THE EFFECT OF TECHNOLOGY USE ON PRODUCTIVITY GROWTH

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ABSTRACT

This paper examines the relationship between the use of advanced technologies and productivity and productivity growth rates. We use data from the 1993 and 1988 Survey of Manufacturing Technology (SMT) to examine the use of advanced (computer based) technologies at two different points in time. We are also able to combine the survey data with the Longitudinal Research Database (LRD) to examine the relationships between plant performance, plant characteristics, and the use of advanced technologies. In addition, a subset of these plants were surveyed in both years, enabling us to directly associate changes in technology use with changes in plant productivity performance.

The main findings of the study are as follows. First, diffusion is not the same across the surveyed technologies. Second, the adoption process is not smooth: plants added and dropped technologies over the six-year interval 1988-93. In fact, the average plant showed a gross change of roughly four technologies in achieving an average net increase of less than one new technology. In this regard, technology appears to be an experience good: plants experiment with particular technologies before deciding to add additional units or drop the technology entirely.

We find that establishments that use advanced technologies exhibit higher productivity. This relationship is observed in both 1988 and 1993 even after accounting for other important factors associated with productivity: size, age, capital intensity, labor skill mix, and other controls for plant characteristics such as industry and region. In addition, the relationship between productivity and advanced technology use is observed both in the extent of technologies used and the intensity of their use. Finally, while there is some evidence that the use of advanced technologies is positively related to improved productivity performance, the data suggest that the dominant explanation for the observed cross-section relationship is that good performers are more likely to use advanced technologies than poorly performing operations.

Keywords: Productivity, Advanced Technology

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I. INTRODUCTION

In recent years there have been a number of studies examining the relationship between the use of advanced technologies and plant performance in U.S. manufacturing industries. A persistent finding is that the use of advanced technology is positively related to plant performance measured along a number of dimensions: sales growth, profit margin, market share, productivity, employment growth, survival rate, and wages (Alexander, 1994).

While these studies have provided important new insights and demonstrated that plants that use advanced technologies outperform those that do not, researchers have been unable to distinguish the source of the observed performance differences. Do the positive correlations reflect the independent effects of technology on performance, or do they reflect the contributions of good managers who tend to adopt the best practices? In addition to being of academic interest, this distinction is important because it affects the mix of policies that might be pursued. For example, if the dominant source of enhanced performance is good management and a skilled workforce, policies to improve education and training might be relatively more important than those that seek to subsidize applied R&D.

In this study we exploit the 1988 and 1993 Survey of Manufacturing Technology (SMT) and the Longitudinal Research Database (LRD) to study several key questions relating to technology use and plant performance over time. First, we compare the 1988 and 1993 plant level labor productivity performance, measured by value added per employee. We find that, by and large, the 1993 survey data provide results on the relationship between productivity and advanced technology use that are similar to those found for the 1988 survey (Doms, et. al, 1994; Beede and Young, 1996). Technology use is positively associated with productivity.

The second issue we examine is the extent to which advanced technology use became more widespread over the 1988-93 period. If the benefits of technology use are as substantial as suggested by the earlier studies, then one would expect that their use would increase over time. On the other hand, if the technologies are associated with scale, or are applicable only in certain situations, then they may not be widely adopted. The positive relationship between size and technology use shown in earlier work and observed in the 1993 survey data raises the possibility of scale economies in the surveyed technologies (Dunne and Schmitz, 1993). We find modest increases in technology use overall. Some technologies, most notably those involved in computer-aided design and engineering, showed substantial increases, while others showed no increase in use, and some even experienced a decline in use. Thus, diffusion patterns were not the same across the surveyed technologies.

Lastly, we examine the role that technology use plays in shifts of resources from lower to higher productivity plants, using the subset of plants covered in both SMT surveys. While the results are suggestive, the small and somewhat nonrepresentative sample available for analysis mandates caution in drawing conclusions. Our tentative conclusion is that although there is evidence that the use of technology leads to improved productivity performance, it is the use of technology by good performers that is the dominant feature of the data.

This paper is organized as follows. In the second section we describe the data from the SMT surveys and the LRD, and discuss measures of the key variables. The third section describes the patterns of technology use found in 1993 and compares them to those in 1988 for the population surveyed in each year. Section IV provides analysis of the relationship between technology use and productivity, beginning with cross-section estimates that control for various plant characteristics. We then turn to the analysis of changes in labor productivity over the period in Section V. This section also presents corroborative evidence based on estimates of the probability of plants increasing their technology use over the period. The final section offers some conclusions and suggestions for future work.

II. DATA, MEASURES, AND EMPIRICAL MODEL

A. The Survey of Manufacturing Technology

The 1988 and 1993 Surveys of Manufacturing Technology are stratified samples of plants with more than 20 employees in the five SIC major industry groups 34-38: fabricated metal products, industrial machinery and equipment, electronic and other electric equipment, and instruments and related products. In the 1988 SMT 10,526 plants were surveyed, while in the 1993 survey, 8,336 plants were canvased. In both years simple random sampling of plants was undertaken within strata defined by the three-digit SIC classification of the plant and its size. Three size classes, based on total employment, were used in the sampling process: 20-99, 100-499, and 500 or more workers. Weights were assigned to each sampled plant inversely proportional to the fraction of plants sampled in its size-industry stratum. Using these weights population level estimates of establishment counts and prevalence can be developed for each of the advanced technologies surveyed.[1]

Both SMTs surveyed 17 advanced technologies identified as important by various scientific, trade, and government offices and associations. Table 1 gives a brief description of the technologies; further details are available in the SMT report (1994). The 17 surveyed technologies are generally associated with the use of computers and information technology to design, develop, and control manufacturing production. They can be grouped into 5 classes: design and engineering, fabrication/machinery and assembly, automated material handling, automated sensor-based inspection and/or testing, and communication and control.

The two surveys provide measures of the use of each of 17 surveyed technologies at two points in time. They also provide for the

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[1] Prevalence rate is defined as the percentage of the population that has adopted a particular technology.

possibility of direct measurement of technological change for a subset of plants for which survey data are available in both years.

We use the number of technologies adopted, and groupings of these basic counts, as measures of how extensively a plant uses advanced technologies. This is not a wholly satisfactory procedure for two reasons. First, it does not provide a measure of how intensively a plant uses a particular technology. It is possible for a respondent to report that they use a technology even though the technology affects a very small proportion of the plant's output. This short coming is partially addressed in the 1993 survey, which supplements the technology use information with technology-specific counts of workstations or pieces of equipment that are in place and a measure of when the technology was first introduced. Although we are unable to fully examine them here, we do provide limited information on alternative measures of intensity of use for a subset of technologies.

A second limitation is that simple counts do not take account differences in combinations of technologies among plants. Beede and Young (1996) have shown that plants differ in the combinations of technologies they employ and some of these combinations are significantly associated with plant performance. Related evidence on the importance of combinations is given in a recent paper by Johnson, et. al (1995).[2]

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[2] They argue that some technology groups are complementary to labor (labor-enhancing), while others are substitutes for labor (labor-

While count measures are less than ideal, there are several reasons why most of our analysis focuses on counts. First, this allows us to compare results from the 1993 SMT directly to earlier work for which count data are the only data available. Moreover, experiments with a number of different measures of technology use find that simple technology counts provide useful measures of how advanced a plant's technology is (Dunne, 1994, Dunne and Schmitz, 1994, and Doms, et. al, 1995). In this regard, even though some of the combinations among technologies show statistically significant relationships with performance, technology combinations explain minor portions (less than 2 percent) of the observed variations in plant performance in the 1988 SMT (Beede and Young, 1996).

The SMT surveys also provide several plant variables which are used in the analysis. In particular they provide qualitative information on the type of manufacturing process at each plant (fabrication, machining, and/or assembly). We view the measures based on this information as a proxy for how integrated is the plant's production. The SMT data also include the selling price of the product(s) produced at each plant. Doms, et. al (1995), using the 1988

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saving). In terms of the categories of technologies in the SMT, fabrication/machinery and assembly and automated material handling are labor-saving technologies and design and engineering, automated sensor-based inspection and/or testing, and communication and control are labor-enhancing technologies. An implication of their discussion of the two categories is that the labor enhancing technologies will tend to have greater impacts on productivity growth.

SMT, show that these price classes are positively correlated with skilled labor in the plant. However, we find a weaker statistical relationship between these price variables and productivity in the 1993 data.

B. The Longitudinal Research Database

The data for plant characteristics and performance come from the LRD, which provides longitudinal information on inputs and outputs of manufacturing plants derived from the quinquennial Census of Manufacturers and the Annual Survey of Manufacturers (McGuckin and Pascoe, 1988). The estimates of productivity, capital stock, and labor skill mix for surveyed plants were developed from the LRD's information for 1987 and 1992. We use the census years 1987 and 1992, rather than 1988 and 1993, since data from only a subset of SMT manufacturing plants are available in the LRD for non-census years. Use of the census data maximizes our sample of observations.

Labor productivity is defined as value added per employee; similarly, capital intensity is measured by book value of total capital per employee. Labor skill mix is measured by the ratio of skilled workers to total employment, where skilled workers are proxied by non-production workers. Plant size also is measured by total employment. Geographic location is in terms of the nine Census regions. Table 2 lists all variable names and definitions used in the empirical models. Mean values are also reported for the 1988 and 1993 data, as well as the 1988/93 panel. Value added and capital data are deflated with 4-digit

SIC output and investment indices from the National Bureau of Economic Research, Inc. (Bartlesmann and Gray, 1994).

C. Sample

The samples used in particular analyses always consist of the maximum observations for which all data are available after excluding imputes, missing and extreme values. The samples available were 6,917 plants from the 1988 SMT and 6,122 from the 1993 SMT. These samples are representative and accounted roughly for 17.6 percent (1988) and 14.0 percent (1993) of total establishments in the manufacturing universe and 50.1 percent (1988) and 41.3 percent (1993) of total employment.

There were 1,708 plants with complete data in the LRD and both SMT surveys. While we discuss differences between this panel subsample and the full samples in more detail below, we note here that the longitudinal sample is biased toward medium and large plants with higher advanced technology use rates in both years. The proportions of plants in the panel subsample using the advanced technologies is higher in the over 6 class of technology users and lower in the less than 6 category. As shown in Table 3 -- which provides a comparison of the proportion of the sample in each technology class for the panel and full sample in both 1988 and 1993 -- the bias pattern is similar in both years, suggesting that the change measures may be reflective of the population. Moreover, as discussed below we are able to replicate the cross-section estimates found for the full samples in each year with the data from the panel subsample.

D. Empirical Model

The basic empirical model is a traditional fixed effects Cobb-Douglas production function.

$$\text{Log}(P_{it}) = \beta_o + \beta_1[\text{Log}(K_{it}/L_{it})] + \beta_2 TECH_{it} + \beta_3 X_{it} + \beta_4 \mu_{\iota\tau} + \varepsilon_{\iota\tau}, \quad \text{for } i = 1,...,N, \quad t = 1,...T. \tag{1}$$

The subscript 'i' refers to the plant; 't' denotes the time period, and the $s are coefficients to be estimated. In the discussion below, we drop the 't' subscript for simplicity of presentation. P denotes productivity, measured as value added (thousands) per employee, and K/L is capital intensity, measured as the book value of capital (thousands) per employee. X is a vector of other control variables, including size, age, labor skill mix, product price, manufacturing type, industry, and region. The μ_is are unobserved, fixed plant effects, including management quality, and ε is an error term.

Our TECH variable measures advanced technology in use at the plant and is an index to account for the quality variation in capital. It is well known that when estimating the underlying characteristics of production, accounting correctly for variations in the quality of capital is critical. We expect a positive relationship between plant productivity and our technology variable.

In a similar fashion, the ratio of non-production workers to total employment proxies for a quality index for labor. Non-production workers are often thought to be more highly skilled than production workers.[3] Adoption and use of advanced technologies, particularly computer based equipment, requires skilled labor. Thus, we would expect to find better productivity performance at plants with more skilled labor

Two econometric problems are of concern in estimating this model. First, the plant effects (μ) are unobserved. Of greater concern to us is the estimates of $\$_2$. The TECH parameter estimates are biased upward due to the likely positive correlation between technology and the omitted plant effects (μ). In this case, the positive coefficient of $\$_2$ may be simply picking up the fact that 'good' plants are likely to have advanced technologies, not that technology use improves productivity. We cannot get consistent estimates of β_2 unless we find instruments that are correlated with the TECH variable, but uncorrelated with μ and ε.

In order to eliminate this problem, we estimate the production function model of equation (1), in first difference form:

$$\Delta \log(P_i) = \gamma_o + \gamma_1[\Delta \mathrm{Log}(K_i/L_i)] + \gamma_2(\Delta TECH_i) + \gamma_3(\Delta X_i) + \Delta\varepsilon_i, \quad (2)$$

$$\text{where } \gamma_j = (\beta_{j,93} - \beta_{j,88}) \qquad \text{for all j.}$$

In principle, equation (2) eliminates the time invariant,

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[3] Although there is significant within group heterogeneity between production and nonproduction workers, we follow Dunne and Troske (1996), Doms, et. al (1995), and Dunne, et. al (1996) in assuming the skill content of nonproduction workers is higher than that for production workers.

unobserved plant effect (μ) as well as the time invariant observed plant characteristics, such as size and age class, type of manufacturing, region, and industry.

Unfortunately, a common problem when differenced data are used to measure production relationships is that the effects of errors in measurement of other variables are magnified. This will reduce our ability to identify γ_2 because the signal remaining in the)TECH measure may be overwhelmed by the relatively large measurement errors in capital (Griliches, 1986; Griliches and Mairesse, 1995); resulting in biased and inconsistent parameter estimates.

Finally, we note that while our ultimate object is to examine the direction of causality between productivity growth and the use of advanced technology, this requires estimation of a full structural model. Full structural modeling is beyond the scope of this paper for a variety of reasons, including data constraints.

With these factors in mind, we estimate equation (1) for two cross-sections, 1988 and 1993, in section IV. This allows us to check the robustness and persistence of the relationship between the use of the advanced technologies and the level of productivity. Using our panel of plants covered in both the 1988 and 1993 SMT, equation (2) estimation results are reported in section V. Before turning to this analysis, we discuss the observed changes in technological use between 1988 and 1993.

III. DIFFUSION OF TECHNOLOGIES

In 1993, roughly 75 percent of all manufacturing plants classified in SICs 34-38 used at least one of the 17 advanced technologies. This was a modest increase from the 68.4 percent found in 1988. The number of plants using more than five advanced technologies also increased, from 23.1 percent in 1988 to 29.1 percent in 1993. Because use rates are much higher for large then small plants, use rates are much greater if calculated on a sized weighted basis.

Table 4 shows the percentage of establishments in 1993 using each of the 17 technologies by the five major SICs covered in the survey. The prevalence rates of individual technologies varied widely. Very few of the technologies showed use rates over 50 percent and many, particularly lasers, robots, and automated material sensors, had use rates less than 10 percent. The most prevalent technologies are computer aided design and numerically controlled machine systems. These technologies were identified by Johnson, et. al (1995) as labor enhancing and they reported that "labor-enhancing technologies enjoy the greatest adoption rate." Thus, our results are generally consistent with those for Canada.

In order to focus on differences in use rates between 1988 and 1993, Table 5 presents the use rates, by technology for 1988. Comparison of Tables 4 and 5 reveals significant increases in use rates for some technologies. What is striking about the data is that use actually declines for a few of the technologies and is stagnant for others. Computer design and engineering, consisting of three individual technologies, showed the greatest increases. Moreover, the increases were observed in each major industry group. The only other technology that showed large percentage increases in use rates was local area networks (LAN), most notably for transfers of technical data.

The data in these tables suggest that new entry is not a primary vehicle for introducing advanced technologies. Each major industry group showed positive increases in the number of establishments operating. Industry 38, with by far the most substantial increase in plants, showed little difference from other industries in the change in use rates. This is consistent with Dunne (1994), who found young and old plants used advanced technologies at similar frequencies, and also with Baily, et. al (1991), who found that increases in productivity are associated with shifts in market share to productive continuing plants, not entry or exit.

IV. PRODUCTIVITY AND TECHNOLOGY USE

Table 6 shows regressions of numbers of technologies and a variety of control variables on labor productivity for both 1988 and 1993.[4] Although there are some differences, the coefficients are remarkably similar in each year. Of most interest, the

[4] For ease of presentation, we report only the parameter estimates for the capital intensity, labor skill mix, and technology variables. The full set of parameter estimates is available from the authors.

coefficients on technology use remain strong, positive, and increasing in number of technologies in both years. These coefficients are significant even after accounting for a wide range of control measures including labor skill mix, capital intensity, plant size and age, product price, region, and 4-digit SIC industry effects.

The impact of various plant characteristics is as follows. Labor productivity increases with size, particularly for plants with more than 500 employees. Age has the opposite effect: younger plants are generally more productive, *ceteris paribus*. The type of manufacturing coefficients (e.g., fabrication and/or machining, assembly, all three, or none) are negative. Since the omitted category of this set of dummy variables is plants for which none of the other three categories are relevant, the interpretation of these variables is not clear. Nonetheless, since the coefficient for plants which engage in fabrication, machining, and assembly work is the smallest of the set, these findings suggest that more integrated operations are the least productive.

A. Intensity of Technology Use

These cross-section results provide strong evidence that plants that use advanced technologies more extensively have higher productivity performance. In order to investigate the effect of the depth or intensity of use, as contrasted with the width or breath of use, Table 7 presents three regressions in which measures of intensity of use in design and engineering, fabrication and machining, and communication and control are added. These three variables are based on questions new to the 1993 survey. The data on how many workstations or pieces of equipment in use at a plant provides information beyond simple counts of technologies used. We introduced this measure into the regression on a per-employee basis to reflect intensity of use.

The intensity measures were not applicable for all 17 technologies surveyed. However, they were available for the most prevalent technologies -- design and engineering, fabrication and machinery, and communications and control. We report three regressions involving these variables. The first, estimated for the entire sample, shows a significant positive coefficient for computer assisted design and communication and control technologies. These results suggest that intensity of use is perhaps an independent factor in explaining plant productivity. We also note that the extensiveness of use of advanced technologies remains a significant factor in the productivity equation even after intensity of use is introduced.

A small observed value for the intensity of use measure can arise either because the plant did not use the technology at all or used it sparingly. A plant that did not use one of the technologies for which we have an intensity measure could be highly productive because it used one of the non-measured categories of technology. If this situation was widespread, then it would tend to bias the coefficient on the intensity measure towards zero. By restricting the sample we can eliminate this possible downward bias. Therefore, we estimated the model using a restricted sample including only those plants that had no technology or used the design and engineering or communication and control technologies for which we had a intensity of use measure. As can be seen from columns two and three in Table 7, the coefficients on technology intensity are positive and significant, and about 19% higher in value, relative to the estimates from the full sample (column one), suggesting the bias from this source is moderate.

While these results show a significant and consistent positive relationship between productivity and advanced technology use, the source of the correlation cannot be deduced. All the positive characteristics, arguably including technology use -- size, labor skill mix, capital intensity, etc. -- are associated with good management and progressive firms. It is possible that these relationships are simply reflecting the fact that efficient producers are most likely to use new technologies.

V. PRODUCTIVITY GROWTH AND TECHNOLOGY USE

Our analysis of productivity growth is based on panel data from the 1988 and 1993 SMT. Table 8 displays mean labor productivity for a transition matrix based on technology use in 1988 and 1993. For example, the row\column combination 3-5\3-5 includes plants that used 3-5 advanced technologies in both years. For these plants, productivity increased from 60.4 in 1988 to 66.2 in 1993. In order to protect confidentiality, we omit certain off diagonal elements off diagonal elements for transitions up and down. None of the conclusions drawn are contradicted by the suppressed data.

For all technology cells, real labor productivity increased over the 1988-93 time period, with the exception of the 1-2/0 cell, where productivity declined from 62.8 to 58.7, and the 3-5/1-2 technology cell, which remained virtually static at $66 of value added per employee. Generally speaking, within a 1993 technology use class, productivity increases with more extensive technology use in 1988 (moving down a column).

Table 9 displays the mean labor productivity in both 1988 and 1993 for the entire sample of plants in the 1988 survey and the 1993 survey, respectively. This table is directly comparable to the row and column sample means in Table 8. A comparison of these means suggests that the results shown in Table 8 for the panel subsample are quite similar to those found for the cross-section samples. The levels and the change are similar, with two notable exceptions. Productivity is 18 points higher for plants in the 1993 sample with no advanced technology in place than for the panel subset: 48.7 and 66.5, respectively. Conversely, the 1993 performance of plants using 13-17 of the surveyed technologies is just under 100 for both the 1988 and 1993 sample, but somewhat lower for the panel subset, 78.2 (1988) and 90.1 (1993).

Although comparisons such as these are not conclusive, we believe they support use of the smaller nonrepresentative sample for the growth in productivity analysis. This is particularly true when these comparisons are viewed in the context of the distribution of the panel across the technologies that was presented earlier in Table 3. Recall that while the distribution of the subsample was not the same as the distribution of the representative sample in either year, the differences were similar in each year.

The results of this exercise do not provide any evidence that technology use per se leads, at least immediately, to increased productivity. Tables 8-9 clearly reflect the results of the cross-section regressions presented earlier: greater numbers of technologies are associated with higher productivity. However, in Table 8, the cells showing the greatest growth rate in productivity were not necessarily associated with more extensive use of technology. The rate of growth in productivity was highest for the 0/0 (21.1%), 6-12/3-5 (19.4%), and 1-2/3-5 (16.9%) cells. On average, productivity grew by 13.6% for plants moving down a technology use class, 11.4% for plants remaining in the same technology class, and 11.2% for plants moving up a technology class. Based on these data we tentatively conclude that the positive association of technology use and productivity is reflective of a correlation of our measure of technology with an omitted variable(s) such as the quality of management or capital.

A. Productivity Growth Regressions

Although Table 8 indicates that changes in the number of technologies in use by a plant effects productivity, there are reasons to examine the relationship further. First, the table does not provide controls for many of the factors which differ across plants, such as changes in the capital intensity and change in labor force skill mix.

Second, the table measures changes by shifts across technology classes. While these classes are meaningful in the cross-section regressions, they may be too crude and aggregate for use in analysis of productivity growth. Table 8 implicitly measures net change in number of technologies.[5] The average net change in technologies in use was 1.7 for plants with none of the 17 advanced technologies in 1988. For plants with 6 or more technologies the average net change between 1988 and 1993 was negative, indicating a drop in the number of technologies being used.

This aspect of the adoption process, adding and dropping technologies, needs to be considered. In fact, the gross change in the number of technologies in use ranged from 1.7 for the no technology class (1988) to 5.3 for plants using 13 or more technologies in 1988. Therefore, we further investigate the relationship between productivity growth and technology use by

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[5] Net change is measured as the change in the number of technologies reported in 1993 minus the number reported in the 1988 SMT. Gross change is defined as the absolute value of a change in the use of technologies. Therefore, adding a technology counts as one, as does dropping a technology. A gross change of four means that between 1988 and 1993 four technologies were added, or dropped, or a combination of adds and drops.

estimating the first differenced model given in equation (2). The model relates change in (the log of) productivity to changes in the capital intensity, skill mix, and extent of technology use.

To measure change in technology use, we developed measures of both net and gross change. Most plants not only added, but also dropped, one or more of the 17 surveyed technologies. While one third of the sample showed a decline in the extent of their technology use, the average net change was positive, from 4.0 technologies to 4.7. Nevertheless, there was considerable churning -- the average plant showed a gross change of about 4 technologies. The net change measure hides considerable shifting in the actual technological mix reported in the two years.

The high degree of churning, or turnover, in technologies used makes it likely that our technological class variables, as a measure of the extensiveness of technology use, are subject to measurement error. In the context of a dependent variable like change in log productivity, which has relatively small variation, finding any relationship is difficult. We don't, however, want to belabor the point. As we discuss below, this churning appears reflective of real forces. In particular, the high rate of turnover in gross technology use may, in addition to measurement error, be associated with experimentation and acceptance or rejection of particular technologies.

The results of applying the panel data to this model of productivity growth are given in Table 10. Columns 1-3 differ only in the measure of the change of the extent of technology use variable. The first column includes net change in the number of technologies used, while column two includes gross change. The results in the third column replace the change in the number of technologies with a set of class dummies for whether the plant moved up, down, or remained in the same technology class (0, 1-2, 3-5, 6-12, or 13-17) over the 1988-93 period.

It is apparent that this model, regardless of which measure we use for change in technology use, explains essentially none of the observed variation in productivity growth. We believe our lack of explanatory power is due to three factors. First, the errors in variable measurement, as discussed in Section II.

A second possibility is that better performers are moving to newer or better technologies not covered in the survey. Most of the surveyed technologies have been available since the early 1980s, some for considerably longer. However, we do not think the surveyed technologies are obsolete because the survey responses suggest that plants not using the technologies planned to adopt them. Nonetheless, if coverage of new technologies is incomplete, some plants may be switching to out-of-scope technologies and we may well be missing information on the “cutting edge” technologies which are making the difference in plant performance.

A third difficulty, we call a plant-specific “persistence effect”. We know that the variance in productivity across establishments at any given point in time is quite high. We also know that there is a persistence factor in individual plant's productivity: the plant's position within the productivity distribution tends to remain somewhat stable, but with a degradation or regression to the mean over time.[6] Our model, as specified in equation (2), assumed this persistence factor was constant. To adjust for the degradation of the persistence factor, we reestimate equation (2), modifying the "fixed" plant effects (μ) as follows:

$$\Delta\mu_i = \rho_i, \qquad \text{where } \rho_i = f(\text{initial state}_i). \qquad (3)$$

The persistence effect, represented by ρ_i, is a function of the plant's initial state. The function, *f*, is unknown, as is the exact specification of the initial state. We, therefore, use a linear function of the extensiveness of the plant's set of technologies in 1988 and the quality of the plant prior to technology changes as instruments for ρ. The later is proxied by a set of class dummy variables for the industry specific quintile of the 1988 labor productivity distribution the plant was in. In this way, we attempt to minimize transitory factors in the observed productivity measure that do not reflect the permanent or long-run quality of the plant.

When we include the initial conditions, the positive

[6] Bailey, et. al (1992) examine the dynamics of plant level productivity for 23 four-digit manufacturing industries. They found, among other things, that there is significant persistence across time in plant level productivity. Dwyer (1995) found that, for the textile industry, plant "fixed effects" erode over time, with a half life of 10 to 20 years.

relationship between capital intensity and productivity growth becomes statistically significant. However, the change in labor skill mix remains insignificant. The net change in the number of technologies has a positive and significant relationship to productivity growth.[7] This suggests that the observed correlation between productivity and the extent of technology use is not just a matter of good plants adopting new technologies.

In general, all the measures of initial conditions gave results consistent with the hypothesis that a significant fraction of a plant's productivity growth is associated with its status at the beginning of the period. The coefficients on the plant quality variables (initial productivity quintile) are negative, suggesting regression to the mean characterizes the productivity distribution. That is, plants with high observed productivity in a period are likely to show lower growth in productivity and vice versa. The plant's initial number of technologies are positively related to change in productivity, although insignificant for plants with less than 6 technologies. This suggests that experience may be a factor in determining the impact of technology on improved plant performance, which we examine further below.

B. Experience in Using Technology

As mentioned above, the regression results suggest that

[7] We also estimate the model with gross change, expecting it to capture adjustment costs in adding and dropping technologies. However, the estimated relationship is statistically insignificant, perhaps because of omitted, non-survey technology information.

experience may be a factor in determining the impact of technology on changes in plant performance. A comparison of the net and gross change in the number of technologies shows almost four changes in technologies used for every net increase. While we know that some of this is noise in the data, the rather substantial observed turnover suggests that advanced technologies may be something of an experience good. Plants adopt a technology and then through experience decide whether or not to continue to use it. The 1993 survey includes a set of questions designed to indicate how long a plant has used each technology. The answers are subject to recall bias and comparisons to responses in the 1988 survey indicate inconsistencies in some of the answers.[8] Thus we rely on our panel data for measurement of technology adoption after 1988. However, the experience measure that can be derived is of such potential interest that we include some discussion of it here.

Experience with an appropriate technology should, through learning by doing, lead to lower costs and increased productivity. However, our measure of experience, the portion of technologies used more than five years, is not significant in regressions of productivity levels or productivity growth. This may be due to the substantial noise in the survey data. Table 11 shows the average percentage of plant technologies used more than five years for the transition matrix of number of technologies in

[8] The data exhibits the phenomena known as "telescoping," or respondent error in recalling the date of adoption.

use in 1988 and 1993. The table excludes certain off-diagonal elements to ensure confidentiality. These omitted cells do not effect any conclusions drawn.

From Table 11, it is readily observed that the percentage of technologies used for more than five years is higher the greater the number of technologies that the plant uses. For plants with 13 or more technologies in 1993, 71 percent of the technologies had been in place for more than 5 years. In contrast, for those plants with 3-5 technologies in 1993, only 53 percent of the technologies were in use over 5 years. This relationship is evident not just in the sample means. Each column of the Table 11 shows that the experience of plants within the same 1993 use class is higher the greater number of technologies in use in 1988. In other words, those plants with the largest technology use had the greatest experience.

As expected, the trend in the relationship across the rows is in the opposite direction. That is, for any level of technology in 1988, the experience ratios decline with greater 1993 level of technology use. For example, for plants with 6-12 technologies in use in 1988, the percentages are 78 percent, 70 percent, and 64 percent, respectively. Similarly, for plants with 3-5 technologies in 1988, the percentage of the plants with more than 5 years experience in 1993 is 63 percent, 60 percent, and 46 percent, for plants moving down, remaining the same, and moving up in the technology use distribution, respectively. Looking at the diagonal of the table, it is also readily observed that for those plants that did not change their technology group, the greater the number of technologies in place, the higher the portion of plants with extensive experience using the technologies.

These observations are consistent with substantial experimentation and adjustments in the process of arriving at a technological configuration that is optimal for the plant.[9] Is there support for this view? To find out we estimated an ordered probit with three possible outcomes for a plant's change in technology use between 1988 and 1993. Table 12 shows the estimated probabilities of moving to a higher technology use class, dropping down to a lower technology use class, or remaining in the same class, conditional on the plant's initial (1988) technology use class. The values in the table are based on evaluation of the ordered probit at the sample mean values.

The probability of a plant decreasing the number of technologies it uses and dropping down a technology class is 92 percent, if the plant used 13 or more of the surveyed technologies in 1988. Since a plant can't increase its extent of technology use if it is already in the top use class, or decrease its technology use if its is in the lowest use class, these estimates are censored. Even so, there is only an 8 percent chance that a plant with 13-17 technologies in 1988 would still be in that class in 1993. Plants using 6-12 technologies in 1988

[9] Recall that it is possible that best performers are moving to newer technologies not covered in the survey.

had a 53 percent chance of dropping to a lower class by 1993. In contrast, plants with two or fewer technologies had nearly a 60 percent chance of increasing the number of technologies they use, such that they moving to a higher technology use class. These results are not unexpected.

To summarize, plants with more extensive advanced technology use have greater probabilities of dropping in technology class, while those using few advanced technologies are more likely to increase. What is surprising is that in only one category -- 3-5 technologies in use in 1988 -- was the probability of remaining in the same class greater than the probability of changing classes. The typical plant had a relatively high probability of changing its category of technology use. Thus, even though these classes of technology use are quite wide, they do not completely hide the extensive turnover suggested by the comparison of the net and gross change in the actual number of technologies used.

VI. CONCLUSIONS

Before drawing together the main results of this study, we emphasize the importance of technology surveys like the SMT for understanding the role of technology in the evolution of industries and, consequently, in the performance of plants. There are two aspects of the SMT that are worth highlighting. First, the new SMT survey is a direct follow-up to the 1988 survey of advanced technology use. The similarity in design between the two surveys provided a unique opportunity to examine the use and planned use of advanced (computer based) technologies at two different points in time. Data sets like this are rather scarce.

Second, the data complement the basic plant level data collected in the regular censuses and annual surveys, which provide measures of plant performance and other plant characteristics. Moreover, for a subset of the surveyed SMT plants, we have the information on both technology use and plant performance available in both years. This allows us to directly associate changes in technology use with changes in plant productivity performance, controlling for other plant characteristics. While the small and somewhat nonrepresentative sample available for this part of the analysis mandates caution in drawing conclusions, we believe that several important findings emerge.

The main findings of the study are as follows. First, the diffusion rates across the surveyed technologies differ substantially. Second, the adoption process is not smooth: plants add and drop technologies over the six year interval 1988-93. In fact, the average plant showed a gross change in technology use of roughly four in achieving an average net increase of 0.5 new technologies. In this regard, technology appears to be an experience good: plants experiment with particular technologies before deciding to add additional units or drop the technology. Future work needs to examine ways to identify how much of this churning is real and how much is noise.

At the least, these findings indicate that the pace of technological progress at the plant level involves more than simply adding technologies in a uniform way.

Our third finding is that establishments using advanced technologies exhibit high productivity. Fourth, this relationship is observed in both 1988 and 1993 even after accounting for other important factors associated with productivity: size, age, capital intensity, labor skill mix, and other controls for plant characteristics such as industry and region. Fifth, the relationship between productivity and advanced technology use is observed both in the extent of technologies used and the intensity of their use. Finally, while there is some evidence that the use of advanced technologies is positively related to improved productivity performance, the data suggest that the dominant explanation for the observed cross-section relationship is that good performers are more likely to use advanced technologies than poorly performing operations.

Table 1

Description of Technologies

Technology	Description
Computer aided design	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 product.
Numerically controlled machines/computer controlled machines	NC machines are controlled by numerical commands punched on paper or plastic mylar tape, where 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° of freedom, which transfers items from place to place.
Other robots	A reprogrammable, multi functioned 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 LAN technology to exchange technical data within design and engineering departments.
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 loor	Excludes computers used solely for data acquisitions or monitoring. Includes 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 in-coming 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

Definition of Variables and Summary Statistics

Variable	1988	1993	1988/93 Panel
<u>Discrete Variables</u>			
$Tech_0$: No Technologies	.180	.113	.102
$Tech_1$: 1 - 2 Technologies	.248	.208	.184
$Tech_2$: 3 - 5 Technologies	.276	.305	.253
$Tech_3$: 6 - 12 Technologies	.270	.345	.410
$Tech_4$: 13 - 17 Technologies	.026	.029	.051
NoChange: Same Technology Class in 1988 & 1993			.483
MoveUp: Higher Technology Class in 1993 Than 1988			.318
MoveDown: Lower Technology Class in 1993 Than 1988			.199
Assembly: Assembly	.187	.185	
Fab/Mach: Fabrication & Machining	.135	.121	
Fab/Mach/Assemb: Fabrication, Machining & Assembly	.625	.636	
None: None of the above	.054	.052	
$Size_1$: 21 - 99 Employees	.427	.427	
$Size_2$: 100 - 249 Employees	.269	.267	
$Size_3$: 250 - 499 Employees	.130	.134	
$Size_4$: 499 - 999 Employees	.103	.106	
$Size_5$: 1,000+ Employees	.072	.066	
Age_1: < 5 Years	.099	.090	
Age_2: 5-15 Years	.304	.308	
Age_3: 16-29 Years	.309	.299	
Age_4: 30 + Years	.287	.303	
$Price_1$: < $5	.143	.139	
$Price_2$: $5-$100	.264	.262	
$Price_3$: $101-$1,000	.217	.211	
$Price_4$: $1,001-2,000	.055	.052	
$Price_5$: $2,001-10,000	.122	.112	
$Price_6$: $10,000 +	.198	.212	
MU = Multi-Unit Firm	.618	.599	
$LPQuintile_1$: 1988 Labor Productivity in Lowest Quintile		.140	
$LPQuintile_2$ 1988 Labor Productivity in Second Quintile		.188	
$LPQuintile_3$: 1988 Labor Productivity in Third Quintile		.195	
$LPQuintile_4$: 1988 Labor Productivity in Fourth Quintile		.220	

Variable	1988	1993	1988/93 Panel
LPQuintile$_5$: 1988 Labor Productivity in Highest Quintile		.257	
Continuous Variables			
LnLP: Log(Value Added/Labor)	3.881	3.990	
ΔlnLP: LnLP$_{93}$ - LnLP$_{88}$			.100
LnKL: Log(Capital/Labor)	3.186	3.389	
ΔLnKL: LnKL$_{93}$ - LnKL$_{88}$			.301
LnSkill: Log(NonProduction Workers/Labor)	-1.313	-1.268	
ΔLnSkill: LnSkill$_{93}$ - LnSkill88			.033
NTech: Number of Technologies in Use	3.984	4.726	
ΔNet: Net Change in Number of Technologies, 1993-1988			.486
ΔGross: Gross Change in Number of Technologies, 1993-1988			4.162

[1] Deflated with NBER four-digit SIC price index, 1987=1.00.

Table 3

Sample Distribution by Number
of Technologies Used, 1988 & 1993

Number of Technologies	1988		1993	
	Panel	SMT	Panel	SMT
0	0.10	0.18	0.10	0.11
1 - 2	0.18	0.25	0.14	0.21
3 - 5	0.25	0.28	0.25	0.31
6 - 12	0.41	0.27	0.46	0.34
13 - 17	0.05	0.03	0.06	0.03
Total	100.00	100.00	100.00	100.00
N	1,732	6,917	1,732	6,122

Table 4

Percent of Establishments Using
Computer-Based Machines by Two-Digit Industry, 1993

Technology	Two-Digit Industry* 34	35	36	37	38	All
Design & Engineering						
Computer Aided Design	46.5	64.1	64.2	53.9	65.5	58.8
CAD Controlled Machines	19.3	34.8	21.5	25.5	18.5	25.6
Digital CAD	7.0	11.6	16.1	9.6	16.1	11.3
Fabrication/Machining Systems						
Flexible Manufacturing Systems	9.5	11.8	17.0	15.5	14.2	12.7
NC/CNC Machines	40.4	61.9	34.5	44.1	35.1	46.9
Lasers	3.4	4.3	7.8	5.4	6.3	5.0
Pick Place Robots	6.6	5.4	15.2	10.1	11.7	8.6
Other Robots	3.8	3.6	5.3	11.7	3.8	4.8
Automated Material Handling						
Automatic Storage/Retrieval	1.2	2.3	3.8	3.8	4.8	2.6
Guided Vehicle Systems	0.3	1.1	1.7	2.2	1.5	1.1
Automated Sensor Based Inspection						
Materials Sensors	8.1	8.1	11.8	15.6	11.7	9.9
Output Sensors	9.6	10.6	17.5	16.1	14.7	12.5
Communication & Control						
LAN for Technical Data	20.1	29.4	37.1	28.0	40.7	29.3
Factory LAN	14.5	21.0	30.5	23.9	30.0	22.1
Intercompany Computer Network	16.7	15.4	21.9	23.4	15.3	17.9
Programmable Controllers	30.2	29.0	30.7	30.7	29.8	30.4
Computers Used on Factory Floor	20.2	28.1	33.2	26.8	29.0	26.9
Number of Establishments	13,190	14,231	7,472	4,110	3,988	42,991

Source: "Manufacturing Technology: Prevalence and Plans for Use, 1993," Current Industrial Reports. Bureau of the Census, Economics and Statistics Administration, U.S. Department of Commerce.

* Industry 34 -- Fabricated Metal Products, Except Machinery & Transportation Equipment
Industry 35 -- Industrial & Commercial Machinery & Computer Equipment
Industry 36 -- Electronic & Other Electrical Equipment & Components, Except Computer
Industry 37 -- Transportation Equipment
Industry 38 -- Measuring, Analyzing, & Controlling Instruments

Table 5

Percent of Establishments Using
Computer-Based Machines by Two-Digit Industry, 1988

	Two-Digit Industry*					
Technology	34	35	36	37	38	All
<u>Design & Engineering</u>						
Computer Aided Design	26.8	43.2	48.5	39.9	48.9	39.0
CAD Controlled Machines	13.1	21.6	16.0	16.6	14.6	16.9
Digital CAD	6.5	11.0	12.8	10.0	12.5	9.9
<u>Fabrication/Machining Systems</u>						
Flexible Manufacturing Systems	9.0	11.0	11.9	12.6	10.8	10.7
NC/CNC Machines	32.2	56.7	34.9	37.3	33.6	41.4
Lasers	2.9	3.6	7.5	6.0	4.3	4.3
Pick Place Robots	5.7	5.8	13.1	10.4	8.6	7.7
Other Robots	4.4	5.2	6.9	10.5	4.4	5.7
<u>Automated Material Handling</u>						
Automatic Storage/Retrieval	1.0	3.6	4.9	4.7	4.2	3.2
Guided Vehicle Systems	0.8	1.7	1.8	3.3	1.3	1.5
<u>Automated Sensor Based Inspection</u>						
Materials Sensors	6.7	8.5	16.2	12.7	12.2	10.0
Output Sensors	8.3	9.9	22.2	14.4	15.4	12.5
<u>Communication & Control</u>						
LAN for Technical Data	13.4	18.5	24.9	22.0	25.8	18.9
Factory LAN	11.6	16.3	21.1	18.7	21.3	16.2
Intercompany Computer Network	14.9	12.4	16.2	21.7	13.8	14.8
Programmable Controllers	26.8	33.9	38.0	32.0	32.7	32.1
Computers Used on Factory Floor	21.1	28.1	34.5	27.4	32.3	27.3
Number of Establishments	12,746	13,176	7,293	3,425	2,916	39,556

Source: "Manufacturing Technology, 1988," Current Industrial Reports. Bureau of the Census, Economics and Statistics Administration, U.S. Department of Commerce.

* Industry 34 -- Fabricated Metal Products, Except Machinery & Transportation Equipment
Industry 35 -- Industrial & Commercial Machinery & Computer Equipment
Industry 36 -- Electronic & Other Electrical Equipment & Components, Except Computer
Industry 37 -- Transportation Equipment
Industry 38 -- Measuring, Analyzing, & Controlling Instruments

Table 6

Labor Productivity Regressions[1]

Variable	1988	1988	1993	1993
Intercept	3.777* (0.076)	3.749* (0.077)	4.039* (0.083)	4.010* (0.084)
LnKL	0.158* (0.008)	0.160* (0.008)	0.143* (0.008)	0.144* (0.008)
LnSkill	0.070* (0.012)	0.069* (0.012)	0.079* (0.012)	0.079* (0.012)
NTech	0.015* (0.002)		0.015* (0.003)	
$Tech_1$		0.058* (0.020)		0.047H (0.026)
$Tech_2$		0.094* (0.021)		0.090* (0.026)
$Tech_3$		0.127* (0.024)		0.118* (0.029)
$Tech_4$		0.215* (0.048)		0.231* (0.052)
N	6,843	6,843	6,062	6,062
R^2	.232	.232	.264	.263

Numbers in parentheses are standard errors. Definition of variables given in Table 1.
[1] All regressions include dummy variables for size, age, type of manufacturing, mean product price, single/multi-unit firm, region, and four-digit SIC industry.
* Significant at the 95% level.
H Significant at the 90% level.

Table 7

Labor Productivity Regressions, 1993[1]

Variable	1993		
Intercept	4.001* (0.084)	3.978* (0.103)	3.773* (0.102)
LnKL	0.144* (0.008)	0.142* (0.008)	0.163* (0.010)
LnSkill	0.078* (0.012)	0.073* (0.014)	0.061* (0.016)
$Tech_1$	0.039 (0.026)	0.051* (0.029)	0.047 (0.042)
$Tech_2$	0.077* (0.026)	0.095* (0.027)	0.084* (0.031)
$Tech_3$	0.098* (0.029)	0.108* (0.030)	0.112* (0.033)
$Tech_4$	0.200* (0.052)	0.210* (0.053)	0.204* (0.059)
Design & Engine. Int.	0.153H (0.080)	0.182* (0.081)	
Fabricating & Machining Int.	-0.002 (0.002)		
Comm. & Control Int.	0.119* (0.045)		0.142* (0.048)
N	6,062	5,163	3,757
R^2	.265	.267	.295

Numbers in parentheses are standard errors. Definition of variables given in Table 1.

[1] All regressions include dummy variables for size, age, type of manufacturing, mean product price, single/multi-unit firm, region, and four-digit SIC industry.

* Significant at the 95% level.

[H] Significant at the 90% level.

Table 8

Average Labor Productivity,
By Technology Use, 1988 & 1993 Panel

Technology Use, 1988	Technology Use, 1993											
	0		1-2		3-5		6-12		13-17		Sample Mean	
	1988	1993	1988	1993	1988	1993	1988	1993	1988	1993	1988	1993
0	43.6	52.8	42.2	49.8							44.3	52.0
1 - 2	62.8	58.7	50.2	54.9	53.3	62.3					53.2	58.0
3 - 5			66.5	65.9	60.4	66.2	64.3	69.5			62.8	68.4
6 - 12					57.1	68.2	72.2	80.0	75.6	87.9	70.2	78.9
13 - 17							77.3	84.7	82.9	92.1	80.8	87.6
Sample Mean	57.7	66.5	54.3	57.4	56.8	64.7	68.5	75.2	78.2	90.1	63.1	70.1

Table 9

Average Labor Productivity
By Technology Use, 1988 and 1993 Samples

	Technology Use											
	0		1-2		3-5		6-12		13-17		Sample Mean	
	1988	1993	1988	1993	1988	1993	1988	1993	1988	1993	1988	1993
1988 Sample	44.0	49.0	52.5	57.1	59.3	64.9	68.3	78.6	77.8	99.0	57.8	65.1
1993 Sample	46.2	48.7	54.5	56.2	56.5	61.7	66.4	72.0	81.2	98.4	59.2	63.9

Table 10

Change in Labor Productivity Regressions,

Variable	1988/93 Panel			
Intercept	0.091* (0.015)	0.082* (0.027)	0.080* (0.020)	0.712* (0.052)
ΔLnKL	0.025 (0.020)	0.025 (0.020)	0.026 (0.020)	0.030H (0.017)
ΔLnSkill	0.031 (0.029)	0.031 (0.029)	0.030 (0.029)	0.019 (0.026)
ΔNTech (Net)	0.002 (0.004)			0.007H (0.004)
ΔNTech (Gross)		0.002 (0.005)		
MoveUp			0.026 (0.030)	
MoveDown			0.020 (0.035)	
Initial Conditions:				
$Tech_{1,88}$				0.009 (0.047)
$Tech_{2,88}$				0.065 (0.045)
$Tech_{3,88}$				0.149* (0.043)
$Tech_{4,88}$				0.200* (0.068)
$LPQuintile_{2,88}$				-0.560* (0.049)
$LPQuintile_{3,88}$				-0.678* (0.047)
$LPQuintile_{4,88}$				-0.837* (0.047)
$LPQuintile_{5,88}$				-0.926* (0.045)
N	1,708	1,708	,708	1,708
R^2	.002	.002	.002	.219

Numbers in parentheses are standard errors. Definitions of variables are given in Table 1.
* Significant at the 95% level.
H Significant at the 90% level.

Table 11

Average Percentage of 1993 Technologies
In Use More Than Five Years,
By Technology Use, 1988 & 1993 Panel

Technology Use, 1988	Technology Use, 1993					Sample Mean
	0	1-2	3-5	6-12	13-17	
0	0.00	0.00				0.00
1 - 2	0.00	0.55	0.31			0.33
3 - 5		0.63	0.60	0.46		0.50
6 - 12			0.78	0.70	0.64	0.68
13 - 17				0.96	0.92	0.87
Sample Mean	0.00	0.46	0.52	0.60	0.71	0.51

Table 12

Probability of Changing Technologies Use Class,
Conditioned on 1988 Technology Use Class

Technology Use Class, 1988	Move Up a Technology Class	Move Down a Technology Class	Stay in Same Technology Class
0		0.00	0.19
	0.59	0.02	
3 - 5	0.30		0.59
6 - 12		0.53	0.44
	0.00	0.92	

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