**Wage and Productivity Dispersion in U.S. Manufacturing:**
**The Role of Computer Investment**

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Abstract

By exploiting establishment-level data, this paper sheds new light on the sources of the changes in the structure of production, wages, and employment that have occurred over the last several decades. We focus on investigating the following two related hypotheses. First, that most of the recent increase in the dispersion of wages and productivity has occurred across establishments and these changes are linked. Second, that the increased dispersion in wages and productivity across establishments is linked to differential rates of technological adoption across establishments. Our findings are supportive of these hypotheses. Specifically, we find that (1) the between plant component of wage dispersion is an important and growing part of total wage dispersion; (2) much of the between plant increase in dispersion is within industries; (3) the between plant measures of wage and productivity dispersion have increased substantially over the last few decades; and (4) a substantial fraction of the rising dispersion in wages and productivity is accounted for by changes in the distribution of computer investment and capital intensities across plants as well as wage and productivity differentials associated with the same observable characteristics.

## I. Introduction

Striking changes in the structure of production, wages, and employment have occurred over the last several decades. The introduction of computers and, more generally, advanced technologies into the workplace is widely viewed as one of the major factors underlying these changes. In particular, the role of advanced technology and computers has been closely linked to the rising inequality of worker wages. One hypothesis is that the introduction of advanced technologies and/or computers has led to a rising demand for skilled workers which, in turn, has led to a rise in the wages of skilled workers relative to unskilled workers. Competing hypotheses concerning the source of rising wage inequality include shifts in product demand and changes in institutional factors such as the decline of unions and changes in pay norms.

This paper attempts to shed new light on the source of these changes by exploiting establishment-level data to investigate the relationship between the dispersion of wages and productivity across establishments and the role of technical change in accounting for the observed changes in dispersion. The focus on between establishment changes in wages and productivity is a novel feature of our analysis. This focus is motivated by recent theoretical papers that hypothesize that technical change occurs through differential technology adoption by plants in the same industry.[1] If plants do adopt technologies at different rates, and new technology is skill biased, this should lead to cross-plant changes in the dispersion of wages and productivity. This in turn provides an alternative vantage point for evaluating the overall

[1] Acemoglu (2000) and Katz and Autor (1999) provide comprehensive reviews of the recent theoretical and empirical literature analyzing the link between wages, wage inequality and technology.

hypothesis of skill-biased technical change relative to alternative hypotheses of changes in the structure of wages, productivity, and the workforce. That is, if rising wage dispersion is indeed a between plant phenomena, then we can use differences in technology use across plants to examine the role of skill-biased technical change. Accordingly, we perform three exercises in this paper. First, we examine whether the increase in wage dispersion is primarily a within plant phenomenon. Second, we examine whether plant-level changes in wages and productivity appear to be linked. Finally, we ask whether between-plant changes in wage and productivity dispersion can be explained by differential technology adoption across producers.

Our paper can also be viewed as helping to connect various strands of the literature studying wages, productivity, and computers. For example, many recent studies have sought to understand either the relationship between the use of computers and wages (e.g., Krueger (1993), Doms, Dunne, and Troske (1997), Autor, Katz, and Krueger (1998)) or, alternatively, computer use and productivity (e.g., Oliner and Sichel (1994), Greenan and Mairesse (1996), Siegel (1997) and Bresnahan, Brynjolfsson, and Hitt (2000)). One of our main objectives is to investigate these relationships simultaneously.

In a related manner, our analysis builds upon the parallel but separate literatures that exploit plant-level data to study the behavior of wages and productivity. Work by Davis and Haltiwanger (1991) has shown that the overall increase in wage inequality between workers is closely tied to an increase in the dispersion of wages between establishments.[2] Further, much of

[2] Both the earlier and current work focus on manufacturing. However, as shown in section IV, the rising inequality for all workers is closely mimicked by rising inequality for workers in manufacturing. These findings suggest that although our plant-level analysis is confined to manufacturing, it likely has wider applicability. The restriction to manufacturing is dictated by data limitations. Only for manufacturing do we have the ability to investigate the link

the latter change is a within-industry phenomenon so that the full exploration of these differences requires plant-level data as opposed to industry-level data. This finding that the most important component of rising wage inequality is between-plant but within-industry suggests that the increase in relative demand for skilled workers is not due to a simple shift in product demand across industries.[3] Related work on the determinants of plant-level wages (e.g., Doms, Dunne and Troske (1997)) finds that differences in the use and adoption of advanced technology is an important correlate of differences in the mix of workers and wages among plants within industries.

Along these same lines, Baily, Hulten and Campbell (1992), Olley and Pakes (1996), and Foster, Haltiwanger and Krizan (2000) show that there is tremendous within-industry variation in productivity across plants. Further, they demonstrate that much of the increase in aggregate (industry-level) productivity is associated with the reallocation of resources across plants from less productive to more productive plants within the same industry. Unlike with wages, however, there has been little analysis of changes in the dispersion of productivity over time and little analysis of the role of advanced technology and computers in accounting for the observed differences in productivity across plants.[4]

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between productivity, wages, and establishment-characteristics like capital intensity and computers per worker in a comprehensive, integrated manner for an extended period of time.

[3] This inference is based on the presumption that product demand shifts would be related to between industry changes. This, of course, depends upon among other things the level of industry disaggregation. We consider this issue in the analysis that follows.

[4] One exception is the work of Dwyer (1995) who examines the relationship between productivity and wage dispersion for the textile industry. He finds that plants in the textile industry with higher than average total factor productivity residuals also pay higher than average wages.

The paper proceeds as follows. In Section II, we briefly discuss the relevant theoretical literature that helps motivate the subsequent empirical analysis. In Section III we decompose the total dispersion in hourly wages into within and between components over the 1975-92 period. We find that virtually the entire increase in overall dispersion in hourly wages for U.S. manufacturing workers from 1975-92 is accounted for by the between-plant components. This result is quite important as it is at the core of the hypotheses we are investigating.

In Section IV we examine the links between productivity and wages. At the aggregate level, we find that the between-plant dispersion of *both* wages and productivity increased over the 1975-92 period. At the plant level, we find that wages and productivity are strongly positively correlated in both levels and changes. In Section V, we investigate the source of the changes in the dispersion of wages and productivity by examining the role of observable and unobservable plant characteristics in accounting for the differences across plants in wages and labor productivity. The observable characteristics we consider include detailed industry controls, controls for the size and organizational structure of the establishment, measures of capital intensity, and computer investment. We use this information to quantify the contribution to changes in wage and productivity dispersion over time of: (1) changes in the distribution of observable plant characteristics; (2) changes in the wage and productivity differentials associated with these observable characteristics; and (3) changes in unobserved factors. We find that a large percentage of the observed changes in the dispersion of wages and productivity is accounted for by changes in the distributions of computer investment and capital intensities across plants as well as changes in the wage and productivity differentials associated with these observable characteristics. Section VI summarizes the main findings and provides an interpretation in terms of the alternative theoretical models under discussion.

## II. Review of Theoretical Literature

Our empirical analysis focuses on exploring the role of between-plant versus within-plant changes in accounting for changes in wage dispersion, and the role of differences in the use of technology across plants in accounting for between-plant changes in wage and productivity dispersion. There are a variety of mechanisms through which technical change is hypothesized to affect the distribution of wages and the structure of the workforce. Acemoglu (2000) provides a comprehensive review of both the theoretical and empirical literature. Two specific lines of research help frame our empirical analysis. The first avenue of research considers the role of skill-biased technological revolutions. This literature emphasizes the role that the introduction of new technologies plays in changing the relative demand for workers. Papers in this line of research include Greenwood, Hercowitz and Krusell (1997), Greenwood and Yorukglu (1997), and Caselli (1999). The second avenue of research examines the relationship between technological change and organizational change. Here, the premise is that technological change can lead to changes in the organizational structure of firms that affect the distribution of wages and the composition of firm workforces. Kremer and Maskin (2000) and Acemoglu (1999) construct models where technological change can lead to increases in plant-level segregation of workers by skill.[5] That is, it will be more productive for the firm if skilled workers work with

[5] Papers by Bresnahan (1999) and Autor, Levy and Murname (2000) also argue that recent technological changes lead to changes in the organization of production.

other skilled workers, as opposed to skilled workers working in combination with unskilled workers. In the remainder of this section, we use the papers by Caselli (1999) and Kremer and Maskin (2000) to illustrate these ideas and to help develop empirical predictions regarding technological change and the distributions of plant-level wages, skill and productivity.

Caselli (1999) models the effect of a technical revolution on the dispersion of wages and productivity. In the Caselli model there is a distribution of worker types and types of machines. Workers determine their type by investing in training. The cost of learning a given skill varies across workers. A technology is a matching of workers of type *i* who have the appropriate set of skills to operate machines of type *i*. An important feature of this technology assumption for our purposes is that workers are completely segregated by skill across plants. A technological revolution occurs with the development of a new type of machine.[6] Examples of new types of machines mentioned by Caselli are the assembly line, the steam engine, and information technologies or computers. A revolution is skill biased if the skills required to operate the new machine are more costly for workers to acquire than existing skills.[7] Therefore, when a skill-biased revolution occurs, high skilled workers will be the first to use the new machines since it is less costly for them to acquire the new skills (this is the definition of high skilled in the model). Low skilled workers will continue to use the old machines. The model predicts that following a skill-biased technical revolution, because technologies have diminishing marginal returns and all types of machines must have the same rate of return in equilibrium, high skilled workers will

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[6] This is in contrast to an innovation which occurs when an improvement is made on an existing machine.

[7] A revolution is "deskilling" if the new skills required to operate the new machine are less costly to acquire than existing skills.

work with more productive capital (better capital) and with a greater amount of capital. Thus, plants that employ high skilled workers will have a higher capital-labor ratio.

This model has three implications that are relevant for our analysis. First, a skill-biased technical revolution leads to an increase in the dispersion of wages across plants.[8] Since more skilled workers are using more and better capital relative to less skilled workers, their relative wages must increase, increasing the overall dispersion of wages across plants. Second, a skill-biased technical revolution also leads to an increase in the dispersion of labor productivity across plants.[9] Skilled workers are using *more* and *better* machines. Therefore, their productivity, measured as either output per worker or output per hour worked, will rise relative to workers using the old machines, increasing the dispersion of productivity across plants. Third, the relative increases in wages and productivity should be associated with increases in capital in general at the plants that have adopted the new technology and, in the case of the information technological revolution, increases in computers or information technology equipment in particular. Again, both better capital and more capital will flow towards plants with more skilled

[8] Whether this increase in relative wages persists depends on a number of factors outlined in Caselli (1999).

[9] Formally, the Caselli (1999) model predicts rising dispersion in both labor productivity and total factor productivity measured as the residual of output less factor inputs weighted by output elasticities. The production function is assumed to be Cobb-Douglass with a technology multiplicative factor $A_{it}$. Only firms that adopt the technology obtain the highest currently available level of $A_{it}$ . Labor productivity dispersion rises both because of the rising dispersion in $A_{it}$ and the rising dispersion in capital-labor ratios. The open empirical question is whether there are direct measures of whether the latest technology has been adopted. Our use of information about computer investment in our empirical analysis is an attempt to measure such differential adoption directly. Note that in our empirical analysis we focus on labor productivity rather than total factor productivity since we measure labor productivity more accurately for a larger and thus more representative sample of plants. In addition, many of the predictions of the model carry over directly to labor productivity.

workers who are in turn receiving higher wages and becoming more productive relative to less skilled workers.

Kremer and Maskin (2000) also provide a theoretical structure for our empirical analysis. Their model can account for the simultaneous existence of increased wage inequality and increased segregation of workers of different skill levels into different plants. These forces are set in motion by changes in the skill distribution, which can be due to a skill-biased technical change, but need not be. The main features of their model are imperfect substitution among workers of different skills, complementary tasks within a plant, differences in worker skill effects which vary by task, and an exogenous distribution of worker skills.[10] Intuitively, there are two competing forces at work in determining the equilibrium matching patterns at plants. The asymmetry of tasks in the production function favors cross-matching (less segregation) but the complementarity between tasks favors self-matching (more segregation). Unequally skilled workers will be cross-matched up to the point at which the differences in skills are so great that the second effect overwhelms the first and the plant moves to self-matching. When the overall distribution of skills is sufficiently compressed high and low skilled workers will be matched together in the same plant. When the distribution of skills is sufficiently diffuse there will be complete segregation of workers by skill across plants. With a diffuse skill distribution, an increase in the mean skill-level exacerbates wage inequality across plants.

[10] In the Kremer-Maskin model there are a set numbers of tasks that must be performed in order to produce one unit of output and overall productivity is a multiplicative function of each task. Tasks are complementary in the sense that the output from any tasks affects the marginal productivity of all other tasks.

The Kremer-Maskin model has three implications relevant for our analysis. First, increases in the cross-worker dispersion of skill results in increased segregation of workers by skill across plants. Second, if the overall distribution of skills is sufficiently dispersed, an increase in the mean level of worker skill will lead to an increase in the dispersion of wages across skill levels and plants. Third, if the overall distribution of skills is sufficiently dispersed, an increase in the mean level of skill leads to an increase in the cross-plant dispersion of productivity. The Kremer-Maskin model is silent about the sources of the changes in the distribution of skills. They argue that the change could come from an exogenous change in the distribution of skills in the workforce and/or from skill-biased technical change that changes the *effective* skill distribution.

The hypothesis that skill-biased technical change can affect the demand for skilled workers and the structure of wages and productivity is consistent with a large class of models. We focus on the models of Caselli (1999) and Kremer and Maskin (2000) because both speculate that technical adoption and changes in the distribution of wages and productivity will be a between-plant as opposed to a within-plant phenomenon. The general point is that, in principle, the increased demand for skilled workers driven by skill-biased technical change could have occurred within the typical or representative establishment. Accordingly, the rising wage dispersion and/or changes in the skill of workers could be seen within the representative establishment by increases in the within establishment dispersion of wages. In contrast, the between-plant hypothesis predicts that skill-biased technical change will be associated with greater dispersion in wages and technology across establishments with much smaller changes occurring within the representative establishment. This greater dispersion in wages and productivity results from increased skill-segregation which in turn is the result of differential rates of technical adoption across plants. Our use of establishment-level data provides a basis for evaluating the relevance and validity of these predictions that focus on between establishment changes.

To summarize, both the Caselli (1999) and the Kremer and Maskin (2000) models imply that there should be a positive correlation between changes in the dispersion of wages and productivity across plants. In contrast, if changes in institutional factors or shifts in product demand are the source of the increased wage dispersion, we would not unambiguously expect to see a positive correlation between changes in wage dispersion and changes in productivity dispersion across plants. Both Caselli and Kremer-Maskin offer additional predictions about the effects of a skill-biased technical change such as the computer revolution. The Kremer-Maskin model suggests that these changes will also be associated with an increase in the inter-plant segregation of workers by skill. The Caselli model predicts that changes in the distribution of wages and productivity across plants can be accounted for by changes in the distribution of capital in general and computers in particular across plants.

## III. Between-Plant and Within-Plant Components of Wage Dispersion

In this section, we combine data from household and establishment surveys to decompose the variance of hourly manufacturing wages into between-plant and within-plant components. The decomposition methodology is from Davis and Haltiwanger (1991, 1996).[11] The analysis in

[11] The variance decomposition of the total variance of wages into between and within plant components used in this paper draws heavily on the methodology from Davis and Haltiwanger (1991) (hereafter DH). The value-added of the results in our paper on this

this section extends their results over a longer time period and incorporates nonproduction workers who work in auxiliary establishments such as central administrative offices, research facilities, and warehouses. The variance of hourly wages across hours worked in the manufacturing sector can be written as:

$$V = \alpha V^p + (1-\alpha)V^n + \alpha(1-\alpha)(W^p - W^n)^2, \qquad \textbf{(1)}$$

where $\alpha$ denotes production workers' share of hours worked, $V^p$ denotes the variance of wages across hours worked by production workers, $V^n$ denotes the variance of wages across hours worked by nonproduction workers, $W^p$ is the hours-weighted mean of the production worker wage, and $W^n$ is the hours-weighted mean of the nonproduction worker wage. Equation (1) expresses the total variance of hourly wages as the hours-weighted sum of the variances of production and nonproduction workers along with a term reflecting the contribution of differences in the mean wages across production and nonproduction workers. For each worker type, the variance can be further decomposed as:

$$V^j = V^j_{BP} + V^j_{WP} \quad for\ j = p,n. \qquad \textbf{(2)}$$

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between/within decomposition of wage dispersion is threefold. First, we use a more comprehensive data set that permits inclusion of auxiliary establishments (e.g., central administrative offices, research facilities and warehouses) while DH were forced to make crude adjustments for their nonproduction worker statistics to account for the contribution of auxiliary establishments. Second, we use a more general version of the decomposition that permits decomposing the wage gap between production and nonproduction workers into within and between plant components. Third, the decomposition here considers the period 1977-92 while DH considered the period 1973-86. In addition, DH did not explore the related changes in the dispersion of productivity nor did they investigate the role of computers in accounting for changes in the wage and productivity dispersion.

where $V^j_{BP}$ represents the between plant component and $V^j_{WP}$ the within plant component for worker type *j*.

To estimate the components of the decompositions in (1) and (2) for the manufacturing sector we utilize household data from the March Current Population Survey (CPS) and establishment data from the Longitudinal Research Database (LRD).[12] From the individual-level wage observations in the CPS files, we calculate $\alpha$, V, $V^p$, $V^n$, $W^p$, $W^n$ for all workers employed in manufacturing in each of the years under consideration (1975-1992). We also generate the production and nonproduction variances at the two-digit SIC industry level. From the plant-level observations in the LRD, we calculate the between-plant component for each worker type for each of the corresponding years at the two-digit level. For each worker type, we generate the within-plant component in equation (2) by taking the difference between the total variance calculated from the CPS and the between-plant variance calculated from the LRD at the two-digit level.[13] Appropriately aggregating the between-plant and within-plant components across industries yields the decomposition at the total manufacturing level. As part of this aggregation, we decompose the overall between-plant component for each worker type into a between-plant, within-industry component and a between-industry component.

[12] The data appendix provides a detailed discussion of the problems that arise when combining information from household and establishment surveys. These measurement difficulties suggest that the results in Section III must be interpreted with appropriate caution. However, these measurement difficulties should primarily impact levels rather than time series changes.

[13] Summary statistics for the CPS and LRD wage data are presented in Table A1 of the data appendix.

The results from the formal decomposition of total variance into between-plant and within-plant components based upon equations (1) and (2) are reported in Table 1 and Figure 1. Table 1 includes selected years while Figure 1 depicts the patterns of the components for all years from 1975-92. While the formal decomposition is in terms of levels of hourly wages we are concerned about the possible effects of changes in scale. Therefore, the components in Figure 1 are depicted in terms of coefficients of variation.

There are several striking patterns in Table 1 and Figure 1. Focusing first on Figure 1, we see that the increased dispersion in overall hourly wages across workers in manufacturing over the 1975-92 period (measured by the coefficient of variation) is associated primarily with an increase in the dispersion of hourly wages between plants. Between-plant dispersion for both production (PW) and nonproduction workers (NPW) increases over this time period (the dotted lines). In contrast, the within-plant components do not exhibit a positive trend over this period (the dashed lines). Within-plant dispersion for production workers exhibits no trend while within-plant dispersion for nonproduction workers exhibits a negative trend. In Table 1 we see that for total workers the story is still one of rising *between*-plant wage dispersion. However, the *within*-plant wage dispersion across all workers is also rising which differs from the patterns of within-plant dispersion of the two worker types. This divergence in the within-plant patterns is possible because total worker within-plant wage dispersion consists of an additional component–the within-plant wage gap between worker types.[14] This within-plant wage gap can be thought of as the within-plant component of the cross-wage term ($W^p$ - $W^n$) shown in equation

[14] Specifically the decomposition of the within plant component is:
$V_{WP} = \alpha V^{p}_{WP} + (1-\alpha) V^{n}_{WP} + \sum_e s_e \alpha_e (1-\alpha_e) (W_e^P - W_e^N)^2$, where the *e* subscript denotes an establishment and $s_e$ is the establishment's share in total hours.

(1). Over the period of analysis, the within-plant wage gap has been rising. Moreover, the within-plant wage gap's share of total within-plant variance has grown from 25% in 1977 to 49% in 1992. Thus, interestingly, within-plant dispersion by worker type has been steady or even declining but there has been some offsetting increase in the gap between production and nonproduction wages within plants.

The bulk of overall wage dispersion is accounted for by between-plant dispersion and the contribution of this component has been growing over time. Combining the contribution of between-plant wage dispersion for production and nonproduction workers in the lower panel of Table 1 reveals that 53% of the overall variance in 1977 is directly accounted for by between-plant differences in wages. In 1992, the contribution of between-plant differences to overall dispersion is 64%. Table 1 provides a further decomposition of the between-plant components into between-plants, within-industries and between-industries components. For this purpose, industries are defined at the two-digit level. The results indicate that most of the between-plant contribution arises from differences in wages between plants within the same industry.[15] The result that much of the increase is due to an increase in the between-plant dispersion within industries indicates that explanations that rely on shifts between industries (e.g., simple product demand shifts across industries) cannot account for the rising dispersion.

[15] The finding that most of the increase in between plant increase in wage dispersion is a within-industry phenomenon is reinforced in results reported in Section V that consider four-digit industry effects. The results in this section only consider two-digit industry since this is the level of aggregation at which the LRD and CPS statistics can be readily matched. However, for the purposes of investigating the role of between vs. within industry contributions of the between-plant changes in dispersion, there is no need to restrict analysis to the two-digit level. In Section V, we report results that show that the fraction of overall dispersion accounted for by four-digit industry effects falls between 1977 and 1992.

There is greater dispersion among nonproduction workers than among production workers. This fact combined with an increased nonproduction worker labor share over this time period has yielded an increasing share of overall dispersion being accounted for by differences in wages among nonproduction workers. Another contributing factor to overall increases in dispersion is a widening gap between production and nonproduction worker wages. The gap between production and nonproduction worker wages accounts for 8% of overall dispersion in 1977 and 11% of overall dispersion in 1992.

To help quantify the extent of the changes in the components of the wage variation shown in Figure 1, Table 2 shows the Kremer-Maskin (2000) segregation index for all workers, production workers, and nonproduction workers by Census years. This index measures how correlated the skill levels of workers are within a plant. Specifically, it is the ratio of the variance of the mean skill level *between* plants to the variance of the skill level of the *total* population. It is equivalent to the $R^2$ of a regression of skill level on a series of plant dummies. When $R^2=0$ there is no segregation, when $R^2=1$ there is complete segregation. In this case, skill level is measured by wages. From Table 1 and Figure 1, it is evident that the between component has been increasing over time while the within component has been relatively flat, and hence the segregation index will be generally rising over time.[16] This can be seen in Table 2 where, in

[16] Within this general trend of an increase over the years, there is apparently some cyclical variation in the degree of segregation by skill. In addition, it is important to observe that it is possible for the between-plant component of wage dispersion as measured by the coefficient of variation to move in the opposite direction of the Kremer-Maskin index. The denominator in the between-plant component measured by the coefficient of variation is the overall mean wage while the denominator of the Kremer-Maskin index is the total variance. If these two denominators move in different directions so will the two measures. This relationship is what accounts for the finding that between 1982 to 1987 the between plant component rises but the Kremer-Maskin index actually falls. Note that our main focus here is the long run change where

every column, the segregation index is larger in 1992 than in 1977. The change in segregation for nonproduction workers is especially stark.

To sum up, we find that the between-plant components of dispersion are an important fraction of overall wage dispersion and account for much of the increase in overall dispersion in the 1975-92 period. These results parallel and extend similar findings in Davis and Haltiwanger (1991, 1996) and in Kremer and Maskin (2000). Moreover, we believe the evidence in this section makes a strong case that accounting for the sources of the increase in *overall* wage dispersion necessitates accounting for the sources of the increase in *between-plant* wage dispersion. Accordingly, this gives us confidence to proceed with the remainder of the analysis which investigates the sources of between-plant changes in wage dispersion along with potentially related between-plant changes in productivity dispersion. Before proceeding with that analysis, however, we first document the plant-level link between wages and productivity.

## IV. Linking Productivity and Wages

In this section, we provide a basic description of the relationship between wages and productivity at the sector and plant level. The upper panel of Figure 2 presents measures of wage dispersion. Using data from the March Current Population Survey (CPS), the solid line in the upper panel depicts the hours-weighted 90-10 differential of hourly log wages for 1975-92.[17] As

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the coefficient of variation shows a rising between plant measure of dispersion and the Kremer-Maskin index shows a rising share of total variance accounted for by between plant effects.

[17] The 90-10 differential is measured as the difference between the hourly log wage for the worker at the 90th percentile of the hourly log wage distribution for a given year and the hourly log wage of the worker at the 10th percentile of this distribution. In this and subsequent analysis using 90-10 differentials, the respective distributions are the total hours weighted

is now well-known, there has been a sustained increase in the dispersion of wages among workers over this period of time. Somewhat less well-known is that the increase in dispersion among all workers is mimicked by an increase in dispersion among workers employed in manufacturing industries. Again, using the CPS, the dotted line in the upper panel shows that the pattern for workers in manufacturing closely tracks that for all workers. The similar time series pattern suggests that similar factors underlie the changes for all workers and the changes for manufacturing workers. Put differently, although our plant-level analysis is confined to manufacturing, it likely has wider applicability. Finally, the dashed line in panel A shows the hours-weighted 90-10 differential of plant-level log average hourly wages. This differential is constructed using the same plant-level data used in the previous section. This line shows the movement in the between-plant dispersion of wages. It is changes in this dispersion, along with changes in the dispersion of productivity that we will examine in the rest of the paper. Comparing the dashed line with the dotted line again shows that changes in the between-plant component of wage dispersion track fairly closely changes in the overall dispersion of wages–this is another illustration of the main findings of section III.

The lower-panel of Figure 2 depicts the hours-weighted 90-10 between-plant differential of log output per hour across U.S. manufacturing plants. This is the measure of plant-level productivity used throughout the paper. It is defined as the total value of shipments from the plant, measured in constant 1987 dollars, divided by total plant hours.[18] The output data are

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distributions across plants or workers. Details of measurement of wages and productivity from the CPS and LRD are discussed in the data appendix.

[18] We measure labor productivity using gross output rather than value-added because gross output is measured more accurately than value-added and value-added at the establishment

deflated by the four-digit industry price deflators found in the Bartelsman and Gray (1996) productivity data set. Interestingly, this measure also exhibits a sustained increase over this time period. Comparing the upper and lower panels, and in particular the between-plant components of wage and productivity dispersion, suggests that it may be possible to identify common factors underlying the secular increases in wage and productivity dispersion. Both dispersions decline slightly between 1981 and 1982 and between 1984 and 1986, while rising steadily between 1986 and 1992. However, there are some notable differences in the timing of the secular changes. While wage dispersion increases steadily after 1979, productivity dispersion only increases steadily after the early 1980s recession. The differing cyclical fluctuations of dispersion of wages and productivity may reflect a variety of factors such as cyclical variation in capacity utilization and/or factors relevant for the cyclicality of wages. In addition, as Dunne, Haltiwanger and Troske (1997) suggest (and explore) there may be differences in the timing of adjustments in the skill mix of the workforce and adjustments in the technology used at a business. Learning and adjustment costs may imply that changes in the worker mix are not synchronized with either changes in technology or changes in measured productivity in the short-run. While these high frequency timing issues are clearly of interest, in this paper we focus on the long run changes. As

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level is negative (as it can be) in a nontrivial number of cases. The negative value added obviously makes it difficult to use the log of plant-level productivity to compute a dispersion measure. We believe that the 90-10 differential in log productivity and log wages are more robust measures of dispersion than raw productivity and wages. Note, however, that many studies using the LRD have found a very high correlation between labor productivity measured using gross output or value added (see, e.g., Baily, Bartelsman and Haltiwanger (1996) and (2000)). As in the previous section, we estimate the number of hours for nonproduction workers based on the CPS average annual hours worked per nonproduction worker for each two-digit industry and apply these two-digit aggregate average hours worked for a nonproduction worker to the plant-level nonproduction worker variable.

such, in what follows when we analyze the factors driving wages and productivity dispersion, we will primarily focus on the long run change from 1977 to 1992.

Certainly, the aggregate data series suggest that there may be a close link between changes in wage dispersion and changes in productivity dispersion in the manufacturing sector. However, for the analysis we are undertaking, it is also important to establish that there is a link between productivity and wages at the plant level. We begin first by documenting the relationship between productivity and wages at the plant level. The simple cross-sectional correlation between plant wages and plant labor productivity averages .55 between 1977 and 1992 indicating that plants that have higher wages also tend to have higher levels of labor productivity. This correlation is almost constant over time varying between .52 and .57 for all years between 1975 and 1992 and is statistically significant at the .0001 level in all years. Next, we examine the relationship between plant-level changes in wages and plant-level changes in productivity. We construct the correlation between plant-level changes in productivity and plant-level changes in log average hourly wages for 12,904 plants that appear in our data in the four Census years: 1977, 1982, 1987 and 1992.[19] The correlations are .35 for the 1977-1982 period, .36 for the 1982-1987 period, and .39 for the 1987-1992 period and all are statistically significant at the .005 level.

We interpret the simple correlations as demonstrating that there exists a positive cross-plant relationship in the *level* of wages and productivity and a positive cross-plant relationship in the *changes* in wages and productivity. We interpret the aggregate time series presented in Figure

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[19] Census years are the only years for which we can measure changes for all of the surviving plants in our data.

2 as evidence that both cross-plant changes in wage and productivity *dispersion* are moving in a consistent manner over the long run.

To sum up the findings thus far, we have found that much of the increase in overall wage dispersion is due to an increase in the between-plant dispersion of wages across workers. This evidence in itself is interesting as it indicates that the rising wage dispersion is associated with greater segregation by worker skill (where worker skill is measured by wages). In addition, the findings in this section make clear that the rising wage dispersion is accompanied by rising productivity dispersion. These findings alone are consistent with the hypothesis that there are some underlying changes in the technology and/or worker mix across plants driving the changes in wage dispersion. Explanations that rely on shifts between industries (e.g., simple product demand shifts across industries) cannot account for these patterns since we find in Table 1 that most of the increase in wage dispersion is associated with rising wage dispersion *within* industries. While this evidence is suggestive, we have not yet identified observable changes in technology across plants that can account for the dominant role of these between-plant changes. In the subsequent section, we investigate the role of observable factors such as changes in capital intensity and the role of computer investment across plants as potential indicators of the changes in technology across plants.

## V. Analysis of the Sources of Changes in Dispersion of Wages and Productivity

The objective in this section is to investigate the role of observable changes in technology in accounting for the observed changes in wage and productivity dispersion. Our emphasis in this analysis is on the change in capital intensity and computer usage across plants. This emphasis is very much driven by the insights of the theoretical literature discussed in Section II that predicts a close correspondence between changes in capital intensity and the use of advanced technology and changes in wage and productivity distributions across plants.

*A. Specification for Full Distribution Accounting Decomposition Exercises*

In this section of the paper, we examine in greater detail the sources of the change in between-plant dispersion for wages, productivity, and workforce structure. Our approach will follow Juhn, Murphy, and Pierce (1993) (hereafter JMP), and, in particular, Davis and Haltiwanger (1991, 1996) who utilize the JMP full distribution accounting methodology in a similar setting. Davis and Haltiwanger examine changes in between-plant wage dispersion focusing on the role of size in accounting for these changes. In this paper we also control for size but focus on the relative importance of computer investment and capital intensity in accounting for changes in the dispersion of wages *and* productivity. While the influence of computer use and computer investment has been the examined in the context of explaining changes in the mean of the distribution of wages (e.g., Krueger (1993), and Autor, Katz, and Krueger (1998)), and average productivity (Berndt and Morrison (1992), Oliner and Sichel (1994), and Siegel (1997)), little analysis has been undertaken investigating the role of computers in accounting for changes in dispersion of these variables.

The analysis starts with specification of a basic regression model of the following form:

$$y_{it} = X_{it}\beta_t + \mu_{it} \quad \textbf{(3)}$$

where our plant-level variable of interest, $y_{it}$, is wages, productivity, or workforce structure for plant *i* in period *t*, $X_{it}$ is a matrix of observable plant characteristics, $\beta_t$ is a parameter vector, and

$\mu_{it}$ is the residual of the regression.[20] We seek to decompose the change in the dispersion of the dependent variable ($y_{it}$) into three components based on the regression model–changes in the *distribution* of observable plant characteristics (changes in the X's), changes in the differentials associated with the effect of the observables on the dependent variable (changes in the β's), and changes in the distribution of the unobservables (changes in the μ's). That is:

$$y_{it} = X_{it}\bar{\beta} + X_{it}(\beta_t - \bar{\beta}) + \mu_{it} \tag{4}$$

where β is the average effect of the observables on the dependent variable over the whole period. The first term in equation (4) captures the variation due to variation in the distribution of observable characteristics for given effects of these observables. The second term captures variation in the differentials associated with the observable characteristics. The final term (the residual) captures the contributions of changes in the distribution of regression residuals that are unexplained by changes in the β's and changes in the distributions of the X's.

[20] The estimated parameters do not have a direct structural interpretation, rather they are measures of the covariance structure in the data between measures of outcomes and plant characteristics. The theories we outline have predictions about the changes in this covariance structure which we attempt to test. Thus, for example, the estimated coefficient on capital intensity in the labor productivity equation should not be interpreted as a structural estimate of output elasticity from a specification of an intensive production function. The reason for this is that the coefficient may reflect unobserved technology effects that are correlated with capital intensity. In our setting, it is explicitly hypothesized that such unobserved technology effects may be correlated with observables like capital and computer intensity. Moreover, the theories we are investigating suggest that the nature of these unobserved technology effects may have changed over time (e.g., skill-biased technical change that is embodied in observable indicators of technology like capital intensity and computer intensity) so that the covariance between measures of outcomes like productivity and these measures may have changed over time.

The measure of dispersion that we focus on in our decomposition is the difference between the 90th and 10th percentile of the distribution of $y_{it}$.[21] Following equation (4), we decompose the change in the 90-10 differential of $y_{it}$ between 1977 and 1992 into three components.[22] First, using the actual distribution of plant-level labor productivity for 1977 and 1992, we compute the change in the 90-10 differential of $y_{it}$ from 1977 to 1992. Next, we compute the predicted change using the first term in (4) to generate the 90-10 differential in 1977 and the 90-10 differential in 1992 to compute the predicted change from the X's alone. Comparing the predicted to the actual change in the 90-10 differential yields a measure of the change in the dispersion of $y_{it}$ attributable to the change in the distribution of observable characteristics (the X's). Next we compute the predicted change using both the first and second terms of (4). This latter predicted change captures the impact of both changes in the distribution of the X's and changes in the β's. To obtain the *marginal* contribution of just the β's, we compare this change with the change in the overall distribution attributable to the change in the

[21] The careful reader will note that a number of alternative characterizations of dispersion are considered in the paper. In Section II, the variance decomposition is conducted in natural units (as required formally) and components of the decomposition in Figure 1 are depicted in terms of coefficients of variation. In Figure 2, as well as in this section, we focus on the 90-10 differentials of log wages per hour at the plant-level and log productivity at the plant-level. Comparing across dispersion measures (e.g., standard deviation of log wages, coefficient of variation in natural units, 90-10 differential in log wages), we find similar qualitative and quantitative patterns in the behavior of between-plant wage and productivity dispersion. For the analysis in this section, we focus on the 90-10 differential in log wages and productivity since we believe this approach provides the most robust characterization of the relationship between changes in plant-level observables and changes in wage and productivity dispersion.

[22] A more detailed explanation of the JMP methodology can be found in Juhn, Murphy and Pierce (1993), Davis and Haltiwanger (1991, 1996) and Goldin and Margo (1992).

distribution of the X's.[23] The marginal contribution of changes in the distribution of the residuals is then just the total change in the 90-10 differential of the actual distribution minus the change due to changes in both the X's and the β's.

*B. Basic Characteristics of the Plant-Level Data.*

The data used to examine between-plant changes in the dispersion of productivity, wages, and workforce composition come from the same source as the plant-level wage data employed in the prior section. This analysis focuses on explaining the changes in dispersion in five plant-level variables: the log of average plant hourly wages, the log of average plant production worker hourly wages, the log of average plant nonproduction worker hourly wages, the nonproduction labor share of employment, and the log of output per hour. The wage and productivity variables are measured in the same fashion as in the preceding section. The nonproduction labor share variable is our attempt to capture changes in the composition of the workforce in manufacturing establishments. It is measured as the total wages paid to nonproduction workers divided by the total wages paid to all workers in the plant. In papers such as Autor, Katz and Krueger (1998), Berman, Bound and Griliches (1994), Caselli (1999), Dunne, Haltiwanger, and Troske (1997), and Kremer and Maskin (2000) this variable is interpreted as representing a measure of workforce skill.[24]

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[23] We should note that it is possible to get different results depending on the order of the decomposition as well as which year serves as the base year. We deliberately chose to put observable quantities first to give them the greatest opportunity to account for the changes in dispersion.

[24] Both Dunne, Haltiwanger and Troske (1997) and Berman, Bound and Griliches (1994) discuss at considerable length the pro's and con's of using nonproduction labor share as a measure of skill. It is well documented that nonproduction workers are generally more educated than production workers as a group. However, it is also the case that the nonproduction worker

The observable plant characteristics contained in the X matrix include four-digit SIC industry controls, nine census region dummies, nine size class dummies, a multi-unit dummy variable, a measure of capital intensity, and computer investment as a fraction of total investment. While the specification is relatively parsimonious, it allows us to examine two variables of interest–computer investment and capital intensity. In what follows, we permit the coefficients on each of the plant measures (i.e., size dummies, multi-unit dummy, capital intensity and computer investment) to vary by two-digit industry.

The computer investment variable at the plant-level is measured as computer investment as a fraction of total investment.[25] While we would prefer to have a measure of the stock of the computing equipment at each point in time, this information is unavailable. Therefore, we use computer investment in the plant as a proxy for computer usage in the plant (see Berman, Bound

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group includes both workers that would be considered more skilled than the typical production workers (engineers, managers, programmers) but also includes a set of workers that may be less skilled (janitors, guards). Thus, one should be somewhat cautious in interpreting the nonproduction labor share as an index of workforce skill.

[25] In a prior version of this paper, we constructed a relative measure for each plant-year observation computed as the ratio of computer investment per worker at the plant-level to the mean of this variable across all plants in the year. A downside of this alternative procedure is that since average computer investment per worker is increasing over time, dividing through by this in each year implies mechanically a reduction in dispersion in this relative measure. Conceptually, this relative measure is different as well since what matters is the relative differences across plants in a given year rather than any changes in the overall distribution of computer usage. Details of the results using this alternative measure can be found in Dunne et. al. (2000). Using this alternative measure, we still found that computer usage mattered but that the impact was primarily in terms of the wage and productivity differentials associated with this relative measure. Changes in the differentials in relative computer investment playing an important role are consistent with changes in the distribution of actual computer investment across plants playing an important role. We think the current specification is superior both because it is somewhat easier to interpret and the measurement of the variables is consistent with measurement in the related literature.

and Griliches (1994) for a justification). Berman, Bound and Griliches (1994) and Autor, Katz and Krueger (1998) use this same variable as their measure of computer use (though at the industry level). The use of the computer investment variable restricts our analysis to census years (the only years the computer investment question is asked) and reduces the sample size because of the lower response rate to this question.[26]

We measure capital intensity at the plant level as the real value of capital divided by total worker hours. Following Baily, Hulten and Campbell (1992) we construct the real value of capital by multiplying the book value of capital at the plant by the ratio of the real value of capital to the book value of capital in the two-digit industry.

Before proceeding to the analysis, it is important to emphasize that by controlling for many factors simultaneously, we are able to isolate the marginal contribution of each of our variables. For example, consider the contribution of computer investment. Since we are also controlling for size and capital intensity, we are not simply picking up size and capital deepening effects on wages and productivity with our computer investment measure.

Table 3 presents some basic descriptive statistics for each of the variables for the years 1977 and 1992. The statistics are hours-weighted means and 90-10 differences. Panel A represents all plants used in the analysis in Section III. Panel B represents a restricted sample that includes all plants that report detailed investment data. The restricted sample forms the basis of the regression and decomposition analyses in this section. The basic statistics show that for the wage, productivity, and nonproduction labor share variables between plant dispersion has

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[26] See Troske (1996) for a discussion of the computer investment question on the Annual Survey of Manufactures (ASM). On average 60% of plants in the ASM respond to this question in each year.

increased over the 15 year period for both samples. These patterns for productivity and wages were noted earlier in the paper.

The bottom two rows of Panel B report the summary statistics for the capital-labor ratio and the computer investment variables. The mean of the capital-labor ratio has risen markedly over the period while the dispersion in the capital-labor ratio has risen more modestly over the period. It is important to note that the dispersion of the capital-labor ratio is quite large implying that even a small change in the wage or productivity differential associated with capital intensity can have a very large impact on the distribution of wages or productivity. With respect to computer investment, both the mean and 90-10 difference have increased over time. The sharp rise in the mean of computer investment as a fraction of total investment represents two forces at work. First, the percentage of plants that report positive investment expenditures on computing equipment rises sharply over the period. In 1977, 10.2% of plants report positive computing expenditures while 61.9% report positive computing expenditures in 1992. Second, the mean computer investment as a fraction of total investment for plants with positive spending on computer investment increased over the period.

C. *Summary Statistics on Basic Regression Results*

Before proceeding to the JMP full distribution accounting exercises, we present summary information on the basic regression results. Table 4 presents selected summary parameter estimates from the regressions involving each of the five dependent variables under consideration: hourly wages, production worker wages, nonproduction worker wages, nonproduction labor share, and labor productivity. To implement the JMP exercises, the specifications are estimated for each year and are also estimated pooling the data across years (to obtain the fixed β component).   Recall that the regression models allow for the coefficients on the computer investment and capital intensity variables to vary across two-digit industry.  Thus, for each dependent variable, we have 19 computer investment coefficients and 19 capital intensity coefficients in each year (as well as the coefficients from the pooled specification).[27]

Table 4 reports the mean and the range of the coefficients for the computer and capital variables for the base specification.  For each of the dependent variables under consideration, the computer investment per worker coefficients change substantially over time.  For example, in 1977, the average computer investment coefficient in the hourly wage regression is .0417.  However, by 1992, the average coefficient increases substantially to .1047  This upward trend in the computer investment coefficients is exhibited for all five dependent variables. The average capital intensity coefficient has also tended to increase over time. For example, the average capital intensity coefficient in the hourly wage regression increases from 0.0867 in 1977 to 0.1026 in 1992.  Of course, considerable caution must be used in translating these changes in average industry coefficients into the implied changes in wage and productivity dispersion since ultimately we need to consider the interaction between the changes in the coefficients for every industry with the changes in the dispersion in capital and computer intensities in each industry. Indeed, it is via the JMP exercises that we consider this interaction since the JMP methodology itself provides the appropriate weighting and aggregation of the changes in characteristics and the changes in differentials associated with these characteristics.

*D.  Full Distribution Accounting Exercises*

[27] Because of small sample sizes, we have combined plants in the Food (20) and the Tobacco (21) industries into one industry, giving us 19 two-digit industries.

Utilizing the information from the regressions, we examine changes in the dispersion of the between-plant wages, labor productivity, and workforce structure using the JMP analysis discussed above. In the results reported in the paper, we do not condition the residual distribution on any observable variables.

Table 5 reports summary measures of the decompositions of the changes in dispersion from 1977-92.[28] To start, we focus on changes in the distribution of hourly wages for all workers (column 1). In the full model, changes in the distribution of observables for fixed β's yield a 10% increase in hourly wage dispersion from 1977-92 (Observables from Panel A as percent of Total–.012/.118), while changes in the β's account for almost 40 % of the 1977-92 change (Beta's from Panel A as a percent of Total–.047/.118). The remaining fraction is accounted for by changes in the distribution of the unobservables.

The results for hourly wages based upon the marginal contribution of computer investment per worker only, capital intensity only or size only are reported in panels B, C, and D respectively. These results are generated as follows. We set all other right-hand side variables at their sample means and use the pooled coefficients for all other variables and then consider the marginal contribution of each of the variables in question to the changes in dispersion. That is, we consider the contribution of the change in the distribution of the variable and its differential in isolation, having controlled for the influence of all of the other variables. Note that this implies that the contribution of unobservables reported when we conduct one of the marginal exercises

[28] See Dunne et al (2000) for the JMP analysis of changes in dispersion for the three subperiods 1977-1982, 1982-1987, and 1987-1992 as well.

includes the influence of time variation in the distribution of the other observable variables and their differentials.

Panel B shows that for computer investment there is a much larger positive marginal contribution of the observable characteristics compared to the observable contribution of all of the variables in the full model and less of a contribution of changes in the $\beta$'s.  How can this happen?  It is important to remember that some variables can act to increase dispersion while others can act to decrease dispersion.  Apparently, there are some of the "observable" variables in the full model that act to decrease dispersion.  In what follows, we will explore which variables act in this manner.

For the marginal contribution of capital intensity, we also find a larger role for changes in the distribution of observables and actually a modestly negative contribution of changes in the differentials associated with capital intensity.  For the marginal contribution of size, we find that changes in the distribution of observables do not contribute very much but that changes in the size wage differentials account for about 33% of the rising dispersion in wages.  This latter result is closely related to the analogous finding in Davis and Haltiwanger (1991) that rising size wage differentials account for a substantial fraction of rising wage dispersion for the 1972-86 period.

Putting the pieces together suggests that for wages, rising dispersion is accounted for by rising dispersion in the distribution of computer investment and capital intensity across plants as well as rising wage differentials associated with computer investment and size.   In addition, there are apparently other variables where changes in the distribution of those variables are actually acting to decrease dispersion (we examine these offsetting variables later in this paper).

Columns 2 and 3 of Table 5 show the results for changes in the dispersion of the component wage variables (the log of the average production worker hourly wage and the log of the average nonproduction worker hourly wage). The results for production workers' wages are similar to the results for average hourly wage. For the full model, we find that the changes in the distribution of observable characteristics for fixed β's yield only a very modest increase in dispersion. In contrast, changes in the differentials associated with the characteristics account for a substantial fraction of the increase in dispersion. For the marginal contribution of computers and capital, it is again changes in the distribution of observables that become important although changes in the β's play an important role as well. For production worker wages, size effects play little or no role. In the case of the nonproduction worker wages, similar results are observed, although unobservables account for a larger fraction of the overall change in dispersion. Other notable differences are that wage differentials associated with capital intensity actually cause a decrease in dispersion for nonproduction workers and size wage differentials generate a very large increase in dispersion for nonproduction workers.

Turning to the nonproduction labor share results (Column 4) we find that changes in the distribution of characteristics for fixed β's and changes in differentials associated with those characteristics play an important role. Looking at the marginal effects, we see that changes in the distribution of computer investment, changes in the distribution of capital intensity, and changes in the size differentials all account for significant shares of the increase in dispersion in the nonproduction labor.

Turning now to the productivity decompositions (Column 5), we observe that the patterns for productivity largely mimic those for wages but with some important differences. Similar to wages, changes in the distribution of observables do not contribute much but changes in the differentials associated with those observable characteristics are important. Looking at the marginal effects, changes in the distribution of computer investment, changes in the distribution of capital intensity, and changes in size differentials all contribute positively to rising productivity dispersion. For productivity, we find that changes in the computer investment and capital intensity differentials actually leads to falling dispersion.

Four reasonably robust patterns emerge from the JMP analysis. First, changes in the distribution of computer investment across plants contribute substantially to rising wage, productivity and nonproduction share dispersion. Second, changes in the distribution of capital intensity across plants contribute substantially to rising wage, productivity, and nonproduction share dispersion. Third, rising size differentials contribute substantially to rising wage, productivity and nonproduction share dispersion. Fourth, the full model results suggest that some other factors are systematically acting to reduce dispersion. We turn to this latter point now.

Table 6 reports results of the JMP analysis under an alternative specification in which 4-digit industry and region effects are not included in the model. We still permit the response to changes in variables like computer investment, capital intensity and size to vary by 2-digit industry but we remove the influence coming from shifts in the distribution of hours across industries and regions and changes in the industry and region differentials. The removal of the industry and region effects has a nontrivial impact on the full model results but relatively little impact on the results of the marginal contributions of computer investment and size. It has some impact on the marginal contribution of the capital intensity effects. The largest change is for the full model. Here we find that observables now account for a substantially larger fraction of changes in productivity dispersion and that in general unobservables play a smaller role for all variables. Apparently, industry/region composition changes together with changes in industry/region differentials are acting to reduce dispersion. We also find that changes in capital intensity differentials act to increase dispersion in wage, productivity and nonproduction share differentials. Allowing cross industry variation in capital intensities to help identify the capital intensity effects yields a greater role for capital intensity differentials. To sum up, industry/region effects play a nontrivial role in the changing dispersion of wages, productivity and labor share. In particular, there is a tendency for industry/region effects to decrease dispersion. For the most part, these industry/region effects do not cloud the main messages from the marginal contribution of computer investment, size and capital intensity. That is, regardless of the role of industry/region effects, we find changes in the distribution of computer investment, changes in the distribution of capital intensities, and changes in the size wage differentials all act to increase dispersion in wages and productivity.

These results document the fact that differences in technology use across plants are closely related to rising wage and productivity dispersion in manufacturing. It is important to emphasize that the finding of an important role for computer usage and capital intensity is based upon an analysis that controls for many other factors as well. Among these other factors is size, and like Davis and Haltiwanger (1991), we find that rising size differentials play an important role. As Davis and Haltiwanger emphasize there may be many factors that underlie rising size wage differentials – although they argue and provide evidence that the rising size wage differentials are consistent with skill-biased technical change. Our value-added here is that we are able to provide more direct measures of alternative use of technology in the analysis and we are able to explore the implications for not only wage dispersion but also productivity dispersion. The co-variation in the direct measures of technology, wages, and productivity across plants provides strong evidence that rising wage and productivity dispersion is due to differential adoption of advanced technology across plants.

## VI. Summary and Interpretation of Findings

This paper has documented and analyzed changes in the dispersion in wages and productivity for the manufacturing sector. Our main findings are that (1) the between-plant component of wage dispersion is an important and growing part of total wage dispersion; (2) much of the between-plant increase in dispersion is within industries; (3) the between-plant measures of wage and productivity dispersion have increased substantially over the last few decades; and (4) a substantial fraction of the rising dispersion in wages and productivity is accounted for by changes in the distribution of computer investment and capital intensities across plants and by rising size wage differentials across plants.

The results are consistent with the hypothesis that the factors leading to rising wage dispersion act through between-plant rather than within-plant effects. Moreover, the results are consistent with the hypothesis that it is the differential adoption of advanced technology that underlies these between-plant differences. Put differently, the results are consistent with models like that of Kremer and Maskin (2000) regarding skill segregation across plants and that of Caselli (1999) regarding the role of differential technology adoption across plants in an environment with skill segregation and skill-biased technical change. These models predict rising *between-plant* wage and productivity dispersion which is consistent with our findings. Moreover, the Kremer and Maskin model predicts an increase in segregation by worker skill across plants which is also consistent with our findings. In addition, the Caselli model predicts that the rising wage and productivity dispersion across plants will be associated with differences in technology adoption across plants in response to a skill-biased technological revolution. Our findings are consistent with this latter prediction in the sense that we find that a substantial fraction of the rising wage and productivity dispersion is accounted for by rising wage and productivity differentials across plants with different capital and computer intensities.

While the results are consistent with a differential technology adoption across plants view of rising dispersion, there are some caveats about ruling out other competing hypotheses. The finding that much of the increases in wage and productivity dispersion are within narrowly defined industries is evidence against explanations that involve between industry effects (such as shifts in product demand say due to changing trade patterns). However, it is possible that there are product demand shifts across plants in the same narrowly defined industry that could account for some aspects of our results. Consider, for example, a shift between products in the same four-digit industry where plants in the same industry differ systematically in their product and skill mix. A shift towards products produced by high skilled workers and away from products produced by low skilled workers could yield rising wage dispersion across plants in the same industry and rising *measured* productivity dispersion. The latter could arise as the four-digit price deflators would not capture the relative price change within the industry implying systematic productivity mismeasurement across plants in the same industry. Even under this scenario one would have to account for the rising wage and productivity dispersion due to changes in computer investment and capital intensities across plants. There might be a systematic relationship between product mix, skill mix, and technology used at the plant, but such a systematic relationship would begin to make this scenario closely linked to a broadly defined notion of skill-biased technical change.

One could likewise argue that some change in institutions would yield a pattern of within industry, between-plant increases in wage and productivity dispersion. Consider the possible impact of deunionization. Deunionization arguably may have yielded less wage compression and a relaxation of work rule constraints that could yield changes in wage and productivity dispersion across plants. However, here again, one would need to account for the fact that this rising wage and productivity dispersion is associated with changes in the distribution of computer investment and capital intensity across plants.

To conclude, we have documented that the rising overall wage dispersion in the U.S. economy is associated with rising wage and productivity dispersion across plants within the same narrowly defined industries. Moreover, a substantial fraction of this rising wage and productivity dispersion is accounted for by changes in the distribution of computer investment and capital intensity as well as rising size-wage differentials across plants. Such findings are consistent with models of increased segregation by skill across plants and rising wage and productivity dispersion from skill-biased technical change that involves differential adoption of new technologies across plants. It may be that there are other models/hypotheses consistent with these findings but they will have to account for both the dominant role of between-plant effects and the important role of differences in capital intensity and computer intensity across plants.

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## Data Appendix

### Combining Household and Establishment Survey Data -- Measurement Issues

Several measurement error issues arise in combining information from household and establishment surveys. Since Davis and Haltiwanger (1991) provide an extensive discussion of these issues in this context, we review only the most salient issues here. First, unlike Davis and Haltiwanger (1991), we incorporate auxiliary establishments into our analysis using data from the Standard Statistical Establishment List (SSEL) which includes the universe of all establishments in each year. Therefore, our establishment-level data contain wage information for all manufacturing workers.

Second, like Davis and Haltiwanger (1991, 1996), we must confront the difficulties associated with the fact that we have hours data only for production workers. We impute hours-per-worker for nonproduction workers in our augmented LRD as follows. Using the CPS, we calculate the ratio of hours-per-worker for production and nonproduction workers at the two-digit level. Using this ratio, and the measured hours-per-worker for production workers at the plant-level in the LRD, we impute the hours-per-worker for nonproduction workers in a plant by requiring the ratios be the same in the CPS and the LRD.[29] Since this is at best a crude procedure, we further adjust the LRD means and variances of hourly wages for nonproduction workers so that the ratio of the LRD to CPS mean of hourly wages for nonproduction workers equals the corresponding ratio for production workers.[30] We carry out this latter adjustment at the two-digit industry level (i.e., we do not require this ratio to hold at the plant-level).

While this methodology for combining household and establishment level data may be imprecise in a given year (especially for nonproduction workers), the time series changes in the respective contributions should be robust as long as the measurement error problems are stable over time. As will become clear, there is considerable evidence in favor of this argument.

Table A1 presents summary statistics for hourly wages for all workers, nonproduction workers, and production workers for selected years. The first two columns are based upon the CPS, the second two columns are from the LRD, the next two columns are from the LRD supplemented with auxiliary establishments, and the last two columns are from the LRD augmented to incorporate the comparability adjustment described above (and also including the auxiliary establishments).[31] All statistics are in 1987 dollars and are on an hours-weighted basis so that CPS and LRD tabulations are in principle directly comparable.

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[29] For auxiliary establishments which, by definition, contain no production workers, we use the average number of hours worked by production workers in a given two-digit industry in the CPS to impute hours worked in these establishments.

[30] This adjustment imposes no restrictions on the ratios of the variances of wages of production and nonproduction workers.

[31] The between-within decompositions use the augmented LRD (columns 7-8), the JMP decompositions use the raw LRD (columns 3-4).

It is apparent from Table A1 that the LRD yields higher average hourly wages for all workers in each year and that this is primarily driven by substantially higher average hourly wages for nonproduction workers (for example, the LRD with auxiliary establishments included has average nonproduction wages that are more than 10% higher than those in the CPS).[32] However, the time series patterns in the mean wages across the different data sets are quite similar. The five year growth rates are similar across the CPS and the LRD for all manufacturing workers, nonproduction workers, and particularly for production workers. In addition, the time series patterns for average hourly wages for the different versions of the LRD exhibit similar patterns. The close correspondence in the time series patterns across the CPS and LRD provides further support for the argument that one can compare the CPS and the LRD to learn about the sources of time series changes in the patterns of wages.

While the means should in principle match up across the CPS and the LRD, the standard deviations of hourly wages may exhibit quite different patterns. The CPS standard deviation will reflect both within-plant and between-plant differences in wages across workers while the LRD

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[32] Note that Davis and Haltiwanger (1991,1996) also found higher average hourly earnings in the LRD and that this was driven primarily from nonproduction workers. One important factor is likely the crude imputation procedure for hours for nonproduction workers which motivates the further adjustment of nonproduction hourly wages in the LRD. Note that we have also discovered some differences between the results reported here and those in Davis and Haltiwanger (1991, 1996). Davis and Haltiwanger (1996) also augmented the LRD with auxiliary establishments for an analysis of wage dispersion in 1982. Their tabulations of 1982 wages from the CPS and the LRD for 1982 yield a substantially smaller gap between CPS and LRD hourly wages. The sources of these differences likely reflect some other differences between the data files used in the respective analyses. Davis and Haltiwanger use public use CPS files with top coded wages and adjust for top coding in the manner developed by Katz and Murphy (1992). In contrast, we are using internal CPS files without top coded wages. Interestingly, we find somewhat lower average wages using the internal CPS files than the public use files adjusted for top coding. Another source of difference is the auxiliary establishment CAO files. Davis and Haltiwanger use auxiliary establishment files processed during the economic censuses while we use auxiliary establishment files directly from the SSEL. The files from the economic censuses have been more thoroughly edited which may be important. In practice, we find higher average wages in our auxiliary establishment files from the SSELs than the auxiliary establishment files from the economic censuses. We created our auxiliary establishment files from the SSELs as opposed to the economic censuses since the latter are available only every five years. We decided not to mix census-based auxiliary establishment files and SSEL-based auxiliary establishment files in non-census years to avoid changes in measurement methodology over time.

standard deviation will only reflect between-plant differences in wages across workers. Accordingly, the CPS standard deviation exceeds the LRD standard deviation in each year for all workers and for each worker type. Interestingly, however, the time series increase in the CPS standard deviation of hourly wages over the 1977-92 period is mimicked by similar time series increases in the LRD standard deviation. Further, the fourth column in Table A.1 indicates that the increase in between-plant wage dispersion for all manufacturing plants is associated with an increase in between-plant wage dispersion for *operating* manufacturing establishments.

Table 1: Between-Plant and Within-Plant Components of Hourly Wage Variance.

| | 1977 (1) | 1982 (2) | 1987 (3) | 1992 (4) |
|---|---|---|---|---|
| *A. Measures of Dispersion* | | | | |
| Total Wage Variance | 43.18 | 42.83 | 58.01 | 61.13 |
| Coefficient of Variation: | | | | |
| Total | .58 | .56 | .64 | .68 |
| Within plant | .43 | .36 | .45 | .45 |
| Within plant, PW | .22 | .19 | .25 | .21 |
| Within plant, NPW | .47 | .32 | .42 | .38 |
| Between plant | .40 | .43 | .45 | .51 |
| Between plant, PW | .41 | .44 | .45 | .47 |
| Between plant, NPW | .44 | .48 | .49 | .56 |
| *B. Shares of Dispersion* | | | | |
| $\alpha V^P$ | .34 | .34 | .27 | .21 |
| $\alpha V_W{}^P$ | .08 | .05 | .07 | .04 |
| $\alpha V_B{}^P$ | .26 | .29 | .20 | .17 |
| $\alpha V_{BPI}{}^P$ | .18 | .20 | .15 | .13 |
| $\alpha V_{BI}{}^P$ | .08 | .08 | .05 | .04 |
| $(1-\alpha)V^N$ | .58 | .58 | .63 | .68 |
| $(1-\alpha) V_W{}^N$ | .31 | .18 | .27 | .21 |
| $(1-\alpha) V_B{}^N$ | .27 | .40 | .36 | .47 |
| $(1- \alpha) V_{BPI}{}^N$ | .25 | .37 | .32 | .42 |
| $(1- \alpha) V_{BI}{}^N$ | .03 | .03 | .04 | .05 |
| $\alpha(1-\alpha) (W^P-W^N)^2$ | .08 | .08 | .10 | .11 |
| $\alpha$ | .68 | .61 | .60 | .57 |

*Notes:*
(1) Measures of Dispersion: PW refers to production workers, NPW refers to nonproduction workers.
(2) Shares of Dispersion: The variance decomposition is based on equation (2) in the text. Superscript denotes worker-type (P= production workers, N= nonproduction workers), subscript denotes component-type (W=within plants, B=between plants, BPI=between plants, within industries, BI=between industries).
(3) All figures are in 1987 dollars and are computed on an hours-weighted basis. As described in the text, the tabulations are based on data from the LRD and CPS.

Table 2: Kremer-Maskin Segregation Index

| | All Workers (1) | Production Workers (2) | Nonproduction Workers (3) |
|---|---|---|---|
| 1977 | 0.47 | 0.77 | 0.47 |
| 1982 | 0.59 | 0.84 | 0.69 |
| 1987 | 0.50 | 0.76 | 0.57 |
| 1992 | 0.56 | 0.83 | 0.69 |

Note: The Kremer-Maskin (2000) Segregation Index is $V_b^i/V_T^i$, where i indexes worker type: all workers, production workers or nonproduction workers, b indicates the variance is between plant, while T indicates the total variance. The index is constructed using augmented LRD data.

Table 3: Descriptive Statistics of LRD Data Set

| | 1977 | | 1992 | |
|---|---|---|---|---|
| | Mean (1) | 90-10 Difference (2) | Mean (3) | 90-10 Difference (4) |
| | *A. All Plants in the Data* | | | |
| Log Hourly Wage | 2.41 | 0.95 | 2.37 | 1.07 |
| Log Production Worker Hourly Wage | 2.32 | 1.03 | 2.24 | 1.11 |
| Log Nonproduction Worker Hourly Wage | 2.66 | 0.96 | 2.64 | 1.13 |
| Nonproduction Labor Share | 0.26 | 0.46 | 0.31 | 0.57 |
| Log Output Per Hour | 3.74 | 1.77 | 4.02 | 1.92 |
| | *B. Restricted Sample* | | | |
| Log Hourly Wage | 2.46 | 0.90 | 2.42 | 1.02 |
| Log Production Worker Hourly Wage | 2.36 | 0.98 | 2.29 | 1.07 |
| Log Nonproduction Worker Hourly Wage | 2.69 | 0.90 | 2.67 | 1.03 |
| Nonproduction Labor Share | 0.27 | 0.46 | 0.32 | 0.58 |
| Log Output Per Hour | 3.82 | 1.71 | 4.12 | 1.88 |
| Computer Investment to Total Investment Ratio | 0.04 | 0.08 | 0.14 | 0.42 |
| Log Capital-labor Ratio | 3.27 | 2.45 | 3.57 | 2.58 |

Note: The restricted sample includes only plants that report detailed investment data.

Table 4: Summary Measures of the Distribution of Regression Coefficients By Two-Digit Industry on Computer and Capital Intensity for Main Specification

| | 1977<br>(1) | 1992<br>(2) | Pooled<br>(3) |
|---|---|---|---|
| | *A. Hourly Wage* | | |
| Computers Mean | .0417 | .1047 | .0754 |
| Computers Range | -.134, .224 | .033, .219 | -.031, .201 |
| Capital-Labor Mean | .0867 | .1026 | .1027 |
| Capital-Labor Range | .033, .151 | .036, .175 | .059, .146 |
| | *B. Production Worker Wage* | | |
| Computers Mean | .0057 | .0309 | .0010 |
| Computers Range | -.351, .221 | -.208, .226 | -.194, .159 |
| Capital-Labor Mean | .0860 | .1017 | .1025 |
| Capital-Labor Range | .017, .150 | .059, .162 | .064, .147 |
| | *C. Non-Production Worker Wage* | | |
| Computers Mean | .0321 | .1109 | .0878 |
| Computers Range | -.216, .340 | .017, .269 | -.047, .211 |
| Capital-Labor Mean | .0548 | .0635 | .0630 |
| Capital-Labor Range | .002, .124 | .007, .173 | .004, .133 |
| | *D. Non-Production Share* | | |
| Computers Mean | .0860 | .1064 | .1034 |
| Computers Range | -.036, .251 | .027, .245 | .020, .233 |
| Capital-Labor Mean | .0046 | .0146 | .0109 |
| Capital-Labor Range | -.064, .040 | -.021, .076 | -.029, .046 |
| | *E. Productivity* | | |
| Computers Mean | -.0581 | -.0048 | -.0421 |
| Computers Range | -.355, .423 | -.184, .333 | -.162, .330 |
| Capital-Labor Mean | .2277 | .2399 | .2418 |
| Capital-Labor Range | .065, .548 | .119, .471 | .116, .429 |

Note: Regressions include four-digit industry and region intercepts and, in addition to the computer and capital intensity variables, the models also includes size and multiunit status interacted with two-digit industry.

Table 5: JMP Full Distributional Accounting Components for Changes in 90-10 Differentials

| | Hourly Wage (1) | Production Wages (2) | Nonprod Wages (3) | Nonprod. Labor Share (4) | Labor Productivity (5) |
|---|---|---|---|---|---|
| Total 1977-1992 Change | .118 | .093 | .128 | .111 | .161 |
| *A. Full Model Decomposition* | | | | | |
| Observables | .012 | .002 | .000 | .039 | -.005 |
| Beta’s | .047 | .045 | .030 | .044 | .093 |
| Unobservables | .059 | .047 | .098 | .028 | .073 |
| *B. Marginal Contribution of Computer Investment* | | | | | |
| Observables | .033 | .020 | .025 | .041 | .033 |
| Beta’s | .012 | .013 | .014 | .003 | -.010 |
| Unobservables | .073 | .060 | .090 | .068 | .137 |
| *C. Marginal Contibution of Capital Intensity* | | | | | |
| Observables | .045 | .035 | .033 | .020 | .086 |
| Beta’s | -.004 | .055 | -.058 | -.029 | -.063 |
| Unobservables | .076 | .004 | .153 | .120 | .139 |
| *D. Marginal Contribution of Size* | | | | | |
| Observables | .004 | -.004 | -.005 | .007 | .010 |
| Beta’s | .039 | .003 | .201 | .028 | .110 |
| Unobservables | .075 | .094 | -.068 | .076 | .040 |

Table 6: JMP Full Distributional Accounting Components for Changes in 90-10 Differentials
Without Industry and Region as Controls

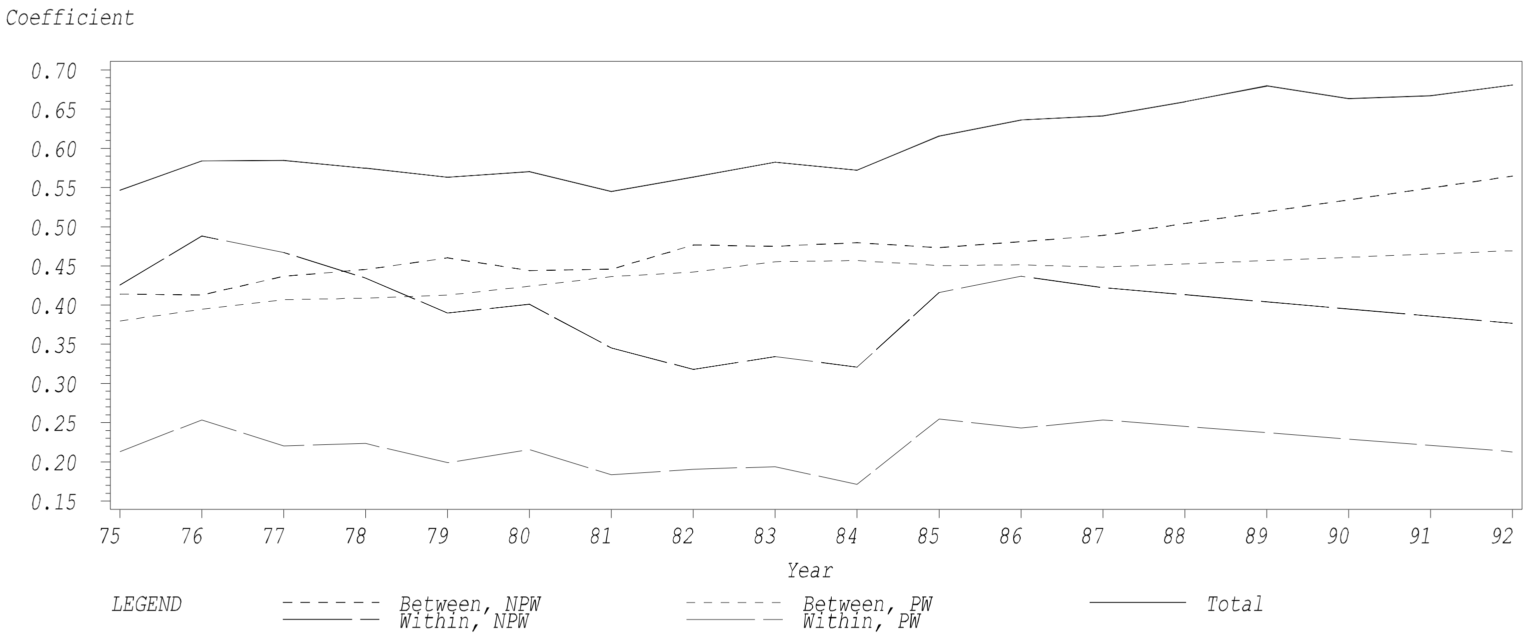
| | Hourly Wage (1) | Production Wages (2) | Nonprod Wages (3) | Nonprod. Labor Share (4) | Labor Productivity (5) |
|---|---|---|---|---|---|
| Total 1977-1992 Change | .118 | .093 | .128 | .111 | .161 |
| *A. Full Model Decomposition* | | | | | |
| Observables | .010 | .005 | .004 | .047 | .091 |
| Beta's | .050 | .052 | .005 | .049 | .018 |
| Unobservables | .058 | .036 | .119 | .015 | .053 |
| *B. Marginal Contribution of Computer Investment* | | | | | |
| Observables | .049 | .024 | .033 | .083 | .054 |
| Beta's | .022 | .019 | .012 | -.003 | -.003 |
| Unobservables | .046 | .051 | .083 | .032 | .110 |
| *C. Marginal Contibution of Capital Intensity* | | | | | |
| Observables | .025 | .027 | .036 | .034 | .008 |
| Beta's | .064 | .122 | .010 | -.094 | .167 |
| Unobservables | .029 | -.055 | .082 | .172 | -.014 |
| *D. Marginal Contribution of Size* | | | | | |
| Observables | .020 | -.005 | .028 | .003 | -.060 |
| Beta's | .167 | .244 | .159 | -.008 | .099 |
| Unobservables | -.069 | -.145 | -.059 | .116 | .122 |

Table A1: Mean and Standard Deviation of Worker Wages (1987 Dollars)

| Year | CPS | | LRD | | LRD with CAOs | | Augmented LRD | |
|---|---|---|---|---|---|---|---|---|
| | Mean (1) | Std. Deviation (2) | Mean (3) | Std. Deviation (4) | Mean (5) | Std. Deviation (6) | Mean (7) | Std. Deviation (8) |
| *A. All Workers* | | | | | | | | |
| 1977 | 11.24 | 6.57 | 11.76 | 4.11 | 12.14 | 4.61 | 11.96 | 4.49 |
| 1982 | 11.62 | 6.54 | 12.07 | 4.45 | 12.59 | 5.21 | 12.30 | 5.01 |
| 1987 | 11.88 | 7.62 | 12.45 | 4.69 | 12.95 | 5.55 | 12.67 | 5.38 |
| 1992 | 11.49 | 7.82 | 11.87 | 4.81 | 12.55 | 5.96 | 12.31 | 5.86 |
| *B. Nonproduction Workers* | | | | | | | | |
| 1977 | 13.97 | 8.93 | 15.04 | 5.98 | 15.58 | 6.35 | 14.96 | 6.10 |
| 1982 | 13.96 | 8.00 | 14.95 | 6.28 | 15.78 | 6.97 | 14.95 | 6.65 |
| 1987 | 14.78 | 9.55 | 16.01 | 6.63 | 16.69 | 7.53 | 15.97 | 7.23 |
| 1992 | 14.47 | 9.82 | 15.25 | 7.16 | 16.35 | 8.30 | 15.80 | 8.17 |
| *C. Production Workers* | | | | | | | | |
| 1977 | 9.98 | 4.62 | 10.68 | 4.06 | 10.68 | 4.06 | 10.68 | 4.06 |
| 1982 | 10.13 | 4.88 | 10.83 | 4.48 | 10.83 | 4.48 | 10.83 | 4.48 |
| 1987 | 9.92 | 5.11 | 10.67 | 4.45 | 10.67 | 4.45 | 10.67 | 4.45 |
| 1992 | 9.23 | 4.76 | 9.91 | 4.33 | 9.91 | 4.33 | 9.91 | 4.33 |

Notes: For "Augmented LRD," the LRD wages for nonproduction workers have been adjusted so that the ratio of hourly wages for production and nonproduction workers in the LRD is the same as that in the CPS at the two-digit industry level.

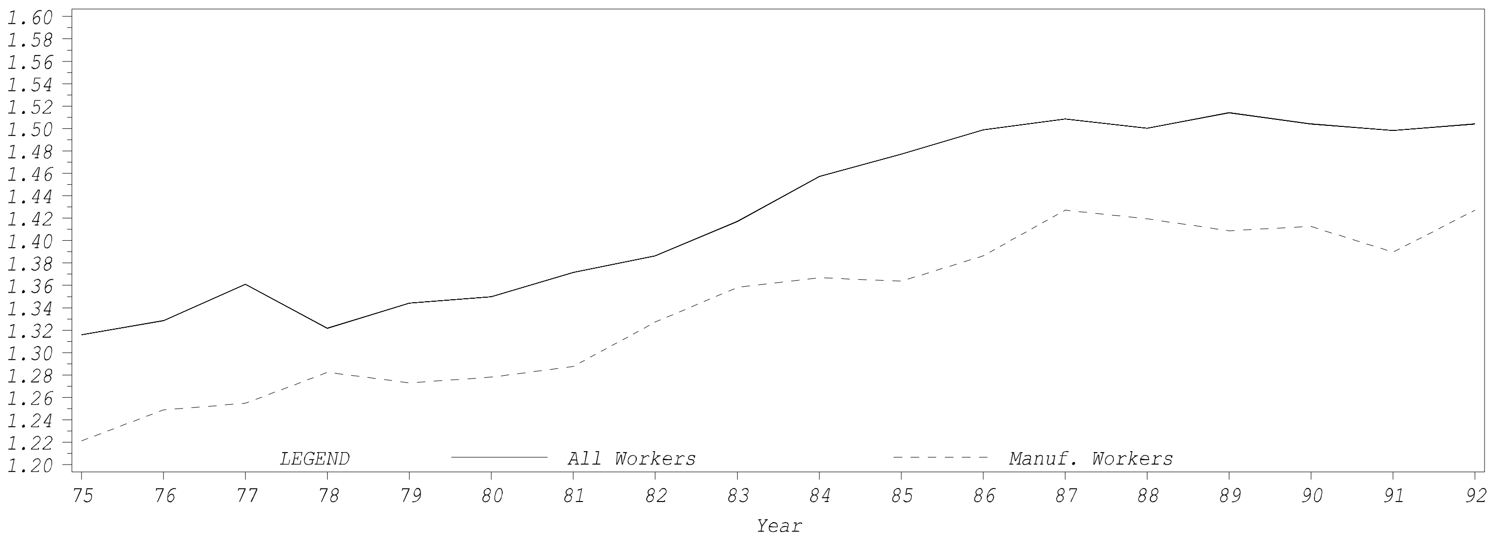
Figure 1: Coefficient of Variation Within-Plant, Between-Plant



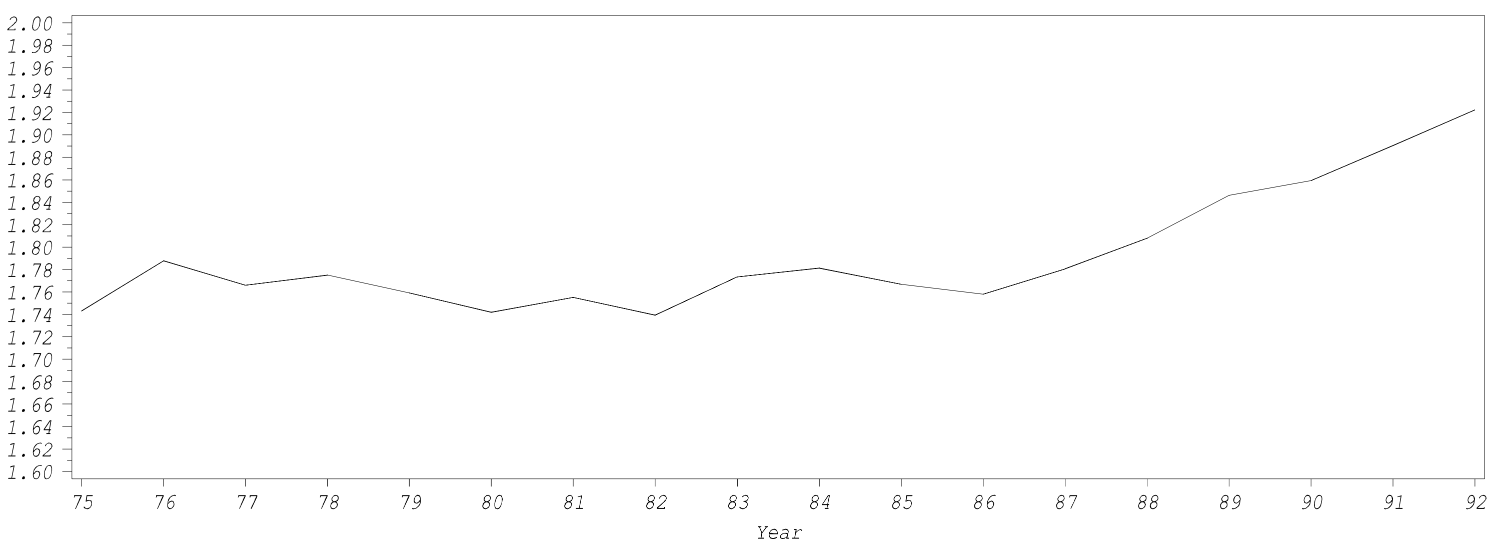

Note: 1988-1991 components are interpolated

Figure 2: Dispersion in Log Worker Wages and Productivity

*A. Wage Dispersion*




*B. Between-Plant Productivity Dispersion in Manufacturing*




*Source: Internal Census Bureau March CPS files and LRD*