

# **MERGERS AND R&D REVISITED**

**Bronwyn H. Hall**

*Nuffield College, Oxford University;  
UC Berkeley; NBER; IFS, London*

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ABSTRACT

Using a newly constructed dataset containing approximately 6,000 United States publicly traded manufacturing firms that existed at some time between 1976 and 1995, I reexamine a series of findings about the relationship between restructuring activity and R&D investment during the 1980s, extending them to 1995. The dataset is essentially a universe of such firms. The results are the following: 1) between 1980 and 1995, employment in these firms fell from approximately 18 million employees to 13 million employees, with most of the decline taking place by 1990. 2) This shrinkage was achieved by internal shrinkage in the sectors associated with the rust belt (primary metals, automobiles, etc.) and by exit (often via leveraged restructuring or going private) in the low to medium technology sectors. The high technology sectors (pharmaceuticals, computing equipment, etc.) did not experience employment reductions. 3) Prior to 1987, firms that exited by going private had a substantially lower R&D-to-sales ratio than other firms, but after that date, there is only a small difference in R&D intensities between those who go private and the others. 4) When an acquisition propensity score is used to create a control sample, post-merger outcomes are significantly different from the controls when the propensity to acquire is high. Both R&D intensities and TFP increase when I condition on the actual merger event in a sample of firms with a high probability of merging.

Bronwyn H. Hall  
Dept. of Economics  
UC Berkeley  
Berkeley, CA 94720-3880

bhhall@econ.berkeley.edu

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### **1 Introduction**

During the 1980s there was a large wave of corporate acquisitions and restructurings in the United States, as well as in several other countries, notably the United Kingdom (*cite?*). Although such activity slowed somewhat as we entered the 1990s, there continues to be considerably restructuring activity in a variety of sectors. This fact perhaps accounts for the continued interest in a set of questions that occupied many researchers during the past restructuring wave: what are the consequences of acquisition, restructuring, and increased debt levels for the long run performance of the firms involved? Do these events have a negative effect on long term investment such as research and development? When they are followed by cuts in such investment, should we interpret these as cuts of “bad” (low expected rate of return) investment projects or the wholesale dismantling of valuable investments in innovative capital? Do they lead to increased productivity, as their proponents often claim, or do they simply maximize short term returns at the expense of longer term returns by reducing maintenance, investment, and intangible product quality characteristics?

In Hall (1994) I surveyed much of the empirical evidence on this topic; many researchers have contributed to the literature examining the effects of restructuring on productivity and technical change and I believe a more or less consistent picture has emerged, although sweeping generalizations need to be tempered by the undeniable fact that experiences have varied widely across industrial sectors. The overall picture is one where a variety of industries facing increased foreign competition and the high real interest rates of the early 1980s found their existing capital stock excessive relative to the returns it was able to generate (Blair, Schary, and others). This was reflected in Q values well below one in a variety of sectors, such as autos, steel, rubber, machinery, and others. An exception to this rule was pharmaceuticals and some parts of the computing/electronics sector (see Hall (1993) for graphs of the evolution of Q by sector between

1971 and 1989). During the 1980s, many firms responded to this pressure by leveraging or going private via leveraged transactions, reduced their employment and occasionally their investment in tangible and intangible assets and by the end of the period, Q was above unity in most industries.

Most authors (Lichtenberg and Siegel, McGuckin and Nguyen) have found that these transactions were followed by productivity improvements in the firms involved, although Long and Ravenscraft dissent somewhat from this view. Although the latter authors also found performance improvements following LBOs, these tended to dissipate after three years, according to the plant level data. In general much of the performance improvement and increases in market value seem to have come from reductions in employment and payroll (see Shleifer, Morck, and Vishny for more evidence on this topic).

Much of this prior evidence has been based on the immediate consequences of the restructuring, both on market value and on performance. In principle, under efficient market assumptions, the same conclusions will hold true for the long run results, because these results are forecast in an unbiased manner by the instantaneous market return to the acquiring or restructuring firm. There are reasons to believe, however, that the assumption of strong market efficiency is a thin reed on which to rest the entire defense of the long run efficacy of corporate capital market institutions in promoting economic growth. For this reason, many economists have turned to an examination of the effects of restructuring activity on various performance measures such as total factor productivity, profitability, or investment rates.

In a series of papers written between 1987 and 1991, I explored the consequences of the 1980s wave of restructuring for R&D investment in publicly traded United States manufacturing firms. These papers reached the following conclusions:<sup>1</sup>

1. For mergers between publicly traded firms, changes in R&D investment rates in the combined firm were no different from those of firms that had not undergone mergers.

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<sup>1</sup>Others have also reached similar conclusions using slightly different data: For example, Margaret Blair, Stephen Kaplan, Long and Ravenscraft, etc.

2. Going private transactions, whether leveraged or not, typically took place in sectors where R&D was not an important part of firms' strategies; this was especially true of LBOs, where almost no R&D was involved, at least through about 1988.
3. R&D investment *was* frequently reduced following a major increase in debt levels, whether or not accompanied by merger. However, these leverage increases happened primarily in medium technology industries such as steel, rubber, petrochemicals, and automotive transport.

Every senior executive I have interviewed in the past several years has confirmed that they view external finance in general, and debt finance in particular, as inappropriate for funding R&D investment.<sup>2</sup> Thus the fact that increases in debt go hand-in-hand with reductions in R&D is not surprising, but may not have a direct causal interpretation. That is, one can interpret the evidence from this period as saying that leveraging occurred where R&D was unprofitable, rather than leveraging taking place and "causing" R&D cuts.

A few questions have been left unanswered by my and others' work on the topic of mergers and R&D. First, most of the research cited here used samples of firms that ended in approximately 1988-89, and there seems to be some evidence that the pattern of restructuring changed in the latter part of the eighties, with larger and more R&D-intensive acquisitions. Are the facts as I have summarized them above still true when we look at data through 1995?

Second, what happened to the firms that cut their R&D spending after restructuring or merger relative to those who did not? Now that we have a few years of post-restructuring data, it is possible to examine this question. This paper attempts to improve on my earlier measures of post-merger R&D performance by adjusting the measures for the likelihood that a firm is involved in a merger.

Third, what are the longer run consequences of this wave of restructuring? Can we trace the apparently improved performance of the manufacturing sector during the 1990s back to this restructuring wave? Casual empiricism suggests that for the sector as a whole, the consequences

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<sup>2</sup>A notable exception is the very special case of early stage venture capital funding, where the investment is closely monitored and the firm gives away a large fraction of its potential return to that investment. Most executives view this as an option of last resort due to the amount of control and equity that is given up.

of the restructuring wave was positive, but can we find evidence of this in the individual firm data?

## **2 Data**

A new dataset was constructed for this investigation by merging six Compustat files: the Annual Industrial, the Full Coverage, and the Annual Research files for two different subperiods: 1957-1976 (back data) and 1976-1995 (current data). Thus there are potentially 39 years of data for any firm. The universe of firms used was all United States-based, publicly traded manufacturing firms, although the dataset itself contains some foreign, non-manufacturing, and subsidiary firms in order to have a complete set of data for firms undergoing acquisition (in some cases, the acquired firm survives as a subsidiary in the file and will therefore not necessarily be present as an independent firm, and in some cases firms are acquired by foreign or non-manufacturing firms). Considerable effort was devoted to tracking the exits from this file, which number over 3000. Firms can exit Compustat for a variety of reasons; these reasons are summarized in Table 1, together with the coding used to collapse them into a few key categories.

In order to construct the dataset, it was necessary to ensure that firms whose names changed or were reorganized had their data merged together, as these are not true exits. Firms that exited for reasons that were not discoverable (they were not listed in the Directory of Obsolete Securities or in Moody's) are treated as right-censored in the hazard rate estimation that follows. After the name-changers and reorganizers had their data combined, there were approximately 50,000 firm-years of data on approximately 6,000 firms. The variables used in this analysis are described in Table 2 below and their means given in Table 3. The constructed variables were constructed in a manner described previously in Hall et al (1989); the goal was to have a measure of Tobin's Q, the ratio of the market value of corporate assets to their replacement value, that corrects both long term debt and the capital stock for the fact that it is recorded in the firm's balance sheet at book value.<sup>3</sup>

### **3 Patterns of Exit**

Figure 1 presents an overall view of the evolution of whole-firm restructuring during the past two decades. The figure shows that firms are far more likely to exit by being acquired by other public firms throughout the period, while both going private acquisitions and various types of bankruptcy increased from the seventies into the early eighties and then declined again in the early nineties.<sup>4</sup> There are two major merger waves, in the late seventies and again in the mid to late eighties, but these waves are mainly in the public acquisitions and not in the going private transactions.

In order to investigate these patterns as a function of technology, I have used the coarse technological classification due to Chandler that I used in Hall (1994). This classification breaks up the manufacturing sector into four groups of firms that are differentiated by the basic nature of their technology and innovative patterns. The first group is the high technology group, where technical change has been very rapid and R&D is a major part of overall firm strategy: electronics, computing equipment, electrical machinery, aircraft and aerospace, scientific instruments, and pharmaceuticals. The second and third groups are those with relatively more stable technologies, but they are divided by the fact that some of them have relatively long planning horizons for changes in plant, equipment, and product due to the nature of the product they produce, while other have relatively short horizons. The long horizon group includes chemicals (except soap and toiletries), petroleum refining, primary metal products, machinery and engines, and transportation equipment, including automobiles but not parts. The short horizon group contains plastics and rubber, stone, clay, and glass, fabricated metal products, and automobile parts. Finally, there is a low technology group where R&D is an unimportant part of

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<sup>3</sup> Future work will use the algorithms suggested by Llewelyn and Badrinath, as implemented by Hall and Kim (1999), although in that paper we report evidence that the use of the improved L-B algorithm makes little difference to regression estimates that use Tobin's  $q$ , either in the cross section or in panel data.

<sup>4</sup>In interpreting these hazard plots, it is important to keep in mind the population from which exit is taking place: for example, between 1980 and 1985, the median firm size fell from 1100 employees to 700 employees as Compustat increased its coverage of smaller OTC firms. To the extent that smaller firms churn more, this will affect the hazard rates. I explore the effects of size further in the next section. In addition, the exit rates at the end of the period could have been affected by the fact that it takes time for deleted securities to be entered in the Directory of Obsolete Securities. However, this fact seems to have affected 1995 exits only: exits for "other" reasons (i.e., including those that were not identified) increased in that year, but were extremely small in number from 1990 to 1994.

the firm strategy in general: food & tobacco, textiles & apparel, lumber & wood products, furniture, paper, printing, and publishing, and miscellaneous manufacturing. These categories are admittedly fairly coarse, and it is possible to find innovative firms in all of them, but they have provided a useful guide to industry differences in the past.

Figures 2 through 4 show the hazard rates for public acquisition, private acquisition, and bankruptcy for the different technology categories. These figures confirm and extend findings in earlier work: although public acquisition and bankruptcy have similar patterns for all 4 sectors throughout the period, going private transactions show very different patterns for the different sectors: rates are low for high technology firms and for stable technology firms with long horizons, although they increase slightly during the late 1980s. There are two explanations for the low rates in these sectors: first, the high debt levels associated with going private are simply not suitable for R&D-intensive firms. Second, in the case of the “smokestack” industries, although many of those firms restructured during the 1980s, going private was typically not a suitable way to achieve this goal, because of the large size of many of the firms. However, by 1990 the going private hazard for these firms had reached nearly two percent, so a significant number of transactions was taking place.

The interesting thing in the plot is the pattern of going private in the low technology and stable technology-short horizon sectors: during the first wave of going private transactions in 1982-1985, the hazard was higher for low technology firms, while during the second (roughly 1986 to 1990) the predominant transaction involved stable technology-short horizon firms. In the next section we explore whether these patterns can be explained by firm characteristics such as R&D intensity, the capital-labor ratio, size, and Tobin’s Q.

#### **4 Firm Characteristics and Exit**

Figures 1 through 4 presented raw hazard rates for merger and bankruptcy, stratified by type and the technology of the sector. To investigate the differences in the underlying forces driving restructuring in the manufacturing sector more thoroughly, it is necessary to build a multivariate model of exit probability allowing for competing risks. I have chosen to use the Cox proportional hazard framework for this purpose, because it allows the underlying hazard to vary



freely from year to year, while allowing the covariates for each individual firm to determine the overall level of its risk of exit. This model is easily extended to treat time-varying covariates, such as are used here, and entry into the sample at different dates. The main drawback to the Cox model in this setting is unavoidable: without making specific functional form assumptions about the survival distributions, it is not possible to identify a model of competing risks unless one assumes independence of the different risks. That is, I must assume that the risk of being acquired by another public firm is independent of the risk of going private or bankruptcy once the covariates have been controlled for.<sup>5</sup>

The probability of an exit of type  $j$  of the  $i$ th firm in year  $t$  is given by the hazard function:

$$Pr(i \text{ exits via } j \text{ in year } t | \text{ surviving until } t) = \exp(-a_{t,j} - X_{i,t-1} \beta_j)$$

where the covariates  $X$  for the  $i$ th firm are measured in the period prior to the (potential) exit. Given a set of firms at risk in the sample in year  $t$ , and allowing for right censoring via exit of a type other than  $j$ , the Cox partial likelihood function for this model in year  $t$  is the following:

$$\log L_p = \sum_{i=1}^N \left\{ \log \mu_i^j(t) - \log \sum_{k \in R(i)} \mu_k^j(t) \right\}$$

where

$$\mu_i^j(t) = \exp(-X_{i,t-1} \beta_j)$$

Note that observations are assumed to be ordered by exit time in each year so that  $i$  is 1 for the first exit, 2 for the second, and so forth.  $R(i)$  is the set of firms at risk when  $i$  exits.<sup>6</sup>

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<sup>5</sup>The validity of this assumption could be tested by estimating a reasonable parametric model for the hazard rate, and I intend to do this in future work. Also, work by Han and Hausman (1981) and Meyer (1991) suggests that it may be possible to relax the assumption of independence in the competing risks model if the right hand side variables are sufficiently continuous and there are enough of them.

<sup>6</sup> A tricky issue in this dataset is defining when the firms become at risk, since in general I do not know the date of entry into the sample. I have assumed the firm becomes at risk when it enters or in 1976, whichever is earlier. In

The results of this procedure are shown in Table 4. The covariates considered were the size of the firm, as measured by the logarithm of employment, the R&D intensity measured by the R&D to sales ratio, a dummy for zero or insignificant amounts of R&D, the capital-labor ratio, the logarithm of Tobin's Q, a dummy for missing or implausibly small (below 0.1) Tobin's Q, the earnings-sales ratio, and a dummy for very negative earnings (the ratio was set to zero in this case).

Table 4 shows clearly that the probability of being acquired, going private, or going bankrupt differs across different types of firms. In general, firms that are acquired by other public firms do not differ greatly from firms that do not exit: they do somewhat less R&D, have a somewhat lower capital-labor ratio, a somewhat lower Q, but do not often have very negative earnings. However, the coefficients associated with these variables are only marginally significant at best, in spite of the fairly large sample size. The fact that firms with negative earnings greater than half sales in absolute value are less likely to be acquired is related to the fact that these firms are likely to be highly R&D intensive growth startups; when the earnings variables are not included, R&D intensity reduces the hazard of being acquired. A test for the predictive power of the 3 technology sector dummies (the omitted category is the low technology sector) confirms the evidence of Figure 2: the hazard for exit by public acquisition does not vary across technology type. These results are consistent with a view of the world that sees merger and acquisition as a normal part of the way firms evolve and grow in response to changes in their environment rather than an abnormal event concentrated in a few sectors.

The easiest type of exit to predict is exit via bankruptcy or liquidation, with an 8-variable chi-squared of 381.5. The primary reason is that the firms going bankrupt are smaller and have a substantially smaller earnings-sales ratio. They also have a lower capital-labor ratio, lower R&D intensity, and lower Tobin's Q. When the earnings variables are not included, however, R&D intensity and the capital-labor ratio are no longer significant. In other words, low earning firms are less likely to go bankrupt when they have tangible or intangible capital to lose. Other things equal, the reduction in risk is about 15 percent for a one standard deviation increase in either

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practice, the model has been estimated with a full set of calendar year dummies and a full set of dummies for the time since entry. The results for the other variables did not change significantly when the calendar year dummies

R&D intensity or the capital-labor ratio, while a one standard deviation increase in the earnings-sales ratio reduces risk by about 40 percent. It is noteworthy that technology sector has no predictive power for bankruptcy once we control for the other variables.

Superficially, the firms that go private look somewhat like those that go bankrupt, but with important differences. They do tend to be relatively less R&D and capital intensive, although not smaller on average. However, in this case low Tobin's Q is a better predictor of exit than low current earnings; that is, firms with poor future prospects are more likely to go private than to go bankrupt, while it is the other way around for firms with poor current prospects. This is consistent with a couple of interpretations: the going private transaction will be financed by earnings, so they should not be negative, and it is induced by a need either to change the way the firm is managed or simply to capitalize on a low price for the assets. Unlike exit via public acquisition or bankruptcy, going private does seem to vary by sector, with firms in the high technology sector and the long horizon stable technology sector approximately 50 percent less likely to exit by going private than firms in the other two sectors. As others have found before, the typical firm that is taken private is in light manufacturing, has positive cash flow, is not growth-oriented or in a growth-oriented sector, and is a good candidate for a leveraged transaction.

In an earlier version of this paper, I explored whether the effects of these covariates have changed over time, focusing especially on size and R&D intensity. I allowed the coefficients of these variables to change approximately every 5 years, choosing periods that roughly correspond to different merger waves (76-82, 83-86, 87-90, 91-95). The tests for coefficient constancy are accepted for public acquisition and bankruptcy and rejected soundly for private acquisitions. Prior to 1987, firms with R&D were extremely unlikely to go private (this is the result in Hall (1988, 1993)), but since then R&D has had very little predictive power. It is not that R&D-intensive firms have been going private, but simply that R&D is no longer a significant predictor of this activity. Looking back at Figure 3, note that this is consistent with the fact that the raw hazard of the four technology sectors appears to be converging after 1987.

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were excluded, although they were jointly significant.

## 5 Measuring Outcomes After Merger

In Hall (1990), I found that merging firms typically had an R&D intensity that was equal to the size-weighted average of their pre-merger R&D intensity,<sup>7</sup> adjusted for the overall change in R&D intensities in the sector (although this last adjustment had little effect). This result is consistent with the view that even in R&D intensive sectors, mergers are not primarily driven by a desire to achieve economies of scale in R&D. Or if they are, this effect is dominated by either an increase in the number of profitable R&D projects available or a decrease in the cost of R&D capital. The one exception to this rule was in mergers that appeared to have been financed by leverage, where one could argue that the reduction was caused by an *increase* in the cost of R&D capital.

A weakness in my earlier work was the lack of a “control” sample of non-merging firms that were otherwise identical to the merged sample. The entire sample was used as a control, but this is unsatisfactory if the non-merging firms differ from merging firms in other respects. In this respect my research strategy faces much the same difficulty that is encountered in many non-experimental situations where one is faced with the problem of evaluating the effect of a “treatment” on the treated population when the experiment is non-randomized. A variety of solutions to this problem exist in the literature. They fall into two major classes: 1) Constructing a sample of controls for comparison by matching on observed characteristics. 2) Constructing a model for selection into the treated sample and estimating it along with the treatment effect. See Heckman et al (1998) for a recent review of both methods and their many variants.

One popular solution to this problem is to use the “propensity score” methodology of Rosenbaum and Rubin (1983, 1984, 1985). In the Rosenbaum-Rubin (RR) approach, one computes the probability of an event (the “treatment”) for a sample of observations (in this case the probability of merger for the sample of firms) and compares the outcome after the event date (the growth in R&D investment or TFP growth) for firms that have the same probability of the event, but may or may not have actually experienced it. The appeal of this method is its simplicity, both in execution and in concept, and the fact that it requires only one major

assumption, that the selection mechanism for merger be “ignorable” conditional on the predictors of

Let  $M=1$  denote the fact that a firm merged and  $X$  denote the predictors of the probability of merging. Let  $z$  denote the outcome in which we are interested, and let  $z_1$  be the value of  $z$  for a firm that merges and  $z_0$  the value for firms that do not merge. Then we are interested in measuring

$$Z = E[z_1] - E[z_0]$$

Using the data, we can easily compute

$$E[z_1|M=1] - E[z_0|M=0]$$

which is just the difference in the outcome  $z$  for the merging and non-merging firms. This is what I did in my earlier work. However, in general this measure will be a biased measure of  $Z$  because the  $M=1$  sample of firms will have different expected outcomes than the  $M=0$  sample of firms. Under the assumption that the outcomes  $z_1$  and  $z_2$  are conditionally independent of the decision to merge given the predictor variables  $X$  (which can be anything that describes the firms prior to merging), RR (1983) establishes the following result:

$$E_{b(X)} [E\{z_1|b(X), M=1\} - E\{z_0|b(X), M=0\}] = E_{b(X)} [E\{z_1|b(X)\} - E\{z_0|b(X)\}] = E[z_1 - z_0]$$

$b(X)$  is called a “balancing score.” Classification by the covariates  $X$  themselves is the finest such score (in the probability measure sense) and the propensity score is the coarsest. In practice, the propensity score can be estimated using a logit or other probability regression as a function of the covariates  $X$ , and then the outcomes  $z_1$  and  $z_0$  can be compared for firms with the same value of the propensity score.

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<sup>7</sup> Size-weighted R&D intensity is computed as the sum of the R&D intensities in the two firms weighted by sales, which is equivalent to computing the ratio of the total R&D in the two firms to their total sales.

In this paper, this idea is implemented in the following way: first the probability that a given firm will acquire another firm is computed using a logit regression, as a function of the firm's size, Tobin's Q, R&D intensity, capital-labor ratio, earnings-sales ratios, industry, year, and a set of dummies for missing or outlier values for some of the variables. The outcome variables are various growth rates computed over the merger period between the pre-merger and post-merger firms. In the case of the merged firms, the pre-merger value is the weighted average of the two firms involved in the merger. For the controls, the growth rates are simply computed over periods of equivalent length. The growth rates investigated are total factor productivity, R&D investment, and the change in the R&D-to-sales ratio. The first and third of these measures are size-adjusted, whereas the second may be positive just because of merger-induced growth.

These outcomes are compared for two groups of firms that merge and don't merge, but that have the same probability of merger  $e(X)$ . The comparisons are done using medians, using a distribution free Kruskal-Wallis or ranksum test, and finally using a Box-plots for the two groups. To perform these comparisons, I divide the firms into a set of coarse groupings based on their acquisition propensity score.<sup>8</sup>

### **5.1 Merger propensity estimates**

Table 5 shows the results of estimating a simple logit equation on all the firms that existed some time during the 20 year period between 1976 and 1995. The covariates chosen are the same covariates used in the survival estimation in Table 4, but they have been lagged one year before the acquisition being considered to avoid endogeneity problems. The first set of columns in Table 5 shows the coefficients from a logit for the probability that a firm will acquire another public firm. Such firms are much larger than other firms and have lower R&D intensities and higher Tobin's Q (perhaps suggesting that they are able to pay for the acquisition using their own stock). They also are less likely to have small cash flow – in fact either more negative or more positive cash flow is associated with acquiring a public firm, a result that may be due to

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<sup>8</sup> This version of the paper presents results only for firms stratified by their propensity to buy other firms, both because that is more predictable and because it makes logical sense since we are looking at outcomes for the acquiring firm. Future work will examine outcomes stratified by the propensity of a *match* between two firms drawn at random from the sample.

changes in the sources and uses of funds during a period involving an acquisition, although I have lagged the variables to avoid this kind of problem.

Adding industry dummies to this equation increases its explanatory power but has little impact on the other coefficients, with the possible exception of the cash flow ratio, which loses some of its predictive power. Industries with a higher than average propensity for acquisition during this period, other things equal, are Stone, clay, and glass, Miscellaneous manufacturing (toys, musical instruments, etc.), Fabricated metals, Electrical machinery, and Rubber and plastics. Industries with a lower than average propensity for acquisition are Soap and toiletries, Lumber and wood, Oil refining, Textiles and apparel, Paper, and Non-automotive transportation equipment.

The second set of columns in Table 5 shows similar logits for the probability that a firm is acquired by another firm on Compustat. It is noteworthy that the explanatory power of the right hand side variables is much smaller for this regression (most of chi-squared shown at the bottom comes from the year dummies). The only significant predictors are having missing or a very high R&D intensity (both of which lower acquisition probability), and missing Tobin's Q, which also lowers acquisition probability. Industries where firms are likely to be acquired by other public firms are Computing equipment, Stone, clay, and glass, Food and tobacco, Paper, Instruments and communication equipment, Pharmaceuticals, and Miscellaneous manufacturing. Together with the results for the probability of acquiring a public firm, this result points to the Stone, clay, and glass and Miscellaneous manufacturing industries as having experienced considerable consolidation via merger during this period. For example, the number of firms in our sample in the Stone, clay, and glass fell from 78 in 1977 to 33 in 1995.

The predicted probabilities derived from these two regressions (including the industry dummies) are shown in Box Plots for the two groups of firms in Figure 6 (the acquirers versus the rest) and Figure 7 (the acquirees versus the rest). Although both show differences in the two groups, the boxes representing the first to third quartile ranges do not overlap in the case of the acquiring firms, whereas there is substantial overlap for those that were acquired with those that were not, confirming that the regressions do a better job of predicted acquirers than acquirees. I will use the propensity to acquire (Figure 6) in the subsequent analysis.

### **5.2 R&D after merger**

Figures 8 and 9 show the changes in my two measures of R&D around the time of merger, the change in the R&D-to-sales ratio and the growth of R&D. These figures and Table 6 pertain only to firms that perform and report R&D both before and after merger, to avoid contamination from firms that do R&D but change their reporting policy around the time of the merger. Thus the sample of all firm-years decreases from about 57,000 observations to 27,000, and the number of acquisitions considered is 479, rather than 884 as in Table 5.

In both cases the changes are measured between the average of up to three years' worth of data before the merger to up to three years' data after, adjusted for the average length of the gap so that they correspond to annual rates. The pre-merger values used are the combined figures for the two merging firms (weighted by sales in the case of the R&D-to-sales ratio). Overall there is very little difference between the two groups of firms, and this is confirmed in Table 6 (bottom row of the first panel), where I show that median measure for each group and each variable. Using a Kruskal-Wallis test, the hypothesis that there is no difference between the two distributions is not rejected at the 10 percent level.

However, when the firms are stratified by their propensity to be acquired (the remainder of the first panel of Table 6), interesting differences do emerge. The observations have been grouped into 6 fairly coarse groups based on their estimated propensity to acquire other firms; the groupings are designed so that the number of acquired firms is approximately equal across them. Both measures of the change in R&D around the time of merger give essentially the same result: firms with a propensity to merge between 2 to 4 percent that actually make and acquisition have a significantly lower increase in their R&D when compared to firms that have not merged.<sup>9</sup> On the other hand, firms with a propensity in the three higher classes (above around 6.5 percent) that actually make an acquisition have a significantly higher increase in their R&D. Thus the overall finding of no change obscures some real heterogeneity among the firms.

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<sup>9</sup>Year means have been removed from the estimated change in R&D intensity and growth in real R&D so that the comparison is not contaminated by sample change over time. The results without year means removed are qualitatively the same.



### 5.3 Productivity after merger

Similar methodology was used to compare total factor productivity before and after merger: an estimate of the TFP growth residual for each observation was computed using a conventional productivity growth regression with year dummies. Differences in this residual for merging and non-merging firms were computed for the 6 different propensity classes. In addition, a conventional productivity growth regression was computed for each propensity group that contained a dummy for merger. The primary difference in the second method is that the slope coefficients are allowed to differ by group.

The bottom panel shows the results of both these approaches, which give essentially the same answer: as in the case of R&D, total factor productivity growth around the time of merger is significantly higher for merging firms that have a high predicted probability of making an acquisition, but for those with a low acquisition probability, TFP growth is about the same as for the non-merging firms. The estimates indicate that TFP growth averages about 1 percent per annum higher for merging firms in the three to six year period around the time of merger, when we compare firms that have high values of the propensity score.

## 6 Conclusions

What should we make of this admittedly interesting finding that the post-merger outcomes of firms with a high acquisition propensity score indicate relative success (both TFP and R&D intensities increase), whereas this not true for firms that *a priori* had a low probability of merging?

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**Appendix A****Employment Change in U.S. Manufacturing Firms: 1976-1995**

This appendix presents a set of summary statistics on the sources of employment change in different manufacturing industries during the past 20 years. It is firm-based rather than plant-based, and in that sense it is complementary to the much more thorough analysis of Davis and Haltiwanger. It is intended merely as an industry-level guide to the changes we associate with the “downsizing” of publicly-traded American manufacturing. I include it as background for the study in the paper, partly because the driving force behind much of the merger activity in the 1980s was the shrinkage of certain industries in the stable technology sector, such as primary metals, machinery, fabricated metals, textiles, petroleum, and auto parts.

Tables A1 through A4 present the employment changes by a set of quasi-2-digit manufacturing industries for 4 roughly 5 year periods between 1976 and 1995. These changes are broken down into changes due to the exit of firms via merger or bankruptcy, entry of new firms, and growth of employment in existing firms (some of this will come from merger). The first thing to note is that the net change in employment in publicly-traded manufacturing firms was positive in the first period (1976-1980), but highly negative after that. The total number of employees in these firms was 18 million in 1980 and 13.3 million in 1995, in spite of the fact that the sampling universe grew slightly during that period. Of these approximately 4.4 million employees, only 0.4 million disappeared in the high technology sector, while over one million disappeared in each of the other 3 sectors.

The three figures summarize the fact that employment reductions in the long horizon stable technology (rust belt) sector were achieved via internal shrinkage, while those in the short horizon stable and low technology sectors were achieved via exit. Together with prior evidence on the relative importance of leveraged restructurings in the rust belt sector and leveraged buyouts (a large share of the going private transactions) in the other two sectors (Hall 1994), this fact points to sector shrinkage as a major motivator for both types of transactions.

Figure 6

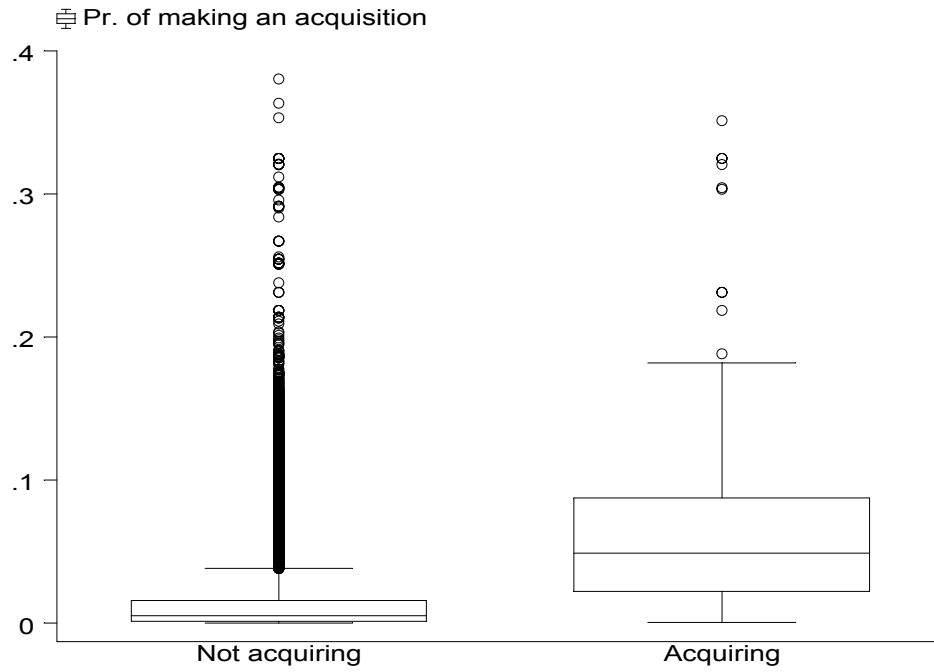


Figure 7



Figure 8

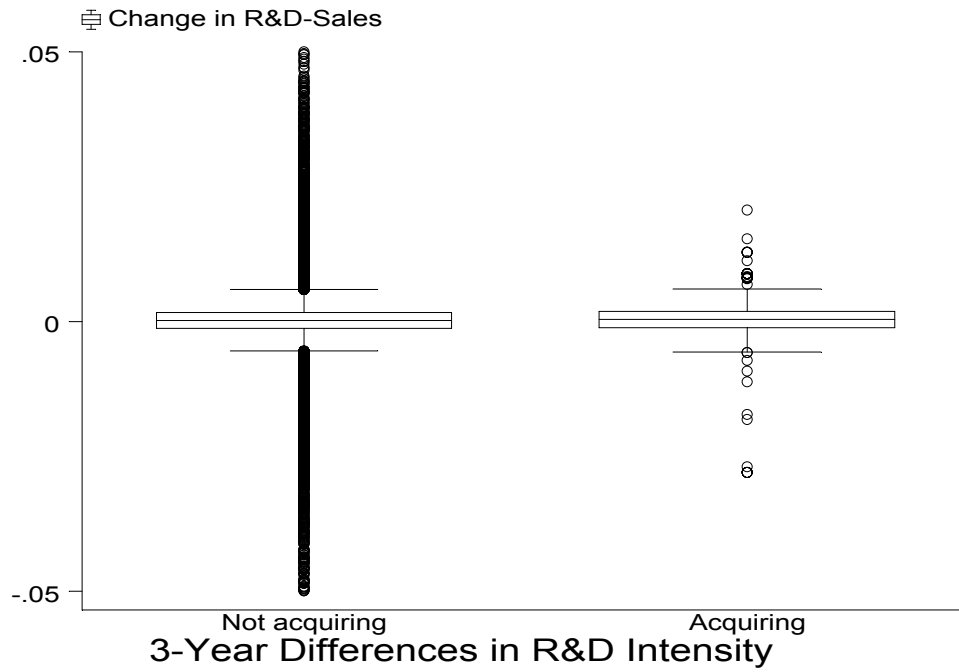


Figure 9

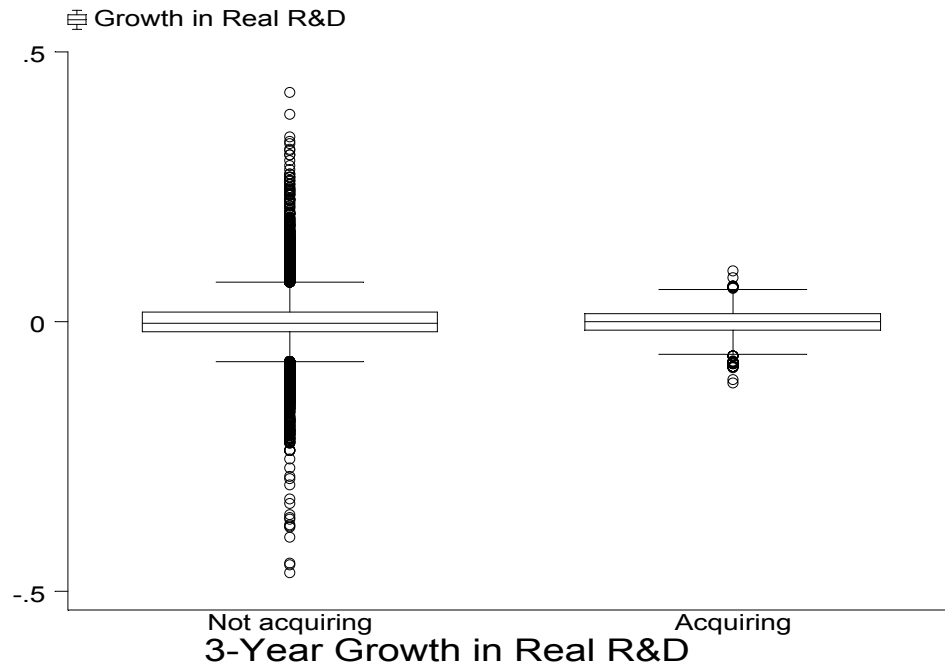
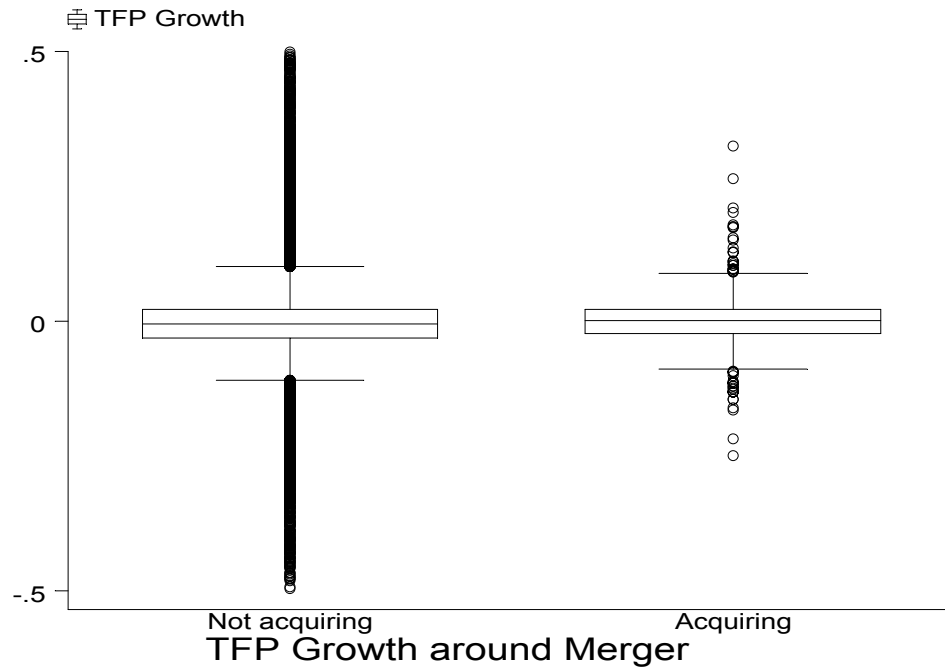




Figure 10



**Table 1**  
**Types of Exit from Compustat Between 1976 and 1995**

Category	Code	Description	Total Number	More than one year of data	Good data 1 or 2 years before exit
Public acquisition	M	acquired by another public firm	814	725	695
	F	acquired by a foreign firm (usually public)	175	167	166
	<b>Total</b>		<b>989</b>	<b>892</b>	<b>861</b>
Private acquisition	P	went private.	556	519	469
	PL	went private through an LBO or MBO	74	71	61
	<b>Total</b>		<b>630</b>	<b>590</b>	<b>530</b>
Bankruptcy or liquidation	B	went bankrupt (Chapter 7 or 11)	165	148	102
	L	liquidated	101	89	61
	D	delisted	71	62	31
	C, DC	charter canceled (usually for nonpayment of taxes)	30	27	8
	<b>Total</b>		<b>367</b>	<b>326</b>	<b>202</b>
Other	NC	Name change	39	35	25
	R, RA	Reorganized or restructured	72	68	44
	NO	No reason given or discoverable in DOS.	23	21	13
	<b>Total</b>		<b>134</b>	<b>124</b>	<b>82</b>
<b>Total Exits 1976-1995</b>			<b>2120</b>	<b>1932</b>	<b>1675</b>

**Table 2**  
**U. S. Manufacturing Sector Variables**

Variable	Source	Description
Sales	CS # 12	Sales (net) (\$M)
Employment	CS # 29	Number of employees (1000s)
R&D spending	CS # 46	R&D expense (\$M)
Capital Expenditures	CS # 30	Property, Plant, & Equipment - Cap. exp. (\$M)
Net Plant	constructed	Net plant adjusted for inflation (\$M)
Net Capital Stock	constructed	Plant, Inventories, and other assets adjusted for inflation (\$M)
Market Value	constructed	Common equity + market value of long term debt + short term assets less short term liabilities + preferred

CS = Standard and Poor's Compustat variable number.

**Table 3**  
**Variable Means and Medians**

Year		1976	1980	1985	1990	1995
Number of firms		2383	2415	2478	2472	2433
High Tech		699	786	1058	1119	1145
Stable Tech - LH		499	511	487	482	459
Stable Tech - SH		424	413	358	317	285
Low Tech		761	705	575	554	544
Employment (numbers)	Mean	1120	1073	708	566	641
	Median	1024	990	625	584	674
R&D to sales ratio (per cent)	Mean	1.49%	1.89%	4.73%	5.66%	7.10%
	Median	0.33%	0.47%	1.31%	1.40%	1.76%
Capital-labor ratio (87\$K per worker)	Mean	20.2	22.4	24.1	24.0	26.5
	Median	20.0	21.8	23.1	23.6	26.1
Cash flow-sales ratio (per cent)	Mean	7.1%	4.9%	-1.1%	1.2%	1.0%
	Median	7.3%	7.2%	7.6%	7.2%	9.2%
Tobin's Q	Mean	0.86	1.05	1.55	1.39	2.33
	Median	0.95	1.00	1.26	1.07	1.87
D (R&D missing)		0.425	0.409	0.337	0.335	0.330
D (Q missing)		0.261	0.166	0.086	0.123	0.055
D (Negative earnings)		0.078	0.103	0.193	0.200	0.173

**Table 4**  
**Hazard Rate Estimation for Exit from Compustat**  
**1976-1995: 50,657 Observations on 5,396 Firms**

Variable	Coefficients											
	Public Acquisition				Going Private or LBO				Bankruptcy or Liquidation			
Number of Exits	861		861		530		530		202		202	
Log employment	0.028	(0.018)	0.031	(0.018)	-0.045	(0.022)	-0.057	(0.022)	-0.206	(0.041)	-0.224	(0.042)
R&D-sales ratio	0.63	(0.82)	0.32	(0.85)	-1.07	(1.59)	-0.07	(1.46)	-2.35	(1.59)	-2.12	(1.52)
D (no R&D)	-0.18	(0.08)	-0.16	(0.09)	0.68	(0.11)	0.55	(0.11)	0.20	(0.18)	0.07	(0.19)
D (R/S>0.5)	-0.94	(0.60)	-0.99	(0.60)	-0.67	(0.76)	-0.58	(0.76)	-0.62	(0.45)	-0.63	(0.45)
Log of capital-labor ratio	0.014	(0.037)	0.031	(0.040)	-0.111	(0.039)	-0.104	(0.041)	-0.036	(0.056)	-0.034	(0.058)
Log Tobin's Q	0.010	(0.052)	0.002	(0.052)	-0.457	(0.068)	-0.438	(0.068)	-0.017	(0.100)	-0.002	(0.099)
D (Q missing)	-0.43	(0.13)	-0.42	(0.13)	0.73	(0.11)	0.75	(0.11)	0.06	(0.21)	0.07	(0.21)
D (Q>10)	-1.78	(1.01)	-1.73	(1.01)	0.08	(1.03)	0.01	(1.04)	-0.58	(0.76)	-0.61	(0.77)
Log (cash flow/sales) positive cash flow	-0.095	(0.046)	-0.104	(0.046)	-0.008	(0.050)	-0.001	(0.052)	-0.209	(0.099)	-0.194	(0.102)
Log (cash flow/sales) negative cash flow	-0.087	(0.055)	-0.087	(0.055)	-0.01	(0.059)	-0.014	(0.059)	0.245	(0.050)	0.247	(0.050)
D (cash flow negative)	0.06	(0.22)	0.02	(0.22)	0.07	(0.24)	0.08	(0.25)	-3.06	(0.36)	-3.03	(0.37)
D (high tech)			0.14	(0.10)			-0.41	(0.13)			-0.45	(0.20)
D (stable tech - long)			-0.05	(0.11)			-0.50	(0.14)			-0.32	(0.22)
D (stable tech - short)			0.08	(0.11)			0.12	(0.11)			-0.39	(0.23)
Log likelihood	-6,794.6		-6,792.8		-4,048.3		-4,034.8		-1,401.0		-1,398.1	
Chi-squared (p-value) for year dummies (DF=18)	169.4	0.0000	169.2	0.0000	77.2	0.0000	76.6	0.0000	103.6	0.0000	104.2	0.0000
Chi-squared (p-value) for tech. Dummies (DF=3)			3.6	0.3460			27.0	0.0000			5.8	0.1220

Standard errors are robust estimates.

**Table 5**  
**Acquisition Probability**  
**1976-1995: 50,657 Observations on 5,396 Firms**

Number Acquisitions/Acquired	Buyers 877		Sellers 1097	
Log employment	0.514	(0.019)	-0.049	(0.016)
R&D-sales ratio	-4.50	(1.44)	0.34	(0.73)
D (no R&D)	-0.13	(0.09)	-0.06	(0.07)
D (R/S>0.5)	1.17	(0.85)	-1.17	(0.51)
Log of capital-labor ratio	0.008	(0.044)	0.018	(0.034)
Log Tobin's Q	0.390	(0.067)	-0.137	(0.049)
D (Q missing)	-2.20	(0.32)	-0.19	(0.10)
D (Q>10)	0.03	(0.41)	-1.30	(0.72)
Log (cash flow/sales) positive cash flow	0.159	(0.069)	-0.031	(0.038)
Log (cash flow/sales) negative cash flow	0.182	(0.076)	-0.019	(0.039)
D (cash flow negative)	-1.31	(1.02)	-1.45	(1.01)
Log likelihood	-3,731.9		-5,179.5	
Chi-squared (p-value) for covariates (DF=20)	1536.4	0.0000	403.6	0.0000

The method of estimation is logit.  
A full set of two-year dummies was included in both models.

**Table 6**  
**Changes in R&D at Merger Controlling for Propensity to Merge**

Estimated Propensity to Merge (number)	Change in R/S			Growth in Real R&D		
	No Acq.	Acq.	K-W Test	No Acq.	Acq.	K-W Test
0 to .01 (33)	0.0005	0.0026	0.03 (.864)	10.9%	10.1%	0.02 (.902)
.01 to .02 (42)	0.0009	-0.0022	8.32 (.004)	19.0%	5.5%	5.04 (.025)
.02 to .04 (79)	0.0008	-0.0006	7.20 (.007)	13.5%	13.9%	0.94 (.334)
.04 to .1 (212)	0.0007	0.0028	11.63 (.001)	9.0%	12.9%	0.01 (.909)
>.10 (92)	0.0008	0.0031	4.59 (.032)	8.2%	26.7%	16.54 (.000)
All (458)	0.0007	0.0012	2.25 (.134)	11.7%	16.2%	0.44 (.507)

K-W Test is the Kruskal-Wallis test that the two groups come from the same distribution  
P-values are shown in parentheses.