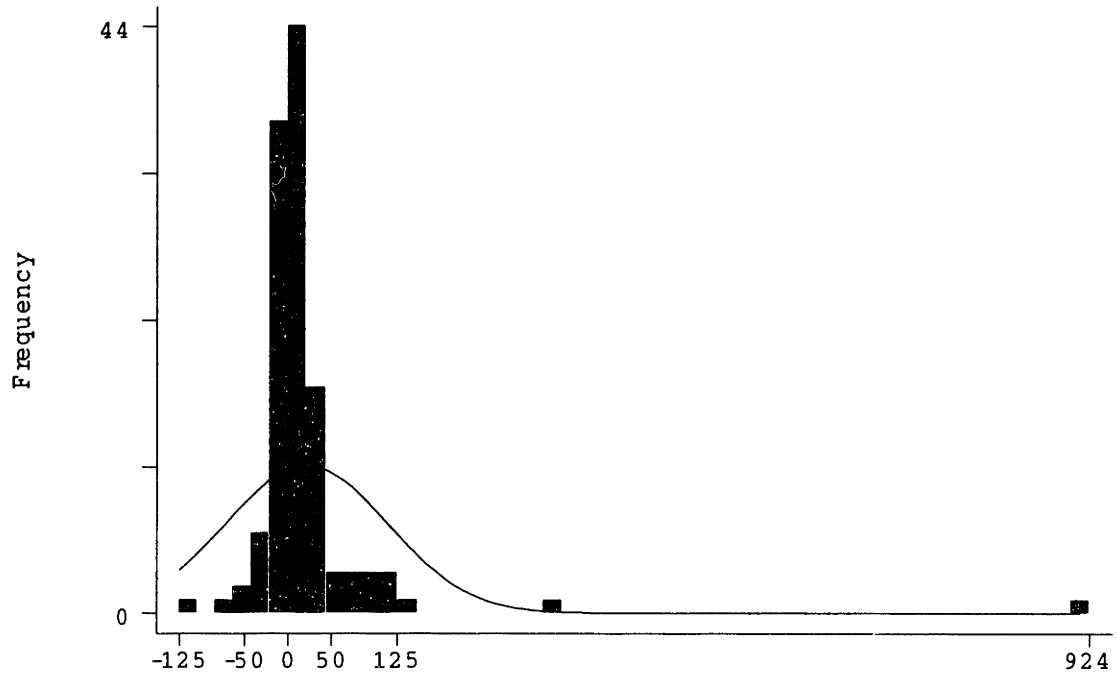


Figure 3. Histogram of Dollar Gains for R&D Firms.



Chapter 3

Decisions of Pharmaceutical Firms for New Product Development

This paper examines the new product development decisions of firms in the pharmaceutical industry over the period 1985-96. Firms choose from a variety of development alternatives. The traditional and predominant development process in this industry has been integrated or in-house development. More recently, however, firms have undertaken non-integrated routes for new drug development. These less integrated methods include: (1) Development via a merger or acquisition, (2) Development through a joint venture or strategic alliance, and (3) Development with a patent license. Strategic alliances and joint ventures in particular have attracted increased attention in the trade press. This paper describes an economic model that incorporates the most important considerations influencing an innovator's choice among these alternatives, and derives estimable equations for this development decision.

We are able to consider the impact of several firm and drug characteristics correlated with uncertainty, asymmetric information, appropriability, and potential synergies upon new product development decisions. We find that a firm's patent stock, number of previous approved drugs and the complexity of the disease that a new product targets significantly affect the decision process. Additionally, contrary to what has been portrayed in the popular press, after controlling for firm and drug characteristics, we do not observe a significant industry shift towards non-integrated development of *marketed drug products* through the end of 1996. These findings are robust to a variety of model specifications.

3.1 Introduction

On March 29, 1991, Chiron Corporation received a product license approval (PLA) from the Food and Drug Administration (FDA) to market its Hepatitis B vaccine, which achieved over $200 million in revenues in the year immediately following its introduction. The significance of this new product introduction was not that it derived from a biotech firm, but that industry giant Merck, well-known for its own innovative prowess, had guided the product through the costly clinical trials, in partnership with Chiron. Shortly after this successful venture, Merck allied itself with Repligen, Inc., in an even more costly effort ($20m in R&D, in addition to complete clinical trial financing and marketing) to market the first human immuno-deficiency virus (HIV) vaccine. In addition to its partnership with Repligen, to hedge its efforts, Merck also licensed a complementary vaccine technology, Bacillus Calmette Guerin (BCG) from MedImmune, Inc. Such a strategy on the part of an industry leader who has been perceived as rather self-reliant in the area of R&D is particularly noteworthy, given Merck's own historical success in new product introduction.[50] More recently (October 1996), a relatively small biotech firm, Onyx Pharmaceuticals, in a joint venture with German giant Bayer, initiated Phase II trials of a mutant adenovirus that had been genetically engineered to kill cancer tumors resistant to chemotherapy. The common characteristic of these major advances in drug therapy is their multi-firm nature.[51]

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[50] Over the period 1964-94, for instance, Merck received approval for 52 new molecular entities, according to drug approval data from the FDA, second only to Wyeth-Ayerst Labs, who received approval for 64 such products. Merck led the way, however, with 33 priority-ranked products vs. 24 for Wyeth-Ayerst. Priority-ranked products are those products that the FDA has ranked as providing a significant therapeutic advance over previously approved remedies.

[51] This contrasts with the following characterization of the pharmaceutical industry made ten years ago by Thomas (1988: 173): "The most striking feature of corporate structures in the modern pharmaceutical industry is the extensive vertical integration between innovation, manufacture, and marketing of new drugs."

During this same five-year period (1991-96), however, we have had the introduction of numerous products through in-house development routes. In particular, in 1994, venlafaxine hydrochloride, a successful antidepressant, was brought to market by American Home Products from its wholly owned subsidiary, Wyeth-Ayerst labs. Merck and Pfizer have brought several successful products to market during the 1991-94 period, from completely in-house sources.[52] Despite the growing number of products being developed via alliances, the majority of products still arrive at the marketplace primarily from in-house development.

Mergers and acquisitions have also been undertaken for the purpose of bringing specific new drug products to market. Three relatively recent examples of this strategy are: (1) The Hoechst $7.12 billion cash acquisition of Marion Merrell Dow in 1995, (2) The UpJohn and Pharmacia merger, a $6.32 billion stock swap deal announced in August of 1995, and (3) The Roche acquisition of Syntex for $5.3 billion, which was completed in October 1994. In these transactions, Hoechst, UpJohn, and Roche explicitly moved to address weak pipelines of new drug products. Since these transactions, the resulting companies have received FDA approval for nine new products.[53] In addition to these examples of acquisition-focused development strategy, there are firms such as Merck and the biotechnology giant, Genentech, which have pursued a diversified development strategy by proceeding with both in-house and external new drug development. This shift in Genentech's development strategy was

[52] Merck brought to market Zocor, while Pfizer brought to market Zithromax and Norvasc.
[53] Hoechst Marion Rousell obtained approval for Allegra and Amaryl. Pharmacia and UpJohn received approval for five new products, while Roche-Syntex received two new drug approvals.

prompted by a negative experience with Eli Lilly.[54] Genentech chose to develop its last ten products through a combination of in-house means, joint ventures, and patent licenses, where five products were developed via the in-house route, and five products were developed through non-integrated means. These examples demonstrate the diversity of development of new drug products.

Given the variety of methods by which pharmaceutical firms can bring new products to market, it is interesting to ask what economic considerations drive these important development decisions. This decision process involves numerous considerations. We focus our analysis on measurable variables that are correlated with the factors suggested by current economic theory as the most relevant for the development of new products. The variables in our analysis derive first, from firm characteristics such as firm size, patent stock, previous approved drugs, publicly traded status, and reliance on drug sales. Secondly, the analysis draws upon drug characteristics such as the disease category, year of patent approval, and whether the drug requires biotechnology or originated from a foreign patent. We then examine the question of how firms organize new product development by considering the relationship between firm and product characteristics and the firm development decision.

This question is particularly interesting in light of recent trends observed by the trade press that innovating firms in the pharmaceutical industry have increasingly turned to multi-firm strategies to get their new drug products to market.[55] Given this observed

[54] Eli Lilly was charged with using Genentech's technology acquired through a restricted patent license for the development of other drug products to compete directly with Genentech. Rather than undergo judicial proceedings, Eli Lilly settled with Genentech out of court.

[55] Sugawara (1992:C1) observes that "A decade ago, in the early days of biotechnology, some enthusiasts predicted that the little companies then emerging around the new technology would soon grow into major operations that would challenge the huge pharmaceutical companies by making many of

trend, we can then ask, is this trend due to *organizational adaptation* by firms in the industry to changing *economic conditions* and *technological focus*, and does this portend a new optimal strategy for R&D and new product development?

Due to the complexity of these questions and the availability of data, we choose to focus on one specific industry, the pharmaceutical industry. Since new biological drug products are in direct competition with conventional drug products, we define the pharmaceutical industry to include human therapeutic products produced by biotech firms as well.[56] Of the various new drug products introduced to the market, we focus our attention on new molecular entities (NMEs), the most innovative of the newly marketed products.[57] We then analyze the process by which these new products ultimately obtain FDA approval in the form of a new drug application (NDA) approval. During the first few decades following the seminal 1964 Drug Act, new drug products were primarily brought to market through integrated means.[58] Over the past decade or so, this appears to be changing. *Windhover's Pharmaceutical Strategic Alliances* (1994), for example, reports that between 1986 and 1994, the total number of strategic alliances involving prescription drugs rose from 125 to over 400. In 1995, 170 strategic alliances involved biotech companies alone. The recent merger and acquisition wave in the industry is well

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their chemical drugs obsolete. But as a series of alliances between established pharmaceutical companies and financially strapped biotech companies suggests, things have not turned out that way."

[56] We do not include biotech products produced for agriculture, plasma substitutes, or veterinary uses because those products are irrelevant for our analysis of new drug development for the human therapeutic market.

[57] The FDA differentiates new molecular entities (NMEs) from "me-too" drugs to determine their allocation of resources for application processing. NMEs receive greater emphasis, because of their potential contributions to the current state of drug therapy. Note that we also include new biological entities (NBEs) in our analysis as well.

[58] See Temin (1980) for a detailed description of how FDA regulations biased new drug development towards large integrated firms.

documented, with about 700 transactions between 1990 and the end of 1996.[59,60] We examine a dataset comprised of over 300 new drug products (to include those products derived from biotechnology) introduced into the U.S. pharmaceutical market from 1985-96, which consists of 318 new drug approvals (NDAs) and 45 product license approvals (PLAs). These data are used to describe the trends in the industry toward multifirm strategies and identify the most significant determinants of these trends.[61] Our analysis addresses several questions regarding this increasing tendency toward non-integrated development. In particular, after controlling for firm and drug characteristics do we still see non-integrated R&D strategies manifesting themselves in newly marketed drug products?

Our findings indicate that several recent trends in the industry that have affected the relative benefits and costs of each of these development routes have not moved the industry toward non-integrated development as evidenced by *successfully introduced products.*[62] This is surprising given the significant synergies that appear to exist between more specialized research intensive firms and the larger established firms experienced at negotiating the lengthy and costly FDA approval process. It is not such a surprising result when one considers that this transition in the organization of R&D is

[59] The source for these transactions are the *Investor's Dealer's Digest* (*1990-95*) and the *Merger Yearbook (1990-95).* The vast majority of these transactions, however, have occurred for reasons other than product development, although in many instances it is difficult to distinguish this category from fully integrated development after transactions are consummated.
[60] See Ravenscraft and Long (1997) for a recent analysis of some of these mergers.
[61] We define the pharmaceutical industry as those firms engaged in the production or research for the production of conventional pharmaceutical products and therapeutic biotechnology products. Restricting biotechnology products to the class of therapeutic products is important, since the broader category includes plant and diagnostic products as well.
[62] We discuss in greater detail the impact of focusing our analysis on FDA approved products in Section IV, our data section.

most likely a difficult and lengthy process. These results remain after controlling for firm characteristics and drug characteristics in a variety of specifications.

One trend that one might expect to move the industry towards less integrated development is the general acceptance of the validity of biotechnology products. As a technology shock reducing the minimum efficient scale for firms, the increasing efficacy of biotechnology has made research-focused biotechnology firms viable.[63, 64] These research-focused firms might then turn to larger drug companies for assistance in development to continue their specialization. Another relevant industry trend that has coincided with this one has been the increased price competition due to regulatory changes and the rise of managed health care. The proliferation of generic drugs and the increased exclusivity for new products due to the 1984 Drug Amendments have increased the returns to efficient research. This increase in returns may in some cases have encouraged the specialization that has continued to encourage the entry of smaller research-focused firms into the biotechnology industry.

Another regulatory change occurred in 1984 to spur the formation of joint ventures. Joint ventures were specifically encouraged by the National Cooperative Research Act of 1984, which was passed to encourage joint research and development ventures.[65] Additionally, new technology in the field of drug discovery such as genomic technology and combinatorial chemistry has continued to favor less scale-intensive and more specialized research over the traditional research methods of established firms. Despite

[63] Williamson (1979: 254) reasons that "To the extent that uncertainty decreases as an industry matures, which is the usual case, the benefits that accrue to integration presumably decline."
[64] On the penetration of biotech therapeutic products into the pharmaceutical industry see Bienz-Tadmor et al. (1992), who document that, "Overall, biotechnology drugs succeed clinically at a considerably higher rate and within less time than do conventional drugs."

these trends, the failed acquisitions of biotech companies by pharmaceutical firms, high profile biotechnology-derived drug product failures to combat sepsis, and other factors which have continued to make technology transfer difficult in this industry, appear to have significantly slowed the adoption of the non-integrated R&D strategy until very recently.[66]

The major findings resulting from our analysis are: (1) The size of the discovering firm (as measured by revenues, market capitalization, or access to capital markets) is strongly correlated with a propensity towards integrated development, (2) A firm's previous patenting expertise (which we use to proxy for asymmetric information) is correlated with a propensity towards non-integrated development, (3) A firm's previous drug development experience is positively correlated with a propensity towards integrated development, and (4) New drugs in difficult disease categories (such as cancer, cardiovascular, and central nervous system [not depression]) tend to be developed in-house.

Before proceeding with a description of the basic model employed in our analysis, we provide a survey of the relevant literature in Section II. Following our description of the drug development process in Section III and a justification for the variables that we consider we describe the data with summary statistics in Section IV. In Section V, we discuss our estimation procedures and results. Section VI considers several plausible

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[65] Specifically, Public Law 98-462 was passed on October 11, 1984, shortly after the 1984 Drug Amendments to "promote research and development, encourage innovation, stimulate trade, and make necessary and appropriate modifications in the operation of antitrust laws."

[66] Longman (1994) describes the well-known failed biotech acquisitions in 1985 by industry giants Eli Lilly (who acquired Hybritech for $375 million) and Bristol-Meyers (who acquired Genetic Systems Corp. for $250 million), due to the departure of essential scientists and managers following these acquisitions. In the words of many observers, these acquisitions were utter failures, because the embodiment of the target firms' value "walked out the door."

interpretations of our results. Section VII concludes by identifying the implications of our results for future drug development and discusses future related research.

3.2 Survey of the Literature

We conduct this survey in two parts. The first part considers the most relevant theoretical literature, and the second reviews the most relevant empirical literature. The question of R&D outsourcing for new product development in the pharmaceutical industry addressed in this paper derives from the central question about the optimal firm organization for research and development. Schumpeter (1942), who asserted that large firms were the "most powerful engines of progress," was on of the first economists to address this question. His assertion was based on the following four assumptions: (1) Capital market imperfections yield an advantage to large firms in obtaining financing for risky R&D projects, (2) There exist scale economies in the technology of R&D, (3) The returns from R&D are higher when the innovating firm has a greater sales volume over which to spread the fixed cost of R&D, and (4) R&D is more productive in large firms because of synergies between R&D and other non-manufacturing activities.[67] Two decades later, Arrow (1962) provided additional support for this view. In that seminal paper, Arrow refers to research as a "risky process" against which there is "bound to be some discrimination." In particular, "The only way, within the private enterprise system, to minimize this problem [of discrimination against worthy risky projects] is the conduct of research by large corporations with many projects going on, each small in scale compared with the net revenue of the corporation." Arrow's perspective at that time is

[67] See Cohen and Levin (1989:1067) for a review of the extensive literature examining the relationship between firm size and innovation.

consistent with the R&D we observed in the pharmaceutical industry over the period 1964-84. During this period, the industry's largest fully integrated pharmaceutical firms introduced the vast majority of new drug products.[68] We can appropriately refer to this period as the era of *integrated new product development.*

This prescription for the organization of R&D, however, appears to be inconsistent with more recent R&D in the industry. Arrow (1983) discusses the relationship between communication channels and the "capital-allocation mechanism" within firms conducting R&D. In this more recent analysis, Arrow modifies his earlier stance on the organization of R&D. Arrow decomposes R&D into a two-stage process requiring first research expenditures to determine the feasibility of a project and secondly, development expenditures to complete the project. He argues that the efficiency of communication about "novel ventures" will be superior in small firms because of their proximity to the technical aspects of the ventures. Researchers in such firms are simply closer to the resource allocation decision. Additionally, small-firm researchers are not influenced by incentives that may adversely affect resource allocation decisions in larger, more bureaucratic firms.[69] Large firms, however, still retain an advantage in financing that suggests that "large firms will be superior if [development] costs are large." Development costs in the United States pharmaceutical market are significant indeed,

[68] Between 1964-83 there were 92 firms responsible for the 383 new molecular entities approved by the FDA, whereas between 1984-94, there were 87 firms responsible for the 294 new molecular entities approved by the FDA.

[69] For instance, consider that in large pharmaceutical firms, research scientists gain in stature when their proposed projects are developed beyond the initial stages regardless of whether or not it yields a marketable product. This manifestation of the standard agency problem suggests particularly high agency costs due to the inherent risky nature of new drug research. Specifically, research activities are particularly difficult to monitor and their risky nature makes the efficient risk-sharing incentive tradeoff acute.

usually comprising up to two-thirds of the total cost to bring a new drug to market.[70] These arguments generally support the current strategy in the pharmaceutical industry that we refer to as the *specialization strategy*.[71]

Another classical perspective on the location of R&D among firms comes from the transaction cost economics literature. Beginning with Coase (1937) who stated that "transactions will be organized in the firm when the cost of doing this is lower than the cost of using the market," and continuing with Williamson (1975,1985), this theoretical approach focuses upon the costs and benefits of integrated versus non-integrated transactions. The primary assumptions underlying the modern version of this theory are that firm managers behave opportunistically and with bounded rationality. Because of this type of behavior, firm organizations which "economize on bounded rationality" and "safeguard transactions against the hazards of opportunism will be favored and will tend to displace inferior modes in these respects."[72] In this theory, transactions are represented in three crucial dimensions: (1) The frequency with which they occur, (2) The degree and type of uncertainty (in particular, that derived from systematic or nondiversifiable risk)[73] to which they are subject, and (3) The condition of asset specificity (the degree to which an asset can be redeployed to alternative uses and by alternative users without sacrifice of productive value). Internal organization rather than

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[70] DiMasi, et al. (1991:121) estimates that pre-NDA development costs exceeded $20 million (1987 dollars) on average.

[71] We refer to this as the "current strategy" because of the frequent reference made to the significance of outsourcing in the pharmaceutical industry. The Pharmaceutical Manufacturers Research Association (1997) estimates that a full 20% of all industry R&D expenditures in 1996 was outsourced (that is $6 billion of $30 billion).

[72] See Williamson (1989) for a recent and concise, but detailed exposition of transactions costs economics. For a more comprehensive discussion, see Williamson (1985).

[73] See Helfat and Teece (1987) for empirical support of the assertion that internal organization (vertical integration) reduces a firm's exposure to systematic risk. They analyze U.S. firms involved in vertical mergers between 1948 and 1979 inclusive, as reported by the Federal Trade Commission, and find a significant reduction in the asset betas following vertical merger transactions.

discrete market contracting best governs transactions characterized by high frequency, a high degree of uncertainty, and requiring investment in transaction-specific assets. The initial transaction cost approach, however, does not explain why vertical integration, which reduces transaction costs, will not always be the preferred firm organization. Nor does this approach give an operational definition of integration.

Following the increased attention to transaction costs and the recommendation by Arrow (1985), several researchers have extended the standard production cost minimization approach to incorporate transactions costs as an additional component of firm costs.[74] This approach is presented in Silver (1984), Riordan and Williamson (1985), and Williamson (1989). Silver focuses upon the importance of information impactedness as the driving force behind the vertical integration decision.[75] He cites numerous historical examples to support his emphasis on the reduction in information transmission costs as the appropriate justification for integration.[76] Silver also points out that the costs of vertical integration derive from increasing production costs resulting from "diseconomies of scope." Riordan and Williamson (1985) and Williamson (1989) include governance costs and asset specificity explicitly in a modified profit maximization model. Given the additional choice variable of asset specificity, firms choose the level of asset specificity to minimize the sum of production and governance costs given output. Therefore, since asset specificity has "greater cost reducing impact, internal organization is progressively favored (Riordan and Williamson, 1985: 373)."

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[74] Arrow (1985: 303) suggests that, "new theories of economic organization take on greater 'analytic usefulness when these are founded on more directly neoclassical lines."

[75] Williamson (1975: 14) defines this as "partly an information asymmetry condition: one of the agents to a contract has deeper knowledge than does the other . . .. But more than asymmetry is implied . . .. It is also costly for the party with less information to achieve information parity."

[76] British sugar companies with operations in Guyana during the nineteenth century for instance integrated forward after demand uncertainty had been resolved (Silver, 1984:72).

Similarly, when the negative bureaucratic effects of internal organization are low, internal procurement will be favored.

Grossman and Hart (1986), hereafter G&H, extend the transaction cost theory. They formalize the theory with an incomplete contracts framework. They consider a two-firm model in which the managers of each firm engage in a two-period relationship governed by a contract that maximizes the sum of the total net benefits of the two firms. Their model "emphasizes the distortions, due to contractual incompleteness, that can prevent a party from getting the ex post return required to compensate her for her ex ante investment." They find that the primary distinction between non-integration and integration is that under non-integration, ex post surplus is divided more evenly, so that each "firm will invest to a moderate extent." This is optimal for cases in which investment into the relationship by both parties is important for the realization of gains from the relationship. On the other hand, integration is preferred when the ex ante investment of one of the firms "is much more important" than the other firm's investment.[77] They operationalize the concept of integration by defining it "in terms of ownership of assets" and demonstrate that residual rights can be allocated through asset ownership to generate optimal firm performance. In contrast to the earlier transactions-costs literature, G&H emphasize that "integration can impose costs as well as benefits."[78]

The theoretical literature on the organization of innovation has followed this more general work addressing the question of when transactions should be completed within

[77] See the discussion in Grossman and Hart (1986: 708).
[78] Building upon the analysis of G&H, Hart and Moore (1990) provide a detailed analysis of "how employees' incentives change as integration occurs . . . as asset ownership becomes more or less

a firm versus through the market. Aghion and Tirole (1994), Holmstrom (1989), and Teece (1992, 1996) emphasize different aspects of the R&D transaction. Aghion and Tirole provide a detailed model of the organization of R&D activity using an incomplete contract framework extending the analysis of G&H and Hart and Moore to the organization of R&D. Their model defines two agents, the research unit and the customer, who negotiate a contract governing the property rights (in the sense of G&H) on any forthcoming innovation, a sharing rule on the verifiable revenue (license fee) obtained by the research unit, and any verifiable amount of customer investment. The two pertinent assumptions underlying the Aghion and Tirole model extension of G&H are: (1) "The research unit has no initial cash endowment, and its income cannot be negative," and (2) "The exact nature of the innovation is ill-defined ex ante," so that the two parties cannot contract for delivery of a specific innovation. They conclude that:

> Whether C [the customer for research output] or RU [the research unit which conducts the research] should own the innovation hinges on two basic considerations: (a) the marginal efficiency of RU's effort compared with the marginal efficiency of C's investment; (b) the ex ante bargaining power of the two parties (who proposes the initial contract), which reflects the extent to which the research unit is the only candidate to perform the research.[79]

With regard to financing, they find that, "Financial constraints . . . bias the organizational form toward the use of creative inputs and away from capital expenditures." This suggests that outsourcing will be undertaken more frequently by firms experiencing lackluster research performance and with difficulties accessing capital markets.

Holmstrom (1989) provides a theoretical foundation for the argument that "Larger firms are at a comparative disadvantage in conducting highly innovative research . . .."

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concentrated." Intuitively, their model predicts integration for complementary assets and non-integration for economically independent assets.

[79] See page 1190.

He employs agency theory to show that "innovation activities may mix poorly with relatively routine activities in an organization." The firm characteristics and managerial style that make for a particularly effective drug manufacturer and distributor do not necessarily carry over to the task of incorporating the latest research technologies. Holmstrom argues that the two primary motivations for integration according to the Williamsonian incomplete contracts approach are: (1) "Incentives for investment in relationship specific assets," and (2) "Improved coordination of decision making." Neither of these two is particularly relevant for innovative activities where relationship-specific investment is "limited to small groups," and large firms frequently make an effort to keep different projects segregated. Additionally, when human capital is a key asset for the realization of firm output, as it is for R&D, "incentives for effort may be significantly diluted by removing title to transferable assets from those whose efforts are central to production" as is done under integration. This is the well-known problem of low-powered incentives.

Teece (1992) approaches the question of the organization of R&D from an organizational theory perspective. He emphasizes the potential synergies that may be realized through non-integrated R&D strategies and concludes that, "Alliance structures can facilitate innovation, and are increasingly necessary as the sources of innovation and the capacities necessary to effectuate commercialization become increasingly dispersed." Teece (1996) contends that whether a firm integrates or not is likely to depend critically on four sets of factors: (1) technology transferability, (2) intellectual property protection, (3) contractibility, and (4) accessibility of complementary competences. Teece further argues that providing adequate incentives for development,

manufacturing, and innovative activities is more costly "within one organization than through separate organizations." This conclusion supports the current industry mantra that to maintain viable new product pipelines established pharmaceutical firms are better served by turning to smaller firms strictly specializing in research.

In sum, there is a diverse and extensive body of theoretical literature analyzing the organization of firm activities, and more recently, the organization of firm R&D activity. We have reviewed the papers we feel are the most relevant for our analysis. We have grouped these approaches by their methodology and the aspects of firm and firm R&D activity, which they emphasize in Table 1.

Before moving to the related empirical work in this area, it is important to briefly mention the conventional wisdom of industry participants given the apparently contradictory theoretical predictions. A recent article in the *Nature Biotechnology* magazine proclaims that significant cooperation in drug R&D is needed to maintain pharmaceutical industry growth.[80] Standard arguments supporting this view include: (1) Rapid technological change has forced established firms to play catch-up through alliances (outright acquisitions are not as effective due to incentive effects), (2) New product development has become so expensive and risky that even the largest firms have been looking to share risk, and (3) Increased competition has forced firms to seek more rapid innovation through partnering.

A good place to begin with in the modern empirical literature is Mowery (1983) who investigated "the role of independent research organizations and the relationship between in-house and contract research during the early years of industrial research in

[80] More precisely, "pharmaceutical and biotechnology firms and other research institutions need to collaborate to an unprecedented degree in order for the drug industry to maintain a 10% growth rate."

American manufacturing." He finds support from the early part of the century, 1900-1940, for the proposition that firms without in-house research facilities were at a competitive disadvantage in R&D competition, despite the significant presence of capable independent contract research organizations. For this reason, he finds that independent research laboratories functioned as *complements* rather than *substitutes* for in-house research. This is relevant for the pharmaceutical industry of the 1990s where a majority of drug firms conducted in-house research in biotechnology in addition to outsourcing this research.[81] Mowery qualifies his findings by noting that the development of industrial research within the manufacturing firm of the early 1900s resulted from the "shortcomings of market institutions as mechanisms for the conduct of research and development." This suggests that the magnitude of transaction costs in the earlier part of this century (because of the lack of legal instruments to facilitate the outsourcing of research) constrained market transactions. Given Mowery's findings, however, it is interesting to note that the outsourcing of R&D dates back well before the advent of the current emphasis on outsourcing.

Pisano (1990, 1991, 1993, and 1997), Arora and Gambardella (1990), Balakrishnan and Kosa (1993), and Gambardella (1995) have conducted industry specific research. Pisano focuses on the biotechnology industry, analyzing integration and collaboration within the industry to develop and commercialize new drug products. In his 1990 paper, he considers 78 (mostly incomplete) biotechnology R&D projects arguing that although collaborative arrangements for development are common in the industry, prohibitive transactions costs have encouraged larger new biotechnology firms (NBFs) to integrate

[81] The Pharmaceutical Research and Manufacturing Association (1997) estimates that in 1997, pharmaceutical companies will spend close to $1 billion on biotechnology research in-house. This

forward. Pisano (1991) concludes, "small-numbers bargaining problems motivate firms to internalize R&D." More recently, Pisano (1997) provides a thorough analysis of 23 biotechnology firms, which emphasizes the role of "process innovation" in the new drug development process, and how this encourages integration over specialization. Pisano's aggregated analysis provides support for the integration strategy of new drug development.

Arora and Gambardella (1990) provide and test a model of the presence of synergies between the different types of firm collaborations, finding that "research agreements with univers ties, minority participations in NBFs, and acquisitions of NBFs are positively correlated even after controlling for firm characteristics." This finding is consistent with the proposition that large firms have not monopolized innovation in pharmaceuticals. Therefore, we can expect substantial new innovation to occur within the "network of inter-organizational relations" among pharmaceutical and biotech firms. Gambardella (1995) provides a thorough overview of the impact of technological advances affecting the industry within the context of relevant economic and institutional factors. Gambardella, unlike Pisano predicts market growth "based on an extensive division of labor" between "flexibly organized, research-intensive suppliers, with comparative advantages in producing ideas, and very big firms with comparative advantages in large-scale development and commercialization." The current analysis is a first step in testing the contradictory predictions of the Pisano (integrated) and Gambardella (specialization) models of new drug development. In contrast to this earlier work, we take a closer look at the economic forces which are driving the industry toward one mode of research organization or the other, or a combination of the two. Additionally, we

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compares to an estimated total of $7.7 billion for biotechnology firms.

consider a comprehensive dataset of approved drug products rather than early stage research projects to determine the prevalence of development strategies through the product approval stage.

3.3 Drug Development

Figure 2 provides a useful schematic of drug discovery and development which is essential for understanding our analysis of new product development decisions within this industry. The first step in bringing a new drug product to market is discovery, which includes the research phase and pre-clinical trials up to the point where a discovering firm submits an investigational new drug (IND) application. This is the portion of R&D that is increasingly being accomplished by biotech firms because of their newer and apparently more productive research technology. The development period begins with the filing of an investigational new drug (IND) application that allows for the testing of the experimental drug product on human subjects. Upon approval of the IND, the FDA allows Phase I trials for drug safety on small groups of human subjects.[82] This is followed by Phase II clinical trials for efficacy on a limited number of carefully selected human subjects, and Phase III clinical trials for safety and efficacy on a larger sample of human subjects. As shown in the figure, this process has on average taken from 10 to 13 years in the past. For our more recent sample, the mean time to FDA approval has fallen slightly but still remains quite lengthy at over 9 years.[83]

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[82] "Before any drug can be tested on humans, the drug's sponsor must submit an investigational new drug application to FDA that summarizes the preclinical work, lays out a plan for how the drug will be tested on humans, and provides assurances that appropriate measures will be taken to protect them." See GAO (1996a: p. 2).

[83] See GAO (1996a, 1996b, and 1996c) for discussions of the reduction in approval times for NDAs.

Discovering firms ultimately choose to develop products in one of four ways: (1) With their own development resources (in-house), (2) Through a merger or acquisition which becomes an in-house development, (3) With a patent license, or (4) Through a joint venture or strategic alliance (see Figure 1).[84] For a drug product to be classified as an in-house development, the same firm that received the NDA approval for the product, must also have discovered the new drug by obtaining the original patents that ultimately led to its NDA approval. If at any point between the patent grant and the NDA approval the product or a portion of the product changes hands, then we have a non-integrated development. The category of mergers and acquisitions is problematic within this scheme. For those instances in which a firm owning a patent that leads to a new drug product is acquired or merges with another company prior to FDA approval for the new drug product, we have new product development via a merger or acquisition. Given that such transactions include a change in property rights regarding the new drug product, one might be inclined to consider these new product developments within the non-integrated category. Since such transactions, however, bring the new product development within in one firm (or in-house) we have chosen to include them within the integrated category in our bivariate analysis. We complete our empirical analysis with and without this group of new product developments.

We posit that firms in this industry are intertemporal profit maximizers who determine their optimal development decision as a function of firm and product characteristics. We can model the decision process using a variety of econometric techniques. If we employ

[84] The distinction between strategic alliances and joint ventures is as follows: joint ventures result from the creation of a new corporate entity separate from either of the two partners, but employing resources, staff, and management from both of the partnering firms, whereas, strategic alliances are short-term, goal-

a sequential model such as a nested logit model, we assume that a firm first focuses on the choice of internal versus external development and then chooses the most appropriate multifirm method given an external development choice. Alternatively, we can assume that the firm treats the different methods of development as varying degrees of integration. Under this decision model, the firm makes a single choice based on its preferred level of integration, given the relative benefits and costs of each method of development. In this case, we estimate the decision with an ordered probit estimation. We do not suggest that either model is a more accurate representation of the decision making process. Examples in the trade press of both decision making processes are abundant. The primary purpose of putting forth these two representations of the development decision process is to provide us with flexibility during our subsequent econometric estimation so that we may better capture the likely correlations between a firm's preference for one choice or another.

As with many economic decisions, we cannot hope to capture the full complexity of the decision process undertaken by firms for new product development. We can, however, attempt to document some of the more important elements involved in this process in accordance with previous theoretical and empirical analyses, and our own inquiry into this process within the U.S. drug industry. We posit that several firm characteristics and several new drug characteristics that we can observe should be correlated with the new drug development decision as we have defined it here. In particular, we include the following firm characteristics in the year of the patent grant in our analysis of firm development decisions: 1) firm size, 2) patent stock, 3) the number

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oriented partnerships in which a bilateral exchange of knowledge takes place. See Tucci (1996) for additional clarification of this distinction.

of previously approved drugs, 4) the number of years since the firm's first drug approval, 5) whether the firm is publicly traded, and 6) the firm's R&D expenditures and dependence on drug sales if it is publicly traded. We also include data on the following drug characteristics: 1) whether or not the drug was developed using biotechnology, 2) the therapeutic class for which the drug was approved (we use this data to categorize products into a difficult disease category), 3) the year of application for the patent from which the drug was derived, 4) whether or not the patent was originally assigned to a foreign inventor, and 5) the number of other approved drugs within the same therapeutic category. See Appendix A for a detailed discussion of the construction of each of these variables. We now turn to a brief discussion of why each of these variables should be included in our analysis and how they might effect the new product development decision.

Firm size is a variable that we normally include in economic analyses which consider firm decisions. Within our analysis, there are several reasons why firm size might be important for the development decision. First, since the development process is a very long and costly process, greater access to capital due to larger firm size may allow larger firms to choose in-house development more frequently than smaller firms. Second, larger firms with multiple ongoing projects may be more capable of sustaining losses from any one development project. This greater ability for undertaking a risk burden should make them more likely to undertake in-house development. We therefore include the firm size variable in our analysis expecting that it will be positively correlated with the level of integration of new product development decisions.

Patent stock represents a firm's accumulated technological expertise as embodied by legally protected intellectual capital. This stock also represents publicly available information about a firm's technical expertise. The primary reason to include this variable in the analysis is that it represents information about a company's expertise that potential development partner firms can analyze which may facilitate non-integrated development options. A second reason is that a higher patent stock may represent a firm's ability to appropriate gains from new product development. Firms that have a number of patents that technically approximate their most important patents can more effectively prevent competitors from encroaching upon their intellectual property assets. The first reason for including this variable in our analysis noted here suggests that a greater patent stock might be associated with less integrated development. Our second reason goes in the opposite direction implying that a greater patent stock might be correlated with more integrated development. The most likely affect of this variable upon the development decision is an empirical question that we answer in the following sections.

The number of *previously approved drugs* for a firm that is in the position to make a development decision as a result of a new discovery is important because it represents that firm's accumulated expertise in drug development. Similarly, the number of *years since a firm's first drug approval* represents also represents a firm's cumulative drug development experience. A firm with a larger number of previously approved products and a greater number of years since its first drug approval is a firm that has greater experience in negotiating the lengthy and complex clinical trials required by the FDA. This greater experience should encourage a firm to opt for integrated development over

non-integrated development. Both of these variables should therefore be positively correlated with the level of integration in the drug development decision.

We also include a variable that indicates whether or not a firm is *publicly traded* in our analysis for two reasons. First, a firm that is publicly traded will have access to equity markets not available to firms that are not. Second, firms that are publicly traded must divulge more information about their operations than firms that are not, which may facilitate non-integrated development. Our first reason here for including this variable suggests that publicly traded firms should be more likely to engage in in-house development than their privately held counterparts. The second reason suggests the reverse relationship. Given the central importance of capital funding for new product development in this industry, however, we anticipate that this variable should be positively correlated with integrated development.

Two final firm characteristics that we include in our analysis which are available for our publicly traded firms are: 1) the level of firm R&D expenditures and 2) the dependence of a firm upon drug sales. The first variable here represents the size of a firm's overall R&D program and is most likely positively correlated with a firm's in-house development capabilities. Greater R&D expenditures should therefore be positively correlated with integrated development. Similarly, the more dependent a firm is upon drug sales (as measured by the proportion of drug sales to overall sales), the more likely that firm should opt for more integrated development.[85]

In addition to this set of firm characteristics, we are also able to include five drug characteristics in our analysis of the firm development decision. The first characteristic

we include is an indicator for drugs derived from *biotechnology*. Such products are more likely to reach approval through non-integrated development when biotechnology has been sufficiently accepted among providers of capital to allow for effective multifirm new drug development.[86] Since this requirement was most likely not met for significant portions during the earlier part of our sample (1985-90 and again in 1994), it is likely that this effect is time-dependent. During the early history of the evolution of the biotechnology industry, funding for biotechnology-derived drug products was difficult to obtain, requiring firms with such products to develop them in-house. As biotechnology became more widely acknowledged as a viable source of new therapeutics, funding became easier, thereby facilitating non-integrated development. By contrast, the early biotechnology firms that evolved into integrated discovery-development firms themselves became more capable of in-house development. This trend would suggest that over time, biotechnology-derived products might become more associated with in-house development. Taken in combination with the greater capital market acceptance of biotechnology, however, we cannot a priori predict the relationship between the level of integration in the development process and whether or not the new product derives from biotechnology. The countervailing trends we have noted here will offset to a degree. Given the continued proliferation of alliances among biotechnology firms over the recent past, however, we might predict that the impetus for non-integrated development due to the greater acceptance of biotechnology would yield the greater effect. This would result

[85] Pisano (1990: 168, 171) makes a similar argument for the same variable, which he labels, FOCUS. He finds for his particular dataset that "Companies more dependent on pharmaceutical sales seemed to be more likely to internalize biotechnology R&D projects."
[86] Venture capitalists and investors in the NASDAQ exchange qualify as the relevant providers of capital.

in a negative correlation between the level of integration and a *biotechnology-year* interactive term.

The second drug characteristic variable we include in our analysis is *a therapeutic indicator*, which identifies products being developed for diseases categorized as particularly difficult by the Center for Disease Control (CDC). We hypothesize that such products would be more likely developed in-house due to the difficulties inherent when attempting to contract over development responsibilities for such drug products. This view is consistent with the transaction cost economics perspective that the more complex a product is, the more costly it is to transfer here across firms. Our difficult disease indicator should therefore be positively correlated with in-house development.

The next two drug characteristics that we include in our analysis come from the underlying patents of the approved drugs in our sample. These are the *application year* of the patent and an indicator, *foreign patent*, which identifies those drug products that emanated from a patent assigned to an entity outside of the United States. The application year variable here allows us to explicitly consider the trend towards non-integrated development (at least for the sample of approved drug products that we consider here) that has been emphasized in much of the trade press. If there has in fact been a trend towards non-integrated development, we should observe a statistically significant negative coefficient on our application year, indicating a negative correlation between time and the level of integrated development among new drug developers. For those drug products originating overseas, we should expect a higher degree of non-integrated development given the relative rigor of the FDA approval process in the U.S. Foreign firms attempting to develop new drug products in the U.S. have often sought

American partners to facilitate negotiation of the different regulatory hurdles in this country. We, therefore, expect a negative coefficient on our foreign patent indicator variable.

The final drug characteristic we include in our analysis is a count of the number of *drugs previously approved* within the same therapeutic category as the drug in our sample. The larger the number of previously approved drugs within the same category, the less uncertainty there should be about the viability of developing the product. A higher number of previously approved drugs within the same therapeutic class, however, may make it more difficult to obtain approval for a drug that can effectively differentiate itself from its competitors. These two effects should move the discovering firm in slightly different directions with regard to the development decision. Reduced uncertainty should facilitate non-integrated development. Reduced expected value, however, may hinder non-integrated development. If we consider that the costs of conducting non-integrated development include transactional costs in addition to the normal costs of development, than a lower reduced expected value for the drug product under development should discourage non-integrated development. The relationship between this variable and the development decision is then ultimately an empirical question. We now turn to our data and results.

3.4 The Data

The construction of our dataset begins with all of the approved new drug applications (NDAs) and product license applications (PLAs) beginning in 1985 to the end of 1996,

obtained from the Food and Drug Administration (FDA).[87] We restrict our data to the new molecular entities (NMEs) because these products represent distinct innovations from previous treatments.[88] Since the FDA must approve all new drugs sold in the U.S., this dataset includes the universe of all new drugs marketed in the U.S. during this time period.[89] Our dataset contains 318 new conventional drug products and 45 new biological products marketed in the US during this time period.[90] A number of conventional drugs from our original dataset of over 400 products, however, did not constitute sufficiently different technology from previous products in their area such that they did not have corresponding patent information (i.e., did not require a new discovery). Since our focus is on the process by which firms take novel discoveries to market in the form of new products, we focused on those products with new patents qualifying for patent term extension consideration, leaving us with our sample of 363 total products.

President Reagan signed the 1984 Drug Price Competition and Patent Term Restoration Act (1984 Amendments) on September 24, 1984. This act requires that firms applying for new drug approvals include relevant patent information to receive consideration for patent term extension. It also includes drug products (vaccines, therapeutics, and diagnostics) with approval under Section 505 of the Act administered

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[87] The *Approved Drug Products with Therapeutic Equivalence Evaluations* (commonly referred to as the "Orange Book") published by the U.S. Department of Health and Human Services published lists new drug products with pertinent patent numbers after September 24, 1984, the effective date of the 1984 Drug Act.

[88] The FDA defines NMEs as "an active moiety that has not previously been approved (either as the parent compound or as a salt, ester, or derivative of the parent compound) in the United States for use in a drug product either as a single ingredient or as part of a combination."

[89] Note that new generic drugs are not included in the analysis, since they do not require approval based on the lengthy clinical trials portrayed in Figure 2.

[90] Note that we only include biological products that are designated for human therapeutic use only, to include several valuable vaccines, and the first biotech product brought to market by Genentech in 1982,

by the Center for Biologics Evaluation and Research (CBER). These two laws have allowed us to construct our unique dataset, which traces marketed drug products back to their originating discoveries or patents. In conjunction with a detailed patent dataset from the U.S. Patent and Trademark Office (USPTO), we have been able to attach all of the relevant patent information for each patent leading to a new drug product, either conventional or biologic. Given this mapping of discoveries to marketed drug products, we identified the methods employed by the discovering firms (which may or may not have been the same firm as the developing firm) to eventually get their discoveries to market. In this identification process we used a combination of FDC Reports ("Pink" and "Blue" sheets), *Windhover's Pharmaceutical Strategic Alliances* (various volumes), and other publicly available sources such as newspapers, business and trade magazines.[91] In general, the majority of successful development occurs in-house.

An important qualifier regarding our data is that we are focused on *successful new product development*. We are therefore conditioning our analysis on those products that reach the NDA approval stage, a minority of all products that undergo some development. A critique of this dataset construction is that by selecting our sample in such a manner we capture only a fraction of all new attempted drug developments. Figure 3 represents a hypothetical depiction of our sample selection. Our analysis, therefore, applies to the most successful drug discovery programs of the entire universe of drug discovery programs.

Humulin (human insulin). We exclude biological products for human diagnostic purposes, veterinary use, or agricultural use.

[91] The publicly available sources were searched through the on-line services: Dow Jones News Retrieval Service© and Lexis-Nexis©.

Of the 363 drug products that we examine, 211 are developed in-house.[92] Table 2 shows the development decisions for the new drug products in our dataset. Several features of this data are striking. First, over 58% of new drug products over our period of analysis 1985-96 have been brought to market with in-house development. Second, the tendency towards integrated development is surprisingly strong for the biotech products in our dataset with 62% of those products being developed in-house. Finally, when we group our observations into the initial six-year period versus the latter six-year period, the widely reported trend towards non-integrated development does not appear very strongly. This publicized trend, however, due to its recent nature, may only characterize the most recent new product development decisions and have yet to be reflected in actual new product approvals. With our sample of approved new pharmaceutical and biotechnology human therapeutic products, we observe relatively little movement towards non-integrated development as the proportion of in-house development remains above 60% through the 1996 approval year. To determine why the expected move towards non-integrated development has not appeared, we continue with appropriate econometric analyses as prescribed by our discussion of the factors expected to influence the new drug development decision.

We present the relevant variables for our econometric analysis in Table 3 along with a brief explanation of how they might affect the development decision consistent with our previous discussion. Table 4 provides summary statistics on the variables used in our estimation and Figure 4 presents a schematic summary of our dataset construction consistent with our previous description.

[92] The data describing these products, and identifying the developing firm was derived from a dataset provided by the FDA under a Freedom of Information Act request.

3.5 Estimation

We estimate four variants of discrete choice econometric models of the development decision. The estimation is ordered from the more restrictive models to the least restrictive. First, we estimate an ordered probit model, which characterizes the development decision as an ordinal choice among increasing levels of integration. Second, we combine our development alternatives into two possibilities, integrated versus non-integrated development and estimate a probit model. Third, we model the development decision as a nested logit model. Last, we estimate a multinomial logit model, which characterizes the decision as a choice among four unranked alternatives.

For the ordered probit model, we rank the four possible development decisions as shown in Figure 1. In this framework, in-house development represents the highest level of integration (coded numerically as 4), merger or acquisition is the next most integrated level (coded as 3), then joint ventures or alliances (codes as 2) and finally, patent licenses which represent the lowest level of integration (coded numerically as 1). Under these assumptions we estimate the following ordered probit model:

$$\Pr(d = i) = \Pr(\gamma_{i-1} < \beta_1 X_{1j} + \beta_2 X_{2j} + ... + \beta_k X_{kj} + \varepsilon_j \leq \gamma_i)$$

where *i=1,2,3, or 4*, $\varepsilon_j \sim N(0,1)$ and the γ's represent the relevant cut points. The basic model includes all of the relevant firm and product characteristics with a time trend represented by the *appyr* variable, and an interactive term, *bioyr*, between the biotechnology indicator, *bio*, and the patent application year (*appyr*). We present the results from this regression in the first column of Table 5.[93] Table 5A reports the

[93] The ordered logit specification was estimated as well with no significant differences.

marginal effects of each of the independent variables, computed at the sample means except for the 0-1 indicator variables, in which case, the marginal coefficient represents the increased probability of moving to the next level caused by a change from 0 to 1 in the indicator. Numerically, this is: $\partial \Pr ob[cell\_i] / \partial x_j$, the marginal increase in the probability of observing a decision in cell i due to a marginal increase in variable j.

The results are interesting as much for the variables that are not significant as for the variables that do enter significantly. First, let us consider the firm characteristic variables. The variable measuring firm size enters significantly with the expected positive sign. Larger firms have the capability to conduct the costly development process in-house and are therefore more likely to opt for integrated development. Our patent count variable, measuring expertise in discovery, enters significantly with a negative sign, suggesting that there may be some specialization among the firms making new drug product discoveries. In other words, firms that are particularly good at new drug discovery as evidenced by high patent stocks, are not always the same firms that market the resulting new drug product. A significant share of these firms proficient in drug discovery has chosen to undertake non-integrated development. The drug count variable, measuring previous drug development experience is significant and positive, suggesting that firms that have already gone through the FDA approval process are more likely to pursue development on their own, rather than seek a partner. The indicator for publicly traded firms enters with a strong positive coefficient as predicted. Those firms with access to equity markets, conditional on firm size and past success, are much more likely to undertake in-house development over non-integrated development.

The therapeutic indicator, showing those products developed for cancer, cardiovascular, and central nervous system diseases is significantly positive, suggesting that discovering firms that have discovered new products in these areas are more likely to want to keep their new discovery in-house. This result could also reflect the higher transactional costs associated with new products that attempt to address particularly complex disease categories. The biotech and foreign indicators enter with the expected negative sign, but are both insignificant. The trend variables, *appyr* and *bioyr,* are both close to zero, which is somewhat surprising in light of the tremendous trade press on alliances within the industry. This result suggests that the movement towards non-integrated development emphasized in the trade press is not yet apparent for successful new drug products. In sum, the primary drug characteristic important for the development decision appears to be the complexity of the disease category that the drug attempts to address. Other characteristics such as whether or not the drug emanated from biotechnology and how recently it was discovered were not as significant as anticipated.

Our conclusions from the trend results, however, must be tempered by the possibility that this trend may take longer to show up in approved products than originally anticipated. A review of current products in the pipeline suggests that the addition of more recent data up through December 1997 may show a slightly greater proportion of new drug products brought to market via non-integrated methods.[94] Still, a majority of

[94] A good example of this recent trend towards non-integrated development is the recently approved treatment for cancerous tumors, Rituxan. This product was co-developed by Idec Pharmaceuticals and Genentech, Inc.

new therapeutic drug products emanate from in-house sources.[95] Despite these very recent trends, twelve years after the 1984 Drug Act and the 1984 Joint Venture Act, integrated R&D continues to be a prominent R&D strategy of firms in the industry.

To avoid the small cell problem we group the observations from the in-house and mergers and acquisitions categories into a combined integrated category, and the joint ventures, strategic alliances, and patent licenses into a combined non-integrated category. We present the results of a probit regression for a sample in Table 6. The dependent variable for these regressions is a 1-0 dummy variable that assumes a value of one for outsourced or non-integrated development and zero otherwise. We present the coefficient estimates as marginal probabilities evaluated at the mean values of the independent variables.[96] These results are consistent with our previous specifications. The coefficients for firm size, firm drug count, and public indicator are the most significant firm characteristics, and our firm patent count variable is significant at the 5% level. The trend coefficients are insignificant, and the therapeutic indicator for difficult products enters significantly with a negative sign, suggesting that complex new drug products are more likely to reach the market via in-house development.

An alternative model of the development decision characterizes the choice as a staged decision. At the first stage, the firm decides whether or not to outsource development, and in the second stage, decides among options within the chosen branch. We implement this using a nested logit framework. We consider the following tree structure:

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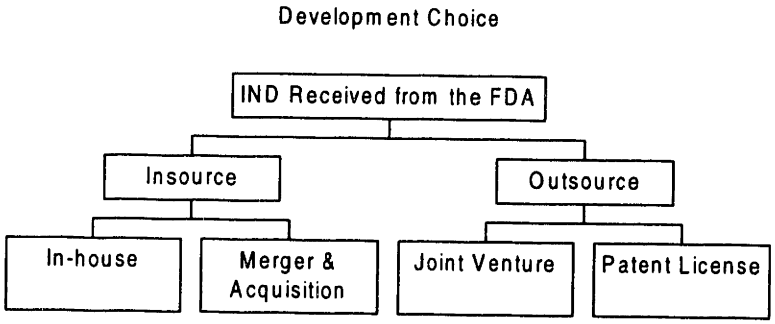
[95] The biggest blockbuster drug of the year (1996), Evista, which has been shown to prevent osteoporosis in women, was discovered and developed in-house by Eli Lilly.

[96] The coefficient estimates for our binary independent variables (*biotech, foreign, public*, and *ccca*) represent the effect of going from zero to one.



We model the choice as a function of the attributes of the choices, the attributes of the individual firm making the choice, and the interaction of individual firm attributes with the choice attributes.[97] Let $\Pi_{ij} = F_{ij} + \varepsilon_{ij}$, where F is a vector of attributes relevant for the firm's profit maximizing development decision, and ε_{ij} is a residual that captures the effects of unmeasured variables. This residual is assumed to be independently and identically distributed with the extreme-value distribution. The probability that a firm will choose the (i,j)th alternative can be represented by the following equation:

$P_{ij} = e^{F_{ij}} \Big/ \sum_{m=1}^{2}\sum_{n=1}^{2} e^{F_{mn}}$ where i = 1,2 (insource versus outsource choice) and j = 1,2 within each nest. If we suppose that $F_{ij} = \beta' X_{ij}$, where X_i is the vector of observed attributes that vary with firm and drug we can write the likelihood of our (i,j)th alternative as $P_{ij} = P_{j|i} * P_i = e^{\beta' X_{ij}} / \sum_{k=1}^{2} e^{\beta' X_{ik}} * (\sum_{j=1}^{2} e^{\beta' X_{ij}} / \sum_{n=1}^{2} e^{\beta' X_{in}})$. We employ full information maximum likelihood to obtain estimates for the log-likelihood, which is:

$\ln L = \sum_{i=1}^{4} \ln[\Pr ob(choice|branch) * \Pr ob(branch)]_i$, where branch = insource or outsource and choice is one of our four development choices.[98] The inclusive value for the ith

[97] See Maddala (1983) pp. 68-73 for a more formal presentation of the nested logit model.
[98] See Greene (1997: 923) for an explanation of why this method is preferred to the sequential estimation method.

branch = $I_i = \ln \sum_{j=1}^{2} e^{\beta' X_{ij}}$. This represents an estimate by our model of the probability that a particular development decision is included in one nest (say outsource) versus the other nests at that level. For a model to be feasible, the inclusive values must fall between 0 and 1, which provides a specification test during our estimation.

Table 7 provides the results for our nested logit estimation. In this table we report the inclusive value for the in-house versus outsource nests, and the elasticity for the four attributes (ln [size], patent count, drug count, therapeutic indicator [*ccca*]) which we found to be significant in the earlier models. Our inclusive value for the insource versus outsource nest is .74, which is not statistically different from a value of one, suggesting that our nested logit model of the development decision does not provide a significant improvement over our non-nested estimations. This coefficient is related to the correlation in the error terms between development branches. A value close to one reflects the inability of our model to clearly distinguish between the decision to insource versus outsource. Since our value is not significantly different from one, we can assert that the nested framework is not the most appropriate framework for our analysis and fail to reject the independence of irrelevant alternatives assumption that is consistent with the multinomial logit estimation.

Our elasticity results, however, are generally consistent with our ordered probit regression, although we observe lower levels of significance here, and incorrect signs for some of the variables for our "internal" options, joint ventures and mergers and acquisitions. As previously noted, the merger and acquisition observations, although seemingly compatible with in-house development, prove problematic during our estimation. The basic results that we are left with, however, are encouraging in that they

further support the relevance of several of our covariates for the pharmaceutical or biotechnology firm's development decision.

Given the difficulty, theoretically and empirically, of ranking the merger and acquisition choice, we re-estimate both the ordered probit and multinomial logit regressions on a subsample excluding the merger and acquisition category. These results do not change our coefficients appreciably from those presented in Tables 5, 5A, and 5B.

The final estimation that we conduct requires the least amount of restrictions on the covariates. Here we relax the assumption that development options can be ordinally ranked, and employ a multinomial regression model. We specify this as:

$$P(d=1)=\frac{e^{X\beta^{(1)}}}{e^{X\beta^{(1)}}+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}};\ P(d=2)=\frac{e^{X\beta^{(1)}}}{e^{X\beta^{(1)}}+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}};$$

$P(d=3)=\frac{e^{X\beta^{(1)}}}{e^{X\beta^{(1)}}+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}}$, where each of the numbered $\beta's$ corresponds to its respective decision group. We estimate the coefficients relative to the case of in-house development where $d = 4$. Our multinomial logit regression results are presented in the second through fourth columns of Table 5. These results suggest that our previous ordering may not be robust. In contrast to the ordered probit results, in which the firm size coefficient exerts a significant and positive effect on the development choice, the firm size coefficients across the alternatives in the multinomial logit model do not monotonically increase from our least integrated option to our most integrated option. Firm size effects increase between the patent license option and the joint venture option, but fall as we move to the merger and acquisition option. In general, our other significant variables in the ordered probit regression such as patent stock,

previous drugs approved and the therapeutic indicator increase or decrease across alternatives in a manner consistent with the order estimation. Constraining the development options to follow our hypothesized ordinal relationship to varying levels of integration, however, does not appear to significantly improve the fit of our model. The cut point estimates in our ordered probit are consistent with the hypothesized ranking but are imprecise.[99]

The firm size and drug count variables are both significant, suggesting that firms with greater internal resources are more likely to develop their discoveries in-house. If a discovering firm has already invested in substantial development resources, as many of the larger pharmaceutical firms have done, it has no need to look externally to appropriate the returns from its discovery. Computing the marginal probabilities at the mean of our explanatory variables for the log (size) and patent stock variables for our first ordered probit specification, however, does not suggest particularly strong effects by these variables. For log (size), d (prob. of in-house development) / d (log [size]) = .05 at the mean value of our log (size) variable which is 5.5 or $244.7 million. This means that for an increase of 10% in annual revenues (a relatively frequent occurrence for pharmaceutical and biotechnology firms over the past decade) integrated development is only 0.5% more likely. For our patent stock variable, d (prob. in-house development)/d (ln [1 + patent stock]) = -.023 at our mean patent stock value of 6.15 or 468 patents. A discovering firm that increases its patent stock by 23 patents, (which is 5% of our mean value for patent stock) is .115% less likely to choose in-house development over other

[99] This result may reflect the fact that our dataset is populated with relatively few observations within the inner categories (joint venture and strategic alliance developments and merger and acquisition developments). Both of these categories will surely add more observations, as more recent data becomes available.

possible choices. A one-half standard deviation increase in a firm's patent stock decreases the probability of in-house development by 6%. These results are consistent with several interpretations. One possibility is that firms specializing in discovery (those with a significant number of discoveries) consider non-integrated development as a means of continuing to specialize in discovery. Another interpretation is that firms with a track record of discoveries are more capable of finding partners to assist them with development due to the elimination of asymmetric information inherent in the partnering process. A larger patent stock allows for potential partners to more effectively determine the expected value of investing in the development of a discovery by that firm.

Additional examination of our marginal effect tables yields the following additional results. Our most significant variable, drugs previously developed, with a coefficient three times its standard error, actually has a relatively small marginal effect on the probability of development choice. We find marginal effects of less than 1% across all possibilities in either specification, at least when computed at the mean level of previous drugs approved for our sample, 11. The distribution for this variable is particularly skewed, however, with over 40% of our sample with at most one previously approved drug product. Given this skewed distribution, a more appropriate measure of the impact of this variable on the development decision is to consider the marginal effect when going from zero to one, or given a one-half standard deviation increase in the number of previously approved drugs. To compute the marginal effect when moving from zero to one, we compute d[probability of in-house]/d[drug count] when the independent variables assume their mean value, and the drug count variable = 0. The marginal effect increases slightly to -0.009 from -0.008 for our multinomial logit and ordered probit

model patent license option. The marginal effect due to a one-half standard deviation increase in the number of previous approved drugs is to induce a 12% higher probability for in-house development.

Our next most significant variable, the therapeutic indicator for difficult diseases has a very strong marginal effect in both the ordered probit and multinomial logit estimations. Drug products which fall into this category are about 10% more likely to be developed in-house versus non-integrated methods. This is a significant and interesting result suggesting that the drugs being developed for the most difficult diseases are more often than not being developed in-house. One possible interpretation of this result is that firms with previous development experience are more capable of undertaking more complex projects because they can more easily afford to withstand negative revenue shocks as compared to firms with fewer or no successful previous products. A more precise interpretation of this result would require a more thorough examination of the development of these specific products, which constitute 19% of our products.

Finally, note the consistency of the marginal effect results across our variables for the patent license and in-house options in Table 5A. In contrast to these marginal effects are the much smaller marginal effects found for the joint venture and merger and acquisition options. Given that the number of observations in those two categories is significantly smaller than for patent licenses and in-house developments, this outcome is not surprising.

Our econometric estimation then suggests that for a variety of estimations several of our hypothesized factors are consistently correlated with firm development decisions. In particular, firm development capability as evidenced by firm size, access to equity

markets, and most importantly the number of previously approved drugs, are very important for predicting integrated new drug development.[100] In addition to these firm characteristics which predict integrated development, our patent stock variable tends to be associated with less integrated development throughout our analysis, suggesting a significant level of specialization in the discovery process even in our sample of approved drug products from 1985-96. The drug characteristic most important for determining the level of integration in the development process is surprisingly not our indicator for biotechnology or foreign origin, but our difficult diseases indicator. The trend towards non-integrated development fails to appear in any of our estimations.

3.6 Interpretation of Results

Given the complexity of the phenomenon that we attempt to model here, it is difficult to link our empirical results directly with any of the various economic theories that attempt to explain the organization of R&D. We can, however, offer several plausible interpretations. Table 8 summarizes our empirical results across the various specifications we employed in our estimation. Four variables are consistently statistically significant throughout our analysis: *lnsize, patcnt, drgcnt, and ccca.* Four other variables are consistently insignificant throughout our analysis: *bio, appyr, bioyr,* and *foreign.* One other variable, *public*, is only significant for our probit regression. Several other variables for which we had partial data, previous alliances, and reliance on drug sales were not included in the results presented here due to their incomplete coverage or in the case of time since first drug (*firstyr*), high collinearity with *drgcnt.*

[100] Interestingly, this contrasts with the finding in Pisano (1990) that firm size is irrelevant for the R&D-sourcing decision for a sample of biotechnology projects.

In general, our results are consistent with several descriptive conclusions. First, scale as evidenced by firm size is important for the drug development process. Second, firm drug development experience as evidenced by previous drugs approved is also very important for the drug development process. Third, specialization in discovery as evidenced by the correlation of patent stocks and non-integrated development does characterize new drug development in the US over the past decade. Fourth, complex drug products are less likely to be developed through outsourced development. Additionally, despite significant potential synergies that could be realized through development outsourcing, biotechnology-derived and/or foreign discoveries have gotten to market through in-house development almost as often as through outsourced development. A viable interpretation of this result is that the transaction costs characterizing outsourced development have not been sufficiently reduced to entice firms to realize the potential synergies from interfirm efforts in new drug development. A more detailed explanation of this result requires additional analysis. The trend towards non-integrated development, which has been highlighted by the trade press, then appears to have progressed in a rather deliberate fashion.

In terms of how these conclusions relate to the economic factors emphasized in the previous literature on the organization of firm activities we refer to Table 3. Firm size is most likely related with all four of the factors we list in the first column of the table. As such, our consistently significant positive coefficient for firm size is difficult to interpret precisely. One interpretation consistent with the conventional wisdom regarding new drug development is that even though biotechnology may have reduced the economies

of scale for drug discovery, it has not reduced the economies of scale for drug development.

The number of previous drugs approved for a firm is a variable that may be associated with asymmetry of information and appropriability. From the empirical results, the association between the number of previously approved drugs and the propensity for integrated development is robust. As indicated in Table 3, the higher the number of previously approved drugs the lower should be the level of asymmetric information between that discovering firm and potential development partners. This would suggest a tendency towards non-integrated development. We observe, however, a strong tendency in the other direction. This suggests that the appropriability effect, which encourages in-house development, appears to be more significant. Alternatively, this result may indicate previous in-house choices and/or success.

The third firm characteristic that enters significantly throughout the analysis is patent count. This variable is arguable correlated with two of the four economic factors listed in Table 3, asymmetry of information and appropriability. Unlike with previous drugs approved, however, this variable is plausibly more closely correlated with reducing asymmetric information between discovering firms and possible development partners. In particular, increased patent stock may be correlated with greater appropriability on the part of a firm, and with less asymmetric information. The appropriability effect here encourages integrated development that would result in a positive patent stock coefficient. The asymmetric information reduction effect is more important, however, resulting in a significant negative relationship between patent count and integrated development. This result is also consistent with specialization in discovery.

The drug characteristic that is significant in our analysis is the indicator for difficult diseases, which is associated with uncertainty. This characteristic is also possibly associated with asymmetric information. The development process for more complex new products is most likely characterized by greater uncertainty and a higher degree of asymmetric information between discoverers and developers. In this case, both effects appear to move development in the same direction, towards integrated development. This interpretation is consistent with our results, which show a strong positive correlation between the complexity of the disease target for new drug products and the level of integration in the development of those products.

Now we turn our attention to an interpretation of the insignificant correlations in our analysis. The biotech and foreign patent indicators that we expected to be negatively correlated with integrated development are not significant in any of our specifications. Biotechnology-derived new drug products comprise a small portion of the sample; and of the products that have actually made it to market, the focus of the analysis, nearly as many have been developed in-house as through outsourced development. This may be due to the difficulty in effectively transferring new biotech drug products for development during the infancy of the biotechnology industry, which is what is reflected in the dataset. A similar interpretation is appropriate for new products derived from foreign patents. The well-known difficulties inherent in coordinating cross-border interfirm new product development may have prevented many firms from choosing non-integrated development, despite the potential synergies from such development. The costs of such transactions may have outweighed the benefits in my instances. Both of these effects may arguably dissipate in the near future, as the biotechnology industry evolves into

maturity, and as cross-national ties among drug and biotechnology firms increase. They appear to exert significant influence, however, for this sample of approved new drugs.

One final interpretation is in order regarding the insignificant results on the time trend variable, *appyr*, and the interaction of the time trend variable with the biotechnology indicator, *bioyr*. We had anticipated that as biotechnology became more widely accepted that non-integrated development would become more feasible, because of the decreasing economies of scale for discovery and increasing returns to specialization in discovery. These effects were not reflected in the analysis for two possible reasons. First, the significant increase in alliances and non-integrated development in this industry is a relatively recent phenomenon, arising primarily in the 1990s. As such, this trend has not had time to be reflected in approved drug products (which normally take six or more years even today) through the end of 1996 (the extent of our sample). Second, industry observers may have underestimated the difficulties in overcoming the high transactions costs involved in effectively carrying out non-integrated development for new drug products. It appears to have taken pharmaceutical and biotechnology firms several years to develop effective interfirm governance structures to make non-integrated new drug development to work.

3.7 Conclusion

The results from our analysis by conditioning on successfully marketed drug products contradicts the general perception that pharmaceutical firms have quickly adopted non-integrated R&D strategies to maintain their innovative capacity in the face of significant change in the industry. The generally perceived trend in new drug development towards non-integrated modes, which appear to provide greater value for

consumers at relatively faster times to market, has not manifested itself to the degree portrayed in the trade press in newly marketed drug products, at least through the end of 1996. This result suggests that the integrated method of new product development has been more successful and resilient than generally believed, given that the industry has been considered an international success by most measures. Political pressure on the FDA to speed approval has no doubt aided the trend towards faster time to market, and the advent of new technologies within the industry such as combinatorial chemistry and genomics has contributed to the move towards less integrated development arrangements. The experience of the pharmaceutical firms themselves, however, appears to have offset these forces to a degree. These conclusions are consistent with two observations made several decades ago by Williamson (1971: 122) regarding vertical integration in general. He observes that, "the extensive variety of circumstances in which internalization is attractive tends not to be fully appreciated" and "a broader a priori case for vertical integration of production exists than is commonly acknowledged."

Through a variety of estimation techniques, several factors are consistently correlated with firm development decisions: size of the firm, patenting expertise, previous drug development experiences, and the therapeutic category of the firm. Their effects are consistent with our a priori hypotheses, but not easily interpretable within the framework drawn from existing theoretical research in the area. Econometrically, we do not find that the ordered probit and nested logit models provide significant improvements in estimation over the basic multinomial logit model. Although some rank ordering and differentiation between insourced and outsourced development appears consistent with the data, it is not strongly supported by the analysis.

Figure 1. Sequential Decision Model vs. Single-Choice Model

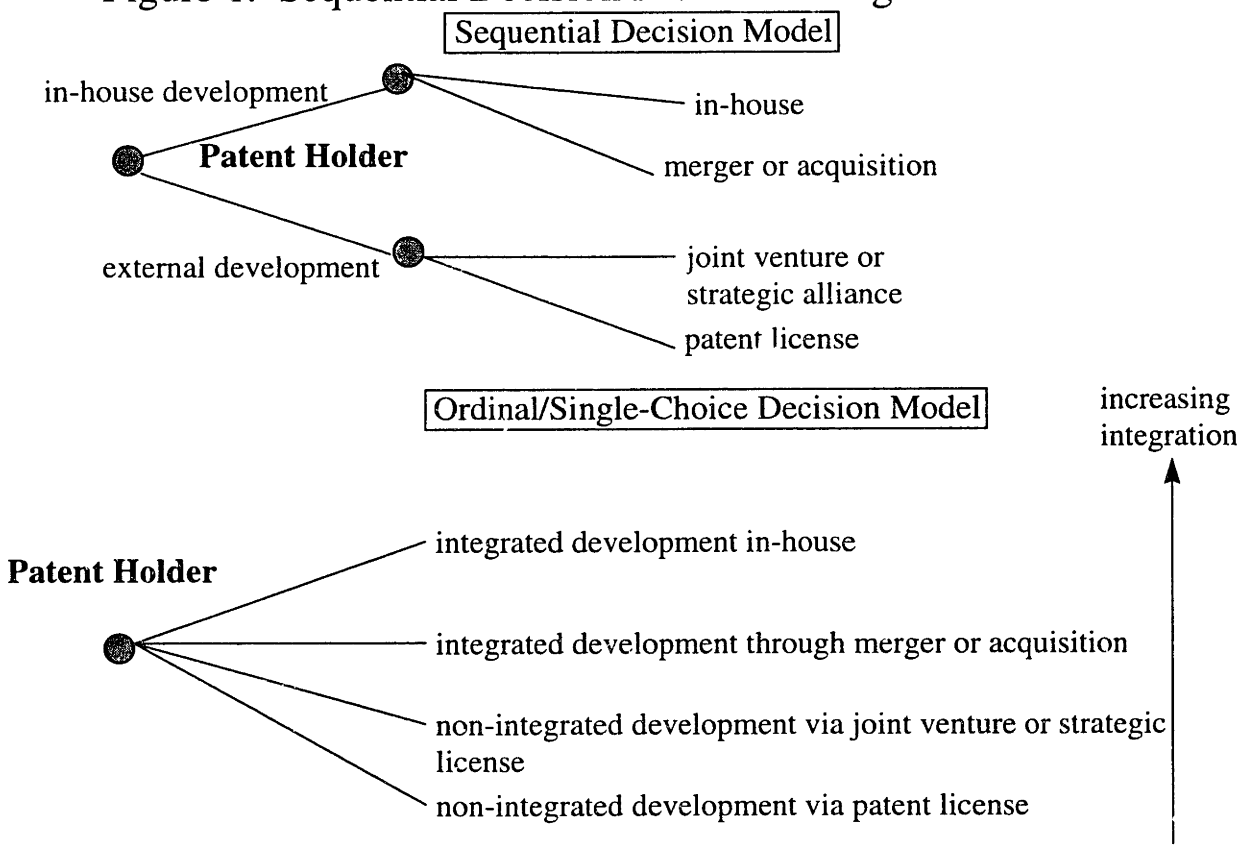
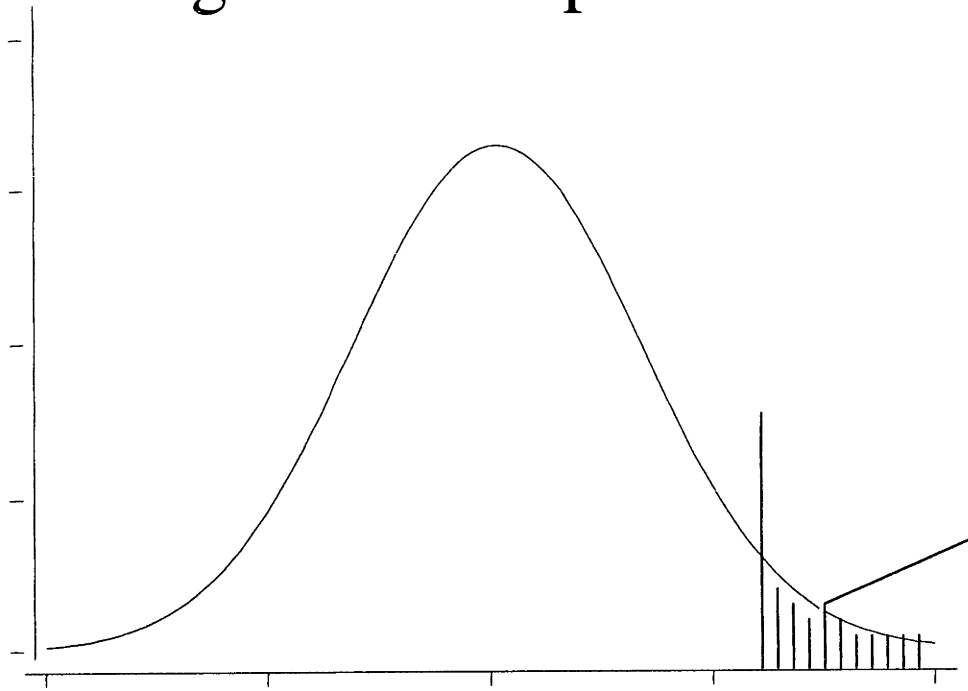


Figure 2. The New Drug Development Process

	Pre-Clinical Testing, R&D	**Clinical R&D**	**NDA Review**	**Post-Marketing Surveillance**
Timing	1-3 years	3-6 years	2 months - 7 years	As long as the drug is on the market
Description	Identify new moleculuar entity via animal and chemical testing	Phase I, II, & III clinical trials (safety, efficacy, and then safety & efficacy combined)		Continued Inspections
End Result	Patent & Investigational New Drug (IND) = FDA approval for testing in humans	Results in NDA Submission	NDA Approval	

Drug Discovery Phase | Drug Development Phase

Figure 3. Sample Selection of Successful Drug Products.



20% of drug products reaching the development stage are included in our study (top quintile)

Probability of Success for New Drug Products in Development
(have IND approval and ready to begin Phase I clinical trials)
The assumptions for this figure are based upon the calculations for new drug success rates in DiMasi (1995).

Figure 4. Schematic of Dataset Construction.

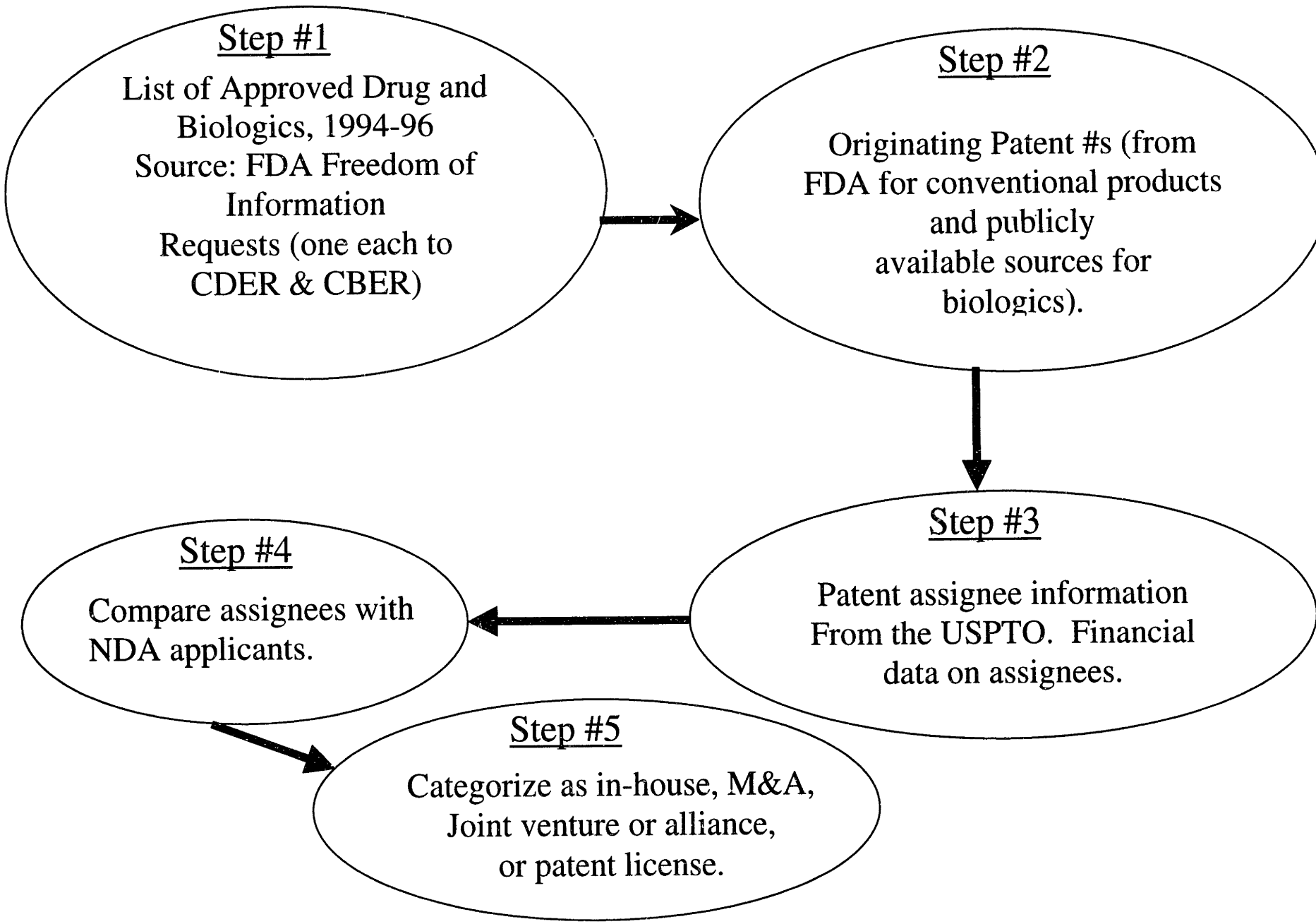


Table 1. A Summary of Theoretical Approaches to the Organization of R&D

Theory	Synopsis	Important Variables	Predictions
Transactions Cost Economics: Coase (1937), Williamson (1975, 1985, 1989)	Given that firms and their managers are characterized by bounded rationality, and behave opportunistically, they will assign transactions (which differ in their attributes) to governance structures (the adaptive capacities and associated costs of which differ) in a discriminating (mainly transaction cost economizing) way.	Three Key Dimensions of Transactions: 1) frequency, 2) degree and type of uncertainty, and 3) degree of asset specificity.	Transactions characterized by high frequency, significant and systematic uncertainty, and a high degree of asset specificity will be conducted within an integrated firm over a non-integrated firm.
Incomplete Contracts and Property Rights: Grossman & Hart (1986), Hart & Moore (1990), Aghion & Tirole (1994)	Integration is defined in terms of the ownership of assets. Firms assign property rights (ownership) to ensure the optimal ex ante investments of each party. "The optimal ownership structure will be chosen to minimize the overall loss in surplus due to investment distortions."	Property rights and ex ante investments	Integration will prevail when the ex ante investment of one firm is more important than the other firm's ex ante investment. Non-integration occurs when the ex ante investments of both firms are important.
Agency Theory: Holmstrom (1989)	Characterizes the organization of R&D as the optimal assignment of tasks across individuals and organizations. "Mixing hard to measure activities (innovation) with easy to measure activities (routine) is particularly costly, since it will either lead to misallocation of attention across tasks or to misallocation of risk."	Tasks accomplished by the firm Characteristics of the firm such as reputation, and monitoring schemes (centralized vs. decentralized).	"For an established corporation, turning up the rate of innovation will...require decentralization. The innovative parts of the business have to be made more independent and financially more responsible." Firms that are effective at executing production and distribution tasks are more likely to outsource for innovation tasks.
Organization Theory: Teece (1992, 1996)	"Formal and informal structures of the firm, as well as the network of external linkages that they possess, has an important bearing on the strength as well as the kind of innovative activity conducted by private enterprise economies."	Whether the firm integrates or not is likely to depend critically on four sets of factors: 1) technology transferability, 2) the degree of intellectual property protection, 3) contractibility, and 4) access to complementary competences	Low transferability, low patent protection, low contractibility, and the lack of access to complementary competences will lead to a greater level of integration.
Extended Neoclassical Theory: Silver (1984), Riordan and Williamson (1985), Williamson (1989)	Integrates the concept of transaction costs into the neoclassical theory of the firm to determine the optimal locus of production.	Production Costs, Transactions Costs	Firms minimize production costs, to include transaction costs.
Conventional Wisdom as Portrayed in the Trade Press: Longman (1997)	The primary means of firm growth in the industry is through innovative new drug products, which are achieved through more efficient research organization that depends primarily upon non-integrated relationships between drug developers and discoverers.	Experience with multi-firm relationships, new drug products, research productivity	In order to maximize research productivity, firms capitalize upon the comparative advantages of their partners.

Table 2. New Drug Product Development Choices (1985-96)

Conventional Drug Product Development

	In-House	Merger & Acquisition	Joint Venture[101]	Patent Licensing	Totals
# of drug products	183	23	13	99	318
% of total	58%	7%	4%	31%	100%

Biotechnology Products Developed for Human Therapeutic Use

	In-House	Merger & Acquisition	Joint Venture	Patent Licensing	Totals
# of drug products	28	3	3	11	45
% of total	62%	7%	7%	24%	100%

All New Drug Products

	In-House	Merger & Acquisition	Joint Venture	Patent Licensing	Totals
# of drug products	211	26	16	110	363
% of total	58%	7%	4%	31%	100%

Product Development Choices: 1985-90

	In-House	Merger & Acquisition	Joint Venture	Patent Licensing	Totals
# of drug products	89	11	5	49	154
% of total[102]	58%	7%	3%	32%	100%

Product Development Choices: 1991-96

	In-House	Merger & Acquisition	Joint Venture	Patent Licensing	Totals
# of drug products	122	15	11	61	209
% of total	58%	7%	5%	29%	100%

[101] Note that the joint venture category throughout our analysis includes strategic alliances as well.
[102] Note that percentages do not always add to 100 due to rounding.

Table 3. List of Variables

Economic Factor	Proxies	Effect on Factor	Drug or Firm Characteristic	Effect of Economic Factor on Development Decision	Hypothesized Net Effect (positive=>integration)
Uncertainty	*Indicator for Difficult Diseases*[103]	+	Drug	+	+
(risk sharing)	Biotech Indicator	+	Drug	+/-	+/-
	# of drugs in therapeutic category	-	Drug	-	-
	Biotech*Trend[104]	-	Drug	-	-
Asymmetry of Information[105]	*Previous drugs developed by firm*[106]	-	Firm	-	-
	Patent stock	-	Firm	-	-
	Publicly Traded	-	Firm	-	+
	Indicator for Difficult Diseases	+	Drug	+	+
Appropriability	Firm size	+	Firm	+	+
	Previous drugs developed by firm	-	Firm	+	+
	Patent stock	-	Firm	+	-
Synergies	Foreign patent	+	Drug	-	-

[103] Difficult diseases are those afflictions, which have been recognized as particularly challenging to cure such as: central nervous system diseases, cancer, heart disease, and AIDs.
[104] Recall that our contention here is that the research community increasingly accepts the new technology incorporated in biotechnology research over the time period under study.
[105] The hypothesized effects here assume controlling for appropriability. Reductions in asymmetric information make the firm a more attractive partner. These same elements, however, improve the firm's ability to appropriate gains from its discoveries.
[106] These two variables, previous drugs developed by the firm and patent stock, have multiple interpretations and are included under both the asymmetric information and appropriability factors.

Table 4. Summary Statistics for Estimating Variables

Variable	Mean	Std Deviation	Minimum	Maximum
Firm Characteristics[107]*:*				
log (firm size)[108] (*lnsize*)[109]	5.5	3.0	-1.1	10.7
log(patent stock + 1)[110] (*patcnt*)	6.15	2.55	0	12.9
Previous drugs (*drgcnt*)	10	13	0	41
Years since first drug (*firstyr*)	19	9.4	0	32
R&D (in millions)[111] (*R&D*)	341	393	.15	1984
Importance of drug sales (*depsal*)	.65	.37	.01	1
Publicly-traded firm (*public*)	.71	.45	0	1
Number of firms	138			
Drug Characteristics:				
Biotech products (*bio*)	.13	.33	0	1
Therapeutic indicator[112] (*ccca*)	.19	.39	0	1
Application year[113] (*appyr*)	1982	6.9	1959	1995
Biotech*Application Year (*bioyr*)	1985	4.7	1976	1995
Foreign patent (*foreign*)	.52	.50	0	1
# of drugs in category (*numclass*)	112.5	134.3	0	401
Number of observations	363			

[107] We had data on the dependence on drug sales, but only for 32 of our observations. We had R&D expenditures for 132 of our observations. Since R&D expenditures were highly correlated with firm size as measured by revenues, we omitted this variable from the following analysis.

[108] Firm size was taken as the log of company sales in the year, which the firm applied for the patent, which ultimately led to a new drug approval from the FDA. The dollar values are in millions of 1991 US dollars. We employed the CPI index for prescription drug products to adjust for inflation. We took data from the COMPUSTAT© and GLOBAL VANTAGE© files when available and then from IMS annual sales tables privately held companies.

[109] Note that the abbreviated name used for each variable in subsequent regression tables follows the full name in parentheses.

[110] We initially considered using patent counts for each assignee that were classified within the explicit drug and biotechnology categories (nclasses: 424,435,514,930, and 935) but found a number of process patents that were classified in chemical or other classes. These patent counts include the USPTO patsic95 and coname95 files. To assure an accurate count we had to be careful to include all possible permutations of assignee names, which represent the firms in our dataset. Note that the distribution for this variable is highly skewed, with a median of 482 patents and 10% of assignees even in this research-intensive group with only one patent.

[111] These data items are only available for publicly traded firms.

[112] We define the therapeutic indicator to assume a value of one when the drug product is for the difficult diseases: cardiovascular, central nervous system, cancer, or AIDs. This indicator is denoted as *ccca* in the regression tables.

[113] In our analysis, the application year is coded as 1 for 1959 and 37 for 1995.

Table 5. Development Choice.
Ordered Probit and Multinomial Logit Regression Results

Model:	Ordered Probit	Patent Licenses	Joint Ventures	M&As
Dependent Variable:	*Development Choice*			
Independent Variables:				
lnsize	0.1179**	-0.2175**	0.1346	-0.2763**
	(0.0408)	(0.0792)	(.1687)	(.1323)
patcnt	-0.0548	0.1062	0.0591	0.0366
	(0.0331)*	(.0669)*	(.1119)	(.1248)
bio	-.0613	0.7734	-1.443	-1.536
	(1.320)	(2.596)	(4.564)	(4.284)
appyr	0.0141	-0.0306	-0.0444	0.0444
	(0.0111)	(0.0216)	(.0456)	(.0375)
bioyr	0.0118	-0.0484	0.0797	0.0143
	(0.0482)	(0.0974)	(.1591)	(.1517)
drgcnt	0.0214**	-0.0454**	-0.1107**	-0.0027
	(0.0073)	(0.0163)	(.0397)	(.0228)
foreign	-0.0453	0.1165	-0.1322	-0.7475
	(0.1485)	(0.2959)	(.6179)	(.4944)
public	0.2787	-0.4911	0.0976	1.137
	(0.2172)	(0.4113)	(.8832)	(.8056)
ccca	0.3017	-0.6268	-0.7342	0.2629
	(0.1772)*	(0.3605)*	(.8068)	(.4917)
log likelihood	-311.36	-299.90		
cut points:				
_cut1	0.394			
	(0.33)			
_cut2	0.537			
	(0.33)			
_cut3	0.750			
	(0.33)			
# obs	363	110	16	25

Note: Standard errors in parentheses with $p<0.05$ = **, $p<0.10$ = *.

Table 5A. Marginal Effects for Ordered Probit Regression
(marginal effects computed at the means of the independent variables)

Variable	Patent License	Joint Venture	Merger & Acquisition	In-house
lnsize	-0.0423**	-0.0033	-0.0036	0.0492**
patcnt	0.0199*	0.0016	0.0017	-0.0232*
biotech	0.2330	0.0184	0.0196	-0.2710
appyr	0.0040	0.0003	0.0003	-0.0047
bioyr	-0.0122	-0.0010	-0.0010	0.0142
drgcnt	-0.0065**	-0.0005	-0.0005	0.0075**
foreign	0.0590	0.0047	0.0050	-0.0686
public	-0.0438	-0.0035	-0.0037	0.0510
ccca	-0.0696*	-0.0055	-0.0058	0.0809*

Note: Standard errors in parentheses with p<0.05 = **, p<0.10 = *.

Table 5B. Marginal Effects for Multinomial Logit Regression
(probabilities vs. in-house development option, marginal effects computed at the means of the independent variables)

Variable	Patent License	Joint Venture	Merger & Acquisition	In-house
lnsize	-.0401**	.0067	-.0136	.0470**
patcnt	.0203*	.0008	.0001	-.0210*
biotech	.2000	-.0483	-.1095	-.0422
appyr	-.0067	-.0011	.0035	.0043
bioyr	-.0108	.0029	.0017	.0062
drgcnt	-.0082**	-.0030**	.0010	.0120**
foreign	.0393	-.0035	-.0498	.0140
public	-.1227	.0050	.0816	.0361
ccca	-.1256*	-.0176	.0304	.1128*

Note: Standard errors in parentheses with p<0.05 = **, p<0.10 = *.

Table 6. Probit of Outsourced Development

Variable Name	Marginal Effects	Coefficient Estimates
log (size)	-.0301	-.055
		(.026)*
patent stock	.0203	.0759
		(.033)**
biotech	.0433	1.305
		(1.19)
application year	-.0078	-.022
		(.012)*
biotech*year	-.0030	-.053
		(.044)
drug count	-.0104	-.031
		(.008)**
foreign	.0344	.145
		(.163)
public	-.1375	-.462
		(.233)**
ccca	-.1313	-.274
		(0.13)**
log likelihood	-190.89	
observations	363	

Marginal effects are computed at the mean values of the independent variables.
(standard errors in parentheses under coefficient estimates with $p<0.05$ = **, $p<0.10$ = *)

Table 7. Nested Logit Regression Results
(direct elasticity effect due to attribute)

Variable Name	Patent License	Joint Venture	Merger & Acquisitions	In-house
Log (size)	-.424**	-.116*	.097*	.510**
Patent stock	.014*	-.017	-.039	-.386*
drugs previously marketed	-.510	-.079	-.096	.216*
Therapeutic indicator	-.117*	-.011	.094	.184*
Inclusive value for Insource Branch				.74 (.39)*
Restricted log likelihood				-482

*** denotes significance at the 5% level.*
** denotes significance at the 10% level.*

Table 8. Summary of Results from Econometric Estimation

Dependent Variable = Level of Integrated Development

Variable | Model	Ordered Probit	Multinomial Logit	Probit	Nested Logit
lnsize	++	++	++	++
patcnt	--	--	--	--
bio	0	0	0	0
appyr	0	0	0	0
bioyr	0	0	0	0
drgcnt	++	++	++	++
foreign	0	0	0	0
public	0	0	++	0
ccca	++	++	++	++

++ denotes a significant positive correlation with the level of integrated development.
-- denotes a significant negative correlation with the level of integrated development.
0 denotes an insignificant correlation with the level of integrated development.

Appendix A. Construction of Variables

The data collected for this analysis were taken from a variety of sources. The purpose of this appendix is to detail this process. The first step was to identify all of the approved new drug products from 1985-96. This information was obtained from two Freedom of Information Act requests submitted to the FDA's Center for Drug Evaluation and Research (CDER) and the Center for Biologic Evaluation and Research (CBER). The information obtained from the FDA included the following vital information: the patent numbers listed on the new drug applications as the primary sources for the approved product, the identity of the applicant, the date of approval, whether the product was classified as a new molecular entity (NME), and the therapeutic category of the approved drug product. The approved product list includes all approved products dating back to 1964. The patent numbers for each of the NMEs were then linked to a patent database constructed at Case Western Reserve University under the auspices of a National Science Foundation Grant supervised by Adam Jaffe and Manuel Trajtenberg. This patent database contains all utility patents granted by the U.S. Patent and Trademark Office from 1962-95. This database allowed the construction of the patent count variable used in the analysis. The patent database also allowed the identification of the discoverers were for each of the approved drug products and when each of the relevant patents were applied for and granted to each of the discovering firms in the sample. Once the discoverers were identified, they were matched with revenue data from the IMS© and Standard and Poor's COMPUSTAT® when they were publicly traded.

Each of the variables was constructed to support analysis at the new drug level, the unit of the observations employed in the analysis. Details for each of the variables follows:

Firm size = log (revenues + 1) where revenues is taken as the inflation-adjusted (CPI-Prescription Drugs) quantity from the IMS dataset in the year a discovering firm received the relevant patent grant. For example, drug A, approved in 1989 received the relevant patent grant in 1984 when it had revenues of $100 million. The firm size variable for this observation then assumes the value log ($100 million + 1). The plus one transformation is included to adjust for the firms that have zero revenues in the year of the patent grant.

Patent stock = log (# of patents + 1) where the # of patents for a discovering firm includes all of the patents granted by the USPTO to the discovering firm during the ten-year period prior to the patent grant year associated with the approved drug.

Previous drugs approved = the number of drugs approved during the ten-year period prior to the relevant patent grant year. Drugs that are jointly developed, i.e. NDA approval is provided to more than one firm at the same time is counted as one drug for each firm.

Years since first drug = the number of years from the time a discovering firm had a previous drug approved to the year of the patent granted relevant for the new drug approved.

R&D expenditures = the inflation adjusted dollars used for R&D in the year of patent grant taken from COMPUSTAT for publicly traded firms.

Importance of drug sales = the proportion of drug sales of total sales as taken from the business segment data of COMPUSTAT for publicly trade firms in the year of patent grant.

Biotech products = 1 if the FDA delegated approval responsibility to CBER.

Therapeutic indicator = 1 if the therapeutic category corresponds to cardiovascular disease, cancer, AIDS or the central nervous system in accordance with standard FDA classification.

Application year = the patent application year for the last patent listed on the NDA application (with the year closest to the drug approval year).

Foreign patent = 1 if the discovering firm had a geographic identifier outside of the U.S.

Number of drugs in category = the number of drugs approved within the same therapeutic category from 1964 to the year of patent grant for the relevant patent of the approved drug product.

Development Decision Classification = in-house if the firm receiving the relevant patent grant and the NDA approval are the same, = patent license of the firm receiving the relevant patent grant licenses the patent during the period between patent grant and NDA approval, = joint venture/strategic alliance if co-development was involved, = merger and acquisition if patent rights were transferred via an acquisition or merger between patent grant and NDA approval. Several on-line resources were used to confirm these classifications: Windhover's Pharmaceutical Strategic Alliances (various volumes), FDC® Reports, the Dow Jones News Retrieval Service®, and Lexis®-Nexis®.

Chapter 4

The Effects of Corporate Downsizing on Women

This paper compares the consequences of displacement for women and men using the displaced workers' supplements to the Current Population Survey from 1984-96.[114] Controlling for worker and job characteristics and year of displacement, women experience approximately the same wage loss as a percentage of previous earnings as men following displacement, although men experience larger absolute wage losses. We compute wage losses here including displaced workers earning zero wages. More importantly, women experience significantly lower rates of reemployment, higher rates of part-time reemployment, higher incidence of leaving the labor force, and longer post-displacement unemployment spells. These findings suggest that the displacement experience of men and women differ substantially, something not emphasized in the previous literature. Additionally, with the 1996 displaced workers' survey, we are able to directly test the importance of job tenure upon displacement rates since for the first time in the history of the survey, tenure is available concurrently for both displaced and nondisplaced workers. Tenure significantly enhances the specifications and strengthens the results. Finally, marital status is an important factor in these. Given the robustness of our results, policymakers considering methods for assisting displaced workers should note well these differences.

[114] This report was funded through Purchase Order No. B-9-4-6-2284 from the Women's Bureau, U.S. Department of Labor. The opinions expressed in this document do not necessarily represent the official positions or policies of the U.S. Department of Labor.

4.1 Introduction

Corporate downsizing, called worker dislocation or displacement by most economists, has captured headlines across the country. The *New York Times'* recent series on this topic, which ran in March 1996, has been published in a book, *The Downsizing of America* (1996). This chronicle of the hardships endured by recently displaced workers has caught the attention of policymakers, academics, CEOs, and workers who are all striving to understand this phenomenon and its impact upon the U.S. workforce. Most of the recent public attention, however, has been focused on only a portion of displaced workers, specifically, white-collar, middle-aged men.[115] This attention follows the focus on male blue-collar workers displaced during the 1980s. Despite the portrait illustrated by the media, "downsized" workers are not, nor have they always been, all males. On the contrary, a significant number of downsized workers have increasingly been female employees (see Tables 2 and 3).[116] This trend becomes particularly disturbing given that "a growing percentage of families are maintained by women alone."[117]

This paper analyzes the effects of corporate downsizing on female workers in the U.S. civilian work force. Specifically, we address three empirical facts regarding the displacement of women in the U.S. work force over the period 1981-95. Researchers have not emphasized the experiences of displaced women in the literature to date. The

[115] See the *Forbes*, April 10, 1996, cover story on displaced AT&T employees for a good example of this media focus.

[116] Table 2 presents the number of displaced workers in various categories by two subgroups: 1) all workers regardless of tenure, and 2) workers with at least three years of tenure. This distinction is consistent with prior research on displacement which regards displaced workers with less than three years of job tenure as undergoing the process of job search (in which a worker may be displaced from his or her job due to a poor match between the worker and the employer).

analysis focuses on three empirical facts established in the analysis: 1) reemployment rates for women have remained significantly lower than that for men over this entire period, despite the fact that labor force attachment for women has increased significantly over this period;[118] 2) the duration of nonemployment is significantly greater for displaced female workers than for their male counterparts; 3) the probability of reemployment into part-time positions following displacement has increased over time for both men and women but is significantly greater for women workers.[119]

The rest of the paper proceeds as follows. The next section reviews the current state of knowledge about worker displacement and about gender differences in the cost of displacement. Section III focuses the analysis on displaced workers with significant labor force attachment and provides a comprehensive picture of displacement trends for both men and women over the 1981-95 time period. The fourth section describes the methodology employed in the analysis for this paper and the regression results. The final section concludes with a summary of the public policy implications of the analysis and recommendations for future research.

4.2 Survey of the Literature

The economic analysis of worker displacement is a relatively recent phenomena first surveyed by Hamermesh (1989). More recent work includes Jacobson, LaLonde, and Sullivan (1993, hereafter JLS) and Farber (1993, 1996). The earlier research described

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[117] Folbre (1995: 310) notes that, "In 1993, 22% of all families with 1 or more children under 18 fell into this category." More recently in a *Wall Street Journal* article, Beck (1997), notes that, "Nearly one in three births in the early 1990s was to an unmarried woman."

[118] The Institute for Women's Policy Research estimates that currently 60% of all U.S. women are employed full or part-time, which suggests a female labor participation rate that is at an all-time high.

[119] We have recently obtained the data from the most recent survey, February 1996, and incorporated it into the tables and figures provided with this paper.

by Hamermesh shows that "displacement has shown a secular increase in the U.S. that is independent of the business cycle." JLS (1993) in their survey consider papers that have used displaced workers' survey data. They find that wage losses for displaced workers are highly skewed toward specific classes of workers, such as those with low education, and high tenure. This result, however, is far from universal.[120] Farber (1993) examines the incidence of job loss and the postdisplacement employment and earnings experience of displaced workers with various characteristics. Using the 1984-92 displaced workers surveys, he finds support for the public perception that "job loss has become relatively more common" but not for the contention that "the costs of job loss have increased." Farber (1996) confirms these findings, noting that "the adverse consequences of job loss, which have always been substantial, do not appear to have changed systematically over time." Fallick's (1996) review of the empirical literature on displaced workers concludes that "outcomes for all displaced workers are heavily influenced by broader economic conditions, and are affected very little by workers' demographic characteristics." This statement, however, focuses on the incidence of displacement and the wage losses of displacement. Fallick's statement also suggests why the displacement experiences of women and men have not been more carefully examined. It is interesting to note that relatively little attention has been focused upon the experiences of displaced women despite the substantial literature on displacement.

Two exceptions to this oversight are Madden (1987) and Crossley, Jones, and Kuhn (1994, hereafter, CJK). Madden (1987) uses the effect of gender on the wage losses of displaced workers to provide "an empirical test of whether human capital or

[120] See Kletzer (1991) who uses a human capital theory framework to generate separate estimates of the effects of tenure and experience on the earnings and earnings losses of displaced blue- and white-collar

discrimination accounts for the sex-wage differential." She employs the human capital theoretic logic that wages due to job displacement will result primarily from job-specific skills since "general skills have the same influence on productivity and wages on the current job and on the prior job." This implies that workers with "general human capital suffer less from displacement." Her analysis of the 1984 Displaced Workers' Survey attempts to correct for sample selection and indicates that women experience an 11 percent drop in their wage growth following displacement relative to their male counterparts. She attributes this loss to discrimination in the labor market. An important shortcoming in this analysis is the Heckman procedure she employs for sample selection bias. Her results are consistent with the finding elsewhere and in this study that the displacement experience of women differs substantially from that of men, but the study does not provide unambiguous support for a discrimination result. CJK (1994) examine data on Canadian displacements in 1982, and find that "women lose more from displacement than men, and that the relative size of this loss increases with tenure." They attribute this differential to "differences in the process of search for a new job." A related paper Sicherman (1996) considers differences in the reasons for departures from a firm by gender. Analyzing detailed data on a large firm in New York City over the period 1971-80, he finds that women may leave jobs for different reasons than men. In particular, "a higher proportion of women than men left their jobs for non-market-related reasons such as household duties and illness in the family; and women were much more likely than men to name higher wages, and not better opportunities, as a reason for switching jobs." Sicherman's analysis does not generalize, however,

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men and women.

because of its focus on only one firm. This paper is useful in confirming some of Sicherman's specific findings with a more widely representative sample.

Although current research does include a female indicator variable in its analysis, little has been done to understand the full effects of displacement or downsizing on an increasingly important segment of displaced workers, women. This analysis uses all of the available displaced workers' surveys from the Current Population Survey (CPS) in an effort to fill this void in the literature.

4.3 Data

To adequately examine the source of differences between the effects of corporate downsizing on men and women, we employ the most comprehensive data available on worker displacement, the Displaced Workers Survey (DWS) Supplement to the Current Population Survey (CPS) for each of the even years from 1984-96. These surveys contain detailed information about displaced workers from 1979-1995.[121] This data allows us to carefully measure the different effects of displacement on female workers and how this has changed over the past 15 years. Due to its wide dissemination (the survey is distributed to nearly 60,000 households monthly), random nationally representative sampling, and the wealth of information contained in the dataset (it contains several hundred variables on each of the respondents), the data give a detailed picture of worker displacement in the US. The Current Population Survey is widely used by many researchers looking at labor market trends in the United States. Since the CPS includes both displaced and nondisplaced workers from a broad cross-

section of the country, it allows for a detailed comparison of displaced and nondisplaced workers by region, industry, occupation, age, education level, marital status, veteran status, and household type. Unlike other data employed in the analysis of displaced workers, such as the Panel Study of Income Dynamics (PSID), the CPS and its displaced workers' supplement provide a much larger and more representative sample of displaced workers.

The two shortcomings of this data, however, are the recall bias that has been established by several researchers and the lack of workers' wages over time, preventing a panel data approach to this analysis.[122] First, due to the five year window for inclusion into the displaced worker's survey supplement, the data suffers from *recall bias* since workers may not recall minor, and in other cases even major, displacements that occurred four or five years ago. To correct for this problem, this paper limits the sample to displaced workers who are displaced in the one to three years prior to the year of each of the seven surveys used in our analysis. This allows us to draw confident conclusions regarding worker displacement for the period 1981-1995, using the 1984-96 surveys. Second, since we do not have accurate wages for displaced workers for time periods prior to displacement we are unable to analyze wage losses prior to displacement. Several researchers have noticed that wages begin to fall for workers prior to their displacement, as firms attempt to avoid plant shutdowns by reducing labor costs via lower wages. The lost wages due to this phenomenon is not measurable with

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[121] The surveys in 1984, 1986, 1988, 1990, and 1992 ask workers if they have been displaced at anytime during the five years prior to the survey. The 1994 and 1996 surveys have reduced the time period to three years prior to the survey to reduce recall bias.

[122] See Topel (1990) and Farber (1993) for a discussion of the "recall bias." Short panels, however, can be constructed using a matching technique described in Welch (1994). Due to the substantial attrition in these samples, however, the short panels lack sufficient size for accurate analysis. See de la Rica (1992).

this dataset.[123] Despite these shortcomings, this data allow us to measure the two important effects of displacement: wage loss upon reemployment and the wage loss during displacement. All of the wage data are provided in current dollars. To make wages prior to and following displacement are compatible we adjust wages for inflation using the consumer price index (CPI-W), which is the most appropriate price index to apply to worker's wages. This correction makes wage comparisons appropriate across different years and does not understate the true wage losses imposed upon displaced workers.

In addition to these adjustments, we further restrict our data sample along dimensions relating to the permanence of displacement. The majority of the analysis is restricted to displaced workers who satisfy the following criteria: 1) they are long tenure workers, meaning that they have spent a minimum of three years at the job from which they were displaced; 2) they were displaced for a non-seasonal (well-defined) reason; 3) they were displaced from either an hourly or salaried position, a part-time or full-time position, but not a self-employed position; 4) they were displaced between one and three years prior to the year of the survey;[124] and 5) they are aged 20 to 64 at the time of displacement. These restrictions focus the analysis upon displaced workers that had a significant attachment to their job, e.g., had been working at their predisplacement job for a minimum of three years, and were displaced for a well-defined permanent reason. The displaced workers' supplement to the CPS asks workers about their specific reason

[123] Jacobson, LaLonde, and Sullivan (1993: 59-60) discuss this effect, stating that, "During the years immediately prior to their separations, their earnings begin to decline." We refer to this effect as the predisplacement "dip." Given the existence of the "dip", the measure of median wage loss, which we compute, will provide a lower bound for earnings losses for displaced workers.

[124] When we focus on displacement rates and report displacement by the year of the survey, we group workers that were displaced one to three years prior to the survey. When we report data by the year of

for displacement. Displaced respondents check one of six possibilities: 1) plant or company closed down or moved? 2) plant or company operating, but lost job because of: slack work? 3) position or shift abolished? 4) seasonal job completed? 5) self-operated business failed? 6) some other reason? The first three of these six possible responses refer to well-defined non-temporary reasons over which the worker, presumably, has no control. Additionaliy, workers displaced for these non-temporary reasons also comprise the vast majority of displaced workers. The last three refer to temporary or ill-defined reasons. Table 1 shows the breakdown by cause of displacement and year of survey.

In the 1994 and 1996 surveys, worker characteristics data is not given for displaced workers who were displaced for ill-defined reasons, responses 4) – 6) above. To ensure comparability across survey years, I focus on workers displaced for permanent, well-defined permanent reasons, plant shut down, slack work, or position or shift abolished.

Displaced workers are further identified by their pay status in their predisplacement positions. They are categorized as hourly status, part-time status, and self-employment status. We initially include all displaced workers regardless of their predisplacement job status, except self-employed workers, for whom displacement is ill defined. To minimize the recall bias and to make the data consistent (since the 1994 and 1996 surveys do not include displacement four and five years prior to the survey), we do not include displaced workers who report that they were displaced four or five years prior to the survey year. The age restriction eliminates many workers who are still in the search process for a more permanent position (workers under 20 years of age) and workers

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displacement, we take workers that were displaced two and three years prior to the year of the survey, so that we get a consistent time series from 1981-95.

who are of retirement age (workers above 64 years of age). In sum, we analyze displaced workers that have exhibited significant attachment to the labor force prior to their displacement as evidenced by their age, and job tenure, and who have been displaced for well-defined reasons reasonably close to the date of each survey we include in our data sample.

The remainder of this section provides detailed summary statistics for variables of interest. Figure 1 provides an overview of the overall trend in worker displacement.[125] This figure shows the trend for all displaced workers as well as the trend for long tenure workers that were displaced for non-temporary, well-defined reasons. This second group of workers tends to be the most adversely affected by displacement and are the focus of the remainder of the analysis. This data indicates that corporate downsizing of workers with strong labor force attachment appears to have become more common.

Tables 2 and 3 provide an overview of displacement by sex. We define the

displacement ratio = $\frac{\#\_of\_displaced\_worker s_{it}}{\#\_of\_nondisplaced\_worker s_{it}}$, where i denotes a specific

category such as women workers, for a specific time period, *t*. The numerator of this ratio, *unless otherwise noted, is restricted to the long-tenured displaced workers who are displaced for non-temporary, well-defined reasons for the remainder of this paper.* Table 2 considers displacement by year of displacement by year of displacement first for all displaced workers and then for long-tenured workers and Table 3 displays these displacement numbers as a percentage of total civilian employment for each year. On average, women compose 40 percent of all displacement and of long-tenured

[125] The displacement ratio computed in this figure is simply the number of workers displaced from the labor force satisfying the criteria discussed above divided by the total number of workers in the labor force satisfying the same criteria.

displacement. The relative displacement ratios for all men and all women average 2.75 percent and 2.35 percent, respectively, over the period of analysis.[126] If the sample is limited to long-tenure workers displaced for non-temporary, well-defined reasons, a different picture emerges. Figure 2 limits the sample to displaced *workers with at least three years of tenure and non-temporary, well-defined reasons of displacement.* In this figure we compute displacement ratios using the available data on nondisplaced workers in the CPS for the corresponding years for which the displaced workers' supplement documents displaced workers.[127] When the sample is restricted to those displaced workers who are strongly attached to the labor force (long-tenure, non-seasonal and non-temporary workers); we get the results represented in Figure 2 and Figure 3. Figure 2 parallels the trend observed in Figure 1; the increase in overall displacement for long tenure workers occurs just after the increase in the proportion of total displacement comprised of women workers. Table 4 shows displacement ratios for long tenure workers displaced for non-temporary reasons by age and sex for each survey year. The upward trend in corporate downsizing apparent in the previous figures is concentrated for both men and women between the ages of 25-54, as shown in the highlighted portion of Table 4.

Figure 4 shows the trends by educational category. We divide the data into five educational categories: less than high school, high school diploma, some college, college graduate, and graduate or professional degree. Figure 4 shows the well-known increase in displacement rates for high school only educated workers as well as the

[126] The relative displacement ratios here compare the trend in the displacement of women to that of men over the last 12 years, showing how the displacement ratio of women has increased from 44.28% in 1984 of the male displacement ratio to 70% in 1996.

well-publicized increase in displacement rates for college graduates. One interesting feature of this graph not observed in previous analyses is the relatively low displacement rates for well-educated women relative to their male counterparts. Education appears to provide women workers with greater protection against job loss than men. We test this econometrically in the next section of this paper. Although displacement rates for workers with lower levels of education remain the highest, workers with college degrees, both men and women have experienced a relative increase in their displacement rate. Throughout our period of analysis, women with graduate degrees experience the lowest displacement rates of any of the categories.

The data can also be analyzed by occupational category, industry, race, ethnicity, and type of household. The seven occupational categories that we use are managerial and professional, technical, sales, clerical, service, craft and repair, and operators/laborers. Seven industry categories are also used: manufacturing; transportation, communications, and other public utilities; wholesale and retail trade; finance, insurance, and real estate; business, repair, and personal services; medical and professional services; and public sector. The fraction of total employment in white collar and service industry jobs has risen over this period. Controlling for these trends, displacement ratios have still risen over time for workers in white collar and service industry jobs. Figure 5 provides the displacement ratios for all long-tenure workers displaced for non-temporary reasons over the period 1981-95 by occupational category and sex. The two blue-collar categories of craft/repair and operators/laborers have the highest displacement ratios, while the white-collar categories have slightly lower

[127] We take relevant tenure data from the Occupational Mobility and Job Tenure Surveys for 1983, 1987, 1991, and 1996. Estimates for tenure are used when not directly available from the surveys.

displacement ratios. This presentation, however, obscures the underlying trends, which have shifted displacement from the blue-collar categories to the white-collar categories. Farber (1996) notes similar findings. Looking at these displacement ratios shows some interesting results. Surprisingly, the displacement ratio for women in the professional and managerial categories as well as the technical category are significantly lower than for men, while women have a slightly higher displacement rate in the craft and repair category, a category traditionally dominated by men. One potential explanation for this finding is that the few women that do make it to the top-tier white-collar categories are very motivated to remain in their jobs and exhibit a stronger labor force attachment relative to the larger group of men in the same category. In contrast, women in blue-collar jobs may be less attached to those positions relative to their counterparts in white-collar jobs.[128]

Finally, Figure 6 examines the trends in displacement rates for each of the seven occupational categories by sex over each of the seven survey years. This figure mirrors Figures 1, 2, and 4 in terms of trends. Additionally, it provides some support for the contention that the increase in displacement rates for women in blue-collar jobs, relative to to their lower displacement rates in white-collar positions, is a function of their relative composition of those two categories of employment. The few women in blue-collar jobs have experienced a steep increase in their probability of displacement that parallels an increase for men. This same trend is not evident in the data on white-collar displacement. To examine these trends more precisely, we must analyze how the

[128] Alternatively, it may be a case of last hired, first fired, and women in blue collar jobs have relatively lower seniority relative to men, than in other occupations.

probability of displacement correlates with occupational category and time trend interaction variables.

These trends in displacement ratios by occupational category are mirrored by the displacement ratios for the seven defined major industry groups. Figures 7 and 8 are the industry counterparts to Figures 5 and 6. When examining the period as a whole, the manufacturing sector, which has traditionally been subject to substantial downsizing during economic cyclical downturns, has the highest displacement ratio of the seven major industry groups. Figure 7 decomposes displacement by industry and sex, and again shows that women's displacement rate is high in an unexpected group: the manufacturing sector. The displacement rate in the manufacturing sector is higher for women than for men. This is very plausible, however, once we consider that the displacement rate measures displacement as a percentage of the pool of workers in that particular group, so that it is a relative measure of displacement rather than an absolute one. In Figure 7 we see the expected trend for the manufacturing sector for both men and women, and other trends such as the monotonically increasing rates for the financial services sector as well as the recent increase in displacement in the public sector.[129]

Table 5 provides breakdowns by household type. The CPS poses a question regarding household type. Household types include: 1) husband/wife primary family (neither in the Armed Forces); 2) husband wife primary family (either/both in the Armed Forces); 3) unmarried civilian male-primary family householder; 4) unmarried civilian female-primary family householder, 5) primary family householder, reported in armed

forces, unmarried; 6) civilian male primary individual; 7) civilian female primary individual; 8) primary individual household, reported in armed forces; 9) & 10) group quarters. Category four, single female heads of household, arguably contains those workers most adversely affected by displacement.[130] The percentage of displacement comprised of single mothers is provided in Table 5. As a percentage of overall displacement, women single-parent households comprise on average, 12 percent of displaced workers, and men single-parent households comprise about 4 percent. Although these women are a minority of all displaced workers, they are significant enough to warrant further study.

4.4 Regression Analysis

Now that we have covered the general trends in displacement for men and women across different age, educational, occupational, industry, and household categories, we consider the specific effects imposed upon men and women due to displacement. In particular, we consider: 1) the wage loss which accompanies displacement, 2) the probability of displacement as a function of worker characteristics, 3) the probability of reemployment, 4) the probability of becoming reemployed in a part-time position, and 5) the duration of unemployment following displacement, and how each of these varies by sex.

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[129] Displacement from the public sector includes service members that have left the U.S. Armed Forces over the period 1991-1995. See the 1996 GAO report entitled, "Federal Downsizing: Better Workforce and Strategic Planning Could Have Made Buyouts More Effective".

[130] An additional question in the CPS asks how many children under 18 are in the household. This question was, unfortunately eliminated from the 1994 and 1996 surveys, and was replaced by the question, how many persons live in your household. To make the data compatible, we assume that

4.4.1 Wage Loss Due to Displacement

Table 6 summarizes the inflation-adjusted wage losses for men and women by year of displacement. We define wage loss here as the difference between a worker's post displacement wage and predisplacement wage. Workers that do not regain employment receive a zero wage. These figures differ from the tables provided in most of the Bureau of Labor Statistics (BLS) press releases because they include both part-time workers and hourly workers. The BLS only includes full-time salaried workers.[131] Additionally, we correct for inflation, which provides a more accurate measure of the actual wage loss for displaced workers (since computations unadjusted for inflation will understate the amount of true wage loss).[132] Table 6 shows that although the absolute wage loss for men exceeds that for women on average, the wage loss as a percentage of previous earnings is about the same for men and women and higher for women in some periods.

To examine the relationship between displacement wage loss and sex, controlling for education level, experience[133], occupational and industry category, veteran and marital status, race, ethnicity, region, and jobs in metropolitan areas, we run the following regression:

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households in category four with at least one child, or two or more persons living in the household, are single mother households.

[131] We feel that it is important for analysis to include these categories of workers, because of our focus on women workers, which tend to comprise higher proportions of hourly and part-time workers.

[132] Since we are examining workers' wages, we use the consumer price index (CPI) as reported by the Federal Reserve Board to adjust for inflation.

[133] We define potential job market experience in the standard manner: experience = age - years of schooling - 5.

$$\ln(\text{inf}\,lation - adjusted\_wages) = \alpha + \delta(displacement) + \gamma(female * displacement) + \beta_1(sex) + \omega(female * year) + \beta_2(education\_level) + \beta_3(\text{exp}erience) + \beta_4(\text{exp}erience)^2 + \beta_5(\text{exp}erience)^3 + \beta_6(\text{exp}erience)^4 + \beta_7(black\_indicator) + \beta_8(hispanic\_indicator) + \beta_9(region\_indicator) + \beta_{11}(occupational\_indicators) + \beta_{12}(industry\_indicators) + \beta_{12}(veteran\_status) + \beta_{14}(marital\_status) + \beta_{15}(metro\_indicator) + \lambda(year\_of\_survey) + \varepsilon$$

Our variable of interest is $\hat{\gamma}$ which measures the relative wage loss for women vs. men displaced workers. The relevant hypothesis test is then:

$$\text{Ho: } \hat{\gamma} = 0 \text{ vs. Ha: } \hat{\gamma} < 0$$

If we reject the null and accept the alternative hypothesis, then we can state that displaced women experience a greater wage loss then their male counterparts when controlling for all relevant worker characteristics. Important features of the specification are the inclusion of a quartic specification for experience, a female*displacement interaction term (which captures the significance of being a female displaced worker and is the variable of interest), and a female*year interaction term (which controls for women's changing relative wages over time). When we use all of the available data for workers displaced during the 1981-95 time period, we obtain the results provided in Table 7. This results support rejection of the null hypothesis above, supporting the contention that female displaced workers do experience a greater wage loss than male displaced workers, controlling for education level, industry grouping, occupational category, experience level, marital status, veteran status, and region of employment. When we consider regressions by year of survey, however, we observe a different picture. In particular, we see a trend towards a greater differential in the wage losses for women vs. men displaced workers, although this trend is difficult to detect when looking

at regressions upon individual survey years (as indicated in Table 7). The difference between the individual survey year regressions versus the pooled regression, is that with the pooled regression, we are able to account for the upward trend in women's wages over the time period, which is unaccounted for in the regressions completed by survey year. The female*year of survey interaction term is positive and significant with a coefficient of .009 (suggesting about a 1% inflation-adjusted wage increase per year for women) and corresponding t-statistic of 8.613, which is highly significant. The fully specified model, as shown above, then correctly adjusts for the upward trend in women's relative wages, allowing us to identify the wage loss for men vs. women displaced workers more precisely. The results presented in Table 7 suggest then that *at best, women displaced workers suffer as large a wage loss as men displaced workers* (since for the survey year regressions, we do not reject the null hypothesis of equal wage loss), and *at worst, suffer a 4% greater wage loss* (as indicated by the more fully specified model using all of the available data).

An important omission from our specification here, however, as argued by Topel (1991) and Whelan (1997), among others is job tenure. Although the importance of job tenure has been debated in the economics literature, we can test directly the impact of job tenure on the probability of displacement and wage determination for the first time without out of sample predictions using the 1996 Displaced Worker's Survey.[134] An improved specification adds a quadratic in job tenure to the standard wage regression. This improved specification slightly reduces the measured impact of job displacement upon wages from 17% to 15% for the latest survey data, which is statistically significant

at the 99% level. This result suggests that it is indeed important to control for job tenure when comparing the wages of displaced and nondisplaced workers, and is consistent with the general findings in Whelan (1997). For our purposes, however, the results of the analysis remain essentially unchanged.

4.4.2 Probability of Displacement

The next aspect of displacement that we consider is the probability of displacement as a function of those variables that we would expect to affect this probability and an indicator for gender. Our purpose here is to see if the apparently higher displacement rate for men remains after controlling for individual worker characteristics. Since our dependent variable here is of the binary form, we employ the probit regression to avoid the coefficient bias inherent in the application of standard linear regression to such analyses. Our specification is:

$$\Pr ob(Displacement = 1, Displacement = 0) = \prod_{displ=0} [1 - F(\beta' X_i)] \prod_{displ=1} F(\beta' X_i)$$

where X_i is a vector of worker characteristics that should influence the probability of displacement and includes years of schooling, potential job market experience (a quartic function), job tenure (which is only directly available for the 1996 survey, but estimated from the Occupational Mobility and Job Tenure Surveys for the other years in our sample), industry group in which employed, occupational category of employment, veteran, marital, and union status, region of employment, year of survey, and whether employed in a metropolitan area. The vector, β_i, is a vector of coefficients

[134] Out of sample prediction methods apply regressions using the Occupational Mobility and Job Tenure Surveys to determine estimated tenure, $\hat{ten}$, which can be included as an explanatory variable on the

corresponding to these worker characteristics, and F (.), is the cumulative normal distribution. To correctly test the validity of the hypothesis asserting differential displacement probabilities for men and women over time (after having controlled for relevant worker characteristics to include some measure of job tenure, either estimated or actual), we can focus on the following test: $\hat{\beta}_{female} = 0$. The results from the combined regression and the individual survey year regressions are listed in Table 8. The control variables generally have the expected sign. For instance, higher levels of education result in a lower probability of displacement, as expected (this effect is strongest for the 1986 survey year data and attenuates over time). Potential job market experience enters significantly and positively (in the 1996 survey data which controls directly for job tenure for instance, the marginal probability increase in displacement is almost 7 percent for each additional 10 years of job market experience). Additionally, the union membership coefficient is highly significant and negative, as expected. The parameter estimates given in Table 8 yield the marginal probability increase or decrease in displacement due to being a woman. The parameter estimates of the female dummy variable coefficient are very small and usually insignificant. These results suggest that after controlling for education level, potential job market experience, job tenure, race, ethnicity, region, occupational category, industry group, veteran, marital and union status, and employment in a metropolitan area, the probability of displacement is statistically equal between men and women workers. This result differs from previous findings by Farber (1996), for instance, primarily due to the careful inclusion of job

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right-hand side of the equation.

tenure.[135] This suggests that although the raw displacement rate for men is higher than that for women as shown earlier in Figures 2 and 3, when we adjust for the worker's characteristics, particularly job tenure, the probability of displacement is very similar.

Now that we have established that the wage loss and probability of displacement are very similar for men and women displaced workers, once we control for worker characteristics, we now turn to three dimensions in which men and women displaced workers differ: reemployment rates following displacement, part-time reemployment following displacement, and duration of unemployment following displacement.

4.4.3 Probability of Reemployment

When looking at overall reemployment for men and women displaced workers we observe a large disparity between the two sexes. Figure 9 looks at the employment outcomes for long-tenure displaced workers over the period 1981-94.[136] We decompose the outcomes here into employment (which includes full-time, part-time, and self-employment), unemployment, and not in the labor force (NILF). The average 7 percent differential in reemployment between men and women displaced workers is evident in Figure 9 and is supported by the pie charts in Figure 10, which show that in the aggregate for all years of displacement, 65 percent of women gain reemployment following displacement, versus 72 percent of men. A larger percentage of displaced women also leave the work force relative to their male counterparts, 21% vs. 9%. When we analyze our data by year of survey rather than by year of displacement, these

[135] For a good portion of the data we are able to match directly with available Occupational Job Mobility and Tenure data. We estimate job tenure for those workers for which direct matches are not available.
[136] Note that since these data are presented by year of displacement, we take the second and third years prior to each of the survey years of displaced data in the manner of Gardner (1995), e.g. from the 1984 survey we use the data on workers displaced in 1982 and 1983.

results are further supported. Table 9 provides the percentage of displaced men and women who become reemployed, remain unemployed, or leave the work force altogether. To determine whether these empirical facts remain after adjusting the reemployment probabilities for individual worker characteristics, we estimate the following probit regression:

$$\Pr ob(\text{Re}employment = 1, \text{Re}employment = 0\_|\_displ = 1) = \prod_{reemployment=0} [1 - F(\beta' X_i)] \prod_{reemployment=1} F(\beta' X_i)$$

where X_i is a vector of worker characteristics that should influence the probability of reemployment, including years of schooling, specific job tenure (a quadratic function), industry group in which employed, occupational category of employment, veteran, and marital status, region of employment, year of survey, and whether employed in a metropolitan area. These variables derive from employment prior to displacement.[137] The vector, β_i, is a vector of coefficients corresponding to these worker characteristics, and F (.), is the cumulative normal distribution. Unlike the analysis completed for the probability of displacement, this analysis conditions on displacement, so that we are looking at the probability of reemployment conditional upon a worker being displaced. The hypothesis test is similar to that which we examined previously, except that now we are looking at reemployment conditional upon displacement as a function of worker characteristics, including sex. If we represent the estimated coefficient of the sex indicator with, $\hat{\delta}$, then our hypothesis of interest is $\hat{\delta} = 0$ vs. $\hat{\delta} < 0$. Rejecting the null hypothesis here suggests that after controlling for worker characteristics, displaced

[137] Since for displaced workers, we have the actual number of years in the displaced job, we call this variable tenure rather than experience to make it consistent with the tenure variable.

women *still* have a significantly lower probability of reemployment than their male counterparts.

The results in Table 10 suggest that we strongly reject the null hypothesis in favor of the alternative that female displaced workers are significantly less likely to become reemployed than their male counterparts. In particular, when we employ all of the available data in our analysis, we find that *after controlling for worker characteristics*, female displaced workers still have an 8 percent lower probability of becoming reemployed then men displaced workers. This differential ranges from a low of 4 percent for the 1992 survey data to a high of 14 percent for the 1984 survey data. In the most recent survey year, 1996, the differential stands at 6%.

These findings, however, must be qualified since not all of the women who are displaced are the primary wage earners for their families. Married women may be more likely to leave the labor force or have a lesser incentive to become reemployed then unmarried women due to their greater family support. We can test this hypothesis by adding a female*married interaction term to our specification and by considering the following hypothesis test: $\hat{\gamma} = 0$ vs. $\hat{\gamma} < 0$, where $\hat{\gamma}$ represents the coefficient on the female*married interaction term. If we reject the null hypothesis in favor of the alternative as we have stated it, then our contention that displaced women that are married will be less likely to become reemployed is consistent with the data. Table 11, provides our results for the female*married interaction term. They strongly support rejection of the null hypothesis here in favor of the alternative that married female displaced workers are significantly less likely to become reemployed than their unmarried counterparts. For the regression employing all survey data and controlling

for time effects with year of survey indicator variables, we obtain a coefficient estimate of -0.176 that is statistically significant at the 1 percent level. This estimate suggests that married women have a probability of reemployment that is on average 18 percent lower than for their single counterparts. The remaining coefficients for the individual survey years range from a high of -0.24 for the 1984 survey to a low of -0.15 for the 1988 survey. All estimates are relatively close to the 18 percent value for the entire period and are highly statistically significant.

These results suggest that the lower reemployment probability for women is strongly correlated with marital status. This paper is the first that we are aware of to consider this hypothesis. We might further speculate that this result might stem from differences in preferences between single and married women to leave the labor force following displacement, and weaker incentives for reemployment for married women who may turn toward non-market activities. To further test this interpretation, we separate the sample into married men and women and single men and women and rerun the analysis on reemployment probabilities. In this analysis, the hypothesis test is: $\hat{\beta}_{single} = \hat{\beta}_{married}$ versus $\hat{\beta}_{single} > \hat{\beta}_{married}$, where $\hat{\beta}_{single}$ is the coefficient of the female indicator for the subsample of displaced single men and women, and $\hat{\beta}_{married}$ is the same coefficient for the subsample of displaced married men and women. If the null hypothesis is consistent with the data, then single women have the same probability of reemployment relative to single men, as married women do relative to married men. If our analysis rejects the null hypothesis in favor of the alternative, however, then single women will have a higher probability of reemployment relative to married women. The results of our probit analysis are presented in table 12, which strongly reject the null

hypothesis in favor of the alternative hypothesis that the probability of reemployment for single women is significantly higher than for married women. These results require additional analysis for a more complete interpretation, but are very suggestive of very different labor market behaviors by displaced married and single women.

4.4.4 Part-time Employment and Reemployment

Another feature of the data on displaced workers that requires examination is the large disparity in part-time employment by men and women. As evidenced in Figure 11, part-time employment has become more prevalent for both displaced men and women, but more so for women displaced workers. We have disaggregated the data into two groups, 1981-90, and 1991-95, due to the redesign of the CPS in January of 1994, which has a substantial affect on the number of workers who report part-time employment, thereby making the two periods incompatible. When we consider the population of *all displaced workers with long tenure*, in the earlier period we see that women experience part-time employment at rates greater than twice the rate of their male counterparts, 18 percent vs. 8 percent of reemployed workers. During the latter period, 1991-95, we find the difference to be greater in absolute terms, but smaller in relative terms, 37 percent part-time reemployment for women versus 23 percent part-time reemployment for men. The reason that we are so interested in part-time reemployment outcomes is the widely accepted fact that part-time jobs lead to lower wages, even controlling for the number of hours worked, and lower benefits.

The U.S. labor market has experienced an increase in part-time employment, but displaced workers appear to move to part-time employment following displacement in greater numbers than the general labor force. Women, in particular, exhibit significant

propensities toward part-time employment. Table 13 provides the percentage of displaced men and women who are in part-time employment pre and post displacement. Since these data are presented by year of displacement, we take data from the second and third year prior of each survey year to form a consistent time-series from 1981-95. We also separate the data to account for the major survey revision in 1994. The empirical regularities apparent in Table 13 include: 1) both male and female displaced workers make significant moves towards part-time employment following displacement (the percentage increase for men is over 100 percent, and for women, about 50 percent); 2) female displaced workers are more inclined to be part-time employees both before and after displacement (on average about 20 percent of women work part-time pre displacement vs. only about 7 percent of men, and about 30 percent of women work part-time post displacement vs. only about 17 percent of men); and 3) although the absolute increase in part-time employment following displacement is greater for women, the relative increase is actually greater for men (see the percentage increase columns in Table 13).

This data on part-time employment pre and post displacement is suggestive of a higher propensity for women workers to go into part-time reemployment following displacement. This may be due, however, to unmeasured worker characteristics, which predispose certain workers, in this case, women workers, toward part-time work to a greater degree than men workers. To examine this question more precisely, we estimate the probability of part-time reemployment as a function of worker characteristics to include whether or not the worker was working part-time prior to the displacement which may serve as a proxy for a worker's propensity towards part-time

employment. Farber (1996) finds that previous part-time employment is the most important determinant of part-time reemployment by applying a logit analysis to part-time reemployment as a function of worker characteristics (age, education, sex, race, and year of displacement) and the reason for displacement.[138] Farber's focus is on the effect of reason of displacement upon reemployment in part-time positions, but he also notes, "Females and non-whites are significantly more likely to be working part-time after displacement." Since he also controls for part-time status on the predisplacement job, this result is "unlikely to be primarily the result of preferences."[139]

To confirm these results we employ a more complete specification of worker characteristics by adding the industry of employment, occupational category, region of employment, veteran and marital status, and an indicator for workers living in a metropolitan area. We present the results from our probit regression in Table 14, where we also find that previous part-time employment is the predominant determinant of postdisplacement part-time reemployment. Additionally, we find strong support for the contention that after controlling for all worker characteristics, female displaced workers are much more likely to become reemployed in part-time positions than their male counterparts. In particular, when we use all of the available data, the coefficient on the female indicator is .115 with a z-statistic of 9.49, which is significant at the 99% level. The interpretation of this finding (as indicated in Table 14) is that displaced women have a 12% greater probability of turning to part-time employment following displacement than their male counterparts.

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[138] See page 28 and Table 13. Farber states, "Not surprisingly, the strongest effect on the probability of part-time employment comes from part-time work on the lost job. This could reflect labor supply preferences or some other unmeasured characteristic that makes full-time work difficult to get for some workers."

In the above analysis we are conditioning upon displacement. An alternative means for examining the effect of displacement and gender upon the probability of part-time employment is to estimate an equation that uses both nondisplaced and displaced workers. In this specification, we estimate the following equation, which does not condition upon displacement, but rather includes it as a regressor in the likelihood function:

$$\Pr ob(Part-time\_Employment=1,\Pr ttimer=0)=\prod_{prttimer=0}[1-F(\beta' X_i)]\prod_{prttimer=1}F(\beta' X_i)$$

where once again, X_i, is the same vector of worker characteristics used in the previous analysis, except that instead of specific job tenure, we use potential job market experience, and include an indicator for displacement to differentiate displaced from nondisplaced workers and a female*displacement interaction term, to determine how displaced women in particular behave with regard to part-time employment relative to nondisplaced women. This specification allows us to control for any preferences on the part of women workers to be employed in part-time positions. We can state our hypotheses of interest in the following manner: 1) Do displaced workers have a higher tendency to be employed in part-time positions than their nondisplaced counterparts? Ho: $\hat{\delta}=0$ vs. Ha: $\hat{\delta}>0$, where $\hat{\delta}$ = the parameter estimate on the displacement indicator. 2) Do displaced women workers have a higher tendency to be employed in part-time positions relative to their male counterparts? Ho: $\hat{\gamma}=0$ vs. Ha: $\hat{\gamma}>0$ or Ha: $\hat{\gamma}<0$. Our results presented in Table 15, strongly reject our first null hypothesis, providing strong support for the contention that displaced workers have a significantly

[139] See Farber (1996), p. 29.

increased probability of being employed in part-time positions due to their displacement. These results also provide mixed support for the rejection of the second hypothesis, in favor of the alternative that of lower part-time reemployment for displaced women workers. When we recall the importance of controlling for a worker's propensity towards part-time employment, however, as demonstrated in Table 14 we must interpret the results we find in Table 15 carefully. We can conclude from Table 15 that displacement has a strong effect on the probability of part-time employment. The mixed results with regard to the relative probabilities of men vs. women displaced workers here, however, are clearly dominated by the much stronger results supporting greater part-time reemployment for displaced women workers shown in Table 14.

4.4.5 Duration of Unemployment and Worker Mobility Following Displacement

Two final areas of interest that we consider are potentially quite important for determining how displaced workers are affected by their displacement: 1) the duration of unemployment following their displacement; and 2) their propensity to undertake a geographic move to seek improved job prospects. The importance of the first of these two factors is self-evident, the longer a displaced worker is unemployed, the greater are his or her wage losses due to unemployment. In addition, mobility appears to have become more important because downsizing has assumed a more regional character. During the early to mid-1980s, when the manufacturing sector experienced significant reductions, the midwestern region of the country suffered disproportionately relative to the rest of the country. Similarly, during the late 1980s and early 1990s, when the defense industry, primarily located along the coastal regions of the country, were hit hard, displacement tended to occur in the northeastern and western regions. Because

of this regionally concentrated nature of displacement, we can hypothesize that workers, who are more mobile, can more effectively escape a depressed region and move to a more successful region, thereby mitigating the most negative effects of displacement. Tables 16 and 17 provide a breakdown of duration and worker mobility during our period of interest. We see that women on average experience a longer period of unemployment following displacement, and are less likely to move following their displacement than their male counterparts. These results are suggestive, but need further analysis, which we defer for now to future research.

4.5 Conclusions

The analysis in this paper demonstrates that there are significant differences between displaced men and women with regard to their postdisplacement experiences. Women tend to experience: 1) a slightly greater wage loss upon reemployment, 2) lower rates of reemployment, 3) higher rates of part-time reemployment, and 4) significantly higher duration of unemployment following displacement. This last finding for women is an important empirical fact that merits additional attention in future research. The occupational, industry, and educational breakdowns for displacement by sex, suggest the possibility of a "glass ceiling" effect for women. Further detailed analysis, should focus on the experiences of these managerial and professional women to determine the validity of this hypothesis. We also find that marital status is an important explanatory variable for our findings regarding differences in reemployment probabilities between displaced men and women. Policymakers, in their continuing efforts to facilitate transitions for displaced workers, should incorporate the findings contained herein into

their policy formulation. Precisely how to effectively incorporate these results into policy formulation is left for future research.

Table 1. Displacement by Reason and Year of Survey (long-tenure displaced workers)

Year of Survey	Plant Shut Down	Insufficient Work	Position or Shift Abolished	*Total for Well-Defined Reasons*	Seasonal Job Completed	Self-operated Business Failed	Some Other Reason
1984	35.68	36.73	9.81	82.22	4.86	3.03	9.9
1986	40.05	31.09	11.12	82.26	4.04	2.95	10.75
1988	40.99	26.63	11.29	78.91	3.09	14.45	0.27
1990	41.59	24.39	11.84	77.82	4.07	3.01	15.1
1992	36.92	30.71	12.01	79.64	3.58	3.02	13.77
1994	27.72	29.7	17.19	74.61	4.55	2.1	18.76
1996	22.09	25.38	16.25	63.72	4.4	1.53	30.34
Mean	35.01	29.23	12.79	**77.03**	4.08	4.30	14.13

Figure 1. Overall Trends in Corporate Downsizing: Displacement Ratios by Year of Survey

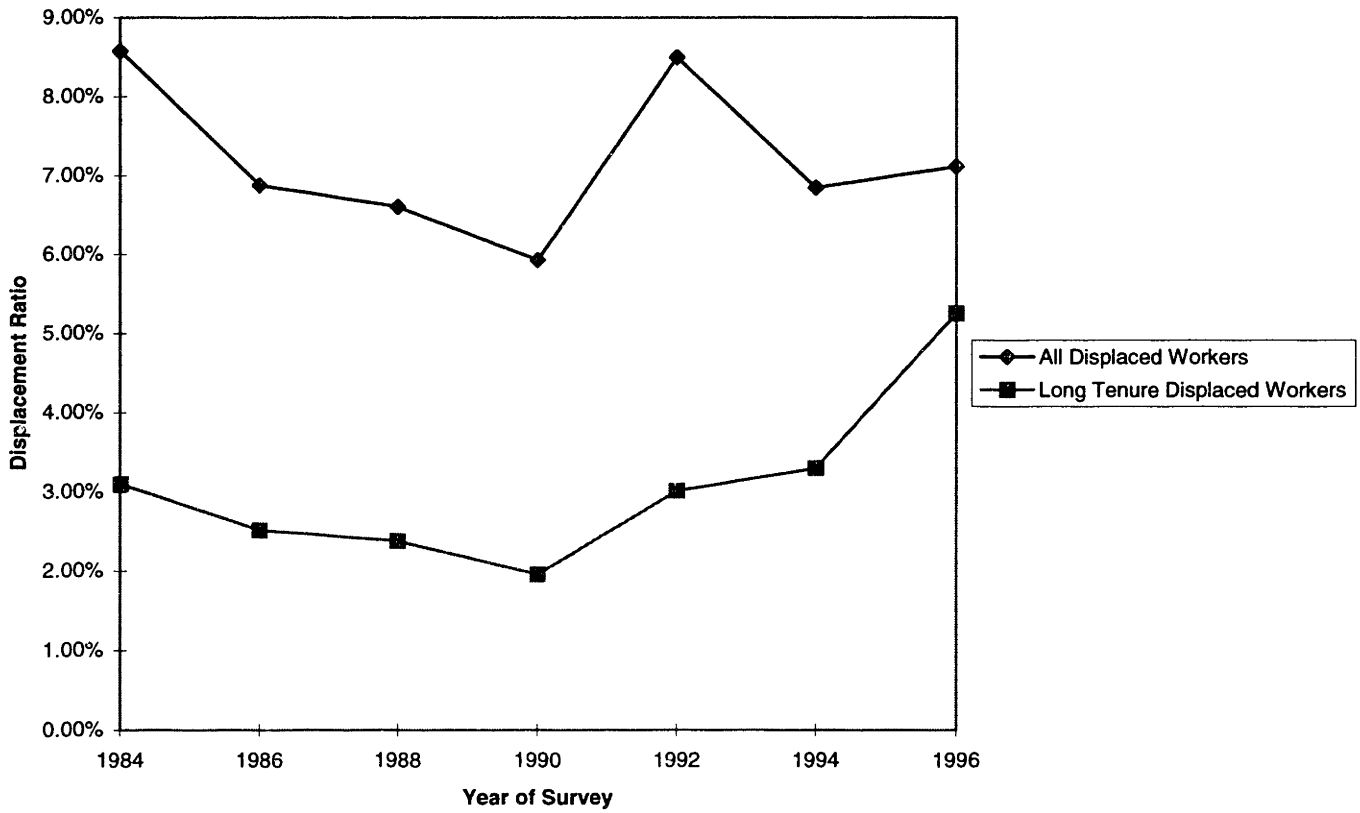

Table 2. Total Displaced Workers and Percentages by Sex[1]

All Displaced Workers

Year of Displacement	Total Displaced	Men Displaced	Women Displaced	% Men	% Women
1981	2,686,933	1,677,759	1,009,174	62%	38%
1982	3,545,904	2,225,694	1,320,210	63%	37%
1983	2,277,689	1,334,510	943,179	59%	41%
1984	2,472,959	1,501,252	971,707	61%	39%
1985	2,414,643	1,482,950	931,693	61%	39%
1986	2,691,749	1,607,803	1,083,946	60%	40%
1987	2,245,345	1,272,644	972,701	57%	43%
1988	2,140,905	1,192,169	948,736	56%	44%
1989	2,749,564	1,618,157	1,131,408	59%	41%
1990	3,107,907	1,817,050	1,290,857	58%	42%
1991	2,632,918	1,593,796	1,039,122	61%	39%
1992	2,789,179	1,643,765	1,145,414	59%	41%
1993	2,186,547	1,245,723	940,823	57%	43%
1994	2,536,155	1,420,017	1,116,137	56%	44%
1995	4,271,756	2,490,417	1,781,339	58%	42%
1981-95	31,755,695	18,967,549	12,788,147	59%	41%

Displaced Workers with at Least 3 Years Tenure

Year of Displacement	Total Displaced	Men Displaced	Women Displaced	% Men	% Women
1981	1,710,931	1,073,426	637,505	63%	37%
1982	2,340,704	1,449,416	891,287	62%	38%
1983	1,549,596	912,811	636,785	59%	41%
1984	1,762,475	1,069,777	692,697	61%	39%
1985	1,652,200	1,046,996	605,203	63%	37%
1986	1,865,495	1,122,424	743,072	60%	40%
1987	1,432,337	799,448	632,889	56%	44%
1988	1,412,363	768,995	643,367	54%	46%
1989	1,792,534	1,077,019	715,515	60%	40%
1990	2,103,349	1,233,762	869,587	59%	41%
1991	1,482,921	922,246	560,675	62%	38%
1992	1,478,776	901,943	576,833	61%	39%
1993	1,748,098	1,010,838	737,260	58%	42%
1994	1,968,422	1,098,607	869,815	56%	44%
1995	3,411,277	1,973,425	1,437,852	58%	42%
1981-9	27,711,476	16,174,089	11,061,979	59%	41%

[1] The source of the data for this table is from the 1984-96 Displaced Workers' Surveys.

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Table 3. Displacement as a Percentage of Total Employment by Sex[2]

(in 000s of workers 20 years and over with long tenure)

Year of Displacement	Total Civilian Employment	Total Male Civilian Employment	Total Female Civilian Employment	Displacement as % of Civilian Employment	Displaced Men as a % of Male Employment	Displaced Women as a % of Female Employment	Difference Between Men & Women
1981	93,172	53,582	39,590	2.88%	3.13%	2.55%	0.58%
1982	92,977	52,891	40,086	3.81%	4.21%	3.29%	0.91%
1983	94,491	53,487	41,004	2.41%	2.50%	2.30%	0.19%
1984	98,562	55,769	42,793	2.51%	2.69%	2.27%	0.42%
1985	100,716	56,562	44,154	2.40%	2.62%	2.11%	0.51%
1986	103,125	57,569	45,556	2.61%	2.79%	2.38%	0.41%
1987	105,800	58,726	47,074	2.12%	2.17%	2.07%	0.10%
1988	108,164	59,781	48,383	1.98%	1.99%	1.96%	0.03%
1989	110,582	60,837	49,745	2.49%	2.66%	2.27%	0.39%
1990	111,653	61,198	50,455	2.78%	2.97%	2.56%	0.41%
1991	111,249	60,714	50,535	2.37%	2.63%	2.06%	0.57%
1992	112,200	61,019	51,181	2.49%	2.69%	2.24%	0.46%
1993	113,700	61,865	51,912	1.92%	2.01%	1.81%	0.20%
1994	116,900	63,294	53,606	2.17%	2.24%	2.08%	0.16%
1995	118,481	64,085	54,396	3.61%	3.89%	3.27%	0.61%
1981-95	1,591,772	881,379	710,470	2.57%	2.75%	2.35%	0.40%

[2] The sources of the data used for this table are from the 1984-96 Displaced Worker's Surveys and the 1996 Economic Report of the President.

Figure 2. Displacement Ratios for Men and Women, by Year of Survey. (long tenure workers)

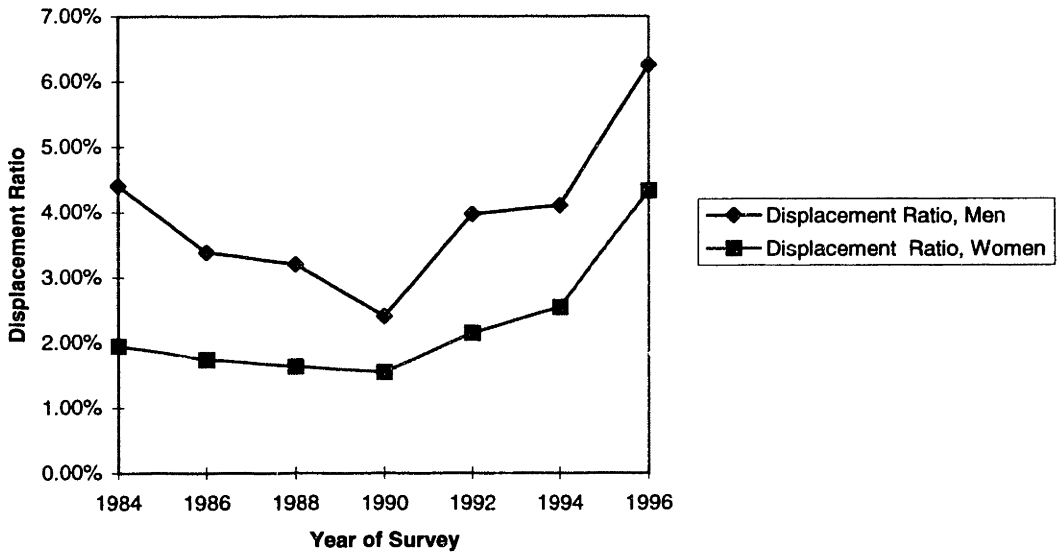


Figure 3. Women's Displacement Ratio as a Percentage of Men (long tenure workers)

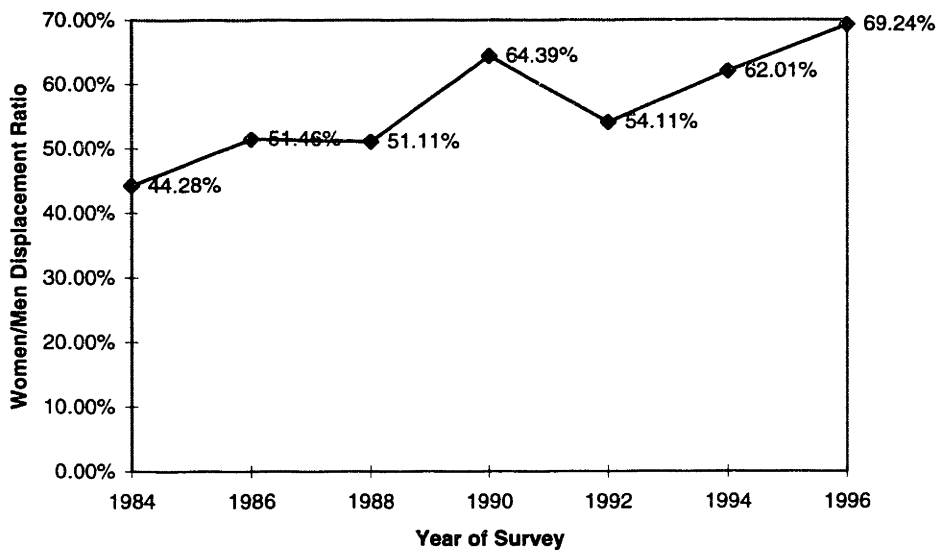
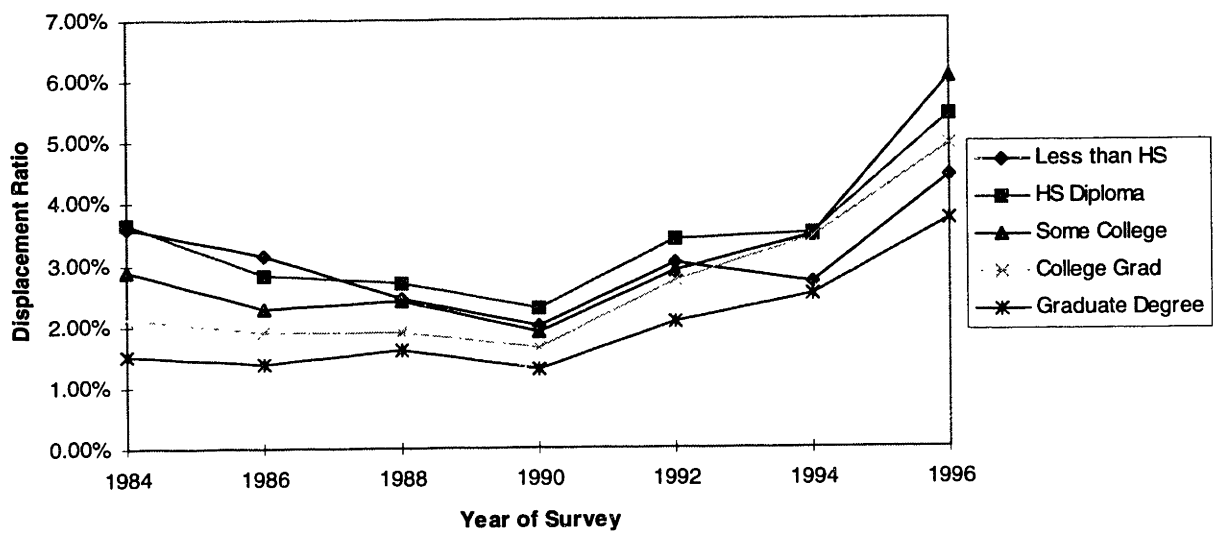


Table 4. Displacement Ratios by Age, Sex, and Year of Survey (long-tenure workers).[3]

Year of Survey	20-24 years		25-34 years		35-44 years		45-54 years		55-64 years	
	Men	Women	Men	Women	Men	Women	Men	Women	Men	Women
1984	2.13%	1.24%	5.83%	2.04%	4.50%	2.13%	4.48%	2.21%	3.88%	1.92%
1986	1.26%	0.69%	3.84%	1.98%	4.16%	1.73%	3.71%	2.17%	3.01%	1.81%
1988	1.03%	0.51%	3.54%	1.63%	3.80%	2.02%	3.81%	1.93%	2.83%	1.69%
1990	0.85%	0.56%	**2.53%**	**1.55%**	**3.08%**	**1.91%**	**2.45%**	**1.79%**	2.25%	1.47%
1992	1.62%	0.74%	**3.93%**	**2.12%**	**4.77%**	**2.47%**	**4.49%**	**2.93%**	3.88%	1.81%
1994	1.04%	0.90%	**3.91%**	**2.82%**	**5.06%**	**2.90%**	**4.67%**	**2.89%**	4.50%	2.27%
1996	2.75%	1.28%	**6.14%**	**4.21%**	**6.56%**	**4.64%**	**6.15%**	**4.17%**	3.84%	2.52%

Figure 4. Displacement Ratios by Educational Category by Survey Year (long-tenure workers)



[3] Note that this table makes computations for long tenure displaced workers displaced for non-temporary reasons.

Figure 5. Displacement Rates by Occupational Category and Sex, 1981-95 (Long-tenure workers)

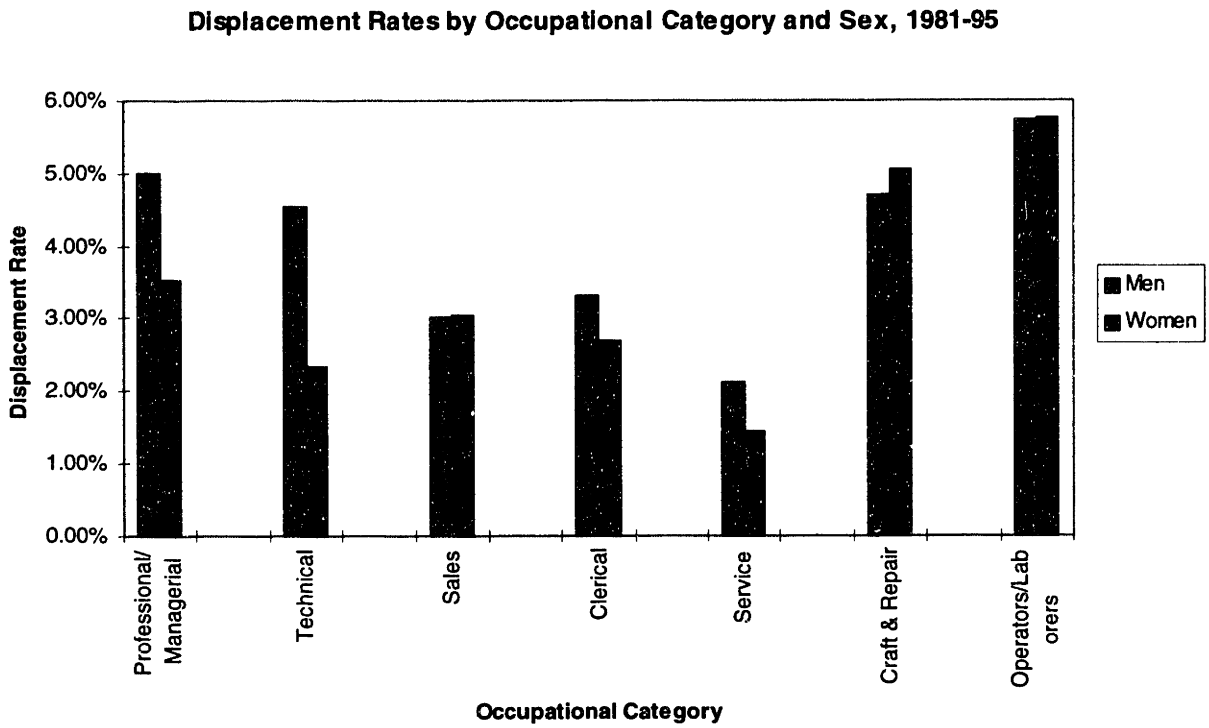


Figure 6. Displacement Ratios by Occupational Category, Sex, and Year of Survey (long-tenure workers)

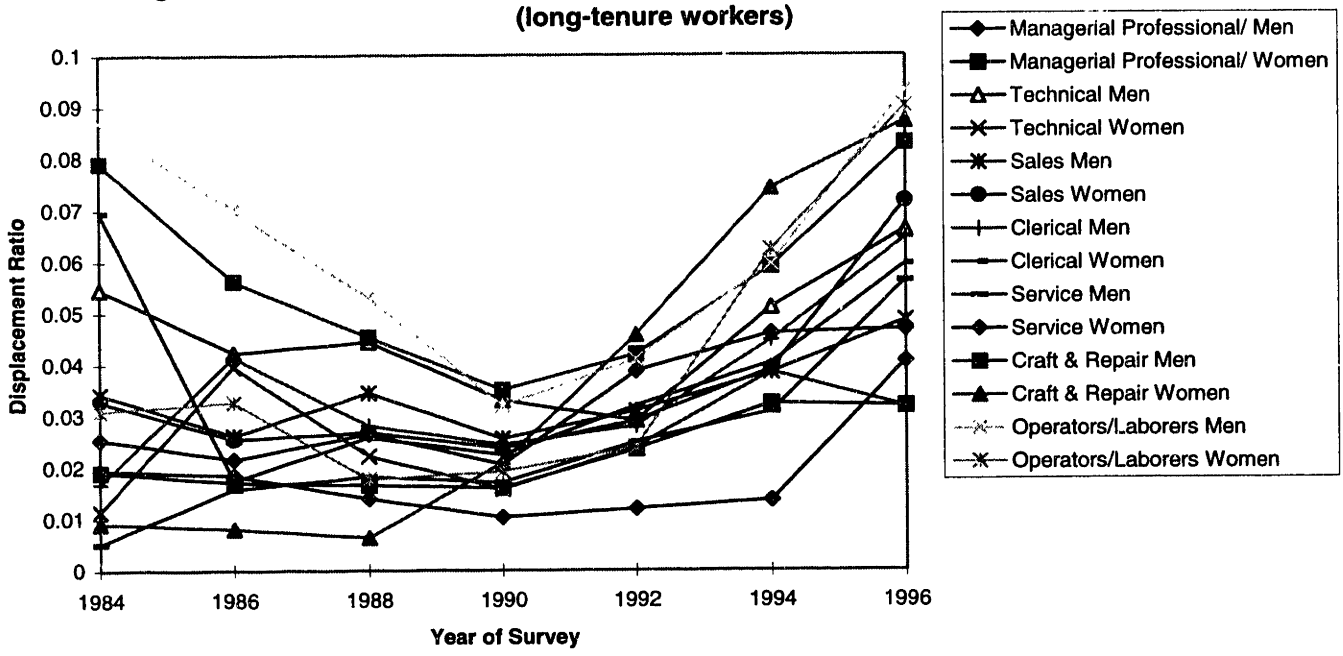


Figure 7. Displacement Rates by Industry Group and Sex, 1981-95 (long-tenure workers)

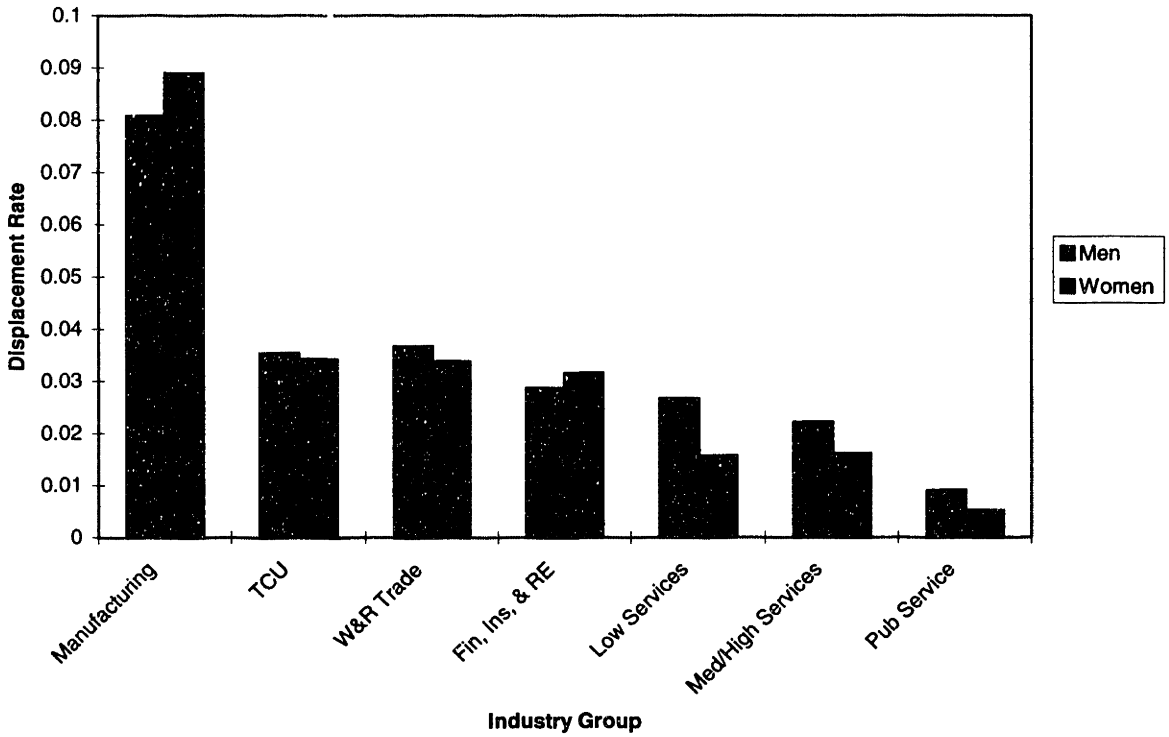


Figure 8. Displacement Rates by Industry Group, Sex, and Year of Survey (long-tenure workers)

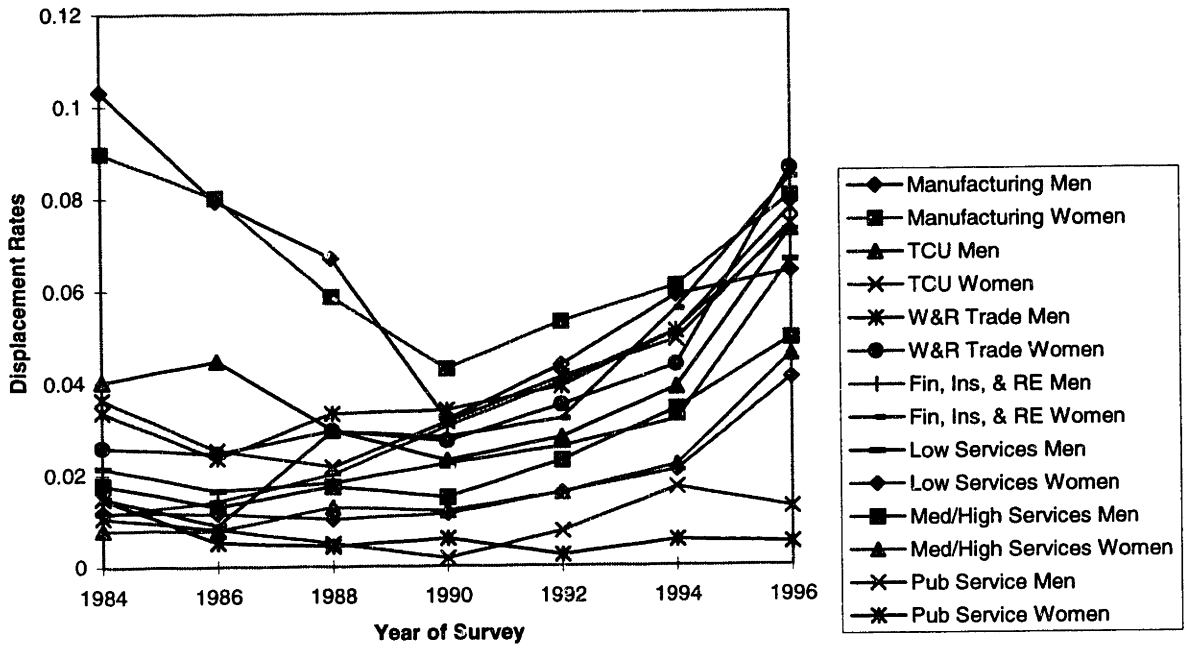


Table 5. Percentage of Displacement Comprised of Single Parents

Year of Survey	Unmarried Female Head of Households	Unmarried Male Head of Households	All Single Parent Households
1984	11.32%	3.38%	14.70%
1986	11.73%	3.82%	15.55%
1988	11.18%	4.30%	15.48%
1990	12.21%	3.80%	16.01%
1992	12.50%	4.30%	16.80%
1994	13.45%	4.27%	17.72%
1996	12.94%	5.33%	18.27%
Average	12.19%	4.17%	16.36%

Table 6. CPI-Adjusted Wage Losses for All Long-Tenured Displaced Workers

Year of Displacement	Displaced Men's Median Wage Loss	Displaced Men's Median % Wage Loss	Displaced Women's Median Wage Loss	Displaced Women's Median % Wage Loss
1981	-55	-15.03%	-47	-21.31%
1982	-66	-15.20%	-25	-12.73%
1983	-47	-14.76%	-33	-15.40%
1984	-43	-12.12%	-16	-5.34%
1985	-67	-19.45%	-42	-19.45%
1986	-82	-18.60%	-51	-24.67%
1987	-73	-20.52%	-40	-17.48%
1988	-49	-13.13%	-29	-9.97%
1989	-46	-12.35%	-23	-12.35%
1990	-71	-20.44%	-33	-12.72%
1991	-60	-15.32%	-46	-19.53%
1992	-46	-11.37%	-43	-15.75%
1993	-26	-6.95%	-30	-14.31%
1994	-21	-4.42%	-6	-4.42%
1995	-18	-5.65%	-9	-5.38%
1981-95	-51	-13.69%	-32	-14.05%

Table 7. Log Inflation-adjusted Wage Regressions

Variable	Time Period	Estimate (t-statistic)	Interpretation	Adj. R^2/ # of Obs
displacement indicator	1981-95	-.238801 (-26.107)**	displaced workers suffer a 24% wage loss relative to nondisplaced workers.[4]	0.3582/ 90,745
Female* displacement interaction term	1981-95	**-.0385 (-2.671)****	*women displaced workers suffer an additional 4% wage loss relative to men*	0.3582/ 90,745
displacement indicator	1981-83	-.2547 (-10.478)**	25% wage loss for displaced workers	0.3804/ 12,552
Female* displacement interaction term	1981-83	-.0393 (-0.923)	we cannot reject the null hypothesis regarding $\hat{\gamma} = 0$	0.3804/ 12,552
displacement indicator	1983-85	-.1838 (-8.072)**	18% wage loss for displaced workers	0.4029/ 13,203
Female* displacement interaction term	1983-85	.00211 (0.056)	we cannot reject the null hypothesis regarding $\hat{\gamma} = 0$	0.4029/ 13,203
displacement indicator	1985-87	-.1578 (-6.764)**	16% wage loss for displaced workers	0.3871/ 13,442
Female* displacement interaction term	1985-87	.0258 (0.698)	we cannot reject the null hypothesis regarding $\hat{\gamma} = 0$	0.3871/ 13,442
displacement indicator	1987-89	-.1341 (-5.340)**	13% wage loss for displaced workers	0.3973/ 13,630
Female* displacement interaction term	1987-89	-.0527 (-1.371)	we cannot reject the null hypothesis regarding $\hat{\gamma} = 0$	0.3973/ 13,630
displacement indicator	1989-91	-.457 (-17.626)**	46% wage loss for displaced workers	0.3897/ 13,389
Female* displacement interaction term	1989-91	-.0406 (-1.125)	we cannot reject the null hypothesis regarding $\hat{\gamma} = 0$	0.3897/ 13,389
displacement indicator	1991-93	-.252 (-9.187)**	25% wage loss for displaced workers	0.3159/ 13,170
Female* displacement interaction term	1991-93	-.0715 (-1.671)*	reject the null hypothesis and accept that $\hat{\gamma} < 0$	0.3159/ 13,170
Displacement indicator	1993-95	-.236 (-9.813)**	23% wage loss for displaced workers	0.2836/ 11,353
Female* displacement interaction term	1993-95	-.0437 (-1.215)	we cannot reject the null hypothesis regarding $\hat{\gamma} = 0$	0.2836/ 11,353

** Indicates significance at the 5% level. * Indicates significance at the 10% level.

[4] These regressions include zero wages for workers that are not reemployed at the time of the survey.

Table 8. Probit Regressions for Probability of Displacement

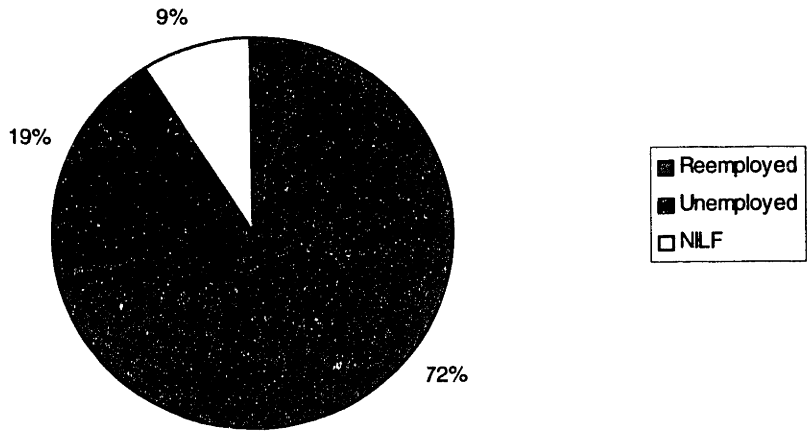
Test of $\hat{\beta}_{female} = 0$

Time Period	Parameter Estimate with z-stat	Interpretation	# of Observations
1981-83	-.0129 (-2.350)**	Reject Null in Favor of Lower Displacement for Women	11,894
1983-85	-.0053572 (-0.989)	Accept the Null Hypothesis	12,447
1985-87	-.00627 (-1.195)	Accept the Null Hypothesis	12,511
1987-89	-.0064809 (-1.244)	Accept the Null Hypothesis	12,873
1989-91	.004662 (1.417)	Accept the Null Hypothesis	12,642
1991-93	-.0108 (-2.051)**	Reject Null in Favor of Lower Displacement for Women	12,093
1993-95	-.001038 (-0.155)	Accept the Null Hypothesis	9,720
1981-95	-.0055 (-2.678)**	Reject Null in Favor of Lower Displacement for Women	84,120

** Denotes significance at the 1% level.

Figure 10. Outcomes: Long-tenure Displaced Men and Women, 1981-95.

Employment Outcomes for Displaced Men, 1981-95



Employment Outcomes for Displaced Women, 1981-95

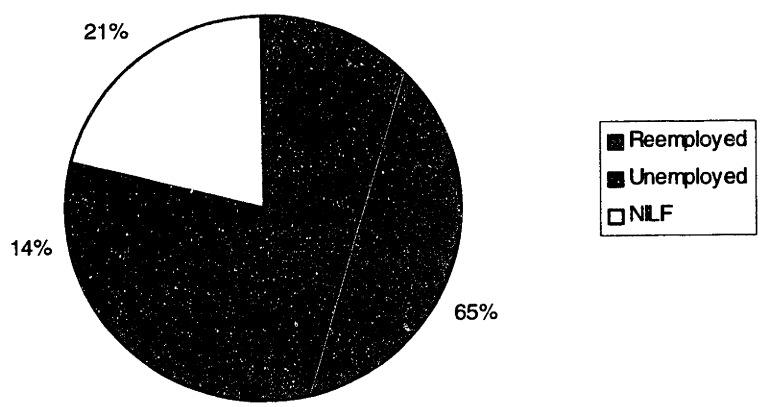


Table 9. Labor Force Status of Displaced Men and Women by Year of Survey
(long-tenure displaced workers)

Year of Survey	Men Reemployed	Women Reemployed	Men Unemployed	Women Unemployed	Men Not in Labor Force	Women Not in Labor Force
1984	65.90%	53.81%	26.64%	22.57%	7.86%	23.62%
1986	69.95%	60.88%	21.67%	17.24%	8.38%	21.88%
1988	73.39%	64.42%	18.60%	15.42%	8.01%	20.16%
1990	74.60%	67.98%	17.31%	13.66%	8.09%	18.35%
1992	62.98%	59.59%	29.07%	21.63%	7.94%	18.78%
1994	69.92%	64.88%	21.74%	18.60%	8.33%	16.52%
1996	74.23%	68.55%	18.76%	14.20%	7.01%	17.25%
All Year Means	70.14%	62.87%	21.97%	17.62%	7.95%	19.51%

Table 10. Probit Regressions for Probability of Reemployment Conditional on Displacement:
Test of $\hat{\delta} = 0$
(coefficient on female indicator)

Time Period	Parameter Estimate[5]	Interpretation	# of Observations
1981-83	-.1421 (-6.937)**	Reject Null in Favor of 14% Lower Reemployment for Women	3,548
1983-85	-.0985 (-4.623)**	Reject Null in Favor of 10% Lower Reemployment for Women	2,878
1985-87	-.057 (-2.667)**	Reject Null in Favor of 6% Lower Reemployment for Women	2,663
1987-89	-.0777 (-3.479)**	Reject Null in Favor of 8% Lower Reemployment for Women	2,269
1989-91	-.0398 (-2.285)**	Reject Null in Favor of 4% Lower Reemployment for Women	3,804
1991-93	-.0833 (-4.836)**	Reject Null in Favor of 8% Lower Reemployment for Women	3,824
1993-95	-.063 (-3.586)**	Reject Null in Favor of 6% Lower Reemployment for Women	3,395
1981-95	-.0782 (-10.661)**	Reject Null in Favor of 8% Lower Reemployment for Women	22,393

** Denotes significance at the 1% level.

[5] T-statistic in parentheses under estimates.

Table 11. Probit Regressions for Probability of Reemployment Conditional on Displacement: Test of $\hat{\gamma} = 0$ (coefficient on female*married interaction term)

Time Period	Parameter Estimate[6]	Interpretation	# of Observations
1981-83	-.241 (-6.425)**	Reject Null in Favor of 24% Lower Reemployment for Married Women Relative to Single Women	3,548
1983-85	-.190 (-4.653)**	Reject Null in Favor of 19% Lower Reemployment for Married Women Relative to Single Women	2,878
1985-87	-.147 (-3.654)**	Reject Null in Favor of 15% Lower Reemployment for Married Women Relative to Single Women	2,663
1987-89	-.203 (-4.871)**	Reject Null in Favor of 20% Lower Reemployment for Married Women Relative to Single Women	2,269
1989-91	-.162 (-4.730)**	Reject Null in Favor of 16% Lower Reemployment for Married Women Relative to Single Women	3,804
1991-93	-.155 (-4.799)**	Reject Null in Favor of 15% Lower Reemployment for Married Women Relative to Single Women	3,824
1993-95	-.167 (-5.050)**	Reject Null in Favor of 17% Lower Reemployment for Married Women Relative to Single Women	3,395
1981-95	-.176 (-12.750)**	Reject Null in Favor of 18% Lower Reemployment for Married Women vs. Single Women	22,393

** Denotes significance at the 1% level.

[6] T-statistic in parentheses under estimates.

Table 12. Probit Regressions for Probability of Reemployment Conditional on Displacement:

Test of $\hat{\beta}_{single} = \hat{\beta}_{married}$

(coefficient on female indicator for single subsample vs. married subsample)

Time Period	Parameter Estimate[7]		Interpretation	# of Observations	
	Single	Married		Single	Married
1981-83	.0399 (1.15)	-.2386 (-9.18)**	Reject Null in Favor of Alternative of Higher Reemployment for Single vs. Married Women	1,151	2,397
1983-85	.0122 (0.34)	-.1586 (-5.86)**	Reject Null in Favor of Alternative of Higher Reemployment for Single vs. Married Women	937	1,941
1985-87	0.0497 (1.41)	-.1179 (-4.30)**	Reject Null in Favor of Alternative of Higher Reemployment for Single vs. Married Women	878	1,785
1987-89	.0394 (1.12)	-.157 (-5.30)**	Reject Null in Favor of Alternative of Higher Reemployment for Single vs. Married Women	890	1,379
1989-91	.055 (2.02)**	-.1078 (-4.66)**	Reject Null in Favor of Alternative of Higher Reemployment for Single vs. Married Women	1,502	2,280
1991-93	.0117 (0.43)	-.1408 (-6.17)**	Reject Null in Favor of Alternative of Higher Reemployment for Single vs. Married Women	1,616	2,208
1993-95	.0246 (0.92)	-.1315 (-5.55)**	Reject Null in Favor of Alternative of Higher Reemployment for Single vs. Married Women	1,457	1,938
1981-95	.027 (2.33)**	-.1506 (-15.65)**	Reject Null in Favor of Alternative of Higher Reemployment for Single vs. Married Women	8,411	1,952

** Denotes significance at the 1% level.

[7] T-statistic in parentheses under estimates.

Figure 11. Part-time Reemployment for Men and Women, 1981-90 and 1991-95. (long-tenure workers)

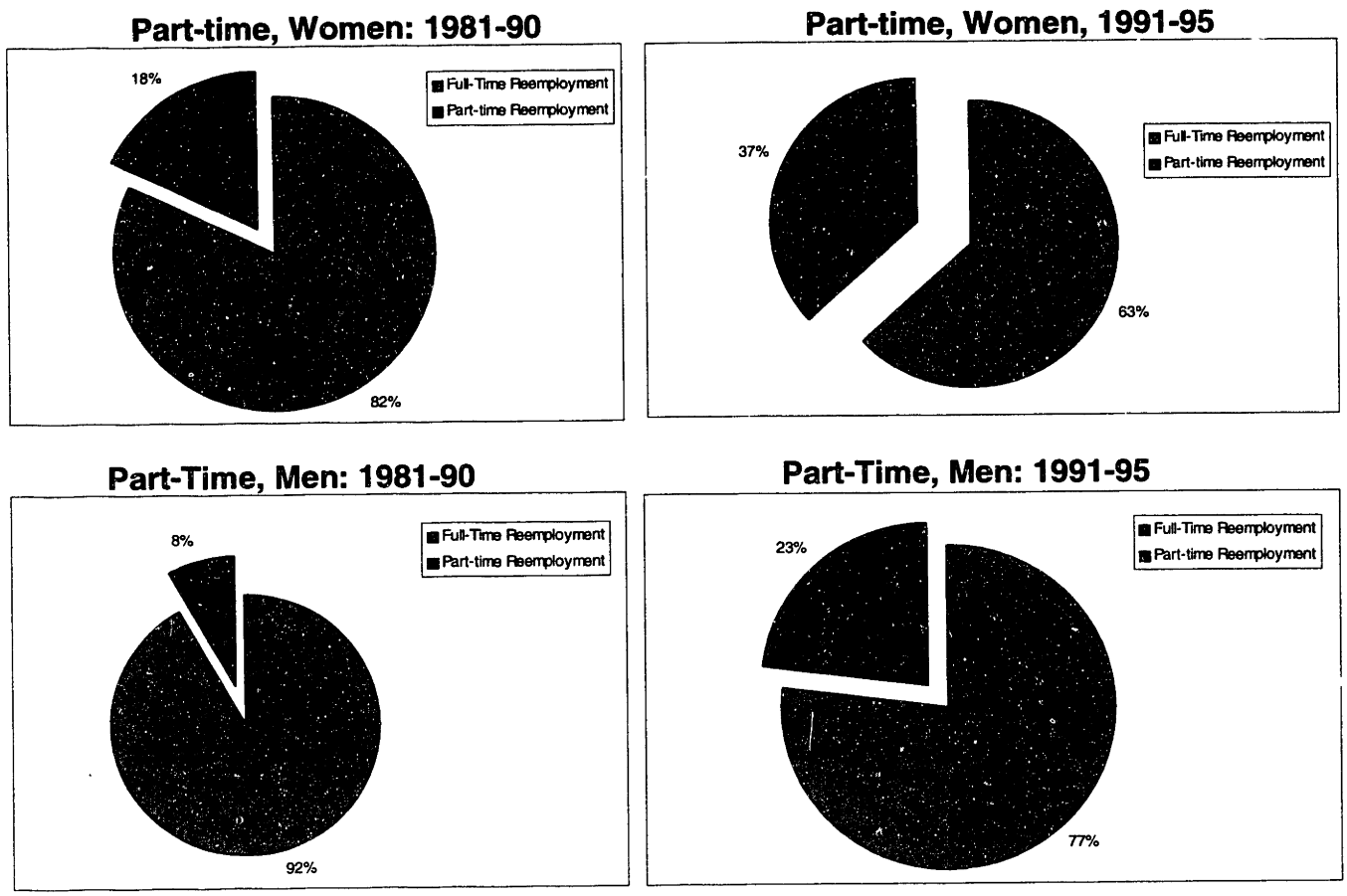


Table 13. Part-Time Employment for Displaced Men and Women Pre and Post Displacement

Year of Displacement	Percentage of Men Working Part-Time Pre-Displacement	Percentage of Men Working Part-Time Post-Displacement	% increase	Percentage of Women Working Part-Time Pre-Displacement	Percentage of Women Working Part-Time Post-Displacement	% increase
1981	5.67%	8.31%	46.56%	19.01%	33.90%	78.33%
1982	5.93%	15.82%	166.78%	19.19%	30.95%	61.28%
1983	5.57%	13.25%	137.88%	21.11%	34.59%	63.86%
1984	4.92%	8.09%	64.43%	18.20%	26.15%	43.68%
1985	5.30%	11.11%	109.62%	22.07%	28.82%	30.58%
1986	4.36%	10.85%	148.85%	21.90%	17.76%	-18.90%
1987	5.90%	8.48%	43.73%	19.41%	22.10%	13.86%
1988	2.75%	7.07%	157.09%	16.45%	15.19%	-7.66%
1989	5.54%	13.73%	147.83%	17.88%	22.73%	27.13%
1990	6.29%	10.08%	60.25%	16.67%	19.19%	15.12%
Avg. 1981-90	5.22%	10.68%	104.46%	19.19%	25.14%	31.00%
1991	6.88%	24.35%	253.92%	20.11%	40.61%	101.94%
1992	9.64%	22.78%	136.31%	20.90%	45.75%	118.90%
1993	9.51%	26.88%	182.65%	19.89%	40.87%	105.48%
1994	7.11%	21.92%	208.30%	21.74%	31.25%	43.74%
1995	7.35%	23.60%	221.09%	23.87%	38.07%	59.49%
Avg. 1991-95	8.10%	23.91%	195.21%	21.30%	39.31%	84.54%

Table 14. Probit Regressions for Probability of Part-time Reemployment Conditional on Displacement and Reemployment (coefficient on female indicator and previous part-time employment)

Time Period	Parameter Estimate[8]		Interpretation	# of Obs
	Female	Previous Part-time		
1981-83	.1899 (4.26)**	.386 (4.71)**	Women have 19% greater chance of part-time reemployment than men. Previous part-time employees have 39% greater chance of part-time reemployment.	454
1983-85	.077 (2.12)**	.382 (4.81)**	Women have 8% greater chance of part-time reemployment than men. Previous part-time employees have 38% greater chance of part-time reemployment.	422
1985-87	.06 (1.67)	.223 (3.98)**	Women 6% greater chance of part-time reemployment than men. Previous part-time employees have 22% greater chance of part-time reemployment.	432
1987-89	.10 (3.52)**	.44 (6.11)**	Women 10% greater chance of part-time reemployment than men. Previous part-time employees have 44% greater chance of part-time reemployment.	405
1989-91	.07 (2.10)**	.24 (3.71)**	Women 7% greater chance of part-time reemployment than men. Previous part-time employees have 24% greater chance of part-time reemployment.	505
1991-93	.17 (7.56)**	.221 (7.58)**	Women 17% greater chance of part-time reemployment than men. Previous part-time employees have 22% greater chance of part-time reemployment.	2,574
1993-95	.06 (2.7)**	.27 (8.9)**	Women 6% greater chance of part-time reemployment than men. Previous part-time employees have 27% greater chance of part-time reemployment.	2,217
1981-95	.115 (9.49)**	.267 (15.27)**	Women have 12% greater chance of part-time reemployment than men. Previous part-time employees have 27% greater chance of part-time reemployment.	7,036

** Denotes significance at the 1% level.

[8] T-statistic in parentheses under estimates.

Table 15. Probit Regressions for Probability of Part-time Employment For All Displaced and Nondisplaced Workers (coefficient on displacement indicator and female*displacement interaction term)

Time Period	Parameter Estimate[9]		Interpretation	# of Obs
	Displacement	Female* Displacement		
1981-83	.1704 (7.296)**	-.0415 (-2.005)**	Displaced workers have a 17% higher probability of part-time employment, but displaced women have a 4% lower probability than displaced men	11,068
1983-85	.1355 (5.529)**	-.0518 (-2.558)**	Displaced workers have a 14% higher probability of part-time employment, but displaced women have a 5% lower probability than displaced men	11,474
1985-87	.076 (3.012)**	-.0526 (-2.38)**	Displaced workers have an 8% higher probability of part-time employment, but displaced women have a 5% lower probability than displaced men	12,067
1987-89	.0336 (1.44)	-.029 (-1.20)**	Accept both null hypotheses: Ho: $\hat{\delta} = 0$ and Ho: $\hat{\gamma} = 0$	12,394
1989-91	.281 (9.149)**	-.03 (-1.5)	Displaced workers have a 28% higher probability of part-time employment, but accept the null that: Ho: $\hat{\gamma} = 0$	12,162
1991-93	.08 (6.267)**	-.018 (-1.07)	Displaced workers have an 8% higher probability of part-time employment, but accept the null that: Ho: $\hat{\gamma} = 0$	50,708[10]
1993-95	.08 (2.7)**	-.044 (-2.74)**	Displaced workers have an 8% higher probability of part-time employment, but displaced women have a 4% lower probability than displaced men	39,422
1981-95	.09 (12.9)**	-.039 (-4.66)**	Displaced workers have a 9% higher probability of part-time employment, but displaced women have a 4% lower probability than displaced men	149,295

** Denotes significance at the 1% level.

[9] T-statistic in parentheses under estimates.

[10] Because of the 1994 CPS Redesign, we have significantly more observations with part-time employment information than in earlier surveys.

Table 16. Duration of Unemployment Following Displacement by Sex, Race, Ethnicity, and Year of Displacement (# of weeks for long tenure workers)[11]

Year of Displacement	All Workers	Male Workers	Female Workers	Difference Male - Female	White Female Workers	Black Female Workers	Hispanic Female Workers
1981	40	37	45	-8	42	68	63
1982	36	35	39	-5	37	57	45
1983	22	20	24	-4	23	30	26
1984	26	23	30	-8	28	47	37
1985	16	15	17	-2	17	16	15
1986	14	13	16	-3	16	14	19
1987	11	10	13	-3	12	15	13
1988	14	14	14	0	13	22	22
1989	12	11	13	-2	13	14	15
1990	15	16	14	1	14	17	18
1991	9	10	9	0	9	10	11
1992	12	9	16	-7	15	22	4
1993	17	16	19	-3	18	27	25
1994	14	14	14	0	14	13	13
1981-94	18	17	20	-3	19	27	23

Table 17. Mobility of Displaced Workers by Sex, Race, Ethnicity, and Year of Displacement
(long tenure workers)

Year of Displacement	All Workers	Male Workers	Female Workers	Male - Female Difference	White Female Workers	Black Female Workers	Hispanic Female Workers
1981	17%	19%	13%	6%	13%	15%	6%
1982	16%	20%	9%	10%	10%	2%	7%
1983	14%	17%	9%	8%	10%	5%	9%
1984	15%	16%	13%	2%	14%	8%	0%
1985	14%	17%	9%	7%	10%	7%	7%
1986	15%	18%	12%	6%	13%	3%	0%
1987	14%	16%	11%	6%	12%	3%	11%
1988	14%	17%	9%	8%	10%	7%	17%
1989	15%	18%	11%	8%	11%	8%	7%
1990	14%	17%	9%	7%	10%	6%	8%
1991	12%	14%	9%	4%	10%	7%	11%
1992	15%	17%	12%	5%	13%	6%	11%
1993	14%	15%	14%	1%	15%	10%	13%
1994	19%	18%	19%	-1%	21%	10%	21%
1995	10%	13%	7%	6%	7%	6%	5%
1981-95	14%	16%	11%	6%	11%	6%	9%

[11] Note that we have purposely omitted the 1995 data here, because by virtue of significant truncation bias, duration will be much lower (the mean duration is about seven weeks for each of the groups for 1995) since workers displaced near the end of the year will not have had the opportunity to have been displaced more than a few weeks because of the timing of the survey in the beginning of 1996. Additionally, duration data from the 1994 data is missing, so that the 1992 data is an estimate.

BIBLIOGRAPHY

Aghion, Philippe, and Tirole, Jean. (1994) "The Management of Innovation," *Quarterly Journal of Economic*, 109 – 4: 1185-1209.

Antonelli, Cristiano. (1995) *The Economics of Localized Technological Change and Industrial Dynamics*. Boston: Kluwer Academic Publishers.

Arora, Ashish and Gambardella, Alfonso. (1990) "Complementarity and External Linkages: The Strategies of the Large Firms in Biotechnology," *The Journal of Industrial Economics*, 38: 361-379.

Arrow, Kenneth J. (1962) "Economic Welfare and the Allocation of Resources for Invention," in *The Rate and Direction of Inventive Activity: Economic and Social Factors*, ed. Richard R. Nelson. Princeton: Princeton University Press.

Balakrishnan, Srinivasan and Koza, Mitchell P. (1993) "Information Asymmetry, Adverse Selection and Joint-ventures," *Journal of Economic Behavior and Organization*, 20: 99-117.

Barr, Stephen. (1996) "Downsizing's Blurry Bottom Line: Government Is Shrinking, but Is It More Efficient?" *The Washington Post*, September 20, p. A1.

Beck, Melinda. (1997) "The Next Big Population Bulge: Generation Y Shows Its Might," *Wall Street Journal*, February 3, p. B1.

Berg, Sanford V. and Friedman, Philip. (1981) "Impacts of Domestic Joint Ventures on Industrial Rates of Return: A Pooled Cross-Section Analysis, 1964-1975," *Review of Economics and Statistics* 63: 293-98.

Bienz-Tadmor, B., Dicerbo, P.A., Tadmor, G. and Lasagna, L. (1992) Biopharmaceuticals and Conventional Drugs: Clinical Success Rates," *Biotechnology*, 10: 521-5.

Blair, Roger and Kaserman, David L. (1978) "Uncertainty and the Incentive for Vertical Integration," *Southern Economic Journal*, July, pp. 266-72.

Bleeke, J. and Ernst, D. (1995) "Is Your Strategic Alliance Really a Sale?" *Harvard Business Review*, January-February, pp. 97-106.

Bower, D. Jane, and Whittaker, E. (1993) "Global R&D Networks: The Case of the Pharmaceutical Industry," *Journal of Industry Studies*, 1 – 1: 50-64.

Bradley, Michael, Desai, Anand, and Kim, E. Han. (1988) "Synergistic Gains from Corporate Acquisitions and their Division between the Stockholders of Target and Acquiring Firms," *Journal of Financial Economics*, 21: 3-40.

Chan, Su Han, Kensinger, John W., Keown, Arthur J., and Martin, John D. (1997) "Do Strategic Alliances Create Value?" *Journal of Financial Economics*, 46: 199-221.

Clark, Kim B. and Henderson, Rebecca M. (1990) "Architectural Innovation: The Reconfiguration of Existing Product Technologies and the Failure of Established Firms," *Administrative Science Quarterly*, 35: 9-30.

Cohen, W. M. and Levinthal, D. A. (1989) "Innovation and learning: The Two Faces of R&D-Implications for the Analysis of R&D Investment," *Economic Journal*, 99: 569-596.

Comanor, William S. (1986) "The Political Economy of the Pharmaceutical Industry," *Journal of Economic Literature*, 24: 1178-1217.

Cook, R. D. (1979) "Influential Observations in Linear Regression," *Journal of the American Statistical Association*, 74: 169-174.

Congressional Budget Office. (1993) "Displaced Workers: Trends in the 1980s and Implications for the Future," A CBO Study. Washington, D.C.: Government Printing Office.

Council of Economic Advisers. (1996) "Job Creation and Employment Opportunities: The United States Labor Market, 1993-1996," A Report by the Council of Economic Advisers with the U.S. Department of Labor, Office of the Chief Economist.

Crossley, Thomas F., Jones, Stephen R. G., and Kuhn, Peter. (1994) "Gender Differences in Displacement Cost: Evidence and Implications," *The Journal of Human Resources*, Vol. 29, pp. 461-479.

Davis, Steven J., Haltiwanger, John C., and Schuh, Scott. (1996) *Job Creation and Destruction*. Cambridge, MA: MIT Press.

Department of Labor. (1995) *Report on the American Labor Force*. Washington, D.C.: The U.S. Government Printing Office.

Devine, Theresa J. (1994) "Changes in Wage-and-Salary Returns to Skill and the Recent Rise in Female Self-Employment," *American Economic Review: Papers and Proceedings*, 84 – 1: 108-13.

DiMasi, Joseph A. (1995) "Success Rates for New Drugs Entering Clinical Testing in the United States," *Clinical Pharmacology & Therapeutics*, 58 – 1: 1-14.

_____, Hansen, Ronald W., Grabowski, Henry G., and Louis Lasagna. (1991) "Cost of Innovation in the Pharmaceutical Industry," *Journal of Health Economics*, 10: 107-42.

_____, Seibring, Mark A. and Lasagna, Louis. (1994) "New Drug Development in the United States from 1963 to 1992," *Clinical Pharmacology and Therapeutics*, 55 – 6: 609-22.

Dinardo, John, Fortin, Nicole M., and Lemieux, Thomas. (1996) "Labor Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach," *Econometrica*, 64 – 5: 1001-44.

Dixit, Avinash K. and Pindyck, Robert S. (1995) "The New Option View of Investment," Sloan School of Management Working Paper #3794-95-EFA.

Drucker, Peter. (1995) "The Network Society," *Wall Street Journal*, March 29, p. A12.

Fallick, Bruce C. (1996) "A Review of the Recent Empirical Literature on Displaced Workers," *Industrial & Labor Relations Review*, 50 – 1: 5-16.

Farber, Henry S. (1996) "The Changing Face of Job Loss in the United States, 1981-1993," *NBER Working Paper #5596*, National Bureau Economic Research, Cambridge, MA.

_____. (1993) "The Incidence and Costs of Job Loss: 1982-91," *Brooking Papers on Economic Activity: Microeconomics*, pp. 73-119.

Fazzari, Steve, Hubbard, Glenn, and Petersen, Bruce. (1988) "Finance Constraints and Corporate Investment," *Brooking Papers on Economic Activity*, 1: 141-95.

Folbre, Nancy. (1995) *The New Field Guide to the U.S. Economy*. New York: The New Press.

Food and Drug Administration. (1997) "Draft Guidance for Industry Consumer-Directed Broadcast Advertisements," *Federal Register*. August 12, 62 – 155: 43171-43173.

Friedberg, Rachel M. and Hunt, Jennifer. (1995) "The Impact of Immigrants on Host Country Wages, Employment and Growth," *Journal of Economic Perspectives*, 9 – 2: 23-44.

Gardner, Jennifer M. (1995) "Worker Displacement: A Decade of Change," *Monthly Labor Review*, April pp. 44-56.

Gibbons, Robert and Katz, Lawrence F. (1991) "Layoffs and Lemons," *Journal of Labor Economics*, 9: 351-380.

Government Accounting Office. (1996) "Federal Downsizing: Better Workforce and Strategic Planning Could Have Made Buyouts More Effective," *GAO/GGD-96-62*, August 26: 1-75.

_____. (1996) "FDA Review Times," GAO/T-PEMD-96-9, May 2: 1-13.

_____. (1996) *European Union Drug Approval: Overview of New European Medicines Evaluation Agency and Approval Process: GAO/HEHS-96-71.* Washington, D.C.: Government Printing Office, April.

_____. (1995) "FDA Drug Approval: Review Time Has Decreased in Recent Years," GAO/PEMD-96-1, October 20: 1-44.

_____. (1994) *FDA Users Fees: Current Measures Not Sufficient for Evaluating Effect on Public Health (GAO/PEMD-94-26).* Washington, D.C.: U.S. GAO.

Gomes-Casseres, Benjamin. (1996) *The Alliance Revolution: The New Shape of Business Rivalry.* Cambridge, MA: Harvard University Press.

Grabowski, Henry, and Vernon, J. M. (1986) "Longer Patents for Lower Imitation Barriers: The 1984 Drug Act," *American Economic Review*, 76: 195-98.

Griliches, Zvi. (1990) "Patent Statistics as Economic Indicators: A Survey," *Journal of Economic Literature*, 28: 1661-1707.

Grossmann, Martin. (1997) "Cost-of-capital for Investment in Biopharmaceutical Research and Development Projects," Unpublished Manuscript, MIT Sloan School of Management.

Grossman, Sanford J. and Hart, Oliver D. (1986) "The Costs and Benefits of Ownership: A Theory of Vertical and Lateral Integration," *Journal of Political Economy*, 94 – 4: 691-719.

Hagedoorn, John and Schakenradd, Jos. (1994) "The Effect of Strategic Technology Alliances on Company Performance," *Strategic Management Journal*, 15 – 4: 291-309.

Hall, Bronwyn H. (1992) "Investment and Research and Development at the Firm Level: Does the Source of Financing Matter," National Bureau of Economic Research Working Paper No. 4096.

Hall, Bronwyn, Griliches, Zvi, and Hausman, Jerry. (1986) "Patents and R&D: Is There a Lag?" *International Economic Review*, 27 – 2: 265- 283.

Hansen, Eric R. (1987) "Industrial Location Choice in Sao Paulo, Brazil: A Nested Logit Model," *Regional Science and Urban Economics*, 17: 89-108.

Hansen, R. (1979) "The Pharmaceutical Development Process: Estimates of Development Costs and Times and the Effects of Proposed Regulatory Changes," in

R. Chien (ed.) *Issues in Pharmaceutical Economics*. Lexington Books, D.C. Heath and Co.: Lexington, MA.

Harrigan, K. (1985) *Strategies for Joint Ventures*. Lexington Books: Lexington, MA.

Henderson, Rebecca and Iain Cockburn. (1996) "Scale, Scope, and Spillovers: The Determinants of Research Productivity in Drug Discovery," *RAND Journal of Economics*, 27 – 1: 32-59.

Holmstrom, Bengt. (1989) "Agency Costs of Innovation," *Journal of Economic Behavior and Organization*, 12: 305-27.

Hoshi, Takeo, Kashyap, Anyl, and Scharfstein, David. (1991) "Corporate Structure, Liquidity, and Investment: Evidence from Japanese Panel Data," *Quarterly Journal of Economics*, 106: 33-60.

Jacobson, Louis, LaLonde, Robert, and Sullivan, Daniel. (1993) *The Costs of Worker Dislocation.* Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Jensen, M. and Meckling, W. (1991) "Specific and General Knowledge, and Organizational Structure," in Werin, L. and Wijkander, H. (Eds.), *Main Currents in Contract Economics*. Oxford: Blackwell Publishers.

Kaserman, David L. (1978) "Theories of Vertical Integration: Implications for Antitrust Policy," *Antitrust Bulletin*, 23 – 3: 483-510.

Kogut, Bruce (1988) "Joint Ventures: Theoretical and Empirical Perspectives," *Strategic Management Journal,* 9: 319-332.

Langlois, Richard N. and Robertson, Paul L. (1989) "Explaining Vertical Integration: Lessons from the American Automobile Industry," *The Journal of Economic History*, 49 – 2: 361-75.

Lerner, Josh. (1995) "Patenting in the Shadow of Competitors," *Journal of Law and Economics*, 38 – 2: 463-95.

Lerner, Josh and Merges, Robert P. (1997) "The Control of Strategic Alliances: An Empirical Analysis of Biotechnology Collaborations" NBER Working Paper #6014.

Longman, Roger. (1994) "Are Acquisitions the Answer for Biotech? Probably Not." *In Vivo*, November, pp. 37-43.

_____. (1994a) "Big Biotech Deals," in *Pharmaceutical Strategic Alliances: A Directory and Analysis of Pharmaceutical Strategic Alliances, 5th Edition*. Norwalk, CT: Windhover Information, Inc, pp. 45-51.

MacKinlay, A. Craig. (1997) "Event Studies in Economics and Finance," *Journal of Economic Literature*, 35: 13-39.

Maddala, G.S. (1983) *Limited-Dependent and Qualitative Variables in Econometrics.* New York: Cambridge University Press.

Madden, Janice Fanning. (1988) "Gender Differences in the Cost of Displacement: An Empirical Test of Discrimination in the Labor Market," *American Economic Review: Papers and Proceedings*, 77: 246-252.

McConnell, John J. and Nantell, Timothy J. (1985) "Corporate Combinations and Common Stock Returns: The Case of Joint Ventures," *The Journal of Finance*, 40 – 2: 519-36.

McFadden, Daniel. (1978) "Modelling the Choice of Residential Location," in A. Karlquist et al. (eds.), *Spatial Interaction Theory and Residential Location*, pp. 75-96.

McKelvey, R. and Zavoina, W. (1975) "A Statistical Model for the Analysis of Ordinal Level Dependent Variables," *Journal of Mathematical Sociology*, 4: 413-20.

Metcalf, Susan. (1996) *Windhover's Pharmaceutical Strategic Alliances, 7th Edition.* Windhover Information Inc.: Norwalk, CT.

Mody, A. (1993) "Learning Through Alliances," *Journal of Economic Behavior and Organization*, 20: 151-70.

Mohanram, P. and Nanda, A. (1996) "When Do Joint Ventures Create Value?" Academy of Management Proceedings, pp. 36-40.

Myers, Stewart C. and Howe, Christopher D. (1996) "A Life-Cycle Financial Model of Pharmaceutical R&D," Program on the Pharmaceutical Industry Working Paper, MIT.

Myers, Stewart C. and Shyam-Sunder, Lakshmi. (1996) "Measuring Pharmaceutical Industry Risk and the Cost-of-Capital," in *Competitive Strategies in the Pharmaceutical Industry*, ed. Robert B. Helms. Washington, D.C.: The AEI Press.

Nelson, Richard R. and Winter, Sidney G. (1977) "In Search of Useful Theory of Innovation," *Research Policy*, 6: 36-76.

New York Times. (1996) *The Downsizing of America.* New York: Random House, Inc.

Oxley, Joanne E. (1997) "Appropriability Hazards and Governance in Strategic Alliances: A Transactions Cost Approach," *The Journal of Law, Economics, & Organization*, 13 – 2: 387-409.

Parkhe, A. (1993) "Strategic Alliance Structuring: A Game Theoretic and Transaction Cost Examination of Interfirm Cooperation," *Academy of Management Journal*, 36 - 4: 794-829.

Pharmaceutical Research and Manufacturers of America. (1997) *Industry Profile: 1997.* Washington, D.C.: PhRMA.

_____. (1991) "Interfirm Diversity, Organizational Learning, and Longevity in Global Strategic Alliances," *Journal of International Business Studies*, 22: 579-601.

Pisano, Gary P. (1997) *The Drug Development Factory.* Boston: Harvard Business School Press.

_____. (1991) "The Governance of Innovation: Vertical Integration and Collaborative Arrangements in the Biotechnology Industry," *Research Policy*, 20: 237-249.

Pisano, Gary P. (1990) "The R&D Boundaries of the Firm: An Empirical Analysis," *Administrative Science Quarterly*, 35: 153-176.

_____. (1989) "Using Equity Participation to Support Exchange: Evidence from the Biotechnology Industry," *Journal of Law, Economics, & Organization*, 5: 109-126.

_____ and Mang, Paul Y. (1993) "Collaborative Product Development and the Market for Know-How: Strategies and Structures in the Biotechnology Industry," *Research on Technological Innovation, Management and Policy*, 5: 109-136.

_____, Shan, Weijan, and Teece, David J. (1988) "Joint Ventures and Collaboration in the Biotechnology Industry," in David C. Mowery, ed., *International Collaborative Ventures in U.S. Manufacturing.* Cambridge, MA: Ballinger Publishing Co.

_____ and Wheelwright, Steven C. (1995) "High-Tech R&D," *Harvard Business Review*, September-October, pp. 93-105.

Preiss, Kenneth, Goldman, Steven L. and Nagel, Robert N. (1996) *Cooperate to Compete: Building Agile Business Relationships.* Boston: International Thomson Publishing Inc.

Ravenscraft, David J. and Long, William F. (1997) "Paths to Creating Value in Pharmaceutical Mergers," NBER Conference on Mergers and Productivity, January.

Recombinant Capital. (1997) http://www.recap.com.

Reinganum, Jennifer F. (1989) "The Timing of Innovation: Research, Development, and Diffusion," in *Handbook of Industrial Organization*, eds., Richard Schmalensee and Robert D. Willig. New York: Elsevier Science Publishers.

Rifkin, Jeremy. (1996) "A New Social Contract," in *Impacts of Changing Employment: If the Good Jobs Go Away*, ed. Arthur B. Shostak, Special Vol. 544, *The Annals of The American Academy of Political Science and Social Science*, pp. 16-26.

Rodriguez, Daniel. (1997) "Measuring the Value of Innovations in the Biopharmaceutical Industry," unpublished manuscript, MIT.

Salinger, Michael. (1992) "Standard Errors in Event Studies," *Journal of Financial and Quantitative Analysis*, 27 – 1: 29-53.

_____. (1992a) "Value Event Studies," *Review of Economic Statistics*, 74: 671-77.

Shlaes, Amity. (1996) "A National Case of the Jitters", *Wall Street Journal*, June 4, p. A14.

Sicherman, Nachum. (1996) "Gender Differences in Departures from a Large Firm," *Industrial and Labor Relations Review*, 49 – 3: 484-505.

Silver, Morris. (1984) *Enterprise and the Scope of the Firm: The Role of Vertical Integration*. Oxford: Martin Robertson.

Sugawara, Sandra. (1992) "Going-It-Alone Gives Way to Partnerships in Biotech," *The Washington Post*, August 25, p. C-1.

Temin, Peter. (1980) *Taking Your Medicine: Drug Regulation in the United States*. Cambridge, MA: Harvard University Press.

Thiel, Karl A. (1997) "Eli Lilly & Co.: Partnering to Fill the Gap," *Bioventure View*, September 1.

Thomas, Lacy Glenn. (1994) "Pricing, Regulation, and Competitiveness: Lessons for the US from the Japanese Pharmaceutical Industry," *PharmacoEconomics*, 6 – 1S: 67-70.

_____. (1990) "Regulation and Firm Size: FDA Impacts on Innovation," *RAND Journal of Economics*, 21 – 4: 497-517.

_____. (1988) "Multifirm Strategies in the U.S. Pharmaceutical Industry," in David C. Mowery, ed., *International Collaborative Ventures in U.S. Manufacturing*. Cambridge, MA: Ballinger Publishing Co.

Tirole, Jean. (1988) *The Theory of Industrial Organization*. Cambridge, MA: MIT Press.

Topel, Robert. (1991) "Specific Capital, Mobility, and Wages: Wages Rise with Job Seniority," *Journal of Political Economy*, 99 – 1: 145-176.

_____. (1990) "Specific Capital and Unemployment: Measuring the Costs and Consequences of Job Loss," *Carnegie-Rochester Conference Series on Public Policy*, 33: 181-214.

Trajtenberg, Manuel. (1990) "A Penny for Your Quotes: Patent Citations and the Value of Innovations," *RAND Journal of Economics*, 21 – 1: 172-187.

_____. (1989) "The Welfare Analysis of Product Innovations, With an Application to Computed Tomography Scanners," *Journal of Political Economy*, 7 – 2: 444-479.

Tucci, Christopher L. (1996) "Firm Heterogeneity, Collaborative Behavior, and Performance of International Strategic Technology Alliances," Unpublished Manuscript.

U.S. Department of Health and Human Services. (1996) *Approved Drug Products with Therapeutic Equivalence Evaluations, 16th Edition*. Washington, D.C.: U.S. Government Printing Office.

Whelan, Karl. (1997) "The Welfare Cost of Worker Displacement: A New Approach," Unpublished Manuscript, Washington Federal Reserve Board.

_____. (1995) *National Drug Code Directory, Volumes I and II, 1995 Edition*. Washington, D.C.: U.S. Government Printing Office.

Williamson, Oliver E. (1985) *The Economic Institutions of Capitalism*. New York: The Free Press.

_____. (1979) "Transaction-Cost Economics: The Governance of Contractual Relations," *Journal of Law & Economics*, 22: 233-261.

_____. (1971) "The Vertical Integration of Production: Market Failure Considerations," *American Economic Review*, 61: 112-123.

Windhover Information Inc. (1996, 1995, 1994, 1993, 1992, 1991, and 1990) *Windhover's Pharmaceutical Strategic Alliances: A Directory and Analysis of Pharmaceutical Strategic Alliances*. Norwalk, CT: Windhover Information, Inc.

_____. (1991) *Health Care Strategist*. Norwalk, CT: Windhover Information, Inc.

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