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DO WAGE DIFFERENCES AMONG EMPLOYERS LAST?

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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 (**Groschen [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 Goshen (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. **Groschen (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) :

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

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^t_{ij})** 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^t_{ij})** 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^t_{ij})** 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^t_{ijk})** 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_γ^2 and $\sigma_{\gamma t}^2$ measure the **importance** and stability of independent **internal** labor markets, respectively; and

4) $\sigma_{\epsilon t}^2$ 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 σ_{at}^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_τ^2) and job-cell-year differentials ($a_{\tau t}^2$), 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 \sum , 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_{jt}^2 and a_{jrt}^2): 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 **Groschen** 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 Goshen (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 (Brawn 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 **shrinkers** 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. **Other-**wise, 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 **rent**, they presumably reflect **long-run**, not short-run, rents.

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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 Hocking, 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:

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

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

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

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 *per* 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 **Groschen (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:

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

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** **oversam-**ple 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 \ln (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	19.7%
1,000-2,499	30.5%		
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.)	$R_C^2 - R_B^2$
2. Joint Occupation and Establishment	$R_A^2 + R_B^2 - R_C^2$
3. Establishment and Industry (controlling for occup. , etc.)	$R_C^2 - R_A^2$
4. Industry (controlling for occupation, etc.)	$R_C^2 - R_A^2$
5. Establishment Within Industry	$R_C^2 - R_C^2$
6. Total Main Effects	R_C^2
7. Occupation, etc. , -Year Interactions	$R_{CT}^2 - R_{BT}^2$
8. Joint Occupation, etc. , and Establishment	$R_{AT}^2 + R_{BT}^2 - R_{CT}^2$
9. Establishment Year-Interactions	$R_{CT}^2 - R_{AT}^2$
10. All Other Interactions (controlling for main effects)	$R_D^2 - R_C^2$
11. Total Between Job-Cell-Years	R_D^2
12. Individual	$100\% - R_D^2$
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. $w_{ijk}^t = \mu + X_i\alpha + \epsilon_{ijk}^t$

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

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

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

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

C. $w_{ijk}^t = \mu + X_i\alpha + \underline{Y}_j\beta + \epsilon_{ijk}^t$

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

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

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_iY_j = **dummies** for occupation i in establishment j, i.e., for job-cell ij,
a, **β** , **β** , **τ** = 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, Tool- Room 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, Tool- room 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

		TYPE OF CORRELATION	Year				
			2	3	4	5	6
1	Pearson		.988	.988	.979	.969	.967
	Rank		.977	.978	.956	.937	.950
2	Pearson		-	.989	.982	.978	.977
	Rank		-	.984	.968	.948	.962
Year 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

		TYPE OF CORRELATION	Year				
			2	3	4	5	6
1	Pearson		.975	.968	.909	.904	.894
	Rank		.970	.962	.891	.869	.856
2	Pearson		-	.974	.925	.924	.906
	Rank		-	.969	.909	.897	.871
Year 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

<i>Source</i>	<i>Suggested Standard Deviation¹</i>
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	ΔR 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)
R²	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)	(3)
Coefficient on Establishment Shrinkage Dummy (std. error) ¹	-0.005 (0.024)	-0.052 ² (0.023)	0.004 (0.013)
Coefficient on Establishment Growth Dummy (std. error) ¹	-0.049 ² (0.024)	-0.011 (0.025)	-0.011 (0.017)
Other Controls	2-Digit SIC, Current Estab. Size	2-Digit SIC, Previous Estab. 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 Mean Suggested Standard Deviation	Area Wage Survey Suggested Standard Deviation ²	Current Population Survey 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.