Establishment Wage Differentials and Occupational Employment: A Study of Aircraft Parts Manufacturing

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Abstract
Studies over the last two decades make clear that firms' attempts to remain competitive in a global economy have taken them in many different directions. The proliferation of strategies has thrown into relief patterns by which differences in the wage structure of establishments appear to be associated with the ways they are organizing work and implementing new technologies. This study investigates these issues using latent variable techniques and a dataset produced by the Bureau of Labor Statistics' Occupational Employment Statistics Survey. The analyses define a latent variable underlying various measures of the wage structure of the establishment that include 1) a measure designed to gauge establishments' usage of particular types of wage policies aimed at increasing qualitative flexibility, 2) those occupational wages that are most highly correlated with the wage structure of the establishment, and 3) the employment share of those occupations that have been identified in earlier analyses as "discriminators' between high and low wage establishments. Data from the Bureau of Labor Statistics' Occupational Employment Statistics Survey is especially well suited to these analyses due to its collection of wage data for all workers in the establishment, as is required to produce measures of the establishment wage structure, and its large size and high degree of industrial and occupational detail, such that relationships between the wages of detailed occupations and other variables can be examined even within detailed industries. The findings suggest that, in the Aircraft Parts industry, establishments' employment share of machinists is correlated with a latent construct defined by the inter-correlation of the wages of Inspectors, the wages of Team Assemblers, and a measure of the establishment wage structure that should co-vary with the incidence of worker cross training and/or a pay-for-skills policy in the establishment.

Key Words : factor structured logit, mixed logit, latent variable model, multilevel modeling

1. Introduction

A large literature now documents findings that a substantial portion of the churning in labor markets over recent decades has occurred within industries; increases in earnings variance, occupational upgrading, and a proliferation of strategies for the internal organization of the establishment including the implementation of new technologies have all occurred within industries.[1] These trends are mirrored in cross sectional studies as heterogeneity among establishments within even narrowly defined industries on a score of characteristics including wages, technology usage, and internal organization. A number of

[1] See Wever, Kirsten 1995. Chapter 1 for discussion of the US institutional framework of labor/management relations and the causal dynamics of this proliferation.

studies find that establishments' wage differentials are correlated with measures of their internal practices, including their technology usage, causing some to suggest that establishment wage policies and technology usage appear to be codetermined to some degree.

An overarching question has been the degree to which the observed heterogeneity reflects differences among organizations in the constraints affecting their responses to technology-driven imperatives versus differences in the policy choices of organizational decision makers that arise from differences in organizational culture, environmental constraints, and assumptions about worker motivation and organizational functioning.

The study investigates these questions using latent variable techniques aimed at uncovering the causal factors underlying the pattern by which the wages and employment shares of particular types of occupations are correlated with the establishment wage differential (establishment average wage). Previous studies by this author (Osburn, 2000) have shown that those occupational wages most highly correlated with the establishment wage differential are those occupations most directly involved in the primary activities of the establishment, and those most directly involved in the most technical and complex activities. In aircraft parts manufacturing, these occupations include Machinists, Inspectors, and Team Assemblers, as well as Tool and Die makers and Numerically-Controlled Machine Tool Setters and Operators.

The study attempts to account for this pattern using measures of the establishment wage structure designed to gauge establishments' usage of wage policies aimed at increasing qualitative flexibility, including worker cross training policies and/or pay-for-skills, and worker sorting. The analyses attempt to determine which occupations' wages and/or employment "stick" with these more content-laden measures of the wage structure. Those occupations whose wages or employment are both 1) most highly correlated with the overall wage differential of the establishment, and 2) most highly correlated with one of these measures of the wage structure, signal their role as either a target or complementary skill set for the corresponding wage policy. To the degree that the measure of the wage structure and of these individual occupational employment and wages actually co-vary across establishments in the industry, such that a portion of the variance of each is explained by this shared variance, the analyses suggest the role of establishment wage/incentive policy as an important driver of both the wage and employment structure of the organization.

The Bureau of Labor Statistics' Occupational Employment Statistics (OES) Survey is a valuable tool for the study of these issues due to 1) the collection of wages and employment for all workers in an establishment and 2) the large size and high degree of industrial and occupational detail of the survey. The collection of wage data for each worker in the establishment enables the construction of detailed measures of the wage structure of the establishment designed to gauge establishments' usage of particular types of wage policies. One of the measures used here is the well known Kremer-Maskin segregation index, which gauges the degree to which wages in the establishment conform to a uniform deviation from the market wage for each occupation. An establishment with a KM index equal to 1 pays all workers the same percentage above or below the market wage for his/her occupation, and exhibits perfect sorting. Another measure devised here and discussed in Section 4.1 measures the degree of within-occupation wage variation within the establishment relative to the degree of between-occupation wage variance. This measure is designed to gauge establishments' usage of policies similar to worker cross training/pay-for-skills.

The main analysis defines a latent variable that measures the shared variance between 1) the wages of Inspectors and of Team Assemblers, 2) the establishment employment share of Machinists, and 3) a measure of the establishment wage structure designed to gauge establishments' use of worker cross-training type policies (subsequently WOBO). The results suggest that this latent variable explains approximately 68% of the variance of WOBO, about 52% and 32% of the variance of the wages of Team Assemblers and Inspectors, respectively, and 47% of the variance of the employment share of Machinists in a group of establishments of particular size containing data for each of these variables.

More rudimentary coefficient alpha estimates of the shared variance between these variables in groups of establishments of given size suggest clear differences in the policies used by large versus small establishments. In smaller establishments, the occupational wages most highly correlated with the overall wage level of the establishment, that is, the wages of Inspectors and Team Assemblers, are highly correlated with measures designed to gauge establishments' usage of cross-training and other similar policies. In larger establishments, these same occupational wages are most highly correlated with measures of the wage structure designed to gauge worker sorting policies. The average wage level of the establishment is also positively correlated with this measure of the wage structure in larger establishments. In general, the analyses suggest that, in Aircraft Parts manufacturing, the wage and employment structure of establishments is affected by their attempts to enhance qualitative flexibility through policies such as worker cross-training, pay-for-skills, and worker sorting.

While these findings accord with previous studies, they add a level of occupational detail made possible by the size and detail of the OES data, such that policies aimed at enhancing qualitative flexibility are clearly seen to be associated with Team Assemblers, Inspectors, and Machinists in both large and small establishments in Aircraft Parts manufacturing.

The following section describes the OES dataset. Section three briefly reviews explanations of inter-establishment wage differentials and recent findings that link the wage structure of the establishments with their technology usage. Section three also discusses the recent generalization of latent variable modeling that has expanded the range of problems for which it is useful to include mixed discrete/continuous models such as the one examined here. Section four describes the model. Section five discusses the estimation and evaluation of the model. Section six discusses the results. Section 7 offers some conclusions and directions for further study.

2. The OES Data

The OES identifies the detailed occupation and wage category of every employee in the establishment, where occupational categories include the 800 detailed occupational classifications defined by the Standard Occupational Classification and wage categories include 12 wage ranges defined by the OES Survey.[2] For each survey round, data are collected from a total of approximately 1.2 million establishments over a three year period, using six biannual collection panels.

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[2] The wage interval midpoints in the OES Survey are estimated using data from the Bureau of Labor Statistics' National Compensation Survey.

The large size of the OES Survey also makes it possible to conduct some analyses using the OES data for single detailed industry cells. Data by detailed industry is necessary for this study because of the important role of production technology in the internal organization of the establishment, from the organization of work performed to the organization of compensation and incentive systems. Conducting the analyses within detailed industry cells holds constant to some degree factors that muddy wage comparisons across establishments. This study examines the application of the model discussed in Section 4 to the OES data for Naics 336413, Other Aircraft Parts and Auxiliary Equipment Manufacturing, sizes 4/5.

3. Literature Review

3.1 Theories of Wage Differentials and Technology Usage

Inter-establishment wage differentials refer to differences between establishments in the wages of otherwise similar workers, meaning workers in a given industry, establishment size, and occupation, but different establishment. Alternative explanations of inter-establishment wage differentials emphasize the role of unmeasured differences in labor quality, the role of unmeasured differences in establishment pay and human resource policies or other establishment characteristics, or the role of frictional or structural elements in the environment of the establishment that result in differing wage/training/technology usage outcomes. Alternative explanations also emphasize differing mechanisms by which wage differentials are created, including worker sorting, caused by firms' attempts to raise quality by segregating workers by ability and skill, rent sharing or "gift exchange", and efficiency wages among others. [3]

A variety of recent studies using differing measures of technology and different datasets have found correlation between establishment pay policies and their technology usage. Doms, Dunn, and Troske (1997) found that plants that pay the highest wages are disproportionately represented among those who adopt the most advanced technologies. Abowd, Kramarz, and Margolis (1994) found that more highly capital intensive firms pay higher wages. Bresnahan, Brynjolfsson, and Hitt (1999) argue that a range of organizational outcomes may be related to decision makers' success or failure in recognizing certain complementarities that exist between particular ways of employing microprocessor technology, the structure of decision making in the organization, and the skill level of the workforce.

Kremer and Maskin (1996) argue that worker sorting is getting more important over time as firms attempt to remain competitive in the face of skill-biased technological change.[4] Lazear and Shaw (2008, subsequently LS) also find that inter-firm differences in pay levels have continued to grow over time. Like the present study, the LS analyses search for explanations for such differences by looking at what's happening to the wage structure within firms. LS find that within-firm wage variance is clearly correlated with the average wage of the firm, and in fact accounts for a whopping 60-80% of total wage variance.

LS note that the two main explanations for the correlation between within-firm wage variance and the firm's wage differential include the possibilities that 1) high wage/high human capital firms also have higher variance of human capital, very possibly due to the more aggressive use of wage policies aimed at rewarding performance and skills, and 2)

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[3] See Groshen (1999) for a survey of explanations of inter-establishment wage differentials.

[4] See Kremer (1993) for detailed discussion of the worker sorting hypothesis

the statistical artifact created by worker sorting, wherein sorting by ability results in high wage firms having higher wage variance due to the skewness of the overall wage distribution near the top.[5]

A measure of the wage structure devised in this study is designed to gauge establishments' use of wage policies associated with worker cross-training/ pay-for-skill policies. Such policies are often associated with relatively broad occupational definitions coupled with ongoing worker training opportunities and a tight relationship between skill acquisition and pay. They tend to increase within-occupation wage variance in the establishment. Section 4.1 describes a measure of the wage structure, WOBO, defined as the variance of wages in the establishment *within occupations,* relative to the variance of wages in the establishment *between occupations*.

The analyses are motivated by a general hypothesis similar to that of Haltiwanger, Lane, and Spletzer (2007), subsequently HLS, who posit differences among 'types' of establishments resulting from differences in their endowments of technology, capital, organizational structure, and the ability/ mindset of managers. HLS suggest that establishments must learn their 'type' in order to effectively compete, or be selected out by market forces. An important element of this and other structural models is the role of organizational inertia, in which the presence of certain factors in the environment of the organization, such as regulatory quality standards, the particular training, experience, and values of managers, or the historical role of workers in the production process, become embedded in the culture and functioning of the organization in ways that are very difficult to change.[6] HLS conclude that differences among establishments in the variety of organizational outcomes they examined may reflect "inherently difficult to measure characteristics such as managerial ability or related organizational practices". In the present study, measures of the wage structure of the establishment, including WOBO, are a key indicator of establishment 'type'.

3.2 Generalized Latent Variable Modeling

The use of latent variable techniques is often motivated by the complexity of social interaction and the vast array of organizational outcomes that we suspect are molded by the characteristics of that interaction. Latent variable techniques are especially important for attempts to explain differences in organizational outcomes among otherwise very similar organizations or establishments, where we suspect that unobserved heterogeneity in the form of differing organizational cultures or differences in managers' 'model' of worker behavior are driving forces.

The basic idea behind latent variable modeling is to use the inter-correlation between a set of related measures on a subject to infer the underlying causal factor(s) generating heterogeneity between subjects. The shared variance between the measures defines a latent variable which we dub the "causal" factor, and the known characteristics of the members of this inter-correlated set inform our understanding of this causal factor. Each of the

[5] See discussion in Lazear and Shaw (2008), p.15.

[6] Haltiwanger, Lane, and Spletzer (2007) document the substantial persistence of such differences over a decade or more using a matched employee-employer longitudinal dataset. Their model is similar to the Industrial Relations model first promulgated by John Dunlop and more recent incarnations emphasizing the importance of structural elements in the environment of the organization, including Kline (1988), and Marshall (1994).

measurement items is in turn modeled as the sum of a linear function of this latent variable, and ‘measurement error’. A good model completely explains the dependence between the measurements on a given subject, such that the measurement items are ‘conditionally independent’ given the latent variable.

The incorporation into the analyses of portions of the employment structure of the establishment make use of recent advances that have generalized latent variable techniques to allow, among other innovations, mixed continuous/discrete data types. These stem from the generalization of multilevel modeling, the recognition of the equivalencies between multilevel modeling and more traditional Structural Equation Modeling (SEM), and from the reformulation of the generalized linear model.

Multilevel models account for complex variance structures that result from the existence of nested ‘levels’ in the data by explicitly modeling them in terms of level 1 units, level 2 units., etc. This structure readily generalizes to accommodate different types of correlated data, including longitudinal analyses and explicit models of unobserved heterogeneity as in the SEM framework.[7]

One key to the generalization of latent variable modeling has been the application of the multilevel modeling concept of ‘exchangeability’ between level one units to the role played by the assumption of multivariate normality in traditional SEM.[8] Given a well fitting model, both assumptions imply “conditional independence’, that is, independence of the measurement items conditional on the latent variable. In the maximum likelihood framework of multilevel modeling, this assumption simplifies the likelihood function to a simple Cartesian product of the contributions of each variable in the analysis. In practice, we easily relax the assumption of exchangeability in favor of ‘partial exchangeability’ thus allowing the model for each measurement item, mentioned earlier in this section, to differ in terms of both its coefficient on the latent variable, or ‘factor loading’, and its residual variance.

A second key innovation has been the reformulation of the generalized linear model (GLM) to allow the application of multilevel modeling techniques, opening the way for the joint modeling of continuous and discrete data types. The traditional GLM framework models the conditional mean by conditioning on the observed data.[9] Heagerty (1999) adapted the GLM to the multilevel modeling framework by reformulating the conditional model as one that instead conditions on the latent variable. The reformulated conditional model gives the expected response for different values of the measured covariates, for given values of the latent variable. The familiar generalized linear mixed model optimizes a conditional criterion to estimate the conditional parameters of this model. The more recently developed marginally specified generalized linear model, or “marginalized latent variable model”, instead optimizes a marginal likelihood produced by integrating the conditional likelihood function over the distribution of the random effects.[10] Pairing this model structure with the assumption of conditional independence allows the likelihood terms associated with the logit (or probit) model for the discrete variable to enter the likelihood in the same way as do the continuous variables.

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[7] See Rabe-Hesketh et.al.(2004) p.178-182.
[8] See Muthen (2002) for discussion.
[9] For example, see Sammel et.al. (1997).
[10] See discussion in Heagerty and Zeger (2000)

4. A Latent Variable Model of Establishment Wage Policies and Occupational Employment

The general research strategy is to use latent variables to model the joint distribution of a measure of the wage structure of the establishment, the wages of occupations that are correlated with both this measure and the average wage differential of the establishment, and the employment share of the 'discriminator' occupation(s). In the spirit of Haltiwanger, Lane, and Spletzer (2007), the model envisions the human resource and pay practices of establishments to be a key indicator of establishment 'type'.[11] The variable WOBO, defined in Section 4.1.1 below, is designed to measure the pay practices of the establishment and is central to the main analysis. In particular, WOBO is designed to covary with the degree of firms' commitment to increasing *qualitative* flexibility, as opposed to *quantitative* flexibility, through the use of policies such as worker cross-training and pay-for-skills.

4.1 Variables

All of the wage measures are produced using data that are pre-adjusted for the effect of the local area on wage levels. A mixed effects model is used to estimate the area effect of wages and this effect is partialed out of the dataset. The data for each establishment in the main analysis include a single observed value for each of the measurement items, including WOBO, the employment share of machinists, and the establishment average wage of Inspectors and of Team Assemblers. Additional measures of the wage structure of the establishment are used in auxiliary correlation analyses.

4.1.1 The Wage measures: WOBO, Measures of Occupational Wages, other measures of the Wage Structure of the Establishment

WOBO

WOBO is the ratio of the average within-occupation wage variance in the establishment to the between-occupation wage variance in the establishment (thus the name WOBO), calculated for the group of workers including production workers and their direct supervisors only. WOBO should be higher in establishments that make greater use of worker cross training and pay-for-skills because such policies tie wages closely to worker skills as opposed to occupational category.

WOBO is also higher for establishments that have lower between-occupation wage variance (for the group including production workers and their supervisors only) for a given level of within-occupation wage variance. Thus, for example, WOBO is higher in establishments that have a smaller wage differential between the wages of production workers and their supervisors, as tends to be the case in establishments in which mobility paths to supervisor status are traversed mainly by former production workers rather than by administrative personnel. WOBO thus combines into a single measure a gauge of establishments' usage of policies associated with cross-training/pay-for-skills, and wage compression.

The OES data are collected in 12 intervals, rather than as exact wage rates. For this reason,

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[11] The Industrial Relations model (Dunlop, 1958) outlines interdependences between different types of pay policies, mobility paths, and other personnel policies that result in identifiable 'systems' of personnel governance.

the within-occupation wage variance for a given occupation /establishment is the variance of the 'midpoints' of the OES wage intervals, where each midpoint is weighted by the number of workers in th corresponding earnings interval.[12] The average within-occupation wage variance of an establishment is measured as the average, across occupations in the group including production workers and their supervisors, of the within-occupation wage variances for each occupation, where the weights are the number of workers in each occupation.

The intervalized nature of the OES wage data creates the need to carefully examine this variable to assure that its calculation using the OES data yields results similar to those that use point wage data. This exercise was conducted using point data from the Bureau of Labor Statistics' National Compensation Survey. The correlation between the OES measures and those obtained using the NCS data is .97.

Measures of Occupational Wages
The wages of occupations whose wages are most highly correlated with both the average wage differential of the establishment and the measure WOBO are also important variables, due to the information they carry about the nature of the establishment wage differential. In Naics 336413, Aircraft Parts, these include Team Assemblers and Inspectors.

Other Measures of the Establishment Wage Structure; The Establishment Wage Differential and the Kremer-Maskin Segregation Index
Auxiliary correlation studies examine relationships with other measures of the wage structure including the average wage differential of the establishment (EWD) and the Kremer-Maskin segregation index (KM).

The establishment wage differential (EWD) is constructed as a fixed weight average deviation of the wage of each occupation in the establishment from its average in the industry/size cell (subsequently the occdiff, or OD), where the weight (WT) for each occupation is its average employment share in the industry/size cell.

The Kremer-Maskin segregation index is a gauge of the degree to which the establishment pays all occupations a uniform differential from the market wage for the occupation in the industry/size cell. Using the notation established above, the Kremer-Maskin segregation index for each establishment is ;

4.1.2 The Employment Share of 'Discriminator' Occupations
The 'discriminator' occupations were identified using canonical discriminant analyses in which the variables included the employment shares of the largest occupations that together account for eighty percent of average industry employment, and establishments were classified as high wage or low wage on the basis of the average wage differential of the establishment relative to the median wage differential for the industry/size cell. The analyses were conducted by detailed industry/size cell. A main discriminator occupation

[12] The wage interval midpoints in the OES Survey are estimated using data from the Bureau of Labor Statistics' National Compensation Survey.

for Aircraft Parts, size (4/5) is Machinists.

4.2 The Latent Variable Model

Models for each of the wage variables and the employment share of machinists together comprise a latent variable model for four mixed responses. The model of their joint distribution postulates an unobserved establishment-level latent variable that introduces correlation among them.

4.2.1 Wage Variables

The j measurement items y including WOBO and the occupational wage measures are assumed to be normally distributed continuous variables;

1) $y_{ij} = \beta_j + \lambda_j \eta_i + \varepsilon_{ij}$

where i indexes establishments

$e_{ij} \sim N(0, \psi_j)$ are measurement errors

$\eta_i \sim N(0, \phi)$ is an establishment-level latent variable

λ_j is the factor loading of measurement item j (i.e. its coefficient on the latent variable)

The variance of y_{ij} is composed of two components; the model variance, or variance due to the random effect, $\lambda^2 \operatorname{var}(\eta) = \lambda^2 \phi$, and the residual variance ψ_j;

$Var(y) = \lambda_j{}^2 \phi + \psi_j$

Stacking all wage variables into a vector;

2) $Var(y) = \Lambda \Phi \Lambda' + \Psi$

The conditional likelihood of each establishment's continuous measurement item y_{ij} is;

3) $g(y_{ij} \mid \eta_i; \theta_j) = \frac{1}{\sqrt{2\pi\psi_j}} \exp\left(\frac{-(y_{ij} - \lambda_j \eta_i)^2}{2\psi_j} \right)$

θ_j indexes the parameters λ_j, ψ_j of the model for the wage measures.

4.2.2 Accounting for Structural Missingness in the Wage Variables

The wage data in the OES Survey exhibit both structural and random missingness. A fraction of establishments do not employ one or the other of Inspectors or Team Assemblers, resulting in structural missingness for those wage values, and a small number of establishments employ one or both of these occupations but failed to provide wage information about them. The OES Survey imputes wage information only in the latter case. While it seems quite possible that the latter case would often be associated with structural differences among establishments, it affects a very small fraction of the establishments in the current study and is ignored, and the imputed values are used as true data for those establishments imputed using data from establishments located in the same local area. Establishments containing wages imputed with data from establishments located outside the local area are not used.

Among the advantages of using maximum likelihood estimation and multilevel modeling techniques for latent variable modeling is the flexibility to easily accommodate both random and structural missingness in all variables and to directly test for the role of structural differences in the estimated relationships. In the multilevel framework, missing data are simply handled as unequal size clusters. By contrast, traditional SEM generally requires that all observations have a complete multivariate response in addition to more stringent balance requirements discussed in Rabe-Hesketh, Skrondal (2004).

4.2.3 The Establishment Employment Share of Machinists

The latent variable formulation of the logit model for the binomially distributed employment share assumes that underlying the discrete responses is a continuous latent variable with residual variance ε that follows a logistic distribution;

4) $$d_i{*} = \beta_{0d} + \beta_{1d}{'}x_i + \varepsilon_{id}$$

$$\varepsilon_{id} \sim \left(0, \frac{\pi^2}{3}\right),$$

where d_i =employment of machinists in establishment i;

$$\begin{array}{ll} d_i = 0 \; if & d_i{*} \leq 0 \\ d_i = 1 \; if & 0 < d_i{*} \leq 1 \\ \quad .... & \\ d_i = 2 \; if & 1 < d_i{*} \leq 2... \\ d_i = s \; if & s-1 < d_i{*} \leq s \end{array}$$

The terms $\beta_{0d} + \beta_{1d}{'}x_i$ include an intercept and the effect of establishment size. The inclusion of the latent variable η in 4) defines the model as a mixed logit;

5) $$d_i{*} = \beta_{0d} + \beta_{1d}{'}x_i + \lambda_d \eta_i + \varepsilon_{id}$$

The mixed logit augments the standard logit with a random intercept. It is a weighted average of the logit evaluated at different values of the latent variable η, where the weights, also known as the mixing distribution, are given by the density of η. In this study, the model of the employment share of machinists is a special type of mixed logit in which the random intercept η is defined by the common variance among the measurement items, and the parameter λ_d is more accurately described as a factor loading. Rabe-Hesketh and Skrondal (2001) have aptly term this model a 'factor-structured' logit.

The inverse of the logit transformation yields the logistic distribution of the probability that a worker is a machinist,

$$P_1 = P(d \mid \eta; \theta_D) = \frac{\exp(\beta_0 + \beta_1 x_i + \lambda_d \eta_{i;})}{1 + \exp(\beta_0 + \beta_1 x_i + \lambda_d \eta_{i;})}$$

where θ_D are the parameters of the model for the employment share of machinists.

The conditional likelihood of an establishment's employment share of machinists is distributed binomial in this probability;

6) $$L_i = \left(\frac{\exp(\beta_{0d} + \beta_{1d}{'} x_i + \lambda_d \eta_i)}{1 + \exp(\beta_{0d} + \beta_{1d}{'} x_i + \lambda_d \eta_i)}\right)^d \left(1 - \frac{\exp(\beta_{0d} + \beta_{1d}{'} x_i + \lambda_d \eta_i)}{1 + \exp(\beta_{0d} + \beta_{1d}{'} x_i + \lambda_d \eta_i)}\right)^{ste-d} \begin{bmatrix} ste \\ d \end{bmatrix}$$

where ste indexes total establishment employment.

There exist a number of ways to motivate the underlying latent variable formulation in 5). In the baseline category model, the formulation is a model of the difference between two iid extreme value distributions, log(P_1) and log(1-P_1), which has a standard logistic distribution. The underlying latent variable approach puts the latent variable on the same scale as the linear predictor, allowing for the direct interpretation of the parameter λ_d as the change in d^* per unit change in the latent variable, and facilitating calculation of the share of variance explained by the latent variable model.[13]

McFadden and Train (2000) demonstrated that the mixed logit can be used to attain any desired degree of model fit. This is not true in the current application, because the random intercept can be refuted by a lack of shared variance between the employment share variable and the other measurement items, and the consequent failure to explain a significant portion of the variance of one or more of the other measurement items.

4.2.4 Accounting for Structural Missingness in the Employment Share of Machinists
Approximately forty-five percent of the establishments have zero employment of machinists. Unbiased estimation of the relationship between the wage measures and the employment share of machinists requires that we capture information about the behavior of the wage measures for the group that has zero employment of this occupation.

The zero-inflated binomial model divides the likelihood into separate components for the zero and non-zero units. The likelihood contribution of units for which the employment share is greater than zero is the product of the probability that the employment share is greater than zero and the binomial likelihood, while the likelihood contribution of units for which the employment share is zero is the product of the probability that the employment share is zero and the value of the binomial likelihood when the employment share is zero[14];

$$P_0 = P(d > 0) = \frac{\exp(a_1)}{1+\exp(a_1)}$$

$$P_1 = P(d_i \mid \eta_{;};\theta_D) = \frac{\exp(\beta_0 + \beta_1 x_i + \lambda_d \eta_{i;})}{1+\exp(\beta_0 + \beta_1 x_i + \lambda_d \eta_{i;})}$$

For observations that have zero employment of occupation o, we replace 6) with;
$$L_i = (P_0)(1-P_1)^{ste}$$
For observations that have positive employment of occupation o, 6) becomes;
$$L_i = (1-P_0)(P_1)^d (1-P_1)^{ste-d} \begin{bmatrix} ste \\ d \end{bmatrix}$$
where (suppressing i subscripts)
d = number of machinists
ste = total establishment employment

Weighting adjustments were needed to get the analysis to run smoothly. The establishment average wages of Inspectors and Team Assemblers entered the analysis unweighted by the establishment employment of these occupations, due to convergence problems. Since there exists an average of about 8 machinists per establishment in the data, the latent variable is dominated by the employment share variable in the absence of weighting adjustment. For

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[13] See Hedeker (2003, p.1439) and Bhat and Gossen (2004 , p.23) for discussion.
[14] See Hall (2000)

this reason, the employment share variable was down-weighted to one tenth of its value otherwise.

4.2.5 Identification

As in traditional SEM, the model is identified if the number of variances and covariances among the variables exceeds the number of estimated parameters, implying that the degrees of freedom exceeds the quantity;

$$df = \left(\frac{p(p+1)}{2} - pq - p + \frac{q(q+1)}{2} \right)$$

where
p = number of variables
q = number of factor loadings

We assure that the model is identified by restricting the factor loading on one of the continuous wage variables (WOBO was used) to equal 1, fixing the scale of the latent variable to that of WOBO. Setting the mean of the latent variable distribution equal to zero saves another degree of freedom. The fixed effects portion of the logit model was moved into an offset term for the same reason.

5. Estimation

The assumption that all measurement items are conditionally independent implies that the conditional likelihood function is the simple Cartesian Product of the conditional likelihood of each variable. The unconditional, or marginal likelihood, is the integral of this likelihood weighted by the prior density of the random effects.[15]

$$p_i = \int L_i(\theta_d, \theta_j, \eta) f(\eta \mid \phi) d\eta$$

This integral is intractable and in practice we must either approximate the integrand before integrating over the random effects distribution or approximate the integral.
Gauss-Hermite quadrature approximates the integral by a weighted sum of nodes, or quadrature points, that are the roots of a Hermite polynomial. Pinhero and Bates (1995) discuss a variety of methods of approximation techniques including Gaussian Quadrature, and is a primary reference for SAS Proc Nlmixed. Optimization of the approximated likelihood used the quasi-Newton algorithm.

5.1 Evaluating Model Fit

The share of the variance of each variable that is explained by the latent variable model is derived from the estimated measurement errors together with the simple variance of each variable. Sources of lack of model fit are often made apparent by examination of the correlation of the model residuals and by comparison of the model-implied correlations of the variables against the actual correlations.

5.1.1 Explained Variance

For each of the continuous variables y_j, the portion of variance explained by the model follows from the variance expression in 2);

[15] See discussion in Hedeker (2003, p.1437)

$$R_j^2 = 1 - \frac{\psi_j}{Var(y_j)}$$

Bhat and Gossen (2004, p 23) and Snijders and Bosker (1999, sec.14.3.4) discuss calculation of the R-squared value of the mixed logit. The total variance of the employment share is the sum of the fixed, residual, and latent variable contributions to the variance. The residual variance is fixed by assumption to $\frac{\pi^2}{3}$ and the model variance is $\lambda_d^2\phi$. As described in Snijders and Bosker (1999, sec.14.3.4), we must calculate the variance of the fixed portion of the linear predictor using the data. The share of variance explained by the latent variable model is;

$$R_j^2 = \frac{\lambda_d^2\phi}{\lambda_d^2\phi + \mathrm{var}(fixed) + \frac{\pi^2}{3}}.$$

5.1.2 Correlation Residuals and Model versus Actual Correlations

In a well-fitting model, all variables are independent, conditional on the latent variable, implying that the measurement errors are uncorrelated. The correlations of the measurement errors are termed the correlation residuals. The accepted standard for a well-fitting model is correlation residuals whose absolute value is less than .1.

Comparison of the model correlations of the variables with the actual data correlations is also useful to diagnosing sources of lack of fit. The model correlations are given by the first term on the right hand side of Equation 2.

5.2 Verifying the Solution

McCullough and Vinod (2003) warn that nonlinear solvers such as Proc Nlmixed provide solutions that are incorrect under a number of conditions that are not automatically detected by the software and that must be carefully examined.

The eigenvalues of the Hessian are a measure of the amount of curvature of the parameter space in the direction of each parameter; small eigenvalues are associated with parameters for which the parameter space is flatter and standard errors are larger, while large eigenvalues are associated with parameters that are more precisely estimated. The solution is a minimum if all eigenvalues are positive, indicating that the Hessian is positive definite.

The condition number of the Hessian, the ratio of the largest to the smallest eigenvalue, is an important indicator of ill-conditioning of the data and high multicollinearity. According to McCullough and Vinod, the condition number of the Hessian in the case of a nonlinear solver should be under 6.7E7.[16]

Coull and Agresti (2000) suggest checking the stability of a solution by inspecting the parameter estimates as a function of the number of quadrature points. A stable solution is indicated when further increases in the number of quadrature points has no effect on the

[16] Excessive multicollinearity is also indicated by large off-diagonal elements of the correlation matrix of the parameter estimates.

parameter estimates.

6. Results

Appendix Table A1 provides Pearson correlations between the establishment average wages of detailed occupations and a variety of measures of the wage structure of the establishment. The measures of the wage structure in Table A1 include; 1) the average wage differential of the establishment, 2) WOBO, 3) the Kremer-Maskin segregation index (KM), 4) a measure of the within-occupation wage variance in the establishment (VO), which is also the numerator of WOBO, and 5) a measure of the between-occupation wage variance in the establishment (VE), which is also the denominator of WOBO. VO and VE are included in the table to aid in the interpretation of correlations with the variable WOBO.

In the smallest establishments in this industry (sizes 2 and 3), occupations whose wages are most highly correlated with the wage measures include Machinists, Production Worker Supervisors, General Operations Managers, and a range of clerks. In mid-sized establishments (sizes 4 and 5), the list is dominated by Machinists, Inspectors, a range of skilled metal workers, Team Assemblers, and a range of Clerks. In the largest establishments (sizes 6 and 7) the list for size 4 and 5 establishments is expanded to include a range of engineering-related occupations.

In mid-size establishments, those occupations whose wages are most highly correlated with the establishment wage differential are also the most highly (positively) correlated with the variable WOBO. In the largest establishments, those occupations whose wages are most highly correlated with the establishment wage differential are also the occupations whose wages are most highly (positively) correlated with the Kremer-Maskin segregation index, KM.

Overall, the wages of most of these occupations are negatively correlated with the KM index in the smaller and mid-sized establishments, and positively correlated with the KM index in the largest establishments. Similarly, they tend to be positively correlated with the variable WOBO in mid-sized establishments, but negatively correlated with WOBO in larger establishments.

Table 1 contains Pearson correlations, by size groupings, between each of the wage structure measures and the other variables used in the analysis, including the wages of Inspectors and Team Assemblers, and the establishment employment share of Machinists.

Table 2 reports the results of Coefficient Alpha analyses of these variables for mid-sized and large establishments. The Coefficient Alpha statistic is a measure of the variance shared by all variables in an analysis, and is produced using only those establishments that have data for all wage or wage-structure variables in the analysis. The analyses in Table 2 used 33 establishments in the size 4/5 grouping, and 42 establishments in the size 6/7 grouping.

Both analyses suggest positive correlation between the wages of Inspectors and the employment share of Machinists, and both suggest positive correlation between the wages of Inspectors and of Team Assemblers and the primary wage structure measure (WOBO for sizes 4 and 5, KM for sizes 6 and 7). In the size 4/ 5 establishments, the employment share of Machinists is positively correlated with the variable WOBO.

Table 3 contains the parameter estimates from the latent variable model discussed in Section 4, applied to the 33 size 4/5 establishments used in Table 2. The un-standardized estimates reflect the widely differing scales of the wage versus employment share variables.

Table 4 contains R Squared measures suggesting that the latent variable explains a significant portion of the variance of each variable. The results are similar, with qualifications, to those of analyses conducted earlier by this author that used all (size 4 and 5) establishments in this industry, including those containing data imputed from outside the local area and those for which data for one or more of the wage measures was missing due to zero employment of the occupation in the establishment. The proportions of explained variance for each variable in that analysis were 66%, 26%, 13%, and 13%, for each of the variables including the employment share of Machinists, WOBO, the wage of Team Assemblers, and the wage of Inspectors, respectively. As suggested by these figures, that analysis did not down-weight the employment share of Machinists, and it consequently dominates the latent variable. The results of these earlier analyses containing all 209 establishments are available on request.

Tables 5 and 6, respectively, present the juxtaposition of the model correlations (Sec.5.1.2) with the actual correlations in the data, and the correlation residuals. Table 5 shows that the model significantly over-estimates the correlation between the wage variables and the employment share of Machinists. Table 6 shows that the correlation residuals associated with several pairs of variables are well over .1, suggesting the importance of correlated unmeasured variables that have not been taken into account.[17]

An eigen-analysis of the Hessian shows that the ratio of the largest to smallest eigenvalue is on the order of 10^4.

Finally, Figure 1 contains histograms of the actual and predicted values of the employment share of Machinists, and of the predicted value of the latent variable.

7. Conclusions and Directions for Future Study

The results suggest that the wage and employment variables used in the analysis "stick" together in a way that we might expect in the context of a production process whose degree of success depends on the skill, accuracy, and cooperation of workers in several key occupations. In particular, among mid-size establishments, those establishments that have more highly paid Inspectors and Team Assemblers also appear to both 1) make more intensive use of policies that increase the variance of wages within occupations relative to the between-occupation wage variance, and 2) employ larger shares of Machinists.

The results are consistent with an explanation of inter-establishment wage differentials that locates the source of at least some of the inter-establishment wage variation in the personnel and pay practices of establishments. Future work on this project will examine these same relationships in other industries, follow-up on more of the questions raised by Lazear and Shaw (2008), and conduct additional analyses aimed at improving the model and further investigating these relationships.

[17] See discussion in Kline (1998) p.20-22.

The variable WOBO is highly skewed, invalidating the assumption that all measurement errors are normally distributed and giving rise to the need to estimate this model using nonparametric techniques, similar to those recently investigated by Rabe-Hesketh, Sophia, Andrew Pickles, Anders Skrondal (2003). This is also slated for future work.

Any opinions expressed in this paper are those of the author and do not constitute policy of the Bureau of Labor Statistics

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Table 1. Aircraft Parts Manufacturing - Pearson Correlations by Establishment Size

Sizes 2 & 3 / Sizes 4&5	Estabdiff	KM	WOBO	Shr_Machinists	var_estab	var_occ	Wg Inspectors	Wg Assemblers
Estabdiff	_	-0.90 0.000 168	0.00 0.992 88	0.04 0.636 168	0.25 0.005 121	0.37 0.000 88	0.12 0.530 31	0.48 0.010 28
KM	-0.80 0.000 150	_	0.06 0.593 88	-0.09 0.253 168	-0.15 0.092 121	-0.36 0.001 88	-0.10 0.596 31	-0.46 0.015 28
WOBO	0.13 0.122 142	-0.01 0.950 142	_	-0.16 0.135 88	-0.44 0.000 88	0.22 0.043 88	-0.26 0.238 22	0.35 0.179 16
Share Machinists	0.04 0.647 150	0.01 0.863 150	0.13 0.131 142	_	0.19 0.038 121	0.10 0.345 88	0.10 0.600 31	-0.13 0.520 28
var_estab	0.18 0.030 147	-0.22 0.007 147	-0.15 0.078 142	0.02 0.845 147	_	0.43 0.000 88	0.24 0.192 31	0.08 0.680 26
var_occ	0.31 0.000 142	-0.22 0.008 142	0.28 0.001 142	0.09 0.264 142	0.69 0.000 142	_	0.02 0.946 22	0.46 0.075 16
Wg Inspectors	0.61 0.000 111	-0.42 0.000 111	0.32 0.001 109	0.15 0.125 111	0.19 0.046 111	0.51 0.000 109	_	
Wg Assemblers	0.63 0.000 49	-0.26 0.070 49	0.55 0.000 48	0.19 0.183 49	-0.02 0.892 49	0.42 0.003 48	0.54 0.001 34	_

sizes 6&7	estabdiff	km	WOBO	Shr_Machinists	var_estab	var_occ	Wg_Inspectors	Wg_Assemblers
km	0.80 0.000 108	_						
WOBO	-0.03 0.792 106	-0.07 0.503 106	_					
Shr_Machinists	0.14 0.136 108	0.08 0.427 108	-0.03 0.775 106	_				
var_estab	0.33 0.000 108	0.32 0.001 108	-0.08 0.389 106	-0.21 0.028 108	_			
var_occ	0.23 0.016 106	0.20 0.044 106	0.40 0.000 106	-0.26 0.007 106	0.79 0.000 106	_		
Wg Inspectors	0.72 0.000 100	0.48 0.000 100	-0.03 0.803 98	0.27 0.007 100	0.19 0.065 100	0.10 0.333 98	_	
Wg_Assemblers	0.62 0.000 46	0.40 0.006 46	0.25 0.105 45	0.26 0.086 46	0.06 0.671 46	0.10 0.510 45	0.76 0.000 42	_

Table 2. Aircraft Parts Manufacturing - Coefficient Alpha Correlations by Establishment Size

Sizes 4 & 5 N= 33, Alpha=.75

sizes 6&7 , N=42, Alpha=.71	km	WOBO	Shr_Machinists	Wg_Inspectors	Wg_Assemblers
WOBO		_	0.36 0.040	0.47 0.006	0.60 0.000
Shr_Machinists	0.04 0.820		_	0.33 0.060	0.24 0.180
Wg Inspectors	0.48 0.001		0.41 0.008	_	0.56 0.001
Wg_Assemblers	0.31 0.040		0.28 0.070	0.76 0.000	_

Table 3: Parameter Estimates				
	Parameter Estimates			
Parameter	Unstd.	Std.	SE	Probt
Wage Tm Assemblers	0.448	0.720	0.117	0.001
Wage Inspectors	0.281	0.570	0.096	0.006
WOBO	1.000	0.820		
Emp Share Machinists	4.241	0.680	0.903	<.0001
Variances				
Meas error WOBO	0.080		0.035	0.030
Meas error Wg Tm Assemblers	0.030		0.010	0.004
Meas error Wg Inspectors	0.026		0.007	0.001
Random Effect Establishment	0.402		0.079	<.0001
-2LL = -126.5				
N=132, Subjects = 33				

Table 4. R Squared Wage Variables and Employment Share Machinists			
Share Machinists	WOBO	Wg Tm Assemblers	Wg Inspectors
0.47 (latent variable portion only)	0.68	0.52	0.32

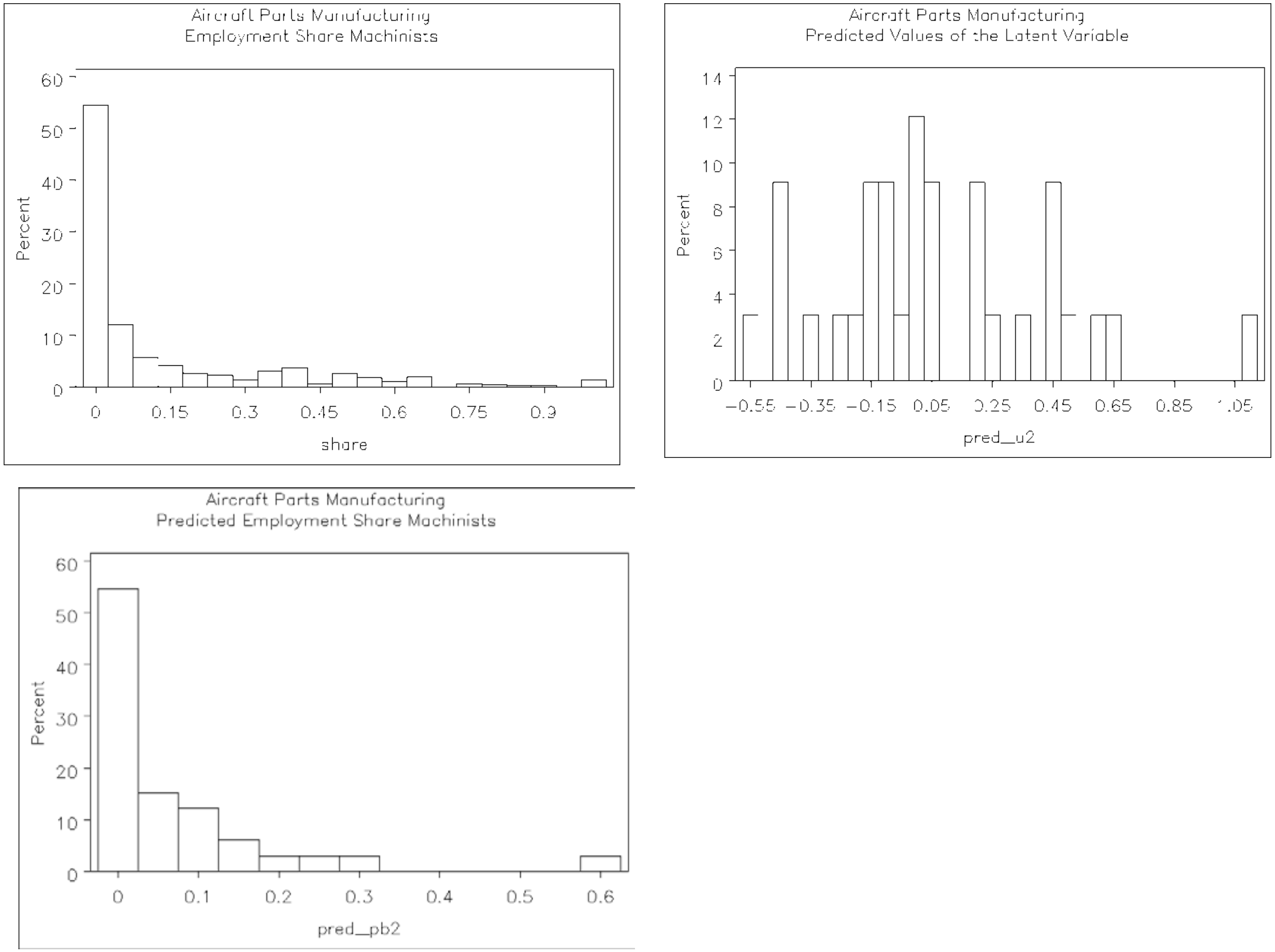
Table 5: Model Correlations and Data Correlations
Size 4 and 5 Establishments
Coefficient Alpha-Comparable Analysis N=33

Data / Model	Wg Tm Assemblers	Wg Inspectors	WOBO	Share Machinists
Wg Tm Assemblers	_	0.56 0.001	0.47 0.006	0.33 0.060
Wg Inspectors	0.41		0.60 0.0002	0.24 0.180
WOBO	0.58	0.47	_	0.36 0.040
Share Machinists	0.41	0.39	0.56	_

Table 6: Correlation Residuals
Size 4 and 5 Establishments
Coefficient Alpha-Comparable Analysis N=33

	Wage Team Assemblers	Wage Inspectors	WOBO	Employment Share Machinists
Wage Team Assemblers	_			
Wage Inspectors	0.16 0.360	_		
WOBO	-0.33 0.060	-0.24 0.170	_	
Employment Share Machinists	-0.50 0.003	-0.39 0.030	-0.24 0.180	_

Figure 1. Model Prediction / Actual Employment Share Machinists



Appendix A1. Pearson Correlations - Wages of Detailed Occupations / Five Measures of the Establishment Wage Structure

1. ed   Establishment Wage Differential
2. wb   WOBO (Within Occupation Wage Variance Relative to Between Occ Wage Var.)
3. km   Kremer-Maskin Segregation Index
4. vo   Within-Occupation Wage Variance (Numerator of WOBO)
5. ve   Between-Occupation Wage Variance (Denominator of WOBO)

Establishment size	Occupation Title	Wage Stucture Measure	Corr	p	N
2	Machinist	ed	0.96	0.000	32
	Prd_supervisor		0.67	0.001	22
2	Prd_supervisor	ve	0.85	0.000	22
	Machinist		0.33	0.122	23
	Machinist		0.89	0.000	32
	Gen_Op_mgr		0.64	0.000	37
3	Secretary	ed	0.54	0.005	25
	Prd_supervisor		0.49	0.001	44
	Office_clk		0.44	0.045	21
	Machinist		-0.88	0.000	24
3	Gen_Op_mgr	km	-0.58	0.002	25
	Prd_supervisor		-0.42	0.017	31
	Prd_supervisor		-0.50	0.004	31
3	Machinist	wb	0.17	0.440	24
	Gen_Op_mgr		-0.03	0.890	25
	Prd_supervisor		0.59	0.000	44
	Office_clk		-0.56	0.008	21
3	Secretary	ve	-0.27	0.213	23
	Gen_Op_mgr		0.16	0.357	35
	Machinist		-0.10	0.599	31
	Machinist		0.53	0.008	24
3	Prd_supervisor	vo	0.27	0.149	31
	Gen_Op_mgr		0.23	0.263	25
	Machinist		0.77	0.000	44
	Welder		0.68	0.001	21
4	Mill machine	ed	0.67	0.000	46
	Inspector		0.64	0.000	59
	Misc Prd		0.64	0.001	23
	Production Plan Clerk		0.43	0.009	36
	Team Assembler		0.40	0.047	25
	Machinist		-0.78	0.000	43
4	Inspector	km	-0.64	0.000	58
	Mill_mach		-0.58	0.000	44
	Gen_Op_mgr		-0.57	0.000	66

Establishment size	Occupation Title	Wage Stucture Measure	Corr	p	N
4	Prd_supervisor	km	-0.54	0.000	71
	Tm Assembl		0.52	0.007	25
	Welder		0.49	0.023	21
4	Bkkp, Act Clks	wb	0.39	0.012	41
	Mill_mach		0.38	0.012	44
	Ship_clerk		0.35	0.006	60
	Inspector		0.24	0.074	58
	Prd_super		0.52	0.000	71
	Office_clk		0.39	0.012	41
4	Misc Prd	ve	0.38	0.075	23
	Prdpln_clk		0.37	0.031	35
	Mill_mach		0.68	0.000	44
	Inspector		0.46	0.000	58
	Welder		0.46	0.037	21
	Misc Prd		0.43	0.039	23
4	Sales_Rep	vo	0.33	0.046	38
	Admin_supr		0.33	0.104	26
	Prd_supervisor		0.31	0.008	71
	Tm Assembl		0.30	0.141	25
	Tm Assembl		0.84	0.000	24
	Tool_n_Die		0.70	0.000	23
	Machinist		0.69	0.000	31
5	Inspector	ed	0.68	0.000	52
	Stock_clrk		0.64	0.000	28
	Janitor		0.64	0.001	24
	Fin Managr		-0.31	0.141	24
	Tool_n_Die		-0.30	0.168	23
	Hlth & Safety Eng.		-0.27	0.191	25
5	Prd_super	km	-0.26	0.060	55
	Sales_Rep		-0.24	0.165	34
	Machinist		-0.22	0.240	31
	Tm Assembl		0.54	0.008	23
	Admin_supr		0.46	0.015	27
5	Office_clk	wb	0.45	0.007	35
	Inspector		0.45	0.001	51
	Janitor		0.41	0.054	23
	Inspector		0.32	0.019	52

Establishment size	Occupation Title	Wage Stucture Measure	Corr	p	N
5	Hlth & Safety Eng.	ve	-0.28	0.171	26
	Prd_super		0.26	0.055	57
	Tool_n_Die		0.24	0.266	23
	Chief_Exec		-0.21	0.229	34
	Office_clk		0.17	0.322	35
	Machinist		0.15	0.433	31
5	Inspector	vo	0.59	0.000	51
	Janitor		0.46	0.026	23
	Tm Assembl		0.43	0.039	23
	Office_clk		0.43	0.010	35
	Enginr_mgr		0.40	0.039	27
	Tool_n_Die		0.37	0.078	23
	Chief_Exec		-0.26	0.159	32
6	Aerosp_Eng	ed	0.82	0.000	33
	Machinist		0.75	0.000	52
	Inspector		0.73	0.000	66
	Drafters		0.70	0.000	32
	Cmptr_cntP		0.69	0.000	32
	Mill_mach		0.66	0.000	44
	Painting		0.63	0.001	23
	ArcftAssem		0.62	0.002	22
6	Aerosp_Eng	km	0.71	0.000	32
	Inspector		0.59	0.000	65
	Elec. Drafters		0.58	0.000	33
	Payroll Clks		0.58	0.000	33
	Drafters		0.56	0.001	32
	Machinist		0.55	0.000	52
	Ship_clerk		0.55	0.000	62
	Mill_mach		0.54	0.000	43
	Prd_super		0.54	0.000	68
	ArcftAssem		0.52	0.013	22
	Tm Assembl		0.51	0.007	27
6	Painting	wb	0.39	0.075	22
	Mill_mach		0.35	0.021	43
	Drafters		-0.35	0.050	32
	Bkkp, Act Clks		0.35	0.011	53
	Tm Assembl		0.33	0.093	27
	Enginr_mgr		-0.33	0.021	49
	Tool_n_Die		0.32	0.115	26
	Painting		0.57	0.005	23

Establishment size	Occupation Title	Wage Stucture Measure	Corr	p	N
	Prd_super		0.50	0.000	69
	ArcftAssem		0.47	0.027	22
	IndPrd_mgr		0.39	0.002	60
6	Inspector	ve	0.36	0.003	66
	Misc Prd		-0.35	0.066	28
	Payroll Clks		0.34	0.050	34
	Tm Assembl		0.34	0.081	28
	Painting		0.71	0.000	22
	Tm Assembl		0.47	0.013	27
	Engineer Tech		0.45	0.009	33
	Tool_n_Die		0.40	0.046	26
6	Welder	vo	0.38	0.090	21
	ArcftAssem		0.36	0.101	22
	IndPrd_mgr		0.34	0.009	59
	Ship_clerk		0.88	0.000	28
	Machinist		0.88	0.000	26
	Inspector		0.87	0.000	34
7	Mill_mach	ed	0.84	0.000	21
	Indus.Mach.Install		0.78	0.000	29
	Stock_clrk		0.70	0.000	23
	Accountants, Aud.		-0.02	0.902	32
	Machinist		0.85	0.000	26
	Ship_clerk		0.73	0.000	27
7	Inspector	km	0.61	0.000	33
	Prd_super		0.60	0.000	34
	Tool_n_Die		0.55	0.005	24
	Drafters		-0.56	0.008	21
	Mech_Eng		-0.47	0.026	22
7	Stock_clrk	wb	0.41	0.057	22
	Sales_Rep		-0.38	0.085	21
	Bkkp, Act Clks		-0.37	0.074	24
	Office_clk		0.29	0.196	21
	Prd_super		0.58	0.000	34
	Tool_n_Die		0.55	0.005	24
	Machinist		0.51	0.008	26
7		ve	0.43	0.052	21
	Prdpln_clk		0.41	0.023	31
	Inspector		0.37	0.029	34
			0.37	0.037	33
	Tool_n_Die		0.45	0.026	24
7		vo	0.43	0.050	21
	Inspector		0.41	0.019	33

Establishment size	Occupation Title	Wage Stucture Measure	Corr	p	N
	Prd_super		0.40	0.021	34
7		vo	-0.37	0.041	31
	Machinist		0.36	0.067	26
	Mill_mach		0.34	0.137	21
	Prdpln_clk		0.30	0.106	30