Technology Usage in U.S. Manufacturing Industries: New Evidence from the Survey of Manufacturing Technology

by

Timothy Dunne*

CES 91-7 October, 1991

Abstract

Using a new dataset on technology usage in U.S. manufacturing plants, this paper describes how technology usage varies by plant and firm characteristics. The paper extends the previous literature in three important ways. First, it examines a wide range of relatively new technologies. Second, the paper uses a much larger and more representative set of firms and establishments than previous studies. Finally, the paper explores the role of firm R&D expenditures in the process of technology adoption. The main findings indicate that larger plants more readily use new technologies, plants owned by firms with high R&D-to-sales ratios adopt technologies more rapidly, and the relationship between plant age and technology usage is relatively weak.

Keywords: Technology Usage, Research and Development, Survey of Manufacturing Technology

*Center for Economic Studies, U.S. Census Bureau. The author thanks Robert Tinari and Stephen Andrews of Industry Division for access to the data used in the paper. Additionally, the author would like to thank Robert McGuckin, Mark Doms, Jim Adams, Stephanie West, Jim Schmitz, Ken Troske and participants of the NBER Summer Institute's Program on Productivity for helpful comments. Any opinions, findings, or conclusions expressed here are those of the author and do not necessarily reflect the views of the Census Bureau.

Economists have long studied the development and diffusion of new technologies. This interest stems from the fact that technological progress is one of the basic engines of economic growth. In Landau (1986) it is stated that "from one-third to one-half of all our growth has come from technical progress and that it is the principal driving force for long-term growth...in industrial societies."[1] In an oversimplification, one can break down the process of technological progress into two stages. First, there is the innovation stage where new products and new techniques are developed.[2] Next, there is the diffusion stage where the new products and new techniques are integrated into the economy. It is the diffusion stage, and in particular the usage of new production technologies, that is examined in this paper.

Early empirical studies by Griliches (1957) and Mansfield (1968) explore the diffusion of innovations in agriculture and manufacturing. These studies examine the speed at which innovations diffuse through sectors and the characteristics of industries and firms which lead to faster technology adoption. In addition to these seminal works, a large number of case studies analyze the patterns of technology adoption for individual industries and individual innovations. Romeo (1975) examines the adoption of numerical controllers in U.S manufacturing firms. More recently, Hannan and McDowell (1984) look at the spread of automatic teller technology in the banking industry, Levin, Levin and Miesel (1987) examine the diffusion of optical scanners, and Kelley and Brooks (1991) investigate the case of programmable controllers. These papers focus on the importance of firm characteristics such as absolute size, market share, work-force skills and industry characteristics such as market concentration, R&D intensity and scale economies as basic determinants of technological adoption and diffusion.

This paper extends this work in several directions. First, it explores a broad set of plant and firm characteristics to explain technology usage. The plant-level characteristics include size, age, and whether the plant engages in defense related production. The firm characteristics are R&D expenditures and ownership type (single or multiplant producer.) In particular, the paper focuses on whether young plants are more likely to bring new production technologies into an industry than older plants and whether firms that are more R&D intensive are more likely to adopt new production technologies. Second, the paper examines a relatively large set of production technologies across a large sample of plants. In this study, statistics on the adoption of 17 individual technologies for roughly 10,000 plants are presented, and detailed analyses of six of these technologies are performed. Lastly, the paper examines the complementarity of new technologies. The question - Do plants which adopt one technology have a tendency to adopt other technologies as well? - is addressed. The overall goal of this research is to provide new evidence concerning the variation in technology adoption across plants, across firms, and across innovations.

This study uses a relatively new data set based on the 1988 Survey of Manufacturing Technology (SMT). The SMT surveys approximately 10,000 manufacturing establishments about the use of 17 individual advanced technologies. These technologies are general innovations primarily used in the design or production of manufactured products. The 17 technologies can be broadly classified into five technology groups including: design and engineering (CAD/CAM), fabrication/machining and assembly (robotics, lasers), automated material handling, automated sensors, and communication and control (computers, networks, programmable controllers). In addition, data on plant characteristics such as size, age, industry, and defense production are also collected.

The investigation of the SMT data shows that technology usage varies systematically with plant-level characteristics. The results indicate that technology use is positively correlated with plant size. This finding is consistent with the previously cited literature (e.g. Mansfield, Romeo, and Kelley and Brooks.) Additionally, plants that are owned by multi-unit firms and plants engaged in defense related production are generally more likely to use advanced technologies. The relationship between plant age and technology adoption is less clear cut and varies across technologies. The findings do indicate that older plants appear to use numerically controlled machines and pick and place robots at higher rates than younger plants. With respect to technology complementarity, technology usage is correlated across technologies. Plants using (not using) one advanced technology tend to use (not use) other technologies. Finally, plants that have high-levels of past R&D expenditures relative to sales have higher rates of technology adoption.

The paper is organized as follows. The second section provides a description of the data used in the empirical analysis. The third section outlines the empirical model and estimation methods. The fourth section gives the empirical results and the last section provides summary comments.

II. Data

To examine technology usage in U.S. manufacturing, we utilize the relatively new Survey of Manufacturing Technology. This survey, conducted by the Census Bureau in 1988, asks manufacturing plants about the use of 17 separate technologies that are grouped into five advanced technologies categories.[3] These main technology categories are design and engineering (DE) made up of computer automated design/computer automated manufacturing (CAD/CAM) technologies and ; fabricated machining and assembly (FMA) including lasers, numerically controlled machines, and robotics; automated material handling (AMH) - this includes automatic storage and retrieval systems and automatic guided vehicle systems; automated sensors (AS) which includes inventory control on materials, parts, and final products; and communication and control which includes Local Area Networks (LAN), programmable controllers and computers used on the factory floor. A list of the 17 individual technologies with a brief description is given in Table 1.

The establishments in the data set were initially drawn from the 1987 Census of Manufactures. A sampling frame of approximately 40,000 establishments with twenty of more employees was created from major industry groups 34 - Fabricated Metal Products, 35 - Nonelectrical Machinery, 36 - Electric and Electronic Equipment, 37 - Transportation Equipment, and 38 - Instruments and Related Products. From this sampling frame, a mailout sample was selected that contained 10,526 establishments. Overall, response rates were high with the Census receiving 9682 reports.[4] Of those not responding, only 121 refused to complete the survey. The rest were either out of business or the addressee could not be located. In addition to data on technology usage the survey also contains information on plant age, industry, employment size class, product market, defense contracting status, and ownership.

Table 2 provides data on the percent of establishments using a technology broken out by major industry group. The data in the tables are weighted to reflect population totals.[5] Looking across technologies those most frequently used are computer aided design, numerically controlled machines, programmable controllers, and computers used on the factory floor. The least employed technologies are automatic storage/retrieval systems, guided vehicle systems, and lasers. Among industries, industry 34 (Fabricated Metal Products) has the lowest percent of establishments using advanced technologies. In the other four industries, the pattern of technology adoption varies quite substantially. Over half the plants in Nonelectrical Machinery (35) utilize numerically controlled machines. Establishments in the Electronic Products (36) and Instruments (38) industries use computer based technologies to a great extent including CAD and CC technologies. Robotics are most prevalent in Transportation and Electronic Products.

Table 3 gives some basic measures of technology usage intensity broken down by industry, plant size and plant age. The second column of Table 3 reports the percentage of establishment utilizing none of the 17 technologies given in Table 1. The third and fourth columns give the percent of establishments that have adopted at least one of the technologies and the percent of establishments that have adopted five or more, respectively. Looking at the sample as a whole, 23.7 percent of the establishments fail to adopt any of the listed technologies while 23.1 percent adopt five or more of the technologies. The pattern of technology usage varies somewhat across the major two-digit industry groupings. The Fabricated Metal Products industry has the lowest overall usage in any of the categories. The percent of establishments using at least one technology is highest in industry 35. However, for those plants using five or more technologies - industries 36 and 37 have the largest percentages.

The pattern of technology usage disaggregated by size is clear cut. As size increases the usage of advanced technologies increases as well. For plants in the 20-99 employment size class, a little over thirty percent use none of the advanced technologies, while only 1.5 percent of plants with greater than 500 employees fail to use any of the technologies. The pattern is similar as technology usage rises. Seventy-nine percent of plants in the largest size group use 5 or more of the technologies while only 13.2 percent of the smallest plants used five or more. Finally, technological usage appears to vary less by age than by size. For the group of plants that adopt no technologies or at least one technology, there is little difference across the four age groups. For plants adopting five or more technologies, the proportion of plants in the over 30 age group is somewhat higher than average while the youngest group is lower than average.

Two points concerning the usage data should be noted. First, the innovations are not specific to a particular industry. Most innovations included in the survey are general in nature and can be used in a wide range of manufacturing industries. Second, while we know whether a plant uses or does not use a specific technology, we do not know the intensity of usage. Therefore, a plant experimenting with a technology and a plant fully utilizing that same technology would both appear as equivalent users of the technology in this survey.

III. Empirical Model

In this section we present an empirical model of technology usage. The goal of the empirical model is to describe how plant technology use varies with plant characteristics. The dependent variable, Y_i, equals one if a plant uses a given technology, zero otherwise. The technology indicator variable is then regressed on a set of plant characteristics and industry controls. To estimate this model, we assume that the error term of the regression, u_i, has mean zero and variance F^2. The equation is then estimated in the form of a probit model (Maddala 1983) where

$$\begin{aligned} \mathrm{Prob}(Y_i=1) &= \mathrm{Prob}(u_i \ \$ - \$'X_i) \\ &= 1 - M(- \$'X_i) \end{aligned}$$

and (1)

$$\begin{aligned} \mathrm{Prob}(Y_i=0) &= \mathrm{Prob}(u_i < - \$'X_i) \\ &= M(- \$'X_i) \end{aligned}$$

M is the cdf of the standard normal, $ is a vector of parameters to be estimated, and X is a matrix of independent variables.[6] The usage probits are estimated separately for six of the individual technologies given in Table 1: Computer Aided Design/Computer Aided Engineering (CAD/CAM), Numerical Controllers/ Computer Numerically Controlled Machines (NC/CNC), Automated Sensors for Materials (AS/Materials), Pick and Place Robots (Robotics), Local Area Networks Used on the Factory Floor (LAN), and Computers Used on the Factory Floor (Computer). These technologies were chosen to reflect technologies that have relatively wide-spread usage - NC/CNC and CAD/CAM, technologies with moderate usage - LAN and Computers, and technologies that have relatively low usage rates - Robotics and Automatic Sensors.

Note in contrast to the standard modeling of technological adoption, this approach does not employ proportional hazard techniques. The reason for this is that the data contain information only on technology usage at a point in time, namely 1988. The data do not indicate when the technology was adopted or how long the plant has been using the technology. This limits the analysis to the examination of a point on the diffusion path as opposed to an estimation of the diffusion curve itself. Therefore, the usage of technology is examined but not the pattern of diffusion.

The X_i matrix in (2) contains variables representing primarily plant-level characteristics. The explanatory variables include a dummy variable to control for whether a plant is owned by single-unit firm or a multi-unit firm. The variable equals one if the plant is owned by a multi-unit firm otherwise it is equal to zero. For the sample of plants under analysis here, 58 percent of the plants are owned by multi-unit firms. A dummy variable is included to capture the effect of defense related production on technological adoption. The dummy variable equals one if the plant produces 25 or more percent of its output under defense related contracts or subcontracts, otherwise it equals zero.[7] Under this definition, roughly 14 percent of the plants in the sample engage in defense related production.

One of the main focuses of this paper is to examine how technology usage varies with the size and age of the plant. Plant size is included in the model to capture differences in relative efficiency across plants. The work of Jovanovic (1982) and Pakes and Ericson (1989) predict size and efficiency are positively correlated. Accordingly, we postulate that large firms will be the most able and likely to take advantage of the newest technologies. Additionally, Schumpterian models of innovation activity also suggest that size and the ability to innovate should be positively correlated.

There are several reasons why one may observe dissimilar technology adoption patterns across plants of different ages. One might expect younger plant to have higher adoption rates because they are recent vintage plants. New plants have the opportunity to choose the newest available technology when they are designed and constructed. Thus, if older plants face convex adjustment costs when updating their technology, then the distribution of new technologies may be skewed toward younger plants.[8] Countering this argument is the possibility that survival is positively correlated with adoption. If plants which fail to adopt new technologies have higher exit rates, then the observed distribution of surviving plants from an entry cohort will be skewed toward plants that adopted. In this scenario, the younger plant cohort has not completed this selection process, and thus, non-adopters will make up a larger percentage of the younger cohorts.

The age and size effects will be included in the model as a set of 11 interacted dummy variables. In the SMT, plants are grouped into three employment size categories - 20-99 employees, 100-499 employees and >= 500 employees. The plant age variable, relative to 1988, provides four age classes - plants built less than 5 years ago, plants built 5 to 15 years ago, plants 16 to 30 years ago, and plants over 30 years old.[9] The three size and four age dummies are fully interacted which yields 12 size-age classes. In the estimation the omitted group represents plant with 20-99 employees and less then five years in operation.

Tables 4a-4f. present usage rates for the six technologies disaggregated by plant age and plant size.[10] The data are broken out into the three size groups and four age classes discussed above. The last row in each table contains the mean usage rate for each size class while the last column contains the mean usage rate for each age class. The data reveal that the usage rates increase with size for all six technologies. This pattern is also found when age is held constant. That is, within an age group usage rate increases with size. The age results, however, are mixed. For the entire sample (the last column in each of the tables), it appears that adoption rates increase as plant age increases. This effect is considerably smaller than the observed size-adoption rate pattern. However, holding size fixed (looking down the columns), the pattern becomes less clear. For many of the technologies, the within size group adoption rates are relatively flat or even decrease with age. These patterns of technology adoption by age and size of plant are more fully explored in the next section.

IV. Empirical Results

The results of the usage probit analysis are reported in four parts. The first set of results provides estimates of the basic adoption model for the six individual technologies. The second part of the analysis examines the possibility of technology complementarity across the individual technologies. The third section examines the importance of firm R&D intensity on technology usage. The final part reports on alternative specifications and alternative definitions of the adoption variable.

Technology Usage Probit Results

Table 5 reports the estimates from the adoption probits for the six individual technologies. The first page of the table presents the findings for the Computer Aided Design/Computer Aided Manufacturing (CAD/CAM), Numerically Controlled/Computer Numerically Controlled Machines (NC/CNC), and Pick and Place Robots (Robotics), while the second page contains the results for the remaining three technologies - Automated Material Sensors (AS/Materials), Local Area Networks used on the Factory Floor (LAN), Computers Used on the Factory Floor (Computers).[11] The base group represented by the intercept in the probits are small (TE 20-99) and young (< 5 years), single-unit plants operating in SIC industry 341 that do not produce defense related products. All the probits include three-digit industry dummies, although, because of space limitations, these parameters are not-reported.

Examining first the size effect, it is clear that adoption rates increase as plant size increases, holding age fixed. For CAD/CAE technology, the probit size-age parameters for age group > 30 years rise monotonically from -.289 to 1.347 going from plants with 20-99 employees to plants with 500 or more employees. This pattern occurs in all six technology probits and for all four age groups. The observed strong size effect is consistent with previous work examining the effect of size on the adoption of technologies (Romeo, Hannan and McDowell, and Kelley and Brooks).

The age results, however, vary considerably across technologies and are generally weaker. For plants in the 20-99 size group, it appears that younger plants have higher adoption rates than older plants in all technologies except NC/CNC and Robotics. The age effects, holding size fixed, are relatively flat for the remaining two size groups except for NC/CNC and Robotics technologies. In these two probits, adoption rates are higher for older plants holding size fixed. Non-interacted models of age and size indicate similar patterns - strong size effects and relatively weak age effects.[12] These age results are consistent with two basic stories. One is that there is no advantage or disadvantage in adopting technologies associated with plant age. A second alternative is that sample selection may be biasing the age parameters downward for young plants. This sample selection stems from the fact that only successful old plants are observed (See Evans (1986) and Dunne, Roberts and Samuelson (1989) for a discussion in the context of plant growth.) These will tend to be the most efficient plants from their cohorts. The young plant cohort, on the other hand, contains both efficient and inefficient plants. The age parameters, therefore, pick up both differences in plant age and differences in efficiencies. In part, the size parameters, which proxy for relative efficiencies, should control for this problem. However, the possibility exists that the age parameters are still biased if size does not sufficiently index relative plant efficiency.

Examining the remaining variables in the model, the multi-unit dummy indicates that plants owned by multi-establishment firms have higher adoption rates. The effect of defense related production on technology usage is also generally positive and statistically significant. A surprising exception is the case of robotics; plants engaged in defense related production use that technology at lower levels.

Overall, the individual probits have similar fits. The Likelihood Ratio Index (See Greene, p. 682) for the 6 probits given in Table 5 vary between a low of .109 for LAN's and a high of .236 for Robotics. The simple correlations between the adoption variable and the predicted probability vary between .40 and .50 across the six technologies. Finally, joint tests of significance on the industry dummies indicate substantial differences in adoption rates across the three-digit industries.[13]

To close out the analysis of the basic usage probit results, Figure 1 presents a graph showing how the probability of usage varies by plant size for the six technologies. In this analysis a continuous measure of size, included in the probits as the log of total employment and log of total employment squared, is used in the graphs.[14] The intercept is constructed as the average of the fitted variables from the probits excluding the size measures. The graph clearly shows the difference in overall usage rates. Robotics and AS/Materials have relatively low usage while CAD/CAM and NC/CNC have relatively high usage rates. In all the technology groups, the probability of usage increases with size, however, the three computer-based technologies - CAD/CAM, LAN, and Computers have somewhat steeper slopes in the small to middle size range (20-500 employees). AS/Materials and Robotics technologies increase more dramatically in the greater than 500 size range. Finally, NC/CNC has the flattest relationship between size and adoption.

The results clearly show that technology usage is positively correlated with size, multi-unit status, and defense contracting (5 of 6). The age results are generally weaker. Young small plants appear more inclined to use new technologies than older small plants. Also, older plants more readily use fabrication technologies such as NC/CNC and Robotics.

Technology Complementarity

In the preceding analysis, the choice of using a given technology is treated as independent of the choice of other technologies. Clearly, these decisions will be related.[15] A plant setting up a factory LAN will by default be using computers on the factory floor. The next section explores the complementarity of various technologies.

To examine whether plants that employ a given technology are more likely to use other technologies, a correlation matrix is constructed based on the residuals from the probit models analyzed above. This residual analysis allows us to examine the basic complementarity of technology controlling for differences in plant and industry characteristics. The residuals from the probit can be viewed as the unexplained portion of the decision to adopt or not adopt an individual technology. If the decision to adopt a given technology depends on the use of other technologies, then one would expect the residuals from the adoption probits to be correlated. Probits for each of the 17 technologies are run to generate separate sets of residuals. For the six technologies under study here, separate correlation coefficients between that technology's residuals and the sixteen other technology' residuals are presented in Table 6.

The first point to note is that all the correlation coefficients are positive and statistically significant different from zero at the one percent level. This indicates that the usage is correlated across technologies. Plants using one advanced technology are more likely to use other advanced technologies, as well. A second observation is that "related" or "derivative" technologies have relatively high correlation coefficients. The two CAD based technologies - CAD controlled machines and Digital CAD - are quite correlated with CAD/CAE technology .302 and .243, respectively. Plants using Automated Material Sensors (Column 4) have a high probability of using Automated Output Sensors (.596), and plants that use LAN's on the factory floor (Column 5) also use LAN's for technical data (.608). Finally, Flexible Manufacturing Systems (FMC), Programmable Controllers, and Computers Used on Factory Floor have relatively high correlations across the entire set of technologies. The high positive correlation for FMC is possibly due to the fact that FMC is a composite technology. FMC technology is used to organize other technologies. The relatively high correlations observed for Computers and Programmable Controllers may stem from the fact that these technologies are building blocks for other technologies. For example, plants using robots may require programmable controllers and computers to operate them.

R&D and Technology Usage

The analysis so far has focused on basic plant-level characteristics and the patterns of technology usage. In this part of the analysis, we examine how technology usage varies by firm-level R&D intensity. One reason that firms may differ in their usage of technology may be due to adjustment costs borne in the adoption process. Firms that choose a new technology bear certain costs associated with the integration of the new capital into the firm. These may be direct costs associated with the training of workers and managers in the use of that new technology and the indirect cost associated with the loss of output due to downtime. Several models of technology adoption and diffusion (Jensen (1982,1988), Cohen and Levinthal (1989) and McCardle (1985)) suggest that information asymmetries along with uncertainty in the profitability of the new technology may affect the speed at which firms adopt technologies. If firms that perform more R&D have higher stocks of knowledge concerning "new" technologies, this may yield informational and cost advantages in the adoption of advanced technologies. The information advantage derives from the fact that the organizations which engage in R&D are more technology aware. The cost advantage comes from the fact that R&D intensive firms are more likely to have expertise in advanced technologies and this leads to lower training and integration costs.

The construction of the R&D variable and the new sample are described below. The ideal measure of a firm's informational capital would be the stock of knowledge prior to the adoption decision. Given that such a measure is unavailable, a variable correlated with the stock of knowledge is used in its place. The measure of R&D employed in this analysis is company-level R&D expenditure divided by company-level sales. This provides a measure of R&D intensity controlling for overall firm size. It is important that the R&D variable represent the stock of knowledge prior to the adoption decision.

Thus, the variable is constructed based on historical R&D expenditure data. For the results presented in Table 7, the R&D-to-sales ratio is constructed for 1974.[16] This will proxy for the pre-adoption level of the firms' stock of knowledge. Other years data for the R&D variable have been explored, specifically 1975 & 1977, all the results presented in Table 6 are robust to the year of the R&D data chosen. The inclusion of R&D data reduces the sample size significantly for two reasons. First, many companies in the 1988 SMT did not exist in the mid 1970's and second, the R&D expenditure survey only samples 3000 companies a year. The latter reason is the source of most of the attrition in the sample. The resulting sample contains 2434 plants representing 673 companies and is skewed toward large, old plants and firms. Because of data limitations, the age-size parameters are included separately.

Table 7 gives the results for the usage probits with 1974 R&D-to-sales ratios included. Plants that belong to firms with high R&D-to-sales ratios have higher usage rates for all six technologies. The NC/CNC result is not significant and the Robotics result is significant at the 10 percent level but not at the 5 percent level. Additionally, the magnitude of the effect is relatively large. For CAD/CAE an average plant in the sample engaging in no R&D has a probability of adoption of .701, at the mean R&D level that adoption probability increases to .745, and one standard deviation above the mean it is .803. For AS/Materials, these numbers are .583, .602, and .640, respectively.[17] Thus, the effect of firm-level R&D on adoption rates is both statistically and quantitatively important. The remaining variables in the model share similar effects to those reported earlier, except that the defense and multi-unit dummies are generally not significant.[18] The size parameters are large and statistically significant, and older plants adopt NC/CNC and robotics technology more readily.

Alternative Specifications

In addition to the preceding analysis, several alternative specifications, samples, and definitions have been explored in this research.

First, within two-digit industry probits are estimated to examine the robustness of the pooled industry results. Probits for each two-digit industry are estimated separately. The results indicate that the within industry probits are consistent with the pooled estimates presented in Table 5. Larger plants have higher adoption rates. The age results are similar in that no strong age patterns emerge.

The second specification allows for a redefinition of the usage variable. In addition to asking if a plant used a particular technology, the survey also requests information on why a particular technology is not utilized. The respondent could answer that the technology is inappropriate to its current production process. In an alternative definition of the zero-one adoption variable, plants that responded that the technology is inappropriate are excluded from the analysis. This reduces the sample size in the individual pooled probit regressions by 20 to 40 percent depending upon technology. The main results are relatively insensitive to this redefinition. Technology usage increases as size increases holding age fixed. Additionally, the age results are invariant to this redefinition of the technology usage variable.

Third, analyses similar to those presented in Table 5 through 7 are carried out on the 11 other technologies listed in Table 1. The results for size and R&D are similar to those presented here. For all 17 technologies, the probability of adoption increases with plant size and the results are statistically significant at the five percent level. The effect of R&D on technology adoption is positive for all 17 technologies and is statistically significant in 13 of the 17. The age results are similar in that they are relatively weak and vary across technology and industry. These results are available from the author by request.

Finally, the adoption rate probits are run using a weighted maximum likelihood approach where the weights used are the survey weights. This procedure gives more weight to smaller establishments which are less represented in the sample. The weighted probits are very similar to the results presented in Table 5. The signs, magnitudes, and significance tests of all the parameters of interest are very similar in both the weighted and unweighted regressions.

V. Summary

This paper provides basic evidence on the patterns of technology adoption in U.S. manufacturing plants. The results show that larger plants, plants owned by multi-unit firms, and plants engaged in defense production have higher adoption rates. Plant age has mixed effects on the adoption of technology depending upon the technology under study. The age results, however, may be biased because of the selection process at work in the older plant cohorts. At a minimum we can say that many older plants employ relatively young technologies and are not trapped into old technologies.

Additionally, the findings indicate that technology usage is correlated across technologies. Plants that use (do not use) one "advanced" technology have a tenancy to use (not use) other "advanced" technologies. The other main finding is that plants owned by R&D intensive firms have relatively high adoption rates. This result lends support to the notion that R&D expenditures generate spillovers in the use of new production technologies. These spillovers may provide R&D intensive firms with cost or informational advantages in the use of new technologies.

The results presented here suggest considerable room for further studies of technology adoption using the SMT. Two possible alternatives are the examination of a more complete set of plant and firm characteristics and the investigation of individual plant history and performance. Utilizing data from the 1987 Census of Manufactures, a more complete description of the relationship between technology and investment, wages, and performance could be undertaken.[18] Similarly, the historical analysis could include a comparison of growth, investment and productivity of plants which use advanced technologies to plants which do not. In particular, it may prove possible to sort through the plant age-selection problem discussed above through the use of data on plant failure and pre-adoption plant characteristics.

Endnotes

1. The cite comes from p. 2 in Landau and Jorgenson (1986). This point is also made in Griliches (1984) (p. 1) where he states that "invention and technical change are the major driving forces of economic growth."

2. A large body of empirical research in this field has centered on the analysis of the first stage. This research has studied the roles of research and development practices, patenting, and firm size and market structure in generating innovations (Mansfield (1968), Griliches (1984), Levin and Cohen (1989), Acs and Audretsch (1988)). In particular, see Levin and Cohen (1989) for a review of the empirical literature on innovation and research and development. See Audretsch and Acs (1987) for a study on the relationship between size and patenting.

3. In addition to information about technological usage, the survey also asked about planned future use and the reason for non-use of the specific technologies. In this study, we employ only the information on use or non-use of the technology.

4. For a complete description of the data and more detailed sets of tables, see Manufacturing Technology 1988 . The figures reported in Tables 2 and 3 come directly from this publication.

5. The weighting scheme used in this survey is described in detail Appendix C of Manufacturing Technology 1988. The figures in Tables 2 and 3 are weighted to reflect population totals.

6. The use of a probit functional form for the technology adoption equation is somewhat arbitrary. Each of the reported probits have been run using a logistic specification. The results of these logits are qualitatively similar to the reported probits in terms of the magnitude and significance of the results.

7. Included as defense contractors are plants indicating that they produce under direct contracts to Department of Defense or are subcontractors to the Department of Defense.

8. For roughly, 3000+ plants in the sample it may be possible to construct the age distribution of the capital stock by tracking the plants investment streams in the Longitudinal Research Database (LRD). However, for the many of the plants in the survey, information is only available every in the Censuses of Manufactures which is carried out every five years.

9. A second limitation of the present analysis is that plant characteristics are only observed at the end of the period. The pre-adoption decision characteristics of the plant are not observable for the entire sample. Pre-adoption characteristics are preferred to post-adoption because there exists the possibility that the adoption decision may partially determine post-adoption characteristics. For example, it might be argued that plants which adopt technologies will have higher growth rates and subsequently have larger average sizes. Preliminary examinations of the historical data (1972, 1977 and 1982 Census of Manufactures data) on the plants in the SMT survey indicate that growth in plant size as measured by employment is relatively uncorrelated with technology usage. Other measures of the plant growth such as growth in the book value of capital, however, are highly correlated with the technology usage. Note, that these explorations only look at plants which are survivors.

10. The numbers presented in Tables 4a-4f differ from those in Tables 2 and 3 in that they represented unweighted sample totals. The age-size and size-only values in the tables change little with the use of weights. However, the age-

only columns do vary across the weighted and unweighted measures. These totals are available from the author on request.

11. Note, the number of plants used varies slightly across the six technologies. The reason for this difference is that are several plants filed incomplete forms. If any on the data, on age, size, or technology adoption is missing then the plant is removed from these tables and the following analyses.

12. Likelihood ratio tests were performed on the restricted vs. unrestricted model with 6 restrictions imposed. The Chi-square statistic for the test is 12.59 at the ninety-five percent level. The test values for the null hypothesis (no age-size interactions) in the CAD/CAE, NC/CNC, Robotics, AS/Materials, LAN, and Computer probits are 25.2, 27.0, 16.2, 9.0, 4.4, and 6.8, respectively. Thus, in half the cases the age size interactions are rejected. Additionally, the possibility for multicollinearity between the age and size variables exists. Dropping size from the regression does not increase the significance of the age results nor change any of the parameters' signs. In fact, when size is removed from the analysis the estimates of the age parameters become less precise.

13. Likelihood Ratio Tests for the inclusion of industry dummies rejects the null hypothesis of no industry effects in all 6 probits. The Chi-square statistic for 39 restrictions at the 95 percent-level is 55.7. The test values for the null hypothesis (no age-industry effect) in the CAD/CAE, NC/CNC, Robotics, AS/Materials, LAN, and Computer probits are 725.0, 1145.6, 325.8, 274.0, 168.8 and 262.0, respectively.

14. The data for employment size come from the 1987 Census of Manufactures (CM). Because of an inexact match between the SMT and the CM, the overall sample size for the probits which generate Figure 1 is reduced by roughly 500 plants.

15. Because no information on the timing of the adoption decision is available in the data, technology effects cannot be directly included in the probits in Table 5. This would involve putting a potentially endogenous regressor on the right hand side. To avoid this obvious complication the analysis of technology complementarity is carried out through an examination of the residuals.

16. The mean value of the R&D-to-domestic net sales ratio is 3.8 percent for 1974. This compares to the published total of 3.1 percent. The main difference is due to the fact that the matched sample (SMT to R&D) is dominated by large firms. The large firm (> 25,000 employees) published ratio is 4.2 percent for 1974 which is more representative of the sample used in this analysis. See Research and Development in Industry: 1987 and previous years for description of data collection and historical data tables.

17. The base probability for the calculations is constructed from the average of the fitted values M(mean of $'X) excluding the R&D parameters.
18. This is due largely to the change in sample. Almost all plants in the remaining sample are multi-unit firms and many engage in defense related production. Thus, there is little variation in these variables in the current sample.

18. For an analysis of the relationship between technology intensity and wages see Dunne and Schmitz (1991).

Bibliography

Acs, Zoltan and David Audretsch, "Innovation in Large and Small Firms: An Empirical Analysis," American Economic Review, 78 (September 1988), 678-690.

Cohen, Wesley M. and Richard C. Levin, "Empirical Studies of Innovation and Market Structure," in Handbook of Industrial Organization, Richard Schmalansee and Robert D. Willig (eds.), (Amsterdam: North-Holland, 1989).

Cohen, Wesley M. and Daniel A Levinthal, "Innovation and Learning: The Two Faces of R&D," The Economic Journal 99 (September 1989) 569-596.

Dunne, Timothy, Mark J. Roberts and Larry Samuelson (1989) "The Growth and Failure of U.S. Manufacturing Plants" Quarterly Journal of Economics, No. 419 (November 1989), 671-698.

Dunne, Timothy and James Schmitz (1991) "Technology and Wages at U.S. Manufacturing Plants," mimeo (August 1991).

Evans, David, "Tests of Alternative Theories of Firm Growth," Journal of Political Economy 95, (August 1987), 657-674.

Greene, William H., Econometric Analysis (New York: Macmillan Publishing Company, 1990).

Griliches, Zvi, "Hybrid Corn: An Exploration in the Economics of Technological Change," Econometrica, XXV (October 1957), 501-522.

Griliches, Zvi, R&D, Patents, and Productivity, (Chicago: University of Chicago Press, 1984).

Hannan, Timothy and John M. McDowell, "The Determinants of Technology Adoption: The Case of the Banking Firm," Rand Journal of Economics, 15 (Autumn 1984), pp. 328-335.

Jensen, Richard, "Adoption and Diffusion of an Innovation of Uncertain Profitability," Journal of Economic Theory, 27 (1982), 182-193.

Jensen, Richard, "Information Cost and Innovation Adoption Policies," Management Science, 34 (February 1988) p. 230-239.

Jovanovic, Boyan, "Selection and Evolution of Industry," Econometrica, 50 (May 1982), pp. 649-670.

Kelley, MaryEllen R. and Harvey Brooks, "External Learning Opportunities and the Diffusion of Process Innovations to Small Firms," Technological Forecasting and Social Change, 39 (March/April 1991), 103-125.

Landau, Ralph, "Technology, Economics and Public Policy," in Technology and Economic Policy, Ralph Landau and Dale Jorgenson (eds.), (Cambridge MA: Ballinger, 1986).

Levin, Sharon, Stanford L. Levin, and John B. Meisel, "A Dynamic Analysis of the Adoption of a New technology: The Case of Optical Scanners," The Review of Economics and Statistics, 69 (February 1987), 12-17.

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

Mansfield, Edwin, Industrial Research and Technological Innovation (New York: Norton, 1968).

McCardle, K., "Information Acquisition and the Adoption of New Technology," Management Science, 31 (1985), 1372-1389.

Pakes, Ariel and R. Ericson, "Empirical Implications of Alternative Models of Firm Dynamics," SSRI Working Paper #8803, University of Wisconsin - Madison, 1988.

Romeo, Anthony A., "Interindustry and Interfirm Differences in the Rate of Diffusion of an Innovation," The Review of Economics and Statistics, 57 (August 1975), 311-319.

U.S. Department of Commerce, Bureau of the Census, Current Industrial Reports, Manufacturing Technology 1988.

Table 1: Description of Technologies

Technology	Description
Computer Aided Design(CAD)	Use of computers for drawing and designing parts or products for analysis and testing of designed parts and products.
CAD controlled machines	Use of CAD output for controlling machines used to manufacture the part or product.
Digital CAD	Use of digital representation of CAD output for controlling machines used to manufacture the part or product.
Flexible Manufacturing Systems/Cell	Two or more machines with automated material handling capabilities controlled by computers or programmable controllers, capable of single path acceptance of raw materials and delivery of finished prod.
Numerically Controlled Machines /Computer Controlled Machines	NC machines are controlled by numerical commands punched on paper or plastic mylar tape while CNC Machines are controlled through an internal computer.
Materials Working Lasers	Laser technology used for welding, cutting, treating, scribing, and marking.
Pick/Place Robots	A simple robot with 1-3 degrees of freedom, which transfer items from place to place.
Other Robots	A reprogrammable, multifunctioned manipulator designed to move materials, parts, tools or specialized devices through variable programmed motions.
Automatic Storage/ Retrieval Systems	Computer controlled equipment providing for the automatic handling and storage of materials, parts, and finished products.
Automatic Guided Vehicle Systems	Vehicles equipped with automatic guidance devices programmed to follow a path that interfaces with work stations for automated or manual loading of materials, parts, tools, or products.
Technical Data Network	Use of local area network (LAN) technology to exchange technical data within design and engineering departments.

(Continued)

Table 1. Description of Individual Technologies (Continued).

Technology	Description
Factory Network	Use of LAN technology to exchange information between different points on the factory floor
Intercompany Computer Network	Intercompany computer network linking plant to subcontractors, suppliers, and/or customers.
Programmable Controllers	A solid state industrial control device that has programmable memory for storage of instructions, which performs functions equivalent to a relay panel or wired solid state logic control system.
Computers Used on Factory Floor	Exclude computers used solely for data acquisitions or monitoring. Include computers that may be dedicated to control, but which are capable of being reprogrammed for other functions.
Automated Sensors Used on Inputs	Automated equipment used to perform tests and inspections on incoming or in process materials.
Automated Sensors Used on Final Product	Automated equipment used to perform tests and inspections on final products.

Source: Manufacturing Technology 1988.

Table 2. Percent of Establishments Using Technology by Two-Digit Industry.

Technology	34	35	36	37	38
Design & Engineering					
Computer Aided Design	26.8	43.2	48.5	39.9	48.9
CAD controlled machines	13.1	21.6	16.0	16.6	14.6
Digital CAD	6.5	11.0	12.8	10.0	12.5
Flexible Machining & Assembly					
Flexible Manufact. Systems	9.0	11.0	11.9	12.6	10.8
NC/CNC Machines	32.2	56.7	34.9	37.3	33.6
Lasers	2.9	3.6	7.5	6.0	4.3
Pick/Place Robots	5.7	5.8	13.1	10.4	8.6
Other Robots	4.4	5.2	6.9	10.5	4.4
Automated Material Handling					
Automatic Storage/ Retrieval Systems	1.0	3.6	4.9	4.7	4.2
Guided Vehicle Systems	0.8	1.7	1.8	3.3	1.3
Automated Sensor Based Inspection					
Materials Sensors	6.7	8.5	16.2	12.7	12.2
Output Sensors	8.3	9.9	22.2	14.4	15.4
Communication & Control					
LAN for Tech Data	13.4	18.5	24.9	22.0	25.8
Factory LAN	11.6	16.3	21.1	18.7	21.3
Intercompany Computer Network	14.9	12.4	16.2	21.7	13.8
Programmable Controllers	26.8	33.9	38.0	32.0	32.7
Computers Used on Factory Floor	21.1	28.1	34.5	27.4	32.3
Number of Establishments (Weighted)	12746	13176	7293	3425	2916

Source: Manufacturing Technology, 1988.

Table 3. Technology Usage by Establishment Characteristics.

Establishment Characteristics	0 Used	At Least 1	5 or More
Major Industry Group			
34, Fabricated Metal Products	32.6	58.6	17.0
35, Industrial Machinery	18.1	75.6	23.1
36, Electronic Equipment	17.1	73.4	30.1
37, Transport Equipment	28.2	62.7	28.7
38, Instruments	21.3	72.3	25.8
Employment Size Class			
20 to 99	30.5	60.9	13.2
100 to 499	10.1	83.2	27.4
500 and over	1.5	93.7	79.4
Age of Plant (Years)			
Less than 5	25.6	74.0	22.4
5 to 15	24.7	75.2	25.2
16-30	25.7	73.9	24.3
Over 30	25.2	74.4	28.1

Source: Manufacturing Technology 1988.

Table 4a. CAD/CAE Adoption Rates: Plant Age by Employment Size Class.

	20-100 TE	100-499 TE	>= 500 TE	Sample Mean
5 or less years	.413 726	.596 292	.892 65	.491 1083
5-15 years	.368 1622	.575 1069	.814 307	.487 2998
16-30 years.	.311 1136	.557 1191	.858 508	.513 2835
Over 30 years	.264 813	.574 1025	.878 757	.565 2595
Sample	.341 4297	.571 3577	.861 1637	.517 9511

Table 4b. NC/CNC Adoption Rates: Plant Age by Employment Size Class.

	20-100 TE	100-499 TE	>= 500 TE	Sample Mean
5 or less years	.307 724	.419 291	.594 64	.354 1079
5-15 years	.329 1610	.476 1067	.617 308	.411 2985
16-30 years.	.380 1133	.544 1187	.737 505	.513 2825
Over 30 years	.329 820	.606 1027	.813 756	.579 2603
Sample	.339 4287	.531 3572	.744 1633	.481 9492

Table 4c. Robotics Adoption Rates: Plant Age by Employment Size Class.

	20-100 TE	100-499 TE	>= 500 TE	Sample Mean
5 or less years	.035 724	.100 291	.344 64	.070 1079
5-15 years	.037 1614	.148 1063	.394 307	.113 2984
16-30 years.	.025 1130	.139 1188	.470 506	.153 2824
Over 30 years	.030 813	.165 1024	.448 756	.205 2593
Sample	.032 4281	.146 3566	.441 1633	.145 9480

Table 4d. AS/Materials Adoption Rates: Plant Age by Employment Size Class.

	20-100 TE	100-499 TE	>= 500 TE	Sample Mean
5 or less years	.084 723	.183 290	.371 62	.127 1075
5-15 years	.069 1611	.193 1062	.446 307	.152 2980
16-30 years.	.058 1135	.137 1186	.423 505	.158 2826
Over 30 years	.047 817	.140 1022	.401 754	.188 2593
Sample	.064 4286	.158 3560	.420 1628	.161 9474

Table 4e. LAN Adoption Rates: Plant Age by Employment Size Class.

	20-100 TE	100-499 TE	>= 500 TE	Sample Mean
5 or less years	.167 723	.278 288	.593 64	.222 1076
5-15 years	.140 1610	.262 1061	.536 308	.224 2979
16-30 years.	.112 1127	.244 1187	.507 507	.239 2821
Over 30 years	.105 818	.231 1018	.517 752	.275 2588
Sample	.130 4279	.249 3554	.521 1631	.242 9464

Table 4f. Computer Adoption Rates: Plant Age by Employment Size Class.

	20-100 TE	100-499 TE	>= 500 TE	Sample Mean
5 or less years	.253 723	.433 293	.703 64	.329 1080
5-15 years	.216 1613	.473 1066	.726 307	.360 2988
16-30 years.	.194 1133	.410 1189	.707 509	.377 2831
Over 30 years	.178 818	.434 1024	.689 756	.427 2593
Sample	.209 4287	.438 3574	.702 1636	.380 9497

Table 5. Technology Adoption Probits.[1]

Variable	CAD/CAE	NC/CNC	Robotics
Intercept	-1.440 (.129)	-1.521 (.128)	-2.241 (.173)
39 3-digit Industry Dummies	Yes	Yes	Yes
Multi-Unit	.196 (.033)	.116 (.034)	.357 (.051)
Defense Contractor	.192 (.047)	.391 (.046)	-.195 (.061)
20-99 TE & 5-15 years	-.079 (.056)	.050 (.062)	.028 (.101)
20-99 TE & 16-30 years	-.228 (.063)	.102 (.066)	-.122 (.124)
20-99 TE & > 30 years	-.289 (.070)	.028 (.071)	-.024 (.131)
100-499 TE & < 5 years	.422 (.091)	.328 (.093)	.397 (.140)
100-499 TE & 5-15 years	.392 (.065)	.459 (.067)	.668 (.107)
100-499 TE & 16-30 years	.353 (.065)	.602 (.067)	.628 (.106)
100-499 TE & > 30 years	.439 (.066)	.709 (.070)	.749 (.107)
>= 500 TE & < 5 years	1.312 (.227)	.771 (.173)	1.165 (.193)
>= 500 TE & 5-15 years	1.006 (.103)	.870 (.094)	1.307 (.122)
>= 500 TE & 16-30 years	1.195 (.090)	1.142 (.085)	1.570 (.1123
>=500 TE & > 30 years	1.347 (.082)	1.330 (.081)	1.553 (.109)
Log Likelihood	-5428.3	-5425.7	-2998.4
Usage Rate	.517	.481	.145
N	9511	9492	9480
LRI	.176	.175	.236

[1]Standard Errors in Parentheses.

Table 5. Technology Adoption Probits (continued).[1]

Variable	AS/Materials	LAN	Computers
Intercept	-1.102 (.123)	-1.071 (.124)	-.913 (.115)
39 3-digit Industry Dummies	Yes	Yes	Yes
Multi-Unit	.185 (.045)	.164 (.038)	.264 (.034)
Defense Contractor	.158 (.051)	.042 (.047)	.159 (.045)
20-99 TE & 5-15 years	-.086 (.085)	-.085 (.069)	-.107 (.063)
20-99 TE & 16-30 years	-.162 (.093)	-.195 (.076)	-.192 (.068)
20-99 TE & > 30 years	-.209 (.105)	-.193 (.083)	-.215 (.074)
100-499 TE & < 5 years	.392 (.113)	.301 (.098)	.411 (.091)
100-499 TE & 5-15 years	.473 (.085)	.286 (.073)	.517 (.067)
100-499 TE & 16-30 years	.254 (.087)	.263 (.072)	.356 (.066)
100-499 TE & > 30 years	.283 (.090)	.232 (.075)	.417 (.068)
>= 500 TE & < 5 years	.860 (.181)	1.032 (.172)	.994 (.178)
>= 500 TE & 5-15 years	1.086 (.105)	.902 (.096)	1.080 (.096)
>= 500 TE & 16-30 years	1.067 (.094)	.875 (.084)	1.050 (.082)
>=500 TE & > 30 years	1.077 (.090)	.954 (.079)	1.018 (.075)
Log Likelihood	-3504.1	-4667.8	-5461.5
Usage Rate	.161	.242	.380
N	9474	9464	9497
LRI	.161	.109	.134

[1]Standard Errors in Parentheses.

Table 6. Cross Technology Correlations: Controlling for Industry and Plant Characteristics.*

Technology	1	2	3	4	5	6
Computer Aided Design	-	.224	.084	.096	.145	.173
CAD controlled machines	.302	.303	.068	.122	.173	.184
Digital CAD	.243	.120	.097	.136	.153	.138
Flexible Manufact. Systems	.112	.170	.211	.162	.153	.174
NC/CNC Machines	.224	-	.081	.093	.099	.186
Lasers	.077	.091	.181	.122	.107	.105
Pick/Place Robots	.084	.081	-	.168	.107	.140
Other Robots	.068	.099	.323	.149	.140	.143
Automatic Storage/ Retrieval Systems	.073	.064	.127	.133	.118	.107
Guided Vehicle Systems	.036	.051	.127	.094	.091	.075
Materials Sensors	.096	.093	.167	-	.159	.164
Output Sensors	.105	.074	.179	.596	.178	.157
LAN for Tech Data	.199	.109	.085	.141	.608	.219
Factory LAN	.145	.099	.107	.159	-	.303
Intercompany Computer Network	.081	.051	.114	.153	.227	.198
Programmable Controllers	.180	.222	.204	.174	.222	.346
Computers Used on Factory Floor	.172	.186	.141	.164	.303	-

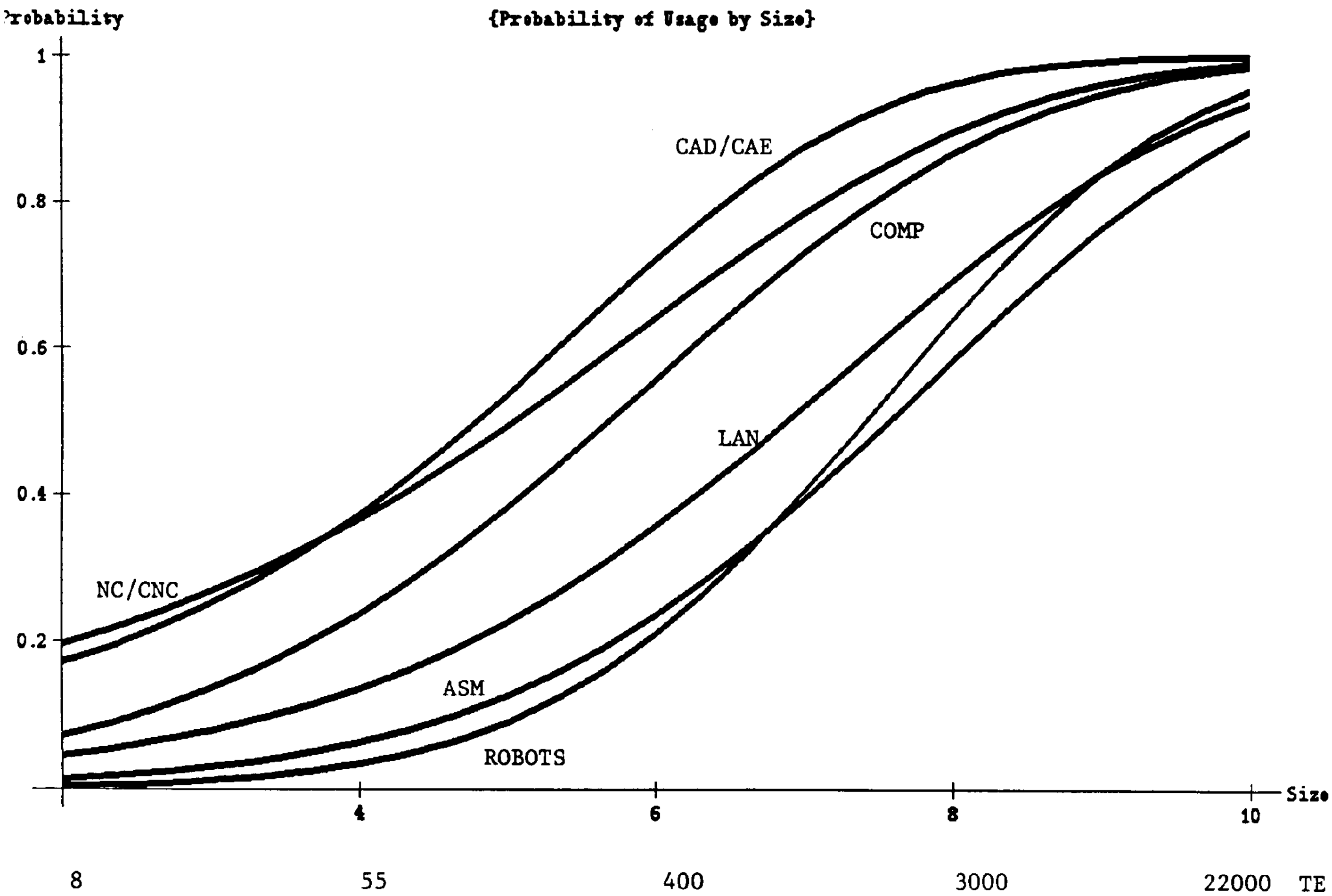
*All correlation coefficients significant at one percent level.

Table 7. R&D and Technology Usage.[1]

	CAD/CAE	NC/CNC	Robots	AS/Mat.	LAN	Comp.
Intercept	-1.482 (.275)	-1.439 (.261)	-2.801 (.356)	-1.482 (.319)	-1.232 (.272)	-.987 (.249)
3-digit Ind	Y	Y	Y	Y	Y	Y
RD/Sales	3.528 (.772)	.841 (.583)	1.170 (.606)	1.672 (.571)	2.797 (.551)	2.250 (.564)
Multi-Unit	.060 (.181)	.027 (.183)	.334 (.245)	.374 (.252)	.298 (.200)	.235 (.178)
Defense	.246 (.108)	.329 (.095)	-.245 (.099)	-.011 (.091)	-.050 (.089)	-.057 (.087)
100-499 TE	.612 (.082)	.553 (.083)	.778 (.125)	.423 (.107)	.303 (.088)	.479 (.081)
>= 500 TE	1.330 (.096)	1.031 (.091)	1.449 (.128)	1.162 (.110)	.845 (.093)	.905 (.088)
5-16 years	-.175 (.134)	.076 (.123)	.386 (.158)	-.098 (.137)	.049 (.125)	.194 (.122)
16-30 years	-.165 (.132)	.198 (.121)	.414 (.156)	-.129 (.134)	-.045 (.124)	.111 (.120)
> 30 years	-.002 (.135)	.320 (.124)	.490 (.157)	-.162 (.136)	-.024 (.126)	.168 (.123)
Log Likelihood	-1181.2	-1329.2	-1186.8	-1217.3	-1448.3	-1528.7
Usage Rate	.702	.625	.271	.265	.373	.564
N	2429	2422	2420	2417	2419	2427

[1]Standard Errors in Parentheses.

Figure 1



Size=Log(Total Employment)
TE= Total Employment Scale