

Working Paper 8906

DO WAGE DIFFERENCES AMONG EMPLOYERS LAST?

by Erica L. Groshen

Erica L. Groshen is an **economist** at the Federal **Reserve** Bank of Cleveland. The author thanks Richard Freeman, John **Dunlop**, Katherine Bradbury, John Bound, and seminar participants at **Boston** and Stanford Universities for their valuable comments. Partial funding from Social Sciences Research Council Grant No. SS-25-83-31 is gratefully acknowledged.

Working papers of the Federal Reserve Bank of Cleveland are **preliminary** materials circulated to stimulate discussion and critical **comment**. The views **stated** herein are those of the author and not necessarily those of the Federal Reserve Bank of Cleveland or of the Board of Governors of the Federal **Reserve** System.

ABSTRACT

Recent interest in efficiency wage and **insider/outsider** models of wage determination has drawn attention to employer-based wage differences. Alternatively, these differences may **simply reflect temporary, random** errors by wage-setters. This paper **provides** strong evidence against the possibility that employer wage variations are **temporary** or **random**, along with additional verification of the existence of substantial employer wage differences within and between industries.

The variance of wages is analyzed in a unique data set: wages paid to individual workers in selected blue- and white-collar occupations from a six-year panel of employers within a single standard metropolitan statistical area. The most conservative estimate of establishment wage differentials in this sample (controlling for very detailed job classification) yields a standard deviation of approximately 12 percent within industry, or 18 percent, including interindustry differentials. Wage differences among employers are shown to be virtually stationary over time and related to establishment size, but not consistently to changes in establishment employment.

I. Introduction

The existence of **large employer-based** wage differences among apparently equivalent workers is often taken as supporting evidence for the existence of efficiency wages or implicit **profit-sharing** (see **Dickens** and **Katz [1987]**, for **example**).¹ The two main alternative hypotheses that have been explored are sorting by worker-quality and by **compensating** differentials, neither of which has found strong support in statistical tests. This paper tests a **third** alternative, whether wage differences among **employers** are the result of random, temporary errors.

If employer differentials are the result of errors, the efficiency of the labor market may be enhanced by their elimination, perhaps through government subsidies of information gathering and dissemination. On the other hand, if these differentials are efficient wages or **profit-shares**, they may be appropriate **second-best** solutions to monitoring or agency problems **endemic** to the labor market, but have implications for other policy, such as trade or antidiscrimination policy, as demonstrated in **Bulow** and **Summers (1986)**, or for **macroeconomic** policy, as shown in **Weitzman (1986)**.

Efficiency wage **arguments** posit causality between **workers'** wages and on-the-job productivity (**Yellen [1984]**, **Stiglitz [1984]**). Thus, **some** employers may maximize profits by **paying** a differential above the **market-clearing** wage, if resulting **increments** in productivity exceed costs of the differential. At least five sources of **increased** productivity have been **modeled**: reduced monitoring (or shirking) costs (for **example**, **Bulow** and **Summers [1986]**), decreased turnover (**Salop [1979]**), sociological considerations (**Akerlof [1982]**), market insulation, and corporate consistency (**Doeringer** and **Piore [1971]**).

In contrast, implicit **profit-sharing** models of wage variation (also called **insider/outsider**, **rent-sharing**, and **bargaining** models) assume the existence of variations in firms' rents and in employees' bargaining power (or agency costs). These conditions introduce the possibility of **rent-capture** by employees, although the models differ in the identity of agents and **enforcement mechanisms**. The players are clearest in the case of **unionism**; otherwise, the **workers'** bargaining agent is not obvious, although **economists** have long noted the existence of informal **organization** by nonunion workers (Dunlop [1957]), including **union-threat effect** versions (Dickens [1986]) and managerial capitalism/agency cost versions (Aoki [1984]).

This paper focuses on the alternative explanation that wage differences among employers simply reflect random errors by wage-setters. Seminal articles by **Stigler** (1962) and **Rothschild** and **Stiglitz** (1976) launched a family of pure information models that use costly job search to explain wage dispersion. Expensive job search **allows** the market to sustain a range of wages because a **worker's** gain from further search becomes uncertain, rather than a known quantity. While mean wages for a particular type of worker are **equal** to the **worker's** marginal product, the costs of information **introduce** an error term with a variance that is a positive function of the search and mobility costs for workers or employers. Thus, if employers adjust all **workers'** wages in tandem, errors may be correlated across occupations for an employer.

Most previous empirical studies of **interemployer** wage differentials have focused on national interindustry differences.² Because of data limitations, these studies have been unable to **control** well for local labor market conditions or detailed occupation, to **compare** differentials between **industries** to those within industry, or to investigate the stability of employer differentials over time.

This paper provides new insight into establishment-based wage variation, using a unique data set prepared for the author by the U.S. Bureau of Labor Statistics. The wages of nonsupervisory white- and blue-collar workers in one city are examined to see whether employer differentials exist within a single labor market, whether they are stable over the course of six years, and whether they are associated with growth or shrinkage of the establishment. Wage variation between industries is also compared to that within industry. In addition, the results are compared to those in the Current Population Survey in order to estimate the importance of interemployer wage variation as a source of wage variation in the economy as a whole.

The results cast light on the nature of wage differences among employers and on the plausibility of other proposed sources of wage variation by employer. A number of previous studies find it unlikely that employer differentials arise from systematic sorting of workers by measured or unmeasured ability within occupation.³ Even stronger empirical evidence tends to refute the hypothesis that wage differences among employers compensate for establishmentwide variations in working conditions.⁴ This paper provides evidence of substantial wage differences among employers within a single city. This finding greatly reduces the possibility that regionwide compensating differentials for cost of living are the main source of employer differentials.⁵

The major contribution of this paper is the finding that interemployer wage differences, and rankings of employers by wage, are virtually stationary over six years. This result eliminates random variations (generated or perpetuated by costly information) as a likely source of employer differentials. The persistence of establishment wage differentials is consistent with earlier

findings that employer wage **differences** are associated with measurable characteristics of employers, such as establishment size and product market (**Groshen [1988b]**).

Process of elimination leaves the door open for the **two** provocative types of models of employer wage variation (efficiency wages and **rent-sharing**) that have generated considerable **interest**. The conclusion identifies several key **characteristics** of **interemployer** wage differentials that need to be accounted for in any version of these models invoked.

II. The Data

The data used in this study are a unique set **compiled** for the author by the U.S. Bureau of Labor Statistics, from Area Occupational Wage Surveys (**AWS**) for a single metropolitan statistical area (**MSA**) over the course of six years. The variables include the wage, sex, occupation, and establishment identifier of individual workers in **nonsupervisory** positions. Wages are the straight-time hourly wages (no overtime or shift **premia** included) of hourly workers, and the average hourly earnings of incentive workers. **Although** confidentiality **restrictions** prohibit the release of **employers'** names, the data include unique establishment identifiers and two plant characteristics: size class and two-digit Standard Industry Classification (SIC) code.

This survey has the **following** advantages: it allows control for **MSA**, it includes many different **industries**, and it is longitudinal **in** establishments. In addition, the surveys **cover** a broad mix of occupations: white- and blue-collar, professional, **skilled**, and **unskilled**. The occupations surveyed belong to four major groups: **clerical/office** workers, professional personnel, custodial/material-movement workers, and **maintenance/toolroom/powerplant** occu-

pations. (Appendix A presents a complete list of the occupations covered in the survey.)

An important feature of these data is specificity of the occupation definitions, which are actually job classifications and are more detailed than four-digit Dictionary of Occupational Titles or Census codes. For example, secretaries are divided into five occupation classes, depending on their responsibilities, and distinguished from other clerical occupations such as stenographers (three classes), typists (three classes), and file clerks (four classes). This level of detail provides strong control for human capital as productively used. (Groshen [1988b] tests this assertion.) For brevity in the discussion that follows, the term occupation will be used instead of AWS job classification, the more accurate term.

In total, the particular survey analyzed below covers 88 occupations and 241 establishments in 42 two-digit SIC categories. Confidentiality restrictions prevent the Bureau of Labor Statistics from releasing the identity of the MSA or the exact years covered. The MSA is described as located in the northeast region of the country and not widely dispersed geographically. The six consecutive years fall between 1974 and 1981.⁶

Table 1 presents a summary of characteristics of the sample. Almost half (108) of the establishments are covered for the full six years; the remainder are fairly evenly split between those present for the first three years and the last three years, except for the few (7 percent) with missing data for one or more years. Thus, the data cover 1,008 establishment-years. In any year, well over half of the establishments are among those covered for the full six years. Approximately 17,000 individuals are surveyed per year, for a grand total of 101,990 observations.

Because the AWS occupations are found in many different industries and firms, the labor markets for such occupations may be more competitive than the markets for more industry-specific or firm-specific occupations. Workers can be expected to be more mobile when their skills are readily transferable among many different employers. Thus, we would expect the wages of workers in AWS occupations to be more standard across employers than would the wages of workers in less common occupations.

However, because they are common to most firms, AWS occupations generally work outside the major productive activities of the establishments surveyed and capture a relatively small proportion of the employees in most establishments. There are two alternatives to this approach. The first, analysis of industry-specific surveys that include the occupations most prevalent in each industry, is taken by Groshen (1988b). The second solution is to contract job classifications into broad occupational categories and survey all occupations and industries, as is done in household surveys. The analysis presented here includes a comparison of the results from the AWS to those from industry surveys and from the Current Population Survey.

III. The Size and Stability of Employer Wage Differences

A. Technique

Of particular interest in the study of interemployer wage differences is a measure of their importance, that is, the relative contribution of employer wage differences to total wage variation. This section partitions the variance of wages into the portions associated with particular effects using analysis of variance (ANOVA) techniques.

At any time, wages are hypothesized to depend on an **individual's** occupation, employer, the interaction between employer and occupation, and an individual **component**. If virtually all productive differences in human capital and **working** conditions are between, not within, **narrowly** defined occupations, then occupation dummies capture all significant differences in human capital and **working** conditions among jobs. **Groshen (1988b)** examines this issue and **finds** that the standard human capital variables (age, education, and race) add little explanatory **power** to regressions with three-digit occupational dummies in the Current Population Survey. Given the detail of the occupation distinctions in these surveys, the human capital variables can be **expected** to explain even less of the **remaining** variation in these data. In order to control as fully as possible for differences in worker quality, the actual estimation includes **dummies** for sex and incentive pay along with occupation. For ease of **exposition**, this set of variables is referred to simply as "**occupation**."

The test for the importance of employer characteristics is to measure the size and significance of employer variables included in a wage equation with human capital variables. The first set of variables are establishment **dummy** variables, to capture the average deviation of employees from their occupation means across all occupations. This effect, the fixed effect of employer on wages, is the main **focus** of this analysis.

Second, variations in employer differentials among occupations are captured by **including** variables for the interaction of occupation and establishment, which **estimates** an additional wage differential for each occupation in each plant. In this paper, this will be called an **employee's** "job-cell."

The equation estimated is as **follows**:

$$(1) \quad w_{ijk} = \mu + X_i \alpha + Y_j \beta + X_i Y_j \tau + \epsilon_{ijk},$$

where w_{ijk} = ln(wage) of employee k in occupation i at employer j,
 μ = mean wage for the population,
 X_i = vector of occupation dummy variables,
 α = vector of occupation wage differentials,
 Y_j = vector of establishment dummy variables,
 β = vector of employer wage differentials,
 $X_i Y_j$ = vector of job-cell dummy variables,
 τ = vector of wage differentials for job-cells, and
 ϵ_{ijk} = randomly distributed error term.

Since all of the independent variables are dichotomous, equation (1) can be rewritten, and wages may be understood, as the sum of a series of differentials:

$$(2) \quad w_{ijk} = \mu + \alpha_i + \beta_j + \tau_{ij} + \epsilon_{ijk}^e$$

where α_i , β_j , and τ_{ij} are the i^{th} , j^{th} , and ij^{th} elements of the α , β , and τ vectors, respectively, and μ is the overall mean wage. Over time, any of these four components may change, introducing coefficients on their interactions with year. These year-interaction coefficients capture trends or temporary deviations from average relative position over the six years and may be estimated in an expanded version of equation (2) :

$$(3) \quad w_{ijk}^t = \mu + \alpha_t + \alpha_i^t + \beta_j^t + \beta_j^t + \tau_{ij}^t + \tau_{ij}^t + \epsilon_{ijk}^t.$$

The differentials can be understood as follows:

- 1) Occupation differential (α_i) is an occupation's average deviation from mean wages, across all establishments. Presumably, these premia reflect productivity and compensating differences among occupations.

2) Occupation-year differential (α_{ij}^t) is an occupation's average deviation from its own mean wage in a particular year, across all establishments. These movements reflect responses to temporary labor supply shocks or adjustments toward new long-run positions.

3) Establishment differential (β_j) is the employees' average deviation from occupation mean in an establishment, across all occupations. Thus, these encompass many differentials proposed in earlier research: size of employer, industry, percentage female, union, etc.

4) Establishment-year differential (β_{ij}^t) is the employees' average deviation from establishment mean in a particular year, across all occupations. These movements reflect responses to temporary shocks or adjustments toward new long-run positions.

5) Job-cell (interaction) differential (τ_{ij}) is paid to a particular job-cell above the occupation and establishment differentials. High variance in this term indicates significantly different internal wage structures among employers.

6) Job-cell-year differential (τ_{ij}^t) is the job-cell deviation from mean in a particular year. High variance in this term indicates instability in the internal wage structures of employers.

7) Within job-cell (individual) differential (ϵ_{ijk}^t) is an individual or residual deviation from the mean for an occupation in an establishment in a year, presumably the result of individual productivity differences or differing compensation strategies on the part of employers (for example, incentive versus day rates). The more that wages are tied to individuals or to short-run performance rather than to jobs, the larger is this component.

Note that equations (1) and (2) express the same model in different notation. Equation (3) estimates the same model as in equations (1) and (2), but is fully interacted with time. If the differentials in equation (3) are mutually independent (this issue will be considered below), the total variance of wages may be partitioned as follows:

$$(4) \quad \sigma_w^2 = \sigma_{\alpha}^2 + \sigma_{\alpha t}^2 + \sigma_{\beta}^2 + \sigma_{\beta t}^2 + \sigma_{\tau}^2 + \sigma_{\tau t}^2 + \sigma_{\epsilon t}^2.$$

The size of each variance component estimate indicates its relative economic importance. And, the variation associated with interactions between a component and year measures the stability of wage differentials associated

with the **component** over time. Our interest is the **economic** and statistical **significance** of the differentials as groups, **summarized** by the relative size of the variance **components** and their interactions, as follows:

- 1) σ_a^2 and σ_{at}^2 measure the **importance** and stability of external occupational labor markets, respectively;
- 2) σ_β^2 and $\sigma_{\beta t}^2$ measure the **importance** and stability of employer wage differentials in wage determination, **respectively**;
- 3) σ_7^2 and σ_{rt}^2 measure the **importance** and stability of independent internal labor markets, respectively; and
- 4) σ_{et}^2 measures the **importance** and stability of individual differences within job-cell.

The essential **complication** to the discussion above is that **variance-component decomposition** as shown in equation (4) is not straightforward when data are unbalanced. An unbalanced design produces multicollinearity between the vectors of dummy variables (X_i and Y_j) in equation (1), which prevents a simple separation of the impacts of X and Y . If an establishment employs a relatively large number of workers in skilled occupations, we cannot distinguish whether a differential paid to those workers is due to their employer or to their occupations.⁷

Thus, the **technique** applied is a **decomposition** of the sum of **squares** of wages, rather than an explicit estimation of variance **components**.⁸ This **method** provides a measure of the ambiguity arising from design imbalance and does not require the imposition of structure on estimated differentials.

The summary of the technique provided in table 2 shows how a **series** of **ordinary least squares** (OLS) regressions is used to make the jump from equa-

tion (3) to equation (4). Wages are regressed successively on different sets of regressors. Changes in the coefficient of determination (that is, the sum of squares explained as a proportion of total) are used to partition the sum of squares of wages into components corresponding to those in equation (4).⁹

Use of the R^2 standardizes a_w^2 to a value of one.

First, in the pooled sample, log wages are regressed separately on vectors of occupation and establishment dummies and then on both sets of dummies together (called the full main-effects model). The marginal contribution of each set of dummies to the full main-effects model (over the equation with the other one alone) measures the portion of wage variation associated unambiguously with that factor. These correspond to minimum estimates of the relative size of the variance contributed by occupation and differentials, or a_α^2 and a_β^2 . The difference between the R^2 of each in the equation alone and their marginal contribution to the full main-effects equation is a measure of their joint (collinear, or ambiguous) explanatory power. To identify the industry effect, industry dummies are substituted for establishment dummies.

Next, the exercise is repeated with interactions between the main effects and year, in order to estimate the relative size of $\sigma_{\alpha t}^2$ and $\sigma_{\beta t}^2$, which indicate the stability of the main-effect estimates. The contribution of all other interaction differentials, including job-cell (a_{jt}^2) and job-cell-year differentials ($a_{j,t}^2$), is the difference between the explanatory power of a regression on job-cell-year dummies and that of the full (time-interacted) main-effects model. The individual contribution ($a_{\epsilon t}^2$) is the variation unexplained by job-cell-year dummies.

B. ANOVA of the Area Wage Survey

Table 3 presents the ANOVA of wage data from the area wage survey. The first column reports the degrees of freedom for each source of variation.¹⁰ The second column reports the percentage sum of squares, or increment to Σ , captured by each source. The total sum of squares reported excludes the effect of annual means, which were extracted prior to the analysis presented. The third column records F-statistics where appropriate.

The top six rows summarize the impact of the main effects: job classification, sex, incentive and establishment.¹¹ Together, these factors account for 90 percent of the observed variation in wages. The joint contribution of the main effects dominates, claiming 51 percent of total variation. This reflects an uneven distribution, or incomplete overlap, of occupations among establishments in the sample. The marginal contributions of establishment over occupation, and vice versa, are 19.3 percent and 19.5 percent, respectively: about equal, and both highly significant statistically. Each explains somewhere between 19 and 71 percent of total wage variation (71 percent is the marginal contribution plus the joint portion of variation).

The fixed establishment component of variation can be divided into the portions between industries and within industry. Between-industry variation is 11.4 percent of total variation (almost 60 percent of the marginal establishment total), leaving 7.9 percent for within-industry variation. Both portions have significant F-statistics. So, while industry captures a large part of the differences between establishment, it does not capture it all.

These results indicate that large establishment differentials exist within MSAs. The estimated establishment differentials have a large range:

from a minimum of -.81 to a maximum of +.56, compared to the mean. In fact, we cannot **reject** the possibility that employer differentials are as important as occupation, sex, and **incentive** pay in the **determination** of wages.

The importance of the interactions with time and between occupation and establishment are examined in depth below. The final category is individual variation, which **accounts** for only 3 percent of total wage variation. This suggests that individuals in the same **job-cell** are paid very similarly.¹²

C. The Uniformity of Establishment Differentials Across Occupational Groups

The tenth row of table 3, "all other **interactions**," measures the contribution of all interactions not explicitly listed in the rows above. These interactions include job-cell and job-cell-year interactions (which measure a^2_{ij} and a^2_{it}): differences in age-earnings profiles, in the relative treatment of job-cells by establishment, and changes in these over time. This group of interactions is **significant** as a whole, but **accounts** for just 6.3 percent of total variation. That is, the most **conservative** estimate of the contribution of employer main effects—19 percent—is three times as **large** as the interaction contribution. The size of this term suggests that relative **occupational wage structures** are probably fairly similar among these establishments.

Another way of examining the consistency of establishment differentials across occupational groups is to obtain and **compare** independent estimates for the four general occupational groups in the sample. Correlations of the **employer** wage differ — across groups are shown in table 4.

The upper panel lists correlations across groups when industry effects are included in establishment effects. For instance, the correlation between the establishment differentials of office workers and those of maintenance,

toolroom and powerplant workers is .635. The correlations are similar in magnitude to those obtained in Leonard (1987) and Greshen and Krueger (1989). Rank order correlations (listed below the standard Pearson correlations) do not differ substantially.

The lower panel shows the cross-occupational consistency of establishment effects within industry. Again, the correlations are generally quite high. In fact, the correlations involving professional and technical workers rise after controlling for industry. The smallest correlation (.306) occurs between office occupations and material movement and custodial workers. Apparently, interindustry differentials account for the bulk of the consistency in interestablishment differentials between these two groups.

In general, though, these results suggest that establishment differentials have consistent size and rank across occupations, even within industry.

D. The Stability of Establishment Wage Differentials

The pattern of establishment and occupation wage levels in this survey remains unchanged over six years. This can be inferred from rows 7 through 9 of table 3, which suggest that occupation and establishment differentials are remarkably stable: occupation and establishment interactions with year contribute a total of less than 1 percent of observed variation. Employer differentials are only slightly less stable than occupation differentials.

Another demonstration of the stability of establishment differentials is the lack of decay in year-to-year correlations as the gap between observations lengthens. Table 5 presents correlation coefficients (both Spearman and Pearson) of estimated establishment differentials across time. The correlation coefficients of estimated differentials for the same establishments in different years are strikingly high, starting at .99 for one-year differences

and barely decaying to .97 for estimates six years apart. The picture for rank-order correlations is much the same: **coefficients decline** only to .95 after six years.¹³

The lower panel of table 5 shows the persistence of within-industry establishment differentials. Although somewhat **lower** than the persistence of differentials that include **industry** effects, the correlations are still remarkably high: they **decline** only to **.894** (.856 in rank order) over the course of six years.

So, not only are employer differentials stable in size over **time**, but the relative rank of employers by size of differential is also stationary for periods as long as six years. **Furthermore**, the lack of any rapid decay over the period suggests that the patterns are probably stable for much longer than the six years included in the survey.

E. Conversion into Standard Deviations

Table 3 partitions the **sums** of squares, but does not indicate estimated variances for the **components** of interest. Table 6 presents results of multiplying the **percentage** of the sum of squares due to each factor by the total variance of the **sample**, and then taking the square root to generate the suggested standard deviation. In order to stack the deck against the investigated effect, the joint effects from table 3 are allocated **completely** to occupation.

The results can be converted to standard deviations in two ways. First we **see** the entire establishment effect, including the **industry** effects. This **generates** a standard deviation of **.18**, which we can interpret as a percentage of the mean because wages were estimated in log **form**. We can also extract two-digit industry effects **from** the estimated establishment effects.

This leaves **intra-industry** variation with a standard deviation of 12 percent, strikingly similar to the estimate of 11 percent in the industry surveys in Groshen (1988b). The similarity of these **results**, despite the very different sources, lends confidence to the findings.

How big are these **numbers** in practical terms? The experiment that this research tries to **simulate** is the random transfer of a worker in one establishment to a job in the **same** occupation at another establishment. What is the **expected** wage change **from such** a switch?¹⁴

Converting the suggested **standard** deviations in table 6 to **expected** wage changes, a random switch in establishment within **industry** (within job classification, sex, city, and incentive class) yields an **expected** 12 percent change (in absolute value) in wages; a switch that might be between industries is expected to **generate** a 19 percent wage change. These **differences** are **comparable** to average wage differences between union and nonunion employers, and correspond to differences of \$2,100 and \$3,300 per year, respectively, of the average wage of \$17,000 earned by a blue-collar production worker in manufacturing in 1984. Switching employers within **industry** results in a very **large** expected income change, as **large** as that from a switch in occupation within **industry**. In addition to the stability they show, the **sheer** size of these differentials makes it unlikely that they are caused by random variations.

F. Employer Differentials and Wage Variation in the Current Population Survey

A **large portion** of current **research** in labor economics is based on log wage regressions of Current Population Survey (CPS) data, but at least half of

the wage variation in the CPS remains **unexplained** after inclusion of traditional measures of human capital. What portion of that "**unexplained**" variation is actually due to employer differentials?

Appendix B compares variance components estimates for the **six-industry Industry Wage Survey (IWS)** average in Groshen (1988b), for the AWS, and for the May 1977 CPS. The IWS estimates are the **simple** means from ANOVA of the wages of production workers in six manufacturing industries. The AWS estimates are repeated from table 6, except that the effects of all interactions with time have been **removed**.

Since these three data sources are quite different, **adjustments** for the differences are necessarily speculative. The conclusion reached is that, compared to total wage variation in the CPS, estimated variation due to establishment differentials is **large**, even by **conservative** measures.

IV. Establishment Size, Growth, and Shrinkage Differentials

The employer wage differentials estimated above are presumably linked to characteristics of the employers, **some** of which have been identified, such as size of firm and size of establishment (Brown and Medoff [1987]). This section investigates the link between wages and another characteristic of establishment—**growth** or shrinkage of employment.

In these data, growth and shrinkage dummy variables can be created from **changes** over **time** in size class. Since Leonard (1989) finds that the size of establishment is surprisingly volatile, the first **attempt** to measure the influence of size change on wages uses net change in the size of employ-

ment at an establishment to measure growth and shrinkage. Dummies for growth and shrinkage were entered separately in order to allow for lack of symmetry in lags or for stickiness in either direction.

The upper panel of table 7 compares the contribution to explanatory power of size and the size change (row 3 of the table) to that of establishment dummies (row 2), controlling for occupation and industry (row 1). The purpose is to measure how much of employer variation within industry can be linked to size and size change. The results indicate that establishment size alone and dummy variables for establishment growth and shrinkage account for more than 19 percent of within-industry wage variation by employer in the AWS. Only 3 percent of this is contributed by the growth and shrinkage variables.

The lower panel of table 7 presents the coefficient estimates for the regression equation in row 3 in the upper panel. Except for the smallest size class, wages increase monotonically with size, and we estimate a negative differential for growth and a negligible one for shrinkage.

Table 8 presents the results of four other attempts to link estimated establishment differentials and changes in estimated differentials to growth or shrinkage of the establishment. The question is whether size change leads to greater or smaller wage changes than would be expected just from the adjustment to wages of the new size class.

If **growth** or shrinkage is exogenously determined and information is costly, then an employer's **growth** may raise its efficient wage under the turn-over version of the efficiency wage hypothesis (see Salop [1979]). The wage increase is **profit-maximizing** because, during growth, the employer needs to attract or retain a higher proportion of workers than it does in a steady

state. Similarly, an employer that needs to shrink its work force may allow relative wages to fall below previous levels. Attraction of new workers is unnecessary and quits are perhaps desirable.

A second explanation for the same association comes from the bargaining model. Suppose that establishment growth resulted from success—that is, high profits—and shrinkage from low profits. Then, growth would indicate the presence of high wages because large rents were available for distribution. By the same logic, shrinkage would indicate lower wages.

However, if growth is endogenous, the zero-sum aspect of bargaining raises the possibility of the opposite relationship. If profits captured by workers would otherwise be used for expansion, then high-growth companies could be those with low wages. And shrankers could be doing so because of their high wages. This is the same prediction and causality generated by the simple competitive model in the short run. Low wages lead to higher profits and, therefore, growth, unless the low wages induce quits, and thus, shrinkage; high wages should erode profits and cause shrinkage. Included here is the observation that since most hires are at the bottom of pay ranges, a hiring surge could appear to lower wages by lowering average tenure in a plant.

To summarize, the turnover version of the efficiency wage hypothesis predicts a positive relationship between growth and wages. The bargaining model is ambiguous, depending on the exogeneity of growth, and the simple competitive model predicts a negative relationship, or none at all.

The first two columns of table 8 present regression coefficients for the effect of establishment growth and shrinkage on estimated establishment differentials, controlling for industry and size. The effect of shrinkage may be negative, occurring before the shrinkage takes place. The effect of growth

is also negative, but relative to the wages of **establishments** in the new size class, not the old one. **This** suggests that wage changes may lag behind growth, but precede shrinkage. **That** is, wages may **be** sticky **upwards** during size change. Since the coefficient on growth is small and insignificant relative to that on past size, and the coefficient on shrinkage is small and insignificant relative to that on current size, the **movement** in wages is apparently not greater than that associated with a change of size category.

However, the third column of table 8 diminishes confidence in the last point. In order to allow for more **complete** adjustment and to increase the **signal-to-noise** ratio, this column presents regressions of net changes in estimated differentials on net changes in size. Neither growth nor shrinkage has a large or significant impact on change in differentials. The sign of the coefficient on shrinkage **switches** to positive but is small. **Growth** is estimated to **reduce** wages by 1 percent (with no controls for size), but the estimate is not significantly different **from** zero.

These data do not conclusively support any of the three hypotheses above. The first two **columns** suggest that wages are sticky upwards. If anything, wages are apparently lower for firms that grow, but shrinkage has little or no effect. And, neither result is stable under alternative formulations (that is, relative to wages of employers of the same size).

Thus, although size changes affect wages because wages **increase** with size, neither growth nor shrinkage appears to have a simple, consistent effect on wages, holding size constant. **The** data reject the efficiency wage and the **exogenous-growth** bargaining predictions of a positive relationship **between** growth and wages. **The** correlation **between** wages and **growth**, if there is one,

appears to be negative. It is even less likely that shrinkage is correlated with wages; but if so, shrinkage is also associated with (slightly) **lower** wages.

V. Conclusion

A. Summary of Findings

The conclusions of this analysis are as follows:

(1) Twenty to 70 percent of wage variance within this MSA is due to **employer-based** differences both between and within industry. The most conservative estimate of the standard deviation due to employer differentials within **industry** is 12 percent. Combined with industry effects, this generates a standard deviation of approximately 18 percent: a major portion of the 50 percent total standard deviation of wages.

(2) Establishment wage **differences** and **rankings** (even within industry) are virtually stationary for periods at least as long as six years, and probably for longer.

(3) While establishment size can account for much of measured employer wage effects within industry, establishment **growth** and shrinkage do not have a **simple**, consistent relationship with employer wage levels or wage *changes*.

Thus, even across occupations as diverse as those **in the area wage survey**, employer differentials are applied relatively uniformly. Compared to occupational means, employers tend to **compensate** janitors as well (or as poorly) as they do industrial nurses, **computer** programmers, millwrights, and stenographers. **Furthermore**, employers are also very consistent in their patterns over time.

Occupation (including sex and incentive) and employer differentials are clearly extremely important in wage determination. These factors, when well identified, as in these surveys, can explain more than 95 percent of wage variation. Thus, other characteristics of the individual (for example, tenure, marital status, or race) must operate through job classification or through employer in order for them to have a large effect on wages. Otherwise, they are not highly influential in the determination of wages.

In short, since a large improvement in earnings can be attained only through a promotion or a change of employer, barriers to entry into highly remunerative occupations or establishments can have a devastating impact on the earnings of otherwise-qualified workers.

B. Implication for Sources of Establishment Wage Differentials

These results cast more light onto the nature of wage differences among employers and onto the plausibility of proposed sources of wage variation by employer. Of the five sources of employer wage differentials that have been modeled (sorting by worker quality, compensating differentials, random variations, efficiency wages, and insider bargaining), evidence in previous studies renders the first two possibilities unlikely.

The evidence presented above rejects the third possibility, random variations, as the source of employer differentials. The strong stability of establishment differentials over time provides compelling evidence against the hypothesis that establishment differentials are temporary fluctuations. If the differentials are random but not temporary, then they are extremely costly for high-wage employers, which suggests that labor-market information must be

even more costly. **But**, the results of this survey and many other private substitutes are available to **firms** on a fairly **timely** basis at no cost (or at the cost of participation).

Furthermore, the extent to **which** the differentials **persistently** (since at least the 1940s) depend on easily identified establishment **characteristics**, such as industry and size of establishment, makes the random variations hypothesis unlikely. For instance, it is implausible that personnel officers of **large firms** have been **consistently** wrong, all mistakenly setting their wages too high for 40 years. Thus, the random variation theory of establishment differentials may be **ruled** out.

The finding of substantial wage differences among employers within a single city also argues against the possibility that **regionwide compensating** differentials for cost of living are the main source of employer differentials, although urban wage gradients within the city are still a possibility.

Process of elimination also suggests the need for serious consideration of efficiency wage and rent-sharing (**insider/outsider**) models. This paper identifies several key characteristics of interemployer wage differentials that need to be present in any version of these models invoked.

First, employer wage differentials are found among **white-collar** workers, as well as blue-collar workers, in a nationally representative set of industries. The **pervasiveness** of these differentials **argues** for explanations that apply **across-the-board** to all occupations in an establishment, and to the establishments **in most** industries. Thus, **occupation-specific** difficulties in monitoring are not a likely source, because the occupations surveyed here are very diverse. Also unlikely are explanations that appeal to the characteristics of a single industry.

Second, although wages and size of establishment have a strong **positive** correlation, plant size change has no **simple**, consistent relationship with wage level. Thus, the versions of efficiency wage and **rent-sharing** models based on **growth** or shrinkage of establishment are unlikely sources of **interemployer** wage differences.

Third, since employer differentials are quite persistent on an annual basis, while annual profit rates of U.S. **companies** are notoriously volatile, if these differentials are ~~recent~~, they presumably reflect **long-run**, not short-run, rents.

References

Akerlof, George, "Labor Markets as Partial Gift Exchange," Quarterly Journal of Economics, vol. 97, November 1982, pp. 543-569.

Aoki, Masahiko, The Cooperative Game Theory of the Firm, New York: Oxford University Press, 1984.

Brown, Charles, "Equalizing Differences in the Labor Market," Quarterly Journal of Economics, Vol. 94, No. 1, February 1980.

_____, and James L. Medoff, "The Employer Size Wage Effect," unpublished paper, September 1987.

Brown, William, John Hayles, Barry Hughes and Lyndon Rowe, "Production and Labor Markets in Wage Determination: Same Australian Evidence," British Journal of Industrial Relations, Vol. 22, No. 2, July 1984.

Bulow, Jeremy I., and Lawrence H. Summers, "A Theory of Dual Labor Markets With Application to Industrial Policy, Discrimination, and Keynesian Unemployment," Journal of Labor Economics, Vol. 4, No. 3, Part 1, July 1986, pp. 376-414.

Dickens, William, "Wages, Employment and the Threat of Collective Action by Worker," National Bureau of Economic Research Working Paper No. 1856, March 1986.

_____, and Lawrence F. Katz, "Industry Wage Patterns and Theories of Wage Determination," National Bureau of Economic Research Working Paper No. 2271, July 1987.

Doeringer, Peter, and Michael Piore, Internal Labor Markets and Manpower Analysis, Lexington, Mass.: D.C. Heath and Co., 1971.

Dunlop, John T., "The Task of Contemporary Wage Theory," in G. Taylor and F. Pierson, eds., New Concepts in Wage Determination, New York, 1957.

Eberts, Randall W., "An Empirical Investigation of Intraurban Wage Gradients," Journal of Urban Economics, Vol. 10, 1981, pp. 50-60.

Gibbons, Robert, and Lawrence F. Katz, "Learning, Mobility, and Inter-Industry Wage Differentials," Massachusetts Institute of Technology, unpublished paper, December 1987.

Groshen, Erica L., "Sources of Wage Dispersion: Does It Matter Where You Work?" Ph.D. Dissertation, Harvard University, 1986.

_____, "Why Do Wages Vary Among Employers?" Federal Reserve Bank of Cleveland Economic Review, First Quarter 1988a.

_____, "Sources of Wage Dispersion: The Contribution of Interemployer Wage Differentials Within Industry," Federal Reserve Bank of Cleveland Working Paper No. 8802, 1988b.

____ and Alan B. Krueger, "The Structure of Supervision and Pay in Hospitals," Federal Reserve Bank of Cleveland Working Paper Nb. 8907, June 1989.

Henderson, C.R., "Estimation of Variance and Covariance Components," Biometrics, June 1953.

Hocking, Ronald R., O.P. Hackney, and F.M. Speed, "The Analysis of Linear Models with Unbalanced Data," in H.A. David, ed., Contributions to Survey Sampling and Applied Statistics: Papers in Honor of H. O. Hartley, New York: Academic Press, 1978.

Leonard, Jonathan S., "On the Size Distribution of Employment and Establishments," Quarterly Journal of Economics, 1989.

____, "Carrots and Sticks: Pay, Supervision, and Turnover," Journal of Labor Economics, Vol. 5, No. 4, October 1987, pp. s136-s152.

Mackay, Donald I., David Boddy, John Brack, John A. Diack and Norman Jones, Labour Markets Under Different Employment Conditions, London: George Allen & Unwin Ltd., 1971.

Nolan, Peter and William Brown, "Competition and Work Place Wage Determination," Oxford Bulletin of Economics and Statistics, Vol. 45, No. 3, August 1983.

Rothschild, Michael, and Joseph E. Stiglitz, "Equilibrium in Competitive Insurance Markets: An Essay on the Economics of Imperfect Information," Quarterly Journal of Economics, Vol. 90, No. 4, November 1976.

Salop, Steven, "A Model of the Natural Rate of Unemployment," American Economic Review, Vol. 69, No. 1, March 1979.

Searle, S.R., Linear Models, New York: Wiley & Sons, 1971.

Segal, Martin, "Post-Institutionalism in Labor Economics: The Forties and Fifties Revisited," Industrial and Labor Relations Review, Vol. 39, April 1986, pp. 388-403.

Smith, Robert, "Compensating Wage Differentials and Public Policy: A Review," Industrial and Labor Relations Review, Vol. 32, No. 3, April 1979.

Stigler, George J., "Information in the Labor Market," Journal of Political Economy, Vol. 70, No. 5, Part 2, October 1962.

Stiglitz, Joseph E., "Theories of Wage Rigidities," National Bureau of Economic Research Working Paper, 1984.

_____, "On Search and Equilibrium Price Distributions," in Economics of Human Welfare, Michael J. Posken, ed., New York: Academic Press, Inc., 1979.

Topel, Robert, "Equilibrium Earnings, Turnover and Unemployment," Journal of Labor Economics, Vol. 2, October 1984.

Weitzman, Martin, The Share Economy: Conquering Stagflation, Cambridge, Mass.: Harvard University Press, 1986.

Yellen, Janet, "Efficiency Wage Models of Unemployment," American Economic Review, Vol. 74, No. 2, May 1984.

Footnotes

1. Groshen (1988a) reviews the empirical and theoretical literature examining employer differentials.
2. Exceptions to this generalization are a group of studies by economists in the 1940s and 1950s summarized in Segal (1986). Groshen (1988b) provides recent evidence of large establishment wage differentials among production workers in six manufacturing industries, using national industry wage surveys.
3. Groshen (1988b) finds it unlikely that intra-industry employer variations are due to sorting by tenure, experience, education, or for variations in unmeasured worker ability correlated with these measures of human capital. Dickens and Katz (1987) find that interindustry differentials cannot be explained by the three measures of human capital. And, Gibbons and Katz (1987) conclude that interindustry wage differences are not associated with unmeasured differences in productive abilities.
4. Attempts to identify the working conditions for which interindustry wage variations compensate have been notably unsuccessful, as have attempts to identify compensating variations in general (Brown [1980] and Smith [1979]).
5. However, urban wage gradients within the city are still possible (Eberts [1981]).
6. These years were characterized by historically high inflation rates, which might be expected to result in more random behavior because of more costly information, and in more real downward wage flexibility on the part of employers.
7. Techniques for estimation of variance components of a model of unbalanced design are detailed in Searle (1971) and Henderson (1953). Restricted maximum likelihood (RML) techniques are introduced in Hoching, Hackney and Sped (1978). RML provides simple estimates of variance components and their standard errors at the expense of imposing a rigid structure on the distribution of level effects and errors. Because the appropriateness of the structure imposed may vary among industries, and because the purpose of this study is to investigate the characteristics of establishment differentials, a nonparametric method was preferred for this analysis. Groshen (1986) provides a complete discussion and examples of the application of alternative ANOVA techniques to similar data.
8. The technique used here avoids the essence of ANOVA's difficulty with unbalanced data. A variance is a sum of squared deviations divided by the appropriate number of observations or degrees of freedom. In data with an unbalanced design, the correct number of degrees of freedom is unknown, so variance estimates must rely on estimates of the correct degrees of freedom. Such estimates require the imposition of structure on the data.
9. The following work concentrates attention on proportions of variance rather than on F-statistics for two reasons. First, because of the large sample sizes, all of the F-statistics are strongly significant (the critical value is 1 in most cases), even if the economic significance is slight. Second, establishment identity is presumably an inefficient measure of the economically

relevant **differences** between establishments. By construction, it captures all **differences** and thus identifies the **maximum** amount of variation that understanding of employer wage policy could explain.

However, as a measure of the source of **employer** differences, establishment may be finer than necessary. If so, the F-statistic can mislead because it averages out the **impact** of all estimated levels. While the **additional** variation explained by unnecessary levels is negligible, the number of degrees of freedom used can be high, reducing the F-statistic. The inclusion of irrelevant levels washes out the significance of the relevant ones.

The F-statistic of a factor X is defined as follows:

$$F_x = [(RRSS - URSS)/k] / [URSS/(n-k)],$$

where RRSS = restricted residual sum of squares, URSS = unrestricted residual sum of **squares**, k = number of **restrictions** or levels in parameter x, and n = degrees of freedom in **unrestricted** equation (that is, number of **observations** minus degrees of freedom used by other regressors).

If k is the number of **correctly** specified levels of the factor X, then let δ = measure of irrelevant fineness in another measure, say Y. That is, suppose instead of using k levels, we use the δk levels of Y, where $\delta > 1$. Then, as long as the levels of X are a linear **combination** of the levels of Y, and n is large relative to δk , the URSS of the equation will be almost the same, the RRSS will be the same, so the F-statistic of the inefficient parameter Y is as follows:

$$F_y \approx [(RRSS - URSS)/\delta k] / [URSS/(n-\delta k)].$$

And, the ratio of F_y to F_x (for n large relative to k) is

$$F_y/F_x \approx (n-\delta k)k / [(n-k)\delta] = [(n/\delta)-k]/(n-k) \approx 1/\delta.$$

The **maximum** of the ratio is one (where $X=Y$, so $\delta=1$); otherwise it decreases monotonically with increasing δ , and **approaches** $1/\delta$ for n large and k small. So the size of the F-statistic depends not only on the **economic** relevance of the parameter measured, but also on the inefficiency with which it is measured. Since the purpose of this work is to identify the potential explanatory power of variables based on establishment, I focus primarily on the percentage sum of **squares** explained by factors rather than **through F-statistics**.

10. The number of degrees of freedom is determined by the number of dummy variables used in the regressions. For example, in the case of establishments, the number of degrees of freedom is the number of establishments **minus** one.

11. The **incentive** dummy equals one when the worker in question has an incentive **component** to his or her earnings. These incentives may be in the form of individual or group piece rates, individual or group bonuses, or **commissions**.

12. This is the result for industries with a **low** proportion of incentive-based compensation in **Groshen (1988b)**.

13. These are quite similar to the results obtained by Mackay, et al. (1971) and Nolan and Brown (1983) in England.

14. This question asks for the expected absolute value of the difference between two identically distributed random variables. Assuming a normal distribution of differentials, the question reduces as follows:

$$E[|\Delta d|] = E[|d_1 - d_2|] = 2^{\frac{1}{2}}(\phi[0]/\Phi[0])\sigma_d = 2^{\frac{1}{2}}(.4/.5)\sigma_d = 1.13\sigma_d,$$

where d = random differential, distributed $N(0, \sigma_d^2)$, and $\phi[0]$ and $\Phi[0]$ are the normal density and the cumulative normal density functions, evaluated at zero.

Appendix A

Occupations Surveyed in the Area Wage Survey

Office Occupations

Secretaries: Classes A, B, C, D, E, and Not Classifiable By **Level**

Stenographers: Senior, General, and Not Classifiable By Level

Transcribing-Machine **Typists**

Typists: Classes A, B, and Not Classifiable By Level

File Clerks: Classes A, B, C, and **Not** Classifiable By Level

Switchboard Operators

Switchboard Operator-Receptionists

Order Clerks: No Level Distinctions, Classes A, B, and Not Classifiable

Accounting Clerks: Classes A and B, and Not Classifiable By **Level**

Bookkeeping-Machine Operators: Classes A, B, and Not Classifiable By Level

Messengers

Billing-Machine **Billers**

Bookkeeping-Machine Billers

Machine Billers, Not Classifiable By Level

Payroll Clerks

Key Entry Operators: Classes A, B, and Not Classifiable By Level

Tabulating-Machine Operators: Classes A, B, and C

Professional and Technical Occupations

Computer Systems Analysts (Business): Classes A, B, C, and Not Classifiable

Computer Programmers (Business): Classes A, B, C, and Not Classifiable

Computer Operators: Classes A, B, C, and Not Classifiable By Level

Drafters: Classes A, B, C, and Not Classifiable By Level

Drafter-Tracers

Electronics Technicians: Classes A, B, C, and Not Classifiable By **Level**

Peripheral Equipment **Operators**

Computer Data Librarians

Registered Industrial Nurses

Maintenance, Toolroom and

Powerplant Occupations

Main ——— Carpenters

Maintenance Electricians

Maintenance Painters

Main ——— Mechanics (**Machinery**)

Maintenance Mechanics (Motor Vehicles)

Maintenance Pipefitters

Maintenance Sheet-Metal Workers

Millwrights

Maintenance Trades Helpers

Machine-Tool Operators (**Toolroom**)

Tool and Die Makers

Stationary Engineers

Boiler Tenders

Material Movement and Custodial

Occupations

Truckdrivers: Light Truck, Medium Truck

Heavy Truck, **Tractor-Trailer**, and

Not Classifiable by Category

Guards: No Level Distinction,

Classes A, B, and Not Classifiable

Shippers

Receivers

Shippers and Receivers

Warehousemen

Order-Fillers

Shipping **Packers**

Material Handling Laborers

Forklift Operators

Power-Truck Operators (Other Than Forklift)

Janitors, Porters, and Cleaners

Watchmen

Appendix B

Decomposition of the Variance of Wages in Three Data Sets

This appendix presents variance components estimates for the **six-industry** Industry Wage Survey (IWS) average in Groshen (1988b), for the Area Occupational Wage Surveys (AWS), and for the May 1977 Current Population Survey (CPS). May 1977 was chosen as a year within the ranges of both the AWS and IWS. The sample includes all **private-sector, full-time** employees between the ages of 18 and 65 with reported average hourly earnings of more than \$1.75 per hour.

The IWS estimates are the simple means from ANOVA of the wages of production workers in six manufacturing industries. The technique used in Groshen (1988b) is identical to that used here, except that all data are cross-sectional, and so differentials are estimated without explicit interactions with year. The AWS estimates are repeated from table 5, except that the effects of all interactions with time have been removed.

These three data sources are quite different, so adjustments for the differences are necessarily speculative. For instance, the standard deviation of wages in the AWS, .40, is double the mean for the six industry wage surveys (.20). As noted above, area wage surveys cover a broader mix of occupations, both blue-collar and white-collar. Moreover, area wage surveys include the effects of interindustry wage variation. The CPS includes all of the sources of variation already mentioned, in addition to the full range of occupations in the economy.

The first two rows of table B-1 present the least comparable numbers across the three surveys: standard deviation estimates for total dispersion

and those due to occupation, sex, region, and **industry** differentials.

Reported AWS and IWS figures allocate the **entire** joint occupation establishment effect to occupation. In the **IWS**, the variance in the first row includes regional variation, but not interindustry variation. In the **AWS**, the variation in the first row includes interindustry variation, but no regional variation.

In the **CPS**, the first row captures both industry and regional **sources** of wage variation, **in addition** to occupation and **sex**. The level of detail of region, sex, and industry are roughly the same in the **AWS** and **CPS**, but **CPS** three-digit occupations lack the detail of the job classifications in the **IWS** and **AWS**. The **CPS** variation **in the first row** is the same as that of the **AWS**, despite the higher total variance in the **CPS**. This suggests that variation within the **CPS** occupational categories is greater than the variation between regions in the country. **Lack** of occupational specificity leaves more wage variation unexplained than the addition of regional controls can capture.

Another way to judge the **impact** of broad occupation data in the **CPS** is to note that **in** the plastics industry, contraction of the 42 BLS job **classifications** into 12 **CPS** occupational categories reduces the R^2 of the equation by one half, **from** 49 percent to 25 percent. In **an ANOVA** as **shown**, at least half of this **difference**—judging **from** the size of the contribution "**joint**" to occupation and establishment—might **then** be claimed by establishment differentials, raising the estimated employer effect in the **CPS**.

The second row shows the remaining variation for each sample. These are quite similar for the **AWS** and **IWS**: a standard deviation of about **.16**. The **CPS**, however, retains a standard deviation of **.31**, almost twice as high.

The next three rows present speculative estimates of the size of the within-industry establishment effect in the **CPS**, in order to provide bounds

for the probable contribution of establishment to CPS wage variation. The first method takes the point estimate of standard deviation from the IWS and AWS: .11. Although this is a large portion of the unexplained standard deviation of .31, the estimate is conservative for two reasons. First, CPS occupations are very broad. The large joint component of variation in the IWS and AWS would shrink with these broad occupations, increasing the size of the estimated establishment impact on variation. Second, the IWS and AWS oversample large establishments and omit the smallest ones. In these data, estimated establishment variance is highest among the smallest establishments. Thus, the CPS should provide more establishment diversity because it samples evenly from all sizes of employer.

The second estimate assigns the AWS establishment percentage of total wage variation to establishment in the CPS, and converts this to a standard deviation of .13. The result is very similar to the first estimate and has the same limitations.

The third method is less conservative and assigns to establishment the same percentage of remaining variation (after occupation, industry, etc.) as is found in the AWS. That converts to a standard deviation of .20.

In order to see if the limited number of occupations surveyed in the AWS accounted for these results, the last column of table 6 presents the same exercises on the subsample of CPS observations for workers in AWS occupations. (They totalled 24 percent of the CPS sample.) The variance of wages is lower in the subsample, but the entire decrease in variance is in the between-occupation portion of variance. This leaves the estimates of establishment effect virtually the same, increasing confidence in them.

But how much of the remaining variation is actually noise? The reasons CPS wage reports may have a larger noise-to-signal ratio than BLS wage surveys are as follows:

- 1) CPS average hourly earnings are somewhat imprecisely defined (they include earnings from overtime or shift premia or from second jobs);
- 2) CPS respondents¹ memories are probably subject to more error than are the establishment records used by the BLS;
- 3) CPS data-cleaning is far less thorough than BLS efforts; and
- 4) CPS occupations are subject to large reporting error.

So, the nonoccupation variation in the CPS is probably biased upwards. Thus, compared to total wage variation in the CPS, estimated variation due to establishment differentials is large, even by conservative measures.

Table 1
Characteristics of Area Wage Survey Sample

Mean Wage	\$5.68
Variance of In (Wage) ¹	.174
Standard Deviation of ln (Wage) ¹	.42
Number of Observations	101,990
Number of Occupations	88
Number of Establishments	241
Male	59.3%
Receive Incentive Pay	2.2%

<u>Establishment Size</u>	<u>Percent of Observations</u>	<u>Major Industry Group (1-Digit SIC)</u>	<u>Percent of Observations</u>
1-19	0.0%	2. Nondurable Manufacturing	10.0%
20-49	0.5%	3. Durable Manufacturing	28.8%
50-99	2.4%	4. Transport. and Utilities	11.0%
100-249	9.3%	5. Wholesale and Retail Trade	17.3%
250-499	16.7%	6. Financial Services	12.8%
500-999	13.4%	7& 8. Personal and Business Services	
1,000-2,499	30.5%		19.7%
2,500+	27.1%		

<u>Year of Observation</u>	<u>Number of Years Observed</u>
1 17.3%	1 3.0%
2 16.7%	2 3.8%
3 16.5%	3 46.4%
4 16.6%	4 4.5%
5 16.5%	5 1.5%
6 16.4%	6 40.8%

¹Net of annual effects.

Source: Tabulations from the BLS Area Wage Survey, unidentified area in the Northeast for six consecutive years between 1975 and 1982.

Table 2

Technique for Partitioning Sum of Squares in Unbalanced Data

Source of Variation	Percent of Total Sum of Squares ¹
1. Occupation, Sex , Incentive (controlling for estab.)	$R^2_C - R^2_B$
2. Joint Occupation and Establishment	$R^2_A + R^2_B - R^2_C$
3. Establishment and Industry (controlling for occup., etc.)	$R^2_C - R^2_A$
4. Industry (controlling for occupation, etc.)	$R^2_C - R^2_A$
5. Establishment Within Industry	$R^2_C - R^2_C$
6. Total Main Effects	R^2_C
7. Occupation, etc., -Year Interactions	$R^2_{CT} - R^2_{BT}$
8. Joint Occupation, etc., and Establishment	$R^2_{AT} + R^2_{BT} - R^2_{CT}$
9. Establishment Year-Interactions	$R^2_{CT} - R^2_{AT}$
10. All Other Interactions (controlling for main effects)	$R^2_D - R^2_C$
11. Total Between Job-Cell-Years	R^2_D
12. Individual	$100\% - R^2_D$
TOTAL	100%

¹The subscripts on the coefficients of determination correspond to the regression models listed below. Occupation, sex, and **incentive** are listed as occupation, for ease of exposition.

$$A. \quad w_{ijk}^t = \mu + X_i \alpha + \epsilon_{ijk}^t \quad AT. \quad w_{ijk}^t = \mu + X_i \alpha + X_i^t \alpha^t + \epsilon_{ijk}^t$$

$$B. \quad w_{ijk}^t = \mu + Y_j \beta + \epsilon_{ijk}^t \quad BT. \quad w_{ijk}^t = \mu + Y_j \beta + Y_j^t \beta^t + \epsilon_{ijk}^t$$

$$C. \quad w_{ijk}^t = \mu + X_i \alpha + Y_j \beta + \epsilon_{ijk}^t \quad C. \quad w_{ijk}^t = \mu + X_i \alpha + Y_j \beta + \epsilon_{ijk}^t$$

$$CT. \quad w_{ijk}^t = \mu + X_i \alpha + X_i^t \alpha^t + Y_j \beta + Y_j^t \beta^t + \epsilon_{ijk}^t$$

$$D. \quad w_{ijk}^t = \mu + X_i \alpha + X_i^t \alpha^t + Y_j \beta + Y_j^t \beta^t + X_i Y_j \tau + X_i^t Y_j^t \tau^t + \epsilon_{ijk}^t$$

where $w_{ijk}^t = \ln$ wage of individual k in occupation, establishment j, and year t

X_i = vector of occupation dummy variables for occupation i

Y_j = vector of establishment dummy variables for establishment j

\underline{Y}_j = vector of **industry** dummy variables for industry j

$X_i Y_j$ = dummies for occupation i in establishment j, i.e., for job-cell ij,

$\alpha, \beta, \beta, \tau$ = vectors of estimated parameters, and

the superscript t denotes variables and parameters that vary over time.

Table 3

Analysis of **Sources** of Wage Variation Within an Area¹

Source of Variation	Degrees of Freedom	Percent of Total Sum of Squares	F-Statistic ⁸
1. Occupation, Sex and Incentive ²	89	19.5%	2,168
2. Joint Occupation, etc., and Establishment	-	50.9	-
3. Establishment and Industry ³	240	19.3	804
4. Industry ³	41	11.4	1,558
5. Establishment Within Industry ⁴	199	7.9	330
6. Total Main Effects	329	89.7	-
7. Occupation, etc. -Year Interactions ⁵	436	0.3	8
8. Joint Occupation, etc. and Establishment	-	0.1	-
9. Establishment-Year Interactions ⁶	767	0.5	7
10. All Other Interactions ⁷	11,230	6.3	16
11. Total Between Job-Cell-Years	12,762	96.9	-
12. Individual	89,222	3.1	-
TOTAL	101,984	100.0%	-
Total Sum of Squares		15,934	

¹All reported figures are net of main annual effects.

²Controlling for industry and establishment.

³Controlling for occupation, sex, and incentive.

⁴Controlling for occupation, sex, incentive, and industry.

⁵Controlling for main effects and establishment-year interactions.

⁶Controlling for main effects and occupation, sex, incentive-year interactions.

⁷Controlling for main effects and their interactions with year.

⁸All F-statistics are significant at well above the 1% level.

Source: Tabulations from BLS Area Wage Survey.

Table 4

Correlations of Estimated Establishment Wage Differentials
Over Four Occupational Groups¹

A. Including Industry Effects¹

	TYPE OF CORRELATION	Professional and Technical	Maintenance, Toolroom and Powerplant	Material Movement and Custodial
Office	Pearson	.854	.635	.631
	Rank	.788	.670	.584
Professional and Technical	Pearson		.622	.503
	Rank		.636	.466
Maintenance, Toolroom, and Powerplant	Pearson			.773
	Rank			.787

B. Controlling for Industry Effects¹

	TYPE OF CORRELATION	Professional and Technical	Maintenance, Toolroom and Powerplant	Material Movement and Custodial
Office	Pearson	.886	.652	.306
	Rank	.892	.652	.134
Professional and Technical	Pearson		.799	.531
	Rank		.759	.486
Maintenance, Toolroom and Powerplant	Pearson			.732
	Rank			.611

¹Results weighted by number of observations in establishment. Estimated establishment differentials are average differentials (taken from independent regressions for each occupational group) over period in which the establishment was observed.

Source: Tabulations from BLS Area Wage Survey.

Table 5

Correlations of Estimated Establishment Differentials Over Six Years

A. Including Industry Effects¹

		Year					
		2	3	4	5	6	
Year	1	Pearson	.988	.988	.979	.969	.967
		Rank	.977	.978	.956	.937	.950
	2	Pearson	-	.989	.982	.978	.977
		Rank	-	.984	.968	.948	.962
	3	Pearson		-	.990	.981	.976
		Rank		-	.977	.952	.964
	4	Pearson			-	.991	.984
		Rank			-	.975	.971
	5	Pearson				-	.989
		Rank				-	.978

B. Controlling for Industry Effects²

		Year					
		2	3	4	5	6	
Year	1	Pearson	.975	.968	.909	.904	.894
		Rank	.970	.962	.891	.869	.856
	2	Pearson	-	.974	.925	.924	.906
		Rank	-	.969	.909	.897	.871
	3	Pearson		-	.950	.932	.909
		Rank		-	.916	.902	.877
	4	Pearson			-	.971	.949
		Rank			-	.967	.938
	5	Pearson				-	.959
		Rank				-	.969

¹Results weighted by number of observations in establishment.

²Results weighted by number of observations in establishment. Industry-year effects are excluded. Establishments in industries with only one establishment are also omitted.

Source: Tabulations from BLS Area Wage Survey.

Table 6

Suggested Standard Deviations for
Area Wage Survey

Source	Suggested Standard Deviation ¹
Occupation	.35
Establishment (Including Industry)	.18
Establishment (Within Industry)	.12
Interactions	.11
Individual	.07
TOTAL	.42

¹Suggested standard deviation=[(category proportion of CSS)x(total variance)]^{1/2}. Joint contribution is allocated to occupation.

Source: Tabulations from BLS Area Wage Survey.

Table 7

Comparison of Regression on Establishment Dummies
with Regressions on Establishment Size in the Area Wage Survey

A. Comparison of Explanatory Power

Eq.	Independent Variables	R ²	▲R ² from Eq. 1
(1)	Occupation, Sex, Incentive and 2-Digit SIC	81.8	-
(2)	Occupation, etc. and Establishment Dummies	89.7	+7.9
(3)	Occupation, etc., SIC, Establishment Size Category and Net Size Change	83.3	+1.5
RATIO OF EXPLANATORY POWER OF ESTABLISHMENT SIZE TO ESTABLISHMENT DUMMIES			.190

B. Coefficients from Regression of ln (Earnings) on Establishment Size

Variable	Coefficient or Number of Dummies	(Std. Error)
Occupation	87	
Male	0.047	(0.002)
Receive Incentive Pay	0.108	(0.004)
2-Digit SIC	41	
Establishment Size		
20-49	-0.172	(0.007)
50-99	-0.221	(0.003)
100-249	-0.193	(0.002)
250-499	-0.141	(0.002)
500-999	-0.093	(0.002)
1,000-2,499	-0.061	(0.002)
2,500+	-	
Net Shrinker	-0.013	(0.002)
Net Grower	-0.071	(0.002)
R ²	83.3	

Source: Tabulations from BLS Area Wage Survey.

Table 8

Effect of Establishment Size Change on Estimated
Establishment Differentials in the Area Wage Survey

	Dependent Variable		
	Current Estimated Establishment Differential (1)	Net Change in Estimated Establishment Differential Over Survey Period (2)	Net Change in Estimated Establishment Differential Over Survey Period (3)
Coefficient on Establishment Shrinkage	-0.005 (0.024)	-0.052² (0.023)	0.004 (0.013)
Dummy (std. error) ¹			
Coefficient on Establishment Growth	-0.049² (0.024)	-0.011 (0.025)	-0.011 (0.017)
Dummy (std. error) ¹			
Other Controls	2-Digit SIC, Current Etab. Size	2-Digit SIC, Previous Etab. Size	Years Spanned ³
R ²	0.712	0.711	0.513
F-Stat. for Size Changes	2.02	2.67	0.28
Sample Size	767	767	231
Weight	Number of observations in establishment		Average number of observations in establishment

¹Growth and shrinkage are defined as positive or negative changes (respectively) in the establishment size category. For Equations 1 and 2, the change is from the last year to present. For Equation 3, it is net change over the survey period.

²Significant at the 5% level.

³Control for years spanned is necessary because the calculation and elimination of annual effects may introduce bias (due to sample variations) in year-to-year comparisons of wage effects.

Source: Tabulations from BLS Area Wage Survey.

Table B-1

**Industry and Area Wage Survey Standard Deviation Components
Compared to Current Population Survey Log Wage Variation**

Source of Variation of Log Wage	Industry Wage Survey	Area Wage Survey	Current Population Survey	
	Mean Suggested Standard Deviation	Suggested Standard Deviation ²	May 1977 ³	All Occup. AWS Occup. ⁴
Total Std. Dev.	.20	.40	.48	.42
occupation, Sex, Region, and/or Industry ¹	.12	.36	.36	.25
Total Remaining	.16	.16	.31	.33
Establishment (known)	.11	.11	-	-
Establishment (Estimated)				
1) AWS & IWS Point Estimate	-	-	.11	.11
2) AWS % of Total	-	-	.13	.12
3) AWS % of Remaining	-	-	.20	.21
Occupation-Establishment Interaction	.06	.10	-	-
Individual	.09	.07	-	-

¹For IWS and CPS, includes SMSA dummy and region (4 regions for CPS). For IWS and AWS includes incentive dummy and joint effects. In CPS, uses 3-digit occupation. CPS and AWS totals include 2-digit industry.

²Effects of interactions with year have been excluded from AWS results.

³The CPS sample includes all private-sector fulltime workers between the ages of 18 and 65 with reported average hourly earnings of more than \$1.75.

⁴Including only observations for occupations included in the AWS sample.

Source: Tabulations from BLS Area Wage Survey, BLS Industry Wage Surveys (see Groshen 1988b), and May 1977 CPS.