# WAGES, EMPLOYER SIZE-WAGE PREMIA AND EMPLOYMENT STRUCTURE: THEIR RELATIONSHIP TO ADVANCED-TECHNOLOGY USAGE AT U.S. MANUFACTURING ESTABLISHMENTS

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## Abstract

We study wages, size-wage premia and the employment structure (measured as the fraction of production workers in an establishment) and their relationship to the extent of advanced-technology usage at U.S, manufacturing plants. We begin by sketching a model of technology adoption based on Lucas (1978) that provides a framework for interpreting the data analysis. We then study a new Census Bureau survey of technology use at manufacturing plants. Workers in establishments that are classified as the most technology intensive earn a premium of 16 percent as compared to those in plants that are the least premium earned by workers in all but the very largest plants. The inclusion of the technology classification variables in standard wage regressions reduced the size-wage premia by as much as 60 percent for some size categories.

Keywords: Manufacturing wages, Technology, Employer Size-Wage Premium

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## 1. Introduction

In trying to understand significant and puzzling wage movements, economists have often turned to explanations based on changes in technology. For example, Welch (1970) argues that skilled-biased technological change was the main force behind the increase in demand for educated workers that kept the return to education from falling in the face of a tremendous expansion in the share of educated workers over the period 1940-60. More recently, Davis and Haltiwanger (1991) have argued that skilled-biased technological change is the most likely suspect behind the significant increase in manufacturing wage inequality over the last thirty years. While these and other studies (e.g. Allen (1991), Mincer (1991), Berman, Bound, and Griliches (1992) and Bound and Johnson (1992)) typically find a significant role for technology in explaining wage patterns, most are forced to rely on rather indirect measures of technology.

In this paper we study a survey of technology usage at manufacturing plants which provides unusually direct information on technology employed at the plant. From this survey we construct measures of "how intensively a plant uses advanced-technology in its production process." With these measures we study the relationship between wages, employment structure (measured as the fraction of production workers at a plant) and plant technology intensity. We examine, for example, the premia paid to workers in plants classified as the most technology intensive. We also ask if differences in technology can "explain" any of the employer size-wage premia puzzle. Since the survey is a point in time survey we are limited to such cross-section analysis and cannot directly confront some of the issues introduced in the above papers. However, if technological change is, on balance, skilled-biased and if changes in technology are responsible for significant wage movements, as argued in the papers above, then we should expect that our direct measures of technology usage at plants should be related to wages, employment structure and size-wage premia at those plants. If our measures were not related to such variables, it would cast some doubt, we believe, on other studies that have used indirect measures of technology in order to explain wage movements over time.

The technology data employed in the paper are from the Survey of Manufacturing Technology (SMT), a Census Bureau survey of advanced-technology usage at U.S. manufacturing plants. The survey requested that the plant manager specify which, if any, of a list of seventeen advanced technologies were used at the plant. From this usage information we construct measures of plant technology intensity. The data on wages and employment come from the Census of Manufactures (CM).

With information from the SMT and CM we are able to examine standard cross-section production-worker wage regressions that include dummy variables for region, industry, plant size (measured by total employment), plant age and measures, defined below, of the technology intensity of the plant. We find that production workers in plants which are classifies as the most technology intensive earn a 16 percent premium as compared to workers in plants classified as the least technology intensive. This finding is consisten with the interpretation that these plants employ a higher fraction of skilled production workers than do the least technology intensive plants.

The premium for working in the most technology intensive plants is greater than the size premium earned by workers at all but the very largest plants. As compared to workers in the smallest plants (plants with employment less than 100), production workers in plants with employment 100-249, 250-499, 500-999, 1000-2499 and over 2500, earn no premium, a 3 percent premium, and 8 percent premium, a 17 percent premium, and a 28 percent premium, respectively.

The relationship between the measures of technology intensity and the size-wage premia is also explored. This was done as follows. We compared the size premiums in the regression above, which included dummy variables for the technology intensity of the plant, to the premiums in a regression with those technology controls deleted.

Including the technological controls significantly reduces the size premium falls from 2 percent to zero. For the establishments with employment 250-499, 500-999, 1000-2499 and over 2500, the size premium falls 59 percent, 41 percent, 30 percent and 24 percent respectively. The size premium falls the greatest amount for the smaller size categories. As will be seen below, there is much greater variability in technology usage at small and medium sized plants as compared to large plants. Hence, the potential for the technology controls to pick up differences across plants is greater for small and medium sized plants.

We also examined the relationship of the technology controls and non-production worker wages. The results for the non-production worker wages closely mirror those for the production workers and will be discussed below. Again the findings are consistent with the interpretation that the most technology intensive plants employ a higher fraction of skilled non-production workers than do the least technology intensive plants.

While skill levels can vary within the production and non-production worker groups, they also vary across the two groups, with non-production workers typically regarded as the more skilled group. Since the CM has information on the fraction of production workers in total employment, we can explore how this ratio is related to technology usage at plants. We find, among other things, that plants which are the most technology intensive employ a smaller fraction of production workers than plants that are classified as the least so. This is consistent with the findings of Berndt, Morrison and Rosenblum (1992).

In the next section we present a model of technology adoption based on Lucas (1978) that is consistent with the findings discussed above. There are two key ingredients in the model. First, technology is assumed, as in the papers discussed above, to be skilled-biased. Plants which intensively use advanced-technology therefore employ a high fraction of high-quality, skilled workers who earn higher than average wages. Second, as often assumed in the industrial organization literature, the cost of adopting technology is independent of size. Since the cost of adopting technology is independent of size, but the benefits are increasing in size, the largest plants, on average, are more likely to adopt advanced-technology.

There is evidence, beyond that in the papers cited above, that the interpretation offered in the model below is a reasonable one. First, there are case studies which suggest that technology is skilled-biased (Bailey (1989), (1990)).[1] Second, many of the advanced technologies on the SMT survey require computer skills. Krueger (1991) argues that there is a substantial wage premium for

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[1]Also related is the literature that discusses complimentarity between skilled labor and technological change (captial), for example, Bartel and Lichtenberg (1987) (Hammermesh (1980)).

having computer skills. In an analysis of Canadian manufacturing plants, Reilly (1992) finds that inclusion of a variable that indicates whether a plant has access to a computer or not significantly reduces the size-wage premium.

The remainder of the paper proceeds as follows. In the next section we sketh a very simple model of technology adoption. This model provides a framework for interpreting the data analysis that follows. The third section describes the data sets used in the paper. Here we also discuss how we construct the measure of technology intensity of the plant. Some summary statistics are also discussed. The cross-sectional wage regressions and analysis are presented in section 4.

## 2. A Model of Technology Adoption

In this section we sketch a very simple model of technology adoption that provides a framework for interpreting the data analysis below. The model joins an idea in Lucas (1978), that variations in size of business reflects heterogeneity is managing skills or "span of control," with a very old idean from the technology literature, namely that while the cost of adopting technology is often independent of the scale of production, the benefits are typically positively related to scale (see, e.g., Arrow (1962)). We will first present a brief summary of the Lucas model and then discuss our simple extension.

We begin by briefly reviewing Lucas (1978). In the model individuals either become managers or employees (and work for other managers). All individuals are assumed to have the same ability as workers but to vary in their ability to manage. Managing skill is indexed by x and is assumed to be distributed in the population according to the cumulatvie distribution function Ã(x). If an individual of type x hires n workers then production of the single commodity equals y(x,n) = xCg(n), where g is increasing and concave. Note, for simplicity, we have dropped the captial input in production, though capital is crucial in Lucas. Note as well that g(C) is assumed to have diminishing returns so that one manager does not employ the entire workforce. If a person of type x becomes a manager, the person chooses n to maximize ð(x,n)=xBg(n)-wBn, where w is the wage paid to workers. The maximized profit, denoted ð*(x), and the choice of labor input, denoted n*(x), are both increasing in x. Each type x decides to either work as an employee, and earn w, or as a manager who employs workers, and earn ð*(x). An equilibrium involves a mangerial type x=z such that types x>z manage and types x<z work a employees.

As a simple extension of this framework, suppose that if an individual becomes a manager that the person has a choice of technologies to employ. Suppose each technology, indexed by è0È, employs two types of labor, skilled (S) and unskilled (U). Larger è's will index more "advanced" technologies. As an illustrative example, suppose each technology è is described by two numbers (a(è),b(è)) and let the production function be given by y(x,S,U,è) = xBa(è)Cg(min[b(è)U,S]), with g(B) again assumed to be concabe. Each technology uses skilled and unskilled labor in fixed proportions. In order to interpret larger è's as more advanced technologies we assume the following. First, more advanced technologies are more skill intensive, that is, b(B) is increasing in è (since bBU = S is a necessary condition for profit maximization, b increasing means S/U is increasing). Second, holding labor input (U,S) fixed, more advanced technologies yield greater output. That is, a(B) is increasing in è. Third, the more advanced the technology, the more costly is the technology to adopt. Note that while for a given è silled and unskilled labor are (perfect) complements, before a technology is chosen there are substitution possibilities.

In addition to the choice of technology, each manager must also choose a skilled and unskilled labor input.[2] For simplicity we assume that the labor input choices satisfy bBU = S, a necessary condition for profit maximization. Let $w_s$ and $w_u$ be the skilled and unskilled wages respectively. We assume $w_s>w_u$. For convenience assume the set of technologies contains two elements, è=0 (call it the "standard" technology), with a=b=1, and è=1 (call it the "advanced" technology), with a>1, b>1. Ignoring the cost of adopting

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[2]For the discussion at hand, the reader can think of the labor that managers hire as production worker labor. So each manager must decide on the input of skilled and unskilled production worker labor.

the advanced technology for the moment, the profict function when employing the advanced technology is

$$xBaBg(bBU) - (w_w + w_sBb)BU \qquad (1)$$

while profits when using the standard technology are

$$xBg(U) - (w_u + w_s)BU \qquad (2)$$

In order to close the model, assume that there is an infinite suppy of unskilled labor at the wage $w_u$, this wage determined outside the model. Those of type x can either work as skilled workers (and earn $w_s$) or managers (and earn ð*(x)), with the distribution of types given by Ã(x). As above, and equilibrium involves a managerial type x=z such that type x>z manage and types x<z work as skilled employees.

We now turn to a brief analysis of the model. The model is only interesting if the cost of adoption is such that it pays for some type x to adopt the more advanced technology. Therefore assume it is profitable for some x to adopt the è=1 technology. The analysis below entails showing that the benefit to adopting the advanced technology increased with x. After this has been established then it is obvious that larger plants will adopt the technology. This follows because the cost of adopting is independent of x.

*Benefit of Adopting Advanced Technology*

In order to distinguish the choices in equations 1 and 2 above, let N denote the choice in equation 1 and U the choice in equation 2.

Then the maximizing choice U* for equation 2 satisfies, where D denotes differentiation,

$$xBDg\ (U^*) = w_u + w_s \qquad (3)$$

and the maximizing choice N* for equation 1 satisfies

$$xBaBDg(bBN^*)Bb = w_u + w_s\ b \qquad (4)$$

The benefit from adopting the advanced technology is

$$B(x) = xBaBg(bBN^*) - (w_u + w_sBb)BN^* - [xBg(U^*) - (w_u + w_s)BU^*]$$

Differentiating the benefit with respect to x,

$$DB(x) = aBg(bBN^*) + xBaBDg(bBN^*)BbBDN^* - (w_u + w_s\ b)BDN^* \qquad (5)$$

$$- [g(U^*) + xBDg(U^*)BDU^* - (w_u + w_s)BDU^*]$$

Substituting equation 4 into the second term of equation 5, and substituting equation 3 into the fifth term of equation 5, we have

$$DB(x) = aBg(bBN^*) - g(U^*) \qquad (6)$$

Letting $f = (Dg)^{-1}$, (i.e., f is the inverse of Dg), we have $U^* = f[(w_u+w_s)/x]$ (from equation 3) and $bBN^* = f[(w_u+w_sBb)/xBaBb]$ (from equation 4). Substituting these into equation 6, we see that $DB(x) = (w_u + w_sBb) - (w_u + w_s) > 0$. Hence, the benefit of adopting the technology increases in x.

Consider the behavior of some variables in the model that will have counterparts in the CM and SMT studied below. The average production workers wage in an establishment in the model is $w=(w_uU + w_sS)/(U +S)$. Denoting the average wage paid in equilibrium by type x as w*(x), it is clear that average wages in the model are (weakly) increasing in x. That is, given that there are only two technologies in the model, there are only two average wages. Those plant run by managers with the largest x's pay the highest average wage.[3] If size is measured as the output of the establishment in equilibrium, Y*(x), the w* is increasing in y*.

Now suppose that there is a random component to production, and than the choice of technology and employment must be made *before* the realization of this component. For example, supppose the production function above is multiplied by a factor ë that has some distribution. The production function above is therefore interpreted as expected production. None of the choices in the model are changed.[4] In this case, w* and y* have a joint distribution, with E(w*|y*) an increasing function of y*. If we calculate expected average wages conditional on size and technology, expected average wages do not depend on size. That is, if è* denotes the choice of technology, then $E(w^*|y^*,è^*)=(w_u+b(è^*)w_s)/(1+b(è^*))$ is *not* a function of y*. Once we know the technology employed at the plant, average wages are determined. As we proceed with the analysis below we will

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[3]We assumed above that it is profitable for some type x to adopt. Hence all types greater than this x will also adopt. In the discusiion in the paragraph, we are implicityly assuming that parameter values are such that there are some types who become managers but who do not adopt the advanced technology.

[4]Of course we need to worry about the situation in which a manager gets a "bad" draw and is not able to meet the payroll out of current receipts. To avoid such problems we assume that individuals have endowments to cover such occurences.

refer back to these conditional expectations from the model.

## 3. Description of Data

The data used in this paper are drawn from two plant level data sets constructed by the Census Bureau - the 1988 Survey of Manufacturing Technology (SMT) and the 1987 Census of Manufactures (CM). The information provided by each data set will be described in turn.

The sampling frame for the SMT was manufacturing was plants which: (1) had 20 or more employees and (2) were in the two-digit manufacturing industries 34 through 38. The industries covered in the sample are Fabricated Metal Products (34), Nonelectrical Machinery (35), Electric and Electronic Equipment (36), Transportation Equipment (37) and Instruments and Related Products (38). The sample consisted of 10,526 manufacturing plants from a population of 39,556 plants.[5]

The SMT consisted of questions about the plant's usage of seventeen advanced-technologies from five major technology groups during the year 1987. The seventeen technologies, and five major technology groups, are listed in the leftmost column of Table 1. The technologies represent relatively new innovations that have general use across a wide range of industries.

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[5] For a detailed description of the data set see Dunne (1991). For detailed information on the individual technologies and the survey methodology see Manufacturing Technology 1988, pp 1-5 and Appendix C1.

The technology usage question on the SMT was a simple one. For each of the seventeen technologies the questionaire asked whether that technology was used in the plant or not. The survey, therefore, provides information about whether a technology is used or not, and not information concerning the degree to which a technology is employed. While this usage information is obviously crude, the SMT is still valuable in that it provides direct measure of technology use at a highly disaggregated level and for a very large number of manufacturing plants. Table 1 provides information on the usage of each advanced-technology in each of the five major industry groups. A row of the table reports the percent of establishment in each 2-digit industry that use that particular technology. The most heavily utilized technologies are Computer Aided Design, Numerically Controlled Machines (NC/CNC Machines), Programmable Controllers and Computers Used on the Factory Floor.

We use the SMT information on technology usage at manufacturing plants to construct measures of "how intensively a plant uses advanced-technology in its production process." Our basic assumption is that if two plants, say plants A and B, each produce a single product but plant A employs more technologies than plant B i producing its product then the production process used in plant A is more technology intensive than the procee used in plant B.[6] More

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[6]Note that for this definition it does not matter whether plant A and B are producing different products or the same product. Also, in this paper products are defined at the 7-digit SIC (Standard

generally, if plant A and B both produce n products, but plant A employs more technologies than plant B in producing these products then the production process used in plant A is more technology intensive than the process used in plant B. Given this basic assumption, we use the SMT information on number of technologies employed at the plant, together with information on the number of categorize plants by the technology intensity of the plant.

The SMT also provides other usefel information - the industry of the plant (4-digit detail), the age of the establishment, the nature of the manufacturing process at the plant (i.e. was the process primarily fabrication/machining, or assembling, or fabrication/machining and assembly, or neither fabrication/machining nor assembly) and "the average market price for most of the products of the plant." Each of these variables will be used the analysis below.

The second data set is the 1987 Censts of Manufactures (CM). Among other things, the CM provides information on the region of the plant, plant employment (both production and non-production worker employment), average plant wages and whether the plant is owned by a firm with a single or many establishments. It also provides the number of 7-digit SIC products that are produced at the plant.

The data set used in the analysis below is obtained by

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Industrial Classification) level.

"matching" the two data sets, the SMT and the 1987 CM. Of the 10,526 plants in the original SMT sampling frame, we are able to find data for 9,996 establishments in the 1987 CM.[7] In each of the surveys, there exists some unit and iten non-response. The SMT has a relatively high response rate of 93.3%. Overall, there are 9,511 usable records from the SMT where both item and unit non-response problems are not present. The CM, on the other hand, has considerably higher non-response rates. Approximately, 2,500 plants are deleted from the CM (leaving 7,600 plants) because the plant-level data contain largely imputed values. These are typically the very smallest plants. Matching the plants that remain in the two data sets yields 6910 usable records.

Table 2 presents average production-worker hourly wages (in dollars) for plants that produce one product, cross-tabulated by plant size (measured by total employment) and number of technologies used at the plant. Since we are fixing the number of products, the number of technologies, by our above assumption, is interpreted as a measure of technology intensiveness. The first number in each cell is the average across plants of the average wage paid in the plants.

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[7]The CM is the manufacturing universe, so the sampling frame for the SMT is the CM. The reason we find less plants in the CM (9,996) than in the SMT "mail-out" (10,526) is because as the CM is "processed" there are records which are deleted from the CM, such as when a record is found to be from an establishment which is not primarily of manufacturing establishment. Also, some records fail to match because of changes in individual plant identifiers during the processing of the two surveys.

The second number (in parentheses) is the standard deviation of these average plant wages, and the third number is the total number of plants in each cell. For example, there 346 plants which use none of the technologies and whose total employment is less than 100 employees. The average production worker wage in these plants is $8.43, with a standard deviation of $4.20. The first point to note is that among small plants there is much more variability in technology usage.[8] Given this fact, the SMT technology variables may do a better job in distinguishing among small and medium sized plants rather than the largest ones. The second point to note is that large plants rather tend to employ more technologies than smaller ones. This has found in other studies as well. For example, as described in Reilly (1992), and analysis of Canada's General Social Survey of 1989 finds that of "individual working in small firms (1 to 19 employees), 22 percent use computers on the job while for large firms (500+ employees) this percentage rises to 48." Reilly also finds a strong positive relationship between establishment size and access to a computer in his data set.

As seen in the sample mean column of Table 2, average wages are increasing in the size of establishments. They are also increasing in the number of technologies employed at the plant, as seen in the

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[8]Davis and Haltiwanger (1992) have argued that some of the differences in growth rates and other variables between large and small establishments may be understood in the context of models where small plants have greater technological heterogeneity.

sample mean row. However, looking with the first three columns, there is a tendency for wages to fall with plant size, at least initially. Such patterns at least suggest that the SMT technology information may provide valuable information concerning plant wage structure.

## 4. Cross-Sectional Wage and Employment Share Regressions

In this section we describe and report results from a simepl empirical model of plant wages and employment structure that includes controls for technology, size and other plant attributes. We first examine production-worker wages, the non-production worker wages and finally we focus on the share of production-workers in total employment.

*Production-Worker Wages*

The dependent variable in the production-worker regressions is the logarithm of plant average annual hourly earnings of production workers.[9] The regressions include dummy variables for 149 four-digit industries and nine Census regions. The regressions also include plant attributes. Each of these attributes are also indicator variables. The attributes are defined, and summary statistics

[9]The cross-sectional regressions reported in Table 3 are unweighted, that is, each plant is treated "equally" in the regression. This is the procedure used in Brown and Medoff. In their study of plant wages, Davis and Haltiwanger weighted plants by their size. In previous versions of this paper we presented weighted regressions as well, the weighted regressions providing qualitatively similar conclusions.

provided, in Table 3. There are indicator variables for plant size (i.e., total employment) (Size2-Size6), advanced technology usage (Tech1, Tech3, Tech6), the number of seven-digit SIC products produced at the plant (Np2-Np3), the average price of most products produced in the plant (Price2-Price6), plant age (Age2-Age4), whether the plant is owned by a multiplant firm or a single plant firm (MU) and the type of production process employed at the plant (Mp2-Mp3).

Before discussing results, we comment on the reasons for including in the regression variables that are not typically found in the literature. It is likely that the four-digit industry controls fail to fully account for market heterogeneity. The average market price terms are included to control for differences in types of products produced within a four-digit industry, so that they hopefully help characterize submarkets within 4-digit industries. One possible interpretation is that they reflect differences in the complexity of the goods produced by plants in the same industry, the assumption being more complex goods are, on average, more expensive (e.g., mainframe computers vs. personal computers). Under this view, plants that produce expensive goods (i.e., complex goods) must hire skilled workers, and thus, pay high wages.[10] The variables

[10]Another interpretation is that they average market price variable is proxying the market power of the firm. Given the broadness of the price categories (see Table 3), we do not believe that these variables proxy differences in the pricing behavior of firms producing similar products.

indicating the type of manufacturing process at the plant are included for reasons mirroring the average price variable. The plant age variables control for how long a plant has been producing and reflect, in part, the average tenure of the workforce.

Table 4 reports regression results, the first column containing a regression that includes all the industry and plant attributes available. The results indicate that larger plants, plants that intensively use technology, plants producing higher priced goods, older plants, and multi-unit plants, all pay higher wages.[11] The premium for a worker in a plant with 2500 or more employees is 28 percent as compared to plants with less than 100 workers. The relationship between technology use and wages is monotonic. Those plants employing 1 or 2 of the technologies pay on average 8 percent higher wages than those employing no technologies; those employing 3 to 5 technologies pay 11 percent, and those employing 6 or more pay 16 percent, higher wages.[12]

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[11]Referring back to the model variables, size is measured as $U^*+S^*$ in the regressions, not $y^*$. If $U^*+S^*$ is increasing in x, then all the discussion above applies to this measure of size as well. Since in equilibrium, $bU=S$, $U^*+S^*=S^*b(\grave{e}^*)^{-1}+S^*$. $S^*$ increases in x ut b increases in x as well, so other restrictions are needed to insure this quantity in increasing in x.

[12]Note that the discussion in section 3 concerning the definition of technology intensiveness sugges that we interact the number of technologies with the number of products produced at the plant. That is, we would like to compare, *among* plants that produce the same number of products, plants that employ different numbers of technologies. In the specification in Table 4, we include the indicator variables for the number of technologies employed and those

A surprising set of variables in column 1 are the indicator variables for averageprice of a plant's products. Plants that produce high priced goods pay significantly higher wages than plants that produce low price products. There is also montonicity in the estimated coefficients. In fact, the size of the coefficient on the highest price group dummy ($10,000 or more) is larger than the coefficient on the biggest size group dummy. Again, this may be an indication of the skill requirements of a workforce that produces sophisticated goods and the fact that 4-digit industry indicators do not control sufficientyly for industry heterogeneity. The production worker share regressions below provode supporting evidence for this interpretation.

*Employer Size-Wage Premia and Technology*

There are a number of points to make regarding the relationship between technology usage and the employer size-wage premia. First, the premium for working in the most technology intensive plants, 16 percent, is greater than the size premium earned by workers at all but the very largest plants. As compared to workers in the smallest plants (employment less than 100), those in class Size2 (employment 100-249, Size3 (employment 250-499), Size4 (employment 500-999),

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for the number of products produced separately, that is, we do not interact the varibles. We have examined the interaction specification (in regressions not reported) and the results are similar to those presented in Table 4.

Size5 (employment 1000-2499) and Size6 (employment over 2500) earn no premium, a 3 percent premium, an 8 percent premium, a 17 percent premium, and a 28 percent premium, respectively.[13]

Second, it is interesting to examine the size-wage premiums in the first regression, which included the technology controls, to the premiums in the second regression, which is identical to the first except that technology controls are deleted. The size premium for each size Size3, Size4, Size5 and Size6 the premium falls 59 percent, 41 percent, 30 percent and 24 percent respectively. The size premium falls the greatest amount for the smaller size categories. Remember that for smaller plants there is more variability in the number of technologies employed at the plant, hence more of a chance that these controls will differentiate among plants. Note that while adding the technology controls significantly reduces the size-wage premium, the do not greatly improve the "fit" of the regression. One interpretation of this small improvement is that size has been proxying for worker quality in establishment level wage regressions. The advanced-technology controls from the SMT "pick up" part of variation in quality that size has been proxying, but that given the crude nature of the technology controls, there is still substantial

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[13]Note that when we calculated the conditional mean of average wages in the model, conditioned on size and technology, that the resulting quantity was not a function of size. In the regression of wages on size and technology, size is still significant. This can be interpreted in the context of the model by recognizing that we do not observe è but some "noisy" signal of it.

variation in quality within the technology groups.

Third, in assessing the influence of the technology controls on the size premium it is also instructive to ask how the other variables in the regression reduce the size premiums. The impact of the price controls on the size-wage premium can be determined by comparing size premiums in the first regression, which included the price controls, to the premiums in the third regression, which is identical to the first except that the price controls are deleted. As can be seen, the price controls do not have much of an impact. For example, the premium falls little for the first three size groups. In a manner similar to the second and the third columns, columns 4-7 present regressiolns in which a single variable is dropped from the set of establishment controls, the multi-unit indicator, the dummy variables for number of products, the dummy variables for type of manufacturing process and controls for the age of the plant, respectively. As can be seen, none of the other variables have as significant an influence on the size premiums as do the technology controls. In fact, the coefficients on the size class variables in the "All Except Tech" columns are larger than those coefficients in any column to the right, that is, the reduction in the size premium is greater for each size class for the technology controls as compared to any control, and typically by a wide margin.

*Non-Production Worker Wages*

Cross-sectional non-production worker wage regressions are presented in Table 5. The structure of Table 5 mirrors that of Table 4. The dependent variable is the logarithm of non-production worker annual wages.[14] The results for non-production workers are similar to those of production workers. Non-production worker wages increase with plant size, the technology intensity of the plant, the average market price of products and plant age. Their wages are lower however in multi-unit plants. The size premia for non-production workers is roughly half that of production workers. The technology premia is also not as larege as that of production workers. For example, those plants employing 6 or more of the technologies pay on average 8 percent higher wages than those employing none of the technologies, in contrast to the 16 percent premium earned by production workers in such plants. But again the technology premium is of the same order of magnitude as the size premium in all but the largest plants.

As done above, it is interesting to examine the size-wage premiums in the first regression, which included the technology controls, to the premiums in the second regression, which is

[14]Note that the dependent variable in Table 5 differs from that in Table 4. On the CM there is information on the wages and number of non-production workers at a plant, but not on the hours worked by non-production workers. Also, the regressions in Table 5 are unweighted, each plant being treated "equally." In previous versions we have presented weighted regressions that have given the qualitatively same conclusion. Finally, note that since there are a smaller number of observations in Table 5, as compared to Table 4, since some plants report zero non-production worker employment.

identical to the first excetp that technology controls are deleted. The size premium for each size class falls significantly when the technology controls are included. For the classes Size2 and Size3 the premium falls from 2 percent and 3 percent to zero, respectively. For the classes Size4, Size5 and Size6 the premium falls 63 percent, 37 percent and 32 percent respectively. Again, the size premium falls the greatest amount for the smaller size categories. Note again that while adding the technology controls significantly reduces the sze-wage premium, they do not greatly improve the "fit" of the regression.

As with the production worker regressions, it is also instructive to ask how the other variables in the regression reduce the size premiums. As can be sees, none of the other variables have as signficant an influence on the size premiums as do the technology controls. In fact, the coefficients on the size class varables in the "All Except Tech" column are larger than those coefficients in any column to the right, that is, the redution in the size premium is greater for eac size class for the technology controls as compare to any control, and typically by a wide margin.

*Production Worker Share in Employment*

The employment structure of plants, as measured by the fraction of production workers at the plant, is studied in Table 6. For simplicity, and for comparability with the previous analysis, we examine the production share of workers in a regression context. In the first regression, which contains all the controls, there is essentially no relationship with size. The most technology intensive plants employ a smaller fraction of production workers than the least technology intensive, though the difference is small (the difference of .025 amount to about 4 percent of the average value of .679 for the production worker share).

The coefficients on the average market price variables are large. They indicate that plants that produce more expensive goods have a much lower production worker share. For plants producing goods averaging $2000-$10000 (Price5) the production workers share is .118 less than plants making godds priced less than 5 dollars and for plants producing goods greater than $10000 it is .167 less. The strong price effect is consistent with the view that more complex products (i.e. expensive goods) require more skilled workers. Thus, plants that make high priced goods require proportionately more non-production workers than plants producing inexpensive goods. The remaining varibles in the model, plant age and multi-unit status are not significant.

Examining the regression in columns 2 and 3 we see that there is a relationship between plant size and the fraction of production workers at a plant, in particular, the very largest plants employ fewer production workers. Including the technology (column 2) or price indicator variables (column 3) removes the relationship with size. Hence, as with the size premia, the technology and price variables pick up differences between small and large plants with respect to the share of production workers employed at the plants. Note that, in contrast to the results on the size premia, the reduction in the share is larger when the price variables are included than when the technology variables are added.

## 5. Conclusion

A number of paers in the literature have argued that changes in technology have been responsible for significant wage movements. These papers have typically been required to use rather indirect measures of technology in developing their arguments. We have studied a survey of manufacturing technology used at U.S. manufacturing plants that provides some direct information on technology usage. If changes in technology usage have a significant impact on the structure of wages, as argued in this literature, then one expects that large difference in technology usage across manufacturing establishments should also mean large differences in cross-sectional wages. We found that differences in technology usage across plants is related to significant wage differences, with technology premia of the same order of magnitude as size premia. Including information about technology usage at plants in standard wage regressions also signficantly reduced the sze-wage premia earned at plants.

References

Allen, Steve, "Technology and the Wage Stucture," North Carolina State University, October, 1991.

Arrow, Kenneth (1962) "Economic Welfare and the Allocation of Resources for Invention," in R.R. Nelson, editor, The Rate and Direction of Inventive Activity, 609-625.

Bailey, Thomas (1989) "Changes in the Nature and Structure of Work: Implications for Skills and Skill Formation," mimeo, November.

Bailey, Thomas (1990) "Economic Change, Organizational Innovation, and Escalating Skill Requirements," Paper presented at the Conference on Changing Occupational Skill Requirments, Brown University.

Bartel, Ann and Frank Lichtenberg (1987), "The Comparative Advantage of Educated Workers in Implementing New Technology," The Review of Economics and Statistics, February.

Berndt, Ernst, Catherine Morrison, and Larry Rosenblum (1992) "High-Tech Capital Formation and Labor Composition in U.S. Manufacturing Industries: An Exploratory Analysis," NBER working paper 4010.

Berman, Eli, John Bound and Zvi Griliches (1992), "Changes in the Demand for Skilled Labor Within U.S. Manufacturing Industries: Evidence From the Annual Survey of Manufacturing," unpublished mimeo.

Bound, John and George Johnson (1992), "Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations," American Economic Review, June.

Brown, Charles and James Medoff (1989), "The Employer Size-Wage Effect," Journal of Political Economy, 97, no. 5, 1027-1059.

Davis, Steve J., and John Haltiwanger (1991), "Wage Dispersion Between and Within U.S. Manufacturing Plants, 1963-1986," Brookings Papers on Economic Activity, Microeconomics, 115-200.

__________________ (1992), "Employer Size and the Wage Structure in U.S. Manufacturing," unpublished mimeo.

Dunne, Timothy (1991), "Patterns of Technology Usage in U.S. Manufacturing Plants," mimeo, Center for Economic Studies.

Dunne, Timothy and Mark J. Roberts (1990), "Wages and the Risk of Plant Closings," Center for Economic Studies Discussion Paper 90-6.

Hamermesh, Daniel (1980), "Commentary," In The Economics of Firm Size, Market Structure, and Social Performance, edited by J. Siegfried.

Kruger, Alan (1991), "How Computers Have Changed the Wage Structure: Evidence From Microdata, 1984-89," unpublished mimeo.

Lowe, G. (1991), "Computers in the Workplace," Perspectives on Labour and Income, 3, 2.

Lucan, Robert E. (1978), "On the Size Distribution of Business Firms," The Bell Journal of Economics, 9, no. 2, 508-523.

Mincer, Jacob (1991), "Human Capital, Technology, and the Wage Structure: What Do Time Series Show?" NBER Working Paper No. 3581.

Reilly, Kevin (1992), "Human Capital and Information: The Employer Size-Wage Effect," unpublished mimeo.

Welch, Finis (1970), "Education in Production," Journal of Political Economy, 35-39.

U.S. Department of Commerce, Current Industrial Report: Manufacturing Technology 1988.