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Do Rising Returns to Skills Affect Employer Wage Structures?

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Abstract

If high-wage employers are largely purchasing high-skill employees, then rising returns to skills should increase inequality between high- and low-wage employers. We test this and related hypotheses with 40 years of detailed wage data from 228 large Midwestern employers and from 12 years of data from 42 New York employers.

As seen in other datasets, wage inequality rises overall and between high- and low-wage occupations. However, despite this rise in the returns to observable skills, inequality between high- and low-wage employers is stable. Moreover, decreased sorting of observable skills does not explain the stability.

In addition to skill differences, wage inequality between employers could be due to transitory shocks and errors. However, these employer wage differentials last many years and their persistence has not declined over time.

While inconsistent with general human capital and transitory shocks as explanations for employer wage differences, these findings are consistent with a stable role for efficiency wage, compensating differences, and rent-sharing as determinants of compensation. As such, the findings also do not support the common assertion that employers' wage structures have weakened due to increased dynamism in labor and product markets.

JEL: J31, J41

Introduction

The theory of general human capital is perhaps the single most influential theory in the social sciences. For example, the theory of human capital has been the leading contender to explain rising inequality over the last quarter of the 20th century.

Human capital theory has also been used to explain inequality within and among employers both at a point in time and as inequality has grown. With a constant degree of sorting by skill, human capital theory suggests that inequality among employers and the variability of wage structures within an employer should have increased proportionately with inequality among occupations. For example, Haltiwanger and Davis (1991) interpret widening inequality among manufacturing plants, particularly between large and small plants, as evidence of rising returns to unobserved skills that are most common at large high-wage plants. Juhn, Murphy and Pierce (1993) have made the same argument concerning the rising earnings gap between whites and blacks.

This basic insight is complicated by shifts in the skill mix of employers. Kremer and Maskin (1995) show that if a model of human capital is sufficiently rich to generate sorting of skills among employers, then rising returns to skill will increase the sorting of employees by skill among employers; that is, high-wage employers will increase their concentration of high-skill occupations. Indeed, this increased sorting suggests that the dispersion of employer wage effects will rise more rapidly than the dispersion of occupation wage effects.

We test these extensions of the human capital model using two unique datasets with information on wage structures within and between large employers. The central test is whether rising returns to skills or more sorting have increased the variation of employer wage effects and internal wage structures, as predicted if these wage differentials represent sorting by human capital. As noted, the test focuses on two dimensions of employer wage structures. The first dimension, an "employer wage effect," arises when an employer pays on average more or less than what similar employees in similar occupations receive elsewhere in the market. The second dimension, an "internal wage structure," arises when an employer pays particular occupations well or poorly. The internal wage structure arises when the relative wages within the firm do not match the relative wages paid in the market. For example, if a high-wage employer pays its security guards poorly, guards at that company that year would have a negative value for their internal wage structure.

Employers may also pay non-market wages because of temporary mistakes and shocks to labor supply or demand. These explanations imply that deviations from market wages are not very persistent. To test the importance of temporary deviations, we also measure the persistence over time at an employer of its wage level and of its idiosyncratic internal wage structure.

Formally, as described below, we estimate the occupation, employer, and internal structure wage effects for each city in each year with a regression of log wages on a complete set of fixed effects for occupations and employers. We then examine trends in standard deviations and autocorrelations of these wage effects over the last 40 years.

We analyze the Cleveland Community Salary Survey, which includes detailed micro data on the pay practices of 228 large Midwestern employers from 1955 to 1996, and with the New York Salary Survey, which includes similar data on 42 New York city employers from 1989 to 2000.

1. An Illustrative Model of Skills, Wages and Employer Wage Effects

This section outlines an illustrative pure human capital model of wage determination. Although we do not expect any such simple model to be literally true, it provides a useful benchmark when we move to the data. The model has a number of implications that hold in the data we examine. Based on these observable factors and one crucial assumption about unobservable factors, human capital theory provides simple predictions. The section closes with a description of one alternative model of employer wage effects, the transitory model. Groshen (1991a) and Levine, et al. (2002) review alternative theories of wage determination.

a. A pure human capital model of employer wage effects

Assume that wages are completely determined by human capital. That is, log(wages), w, reward general skills (S) with a rate of return β:

(1) $w_i = \beta * S_i$ for each individual i.

People are divided into approximate skill groups, which we call occupations. Each of the k occupations has a mean level of skill, $\{S_o^1, S_o^2, \ldots, S_o^k\}$, where k is much smaller than the size of the workforce. That is, an individual's skill level S_i can be broken into $S_{oi,}$ the average skill of person i's occupation, and U_i, skill variation within an occupation (that is, unmeasured human capital):

(2) $S_i = S_{oi} + U_{i.}$

If these occupation distinctions capture most skill variation in the workforce, then wages will vary more between occupations than they do within occupations. This result holds in our data. In the data we analyze, the R^2 from occupation dummies alone is several times the R^2 from a regression with standard experience and education controls in a household survey. That is, if we regress wages against a set of occupation-specific intercepts,

$$(3) \qquad w_i = O * occupation_i + u_{i.,}$$

the standard deviation of the residual u_i is much smaller than the standard deviation of wages. The estimated coefficients on the occupation-specific intercepts, $\hat{O}$, measure the value of the average skills for person *i*'s occupation (b *S_{oi}).

Next, assume that some employers differ in their average skill levels, perhaps due to their technology or competitive strategy. Because mean wages track mean skills, mean wages also differ by employer. Thus, if we run a regression with employer-specific intercepts ($employer_i$), they will show significant variance:

$$(4) \qquad w_i = F_i * employer_i + e_i.$$

Kremer and Maskin (1995) show that the R^2 of this regression, that is, the share of the variance in wages and (in a human capital model) skills between employers, is a theoretically appropriate measure of the sorting of skills among employers.

Sorting of skills among employers that contribute to the employer wage effects from (4) can take two forms: first, disproportionately hiring high-or low-skill occupations, and second, hiring high- or low-skilled workers within all occupations on average. A third form of sorting occurs among occupations at an employer, if the employer hires high- or low-skilled workers within a subset of occupations. For example, a technology-driven employer may hire high-quality engineers, but not spend extra for skills in other occupations. Formally, each employee's skills can be decomposed as follows:

$$(5) \qquad S_i = S_{oi} + S_{fi} + S_{foi} + \mu_i \,.$$

where S_{fi} represents i's employer's average skill level not captured by occupation (that is, its employees' average U_i from equation (2)), S_{foi} represents employer *f*'s average unmeasured skill level for i's occupation beyond S_{fi} (that is, the occupation-employer cell mean of U_i minus S_f), and μ_i captures unmeasured human capital within a job title at a single employer. Substituting equation (-5) into equation (1) yields:

(6) $$w_i = \beta S_{oi} + \beta S_{fi} + \beta S_{foi} + \beta\mu_i$$

for each individual i.

Consider a regression modeled on equation (6), where we regress log wages on occupation, firm and occupation-employer cell dummy variables:

(7) $$w_i = o_i * occupation_i + f_i * employer_i + c_i * occupation\text{-}employer\ cell_i + v_i.$$

If all three forms of sorting are present, then this regression should yield jointly significant estimates of all three vectors of coefficients. These three coefficient vectors provide estimates of wage inequality among occupations (the variance of occupation effects captures the dispersion of βS_{oi}), among employers (the variance of employer wage effects captures the dispersion of βS_{fi}), the role of internal wage structures (the coefficients c_i capture variation due to internal skill and wage structures, βS_{foi}), and the dispersion of skills and wages within a job title at an employers (the dispersion of $\beta\mu_i$). If skills are sorted among employers and within an employer some jobs have above-average skills, then the explanatory power of this regression should also exceed that of equation (3), which controls only for occupation.

If we estimate this equation on data pooled to the level of the employer-occupation cell, we are basically regressing wages against a vector of firm-specific intercepts and a vector of occupation-specific intercepts. The employer-occupation (i.e., internal structure) wage effects are estimated as the residuals from this regression.

(8) $$w_i = o_i * occupation_i + f_i * employer_i + c_i.$$

Finally, consider the variance of wages. Taking the variance of equation (8) yields:

(9) $$\sigma^2_w = \beta^2 * \sigma^2_{So} + \beta^2 * \sigma^2_{Sf} + \beta^2 * \sigma^2_{Sfo} + \beta^2 * \sigma^2_\chi + \beta^2 * 2Cov[S^o, S^f],$$

where the covariance term measures the extent to which firms' sorting of the by and within occupations occur together. That is, a positive covariance implies that firm which tends to employ high-skill occupations will also tend to employ workers with high unmeasured skills within those occupations. The covariance terms between cells and firms or occupations, and between the error and the other terms are zero by construction.

In sum, the model implies the following:

1. Wages vary more among occupation than within occupations.
2. Controlling for occupation, there are significant firm wage effects.
3. Controlling for occupation and firm, there are significant job-cell wage effects.
4. Occupation and firm effects are collinear.

The fact that these conditions are met in the two datasets we analyze (as we show below) and other salary survey data shows that the unmeasured human capital theory can be considered a plausible explanation for many observed wage patterns, and for the existence of employer wage structures in general.

b. Changes over time

The true test of a theory often comes in the behavior of the system in response to a shock. What can we expect if the returns to human capital rise in this system, as happened during the 1980s and early 1990s?

Assume first that sorting of skills among employers remains constant. Looking at equation (9), we see that when the returns to skills (β) rise, ceteris paribus, the standard deviation of each component of wage variation should rise proportionately with the increasing returns to skill, and, thus, with each other. Similar logic applied to a model with only employer wages effects (as in equation (4)) shows that the standard deviation of employer wage effects should also rise proportionally with β. At the same time, the absolute increase in the standard deviation of employer wage effects should be much smaller when controlling for occupation (as in equations 8 and 9) than when employer wage effects are entered alone.

Conversely, if the variances of employer, occupation, and employer-occupation job cells do not rise in tandem, this stripped down human capital explanation for employer wage differences fails.

One obvious way to resolve any discrepancy is to posit that returns to skill have risen and that this increase has led to changes in the forces that sort skills among employers. Kremer and Maskin (1995) model this situation explicitly, and prove that under quite general conditions that a rise in the return to skills should increase sorting. Thus, the variance of employer wage effects should increase at least as quickly as the variance of occupation wage effects. As they phrase this result in their model, the R^2 of employer wage effects in predicting wages should have risen.

Although the model advanced here makes strong assumptions, it also captures many of the insights economists have used to understand changes in wages in the last generation. *Ex post* it is straightforward to add more reasons for changes in sorting or more forms of "skill," each with a different pattern of returns over time. The challenge is for economists to find "fixes" that have testable implications that are also confirmed.

c. Transitory adjustment to labor demand shocks

Should the model described above not hold, textbook economics provides a second explanation for wage differences among employers: random shocks that lead to temporary deviations from the market wage. If an employer has a positive shock to its demand for a category of employees, or for employees company-wide, it may not be able to hire all the employees it wants at precisely the market wage for each occupation. Instead, the employer will temporarily raise wages above the market level to attract additional workers. A key result of these models is that deviations from market wages should erode quickly, as employers fill the vacancies caused by the demand shock.

Results are similar if, instead of actual shocks, deviations from market wages are due to managers' misperceptions of market wage levels. Again, as information disseminates (for example, from the wage surveys we study), wages should rapidly approach the market level.

To examine the role of temporary shocks, we can look at the persistence of deviations from market wages. If shocks largely affect individual occupations, then we should see large transitory deviations from market wages at specific occupations at specific employers. That is, in any given year some employers pay high wages to certain occupations, but those occupations should not still pay above-average wages a few years later. If shocks largely hit an employer as a whole, as might be true if a new product introduction does well on the market, then we should see large transitory deviations from market wages at specific employers. Again, a key result is that the half-life of these deviations should be rather short. Thus, theories of transitory shocks and of errors imply deviations of employer wage effects from the market wage level and deviations of employer wage relativities (the internal wage structure) from the market relativity have a short half-life.

The possibility that employer differentials are the result of errors or transitory shocks has important policy implications. For example, if information problems concerning supply, demand (that is, vacancies), and market wages are a major source of wage dispersion, the efficiency of the labor market may be enhanced by improved information.

2. Data and Methods

a. Data

We analyze data from two wage surveys, the annual Community Salary Survey (CSS) conducted by the Federal Reserve Bank of Cleveland personnel department from 1956 through 1999, and a similar survey conducted by the Federal Reserve Bank of New York personnel department from 1980 to 1999. (Groshen 1996 describes the CSS data in more detail.)

The Banks' personnel departments use the surveys to formulate their yearly salary budget proposals. The Cleveland Bank's survey covers employers in Cleveland, Cincinnati, and Pittsburgh, while the New York Bank's survey covers only New York City. In return for their participation, surveyed companies receive result books for their own use.

The Banks' personnel departments choose participants in each city to be representative of large employers in the area. The industries included vary widely; the main criterion the Banks use is whether the local employer has a large number of occupations that match those descriptions in the survey. Once they join, most employers continue to participate for several decades. On average about 80 employers are present in any given year in the CSS, and 23 in the NY survey.

Each employer judges which establishments to include in the survey. Some employers include all branches in the metropolitan area, while others report wages for only a single facility. We use the intentionally vague term "employer" to mean the employing firm, establishment, division, or collection of local establishments for which the participant reports wages. This ambiguity is useful because it makes it likely that (as intended) the participant's unit has wage and personnel policies that are administered uniformly.

We use detailed occupational codes to measure human capital. In predicting wages, the R^2 yielded by occupation alone in the CSS and NY Survey are typically two to three times that yielded by the demographic, education and broad (1-digit) occupation controls typically found in household data such as the Current Population Survey. Moreover, in the CSS the returns to working in an occupation that typically requires more education has risen about as rapidly as the economy-wide rise in the returns to education (Groshen 1991c).

The surveyed occupations (see Table 1) are office, maintenance, technical, supervisory, and professional personnel. These are the occupations for which external markets are most developed, since they are needed in all industries. Production jobs, which would be specific to a single industry, are not covered. Many jobs are further divided into a number of grade levels, reflecting responsibilities and required experience. Job descriptions for each are at least two paragraphs long.

In many companies, the wage structure determined by the job evaluations is most important for jobs that do not have a clear reference group in the market. In fact, job evaluation is often recommended specifically to help set wages when market wages are difficult to observe. Because our data include only occupations with a clear market, our tests for the importance of wage structures may understate the true extent to which internal wage structures are rigid.

For the years before 1980, each observation gives the median salary of all employees of a given job title in a given year. For some years in the middle of the sample we have only the mean, not the median. Fortunately, in years with both means and medians, results were similar using either measure. After 1980, each observation in the original data set gives the salary of an individual employed in a surveyed occupation by a surveyed employer. Cash bonuses are included as salary, but fringe benefits are not.

The first three columns of Table 2 describe the dimensions of the data set. Variation in the number of employers and occupations is due to occasional missing data, to changes in employer participation over time, and to decisions by the Banks to change the survey's coverage. The CSS covers between 43 and 100 occupations each year; each employer reports wages for an average of 28 of these. The number of employers per year ranges from 41 to 99. Employers have an average of seven incumbents in each job title (this measure is only available in the 1980s and 1990s).

The New York dataset has information on 42 employers, averaging 23 per year (with a minimum of 18 and a maximum of 26). The dataset includes 180 occupations in total. The average employer reports on 36 occupations per year (with a minimum of 3 and a maximum of 126). As in the Cleveland Community Salary Survey, the New York Salary Survey largely includes non-core occupations such as receptionists, auditors, attorneys and custodial workers. As one might expect, more than in the CSS, New York respondents tend to be large financial institutions (as opposed to a mix of financial services and corporate headquarters in the CSS). As such, there are a number of finance-related occupations in the New York survey which do not appear in the Cleveland survey, such as financial analysts, bank examiners, and economists.

Employers in the CSS that also list employment in the Compustat database have median employment of 10,250. This figure includes all part-time and seasonal employees, and all employees of both domestic and foreign consolidated subsidiaries. Roughly a quarter are unionized.

Employers in the CSS and NY Survey employers are not a random sample. However, Appendix 1 summarizes a number of tests showing that the CSS wages are similar to those found in the Current Population Survey, and that the publicly traded participants in the CSS behaved similarly to the Compustat firm in the same industry closest in size.

b. Limitations

Our analysis is subject to several limitations. First, we measure employer wage levels relative to market means measured within wage surveys samples. To the extent that all surveyed employers are large and pay above-market wages, our measure of employer wage levels understate the deviation between average wages of these employers and wages paid on average in the entire labor market.[1]

Moreover, this approach could misstate trends in average employer wage effects compared to the entire market if the samples have diverged from similar companies. We have no reason to believe that the bias from this omission has changed over time. Some indirect evidence suggests that the bias will be small. As noted above, government and large employers? share of jobs is large and has remained relatively constant. In addition, essentially all large employers participate in wage surveys such as the one we analyze (Lichty 1991; Belcher et al. 1985). Finally, Appendix 1 presents evidence CSS participants are representative of their peers. Further, Belman and Levine (1999) report that large and small firm wage levels and several dimensions of their wage structures did not converge between 1979 and 1993 in the U.S.

Second, our measures of relative wages move when a workforce of a job title at an employer changes composition (for example, due to hires and promotions of particularly skilled or unskilled employees). This source of variation parallels a source of unwanted variation in the Employment Cost Index collected by the BLS, which also examines wages within occupation by industry cells. Such compositional changes add noise to our measures. More seriously, our measure could overstate the

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[1] We thank Rob Valletta for pointing this out.

effect of structures if companies maintained rigid differentials between a junior and senior occupation within a job ladder, but have altered the time spent in the junior occupation. Similar problems occur if employers are more likely to manipulate occupational titles to overcome rigidities in the administered wage structure.

Third, our data do not contain information on noncash compensation. There is some evidence that noncash benefits such as employee stock ownership and stock options are increasingly distributed to non-executives (Lawler 1995). Such a trend would bias some of our estimated changes over time. At the same time, most plans distribute relatively little stock to the vast majority of employees (Blasi and Kruse 1991); thus, the bias to our results should be small. Furthermore, Atrostic (1983) and Pierce (1998) find that as individuals**?** wages rise, more of their total compensation is in nonwage benefits. Thus, the differentials estimated here (particularly inter-firm ones) probably understate total effects.

Finally, some companies may retain wage structures between occupations within the organization, but may outsource other occupations in part to avoid paying wages dictated by the internal structure. Although we control for such changes in the occupational mix, we do not address them specifically. This hypothesis remains an active area for extending this research.

c. The wage equation

Because this study relies on salary survey data, it differs in approach from studies that use household surveys. Household data is most naturally directed at identifying how measures of skills (e.g., education) and various demographic measures (such as age and race) correlate with wages. Such regressions typically explain 20 to 30 percent of the variation of wages.

Our alternative approach offers complementary insight into the structure of wages within and between firms. Rather than a household-stratified sample of working individuals, our employer wage survey is a census of individuals working in selected occupations at selected employers. Thus, unlike a household survey, the CSS permits us to investigate wage variations within and between occupations and employers (Groshen 1996).

Until 1980, the CSS provides only job-cell mean or median wages. Within this framework, in each year these wages can be decomposed into the sum of three differentials: an occupation effect, an effect due to working at a specific employer, and an effect due to an employer paying a specific occupation particularly poorly or well (the internal structure differential). The separation is achieved by estimating a wage equation each city and year which includes a complete set of indicator (dummy) variables for each employer and each occupation, as in equation (8). After 1980 the CSS includes individual-level wage distribution within each cell. Thus, we can estimate a more complete decomposition as in equation (7). We do not have identifiers for employees, so we cannot follow a particular employee's pay over time.

d. Decomposing the variance components of wages.

This section describes the trends in the components of wage variation from 1956 through 1996.[2] Because the CSS included within-cell variation only for 1980-1996, we focus on between-job-cell wage variation for the entire time period. We then examine within-cell variation trends separately for 1980-95. From equation (9), we can decompose any year?s between-job-cell variance of wages into four components:

- V(occupation wage effects),
- V(employer wage effects),
- 2Cov(Occupation, employer), and
- V(occupation-employer cell wage effects).

When the composition of jobs is fixed over time, the change in any term in equation (9) will be due to changes in either the returns to attributes or the attributes of occupations and employers over time. As equation (9) notes, the variances of the components sum to total wage variance. Below we discuss standard deviations because they are in natural units; for example, in a normal distribution, the s.d.(employer wage effects) tells us roughly the percentage gap in mean wages between two employers chosen at random.

Other studies decomposing wage variation find mixed results on the relative importance of within- vs. between-employer wage differences in explaining increased wage variation over time. Davis and Haltiwanger (1991) compare changes in total wage variability measured in the CPS with changes in between-plant wage variability in the Longitudinal Research Datafile. They conclude that total wage dispersion grew faster than between-plant wage dispersion for nonproduction manufacturing workers between 1963 and 1988. By contrast, the O'Shaughnessey, Levine and Cappelli (2001) study of managers in 1986 and 1992 finds that most of the increased inequality occurred between, not within,

[2] This section updates Groshen (1991c).

enterprises. Results from these data sets may not generalize. For one thing, both data sets cover only manufacturing firms. In addition, Davis and Haltiwanger (1991) assume that the estimates of wage variation from a survey of households and from a survey plants are comparable--a problematic assumption. The data set studied by O'Shaughnessey, Levine and Cappelli (2001) come from a single compensation consulting firm and covers a limited number of employers. By construction, the employers in that data set use a particular compensation strategy. Thus, the results may not generalize to employers not working under that particular compensation strategy.

The covariance term--Cov(occupation, employer)--enters because occupations are not equally represented within each employer. When this term is positive, high-wage firms (controlling for occupation) employ a disproportionate share of high-wage occupations. If this term grows while the distribution of jobs is held constant, it is because the firms with high and growing returns to their attributes also have more than their share of occupations with high and/or growing returns to their attributes. Other studies that find increased sorting include Groshen (1991c, with this data set), Kremer and Maskin (1995); and industry-level sorting in Belman and Levine (1999) from the CPS. In contrast, O'Shaughnessey, Levine and Cappelli (2001) finds no evidence of increased sorting of skills between employers during a much shorter time period (1986-1992).

In the 1980s and 1990s we can also estimate inequality within an occupation-employer cell. A large standard deviation of wages within cells suggests that skills are diverse within a job title or that employers have strong individual incentive or merit pay programs.

Because the CSS is not a random sample, these surveys are best suited to exploring changes in the returns to attributes rather than changes in the distribution of jobs. Accordingly, we purge the data of changes in composition using a "rolling sample" technique (see Groshen 1991c). Between any two years, the change in variation is measured only for the subsamples of job cells that are present in both years. These changes are then added to the cumulative sum of previous changes plus the initial variance, to estimate the effect for an unchanged job-cell.

e. Persistence of wage components

The central contribution of this paper is an examination of trends in the persistence of wage components over the 40 years of the CSS. Our measure of persistence is the autocorrelation of the three wage components estimated in equation 9: occupation effects (corr(o_t, o_{t-t})), employer effects (corr(f_t, f_{t-t})), and internal wage structures (corr(c_t, c_{t-t})). We perform these autocorrelations for various lag lengths t, with a focus on lags of 1, 5 and 10 years. In results not reported, we replicated all correlations using rank correlations that were less sensitive to outliers; results were similar.

Occupation autocorrelations are expected to be high because represent the continuity in returns to training or experience and compensating differentials that are held in common across firms.

Despite the lack of consensus on the cause of between-employer wage differences, there is strong agreement that these differentials are persistent. Five- or six-year autocorrelations of employer differentials remain at or above 0.9 in a variety of data sets (Levine 1992; Groshen 1989; Abowd et al. 1999; but not Leonard 1989).

The internal structure component measures the distinctiveness of internal pay relationships among firms (the occupation-employer cells). This autocorrelation measures whether employers who pay an occupation or set of occupations well in one year, continues to pay them well in subsequent years. As far as we know, this is the first study of the autocorrelation of the employer-specific internal structure.

3. Results

We first show the pattern of increasing wage inequality and decompose its components. Then we present findings on the persistence (autocorrelations) of occupation, employer and internal structure wage components. All references to changes being ?substantial? imply that a t-test of a time trend or of decade dummies supports the reported change as being statistically significant at the 5 percent level. Results of the statistical tests are available upon request.

a. Trends in total variation.

The fourth column of Tables 2A and B shows that wage variation increased substantially over time, from a standard deviation of about 0.31 log points in the 1950s to about 0.45 log points in the 1990s in the CSS, while it was stable near .43 in the shorter New York survey (1989 to 2000). Because these standard deviations are taken over the medians (or means) of job cells, with a weight of one per cell, they control for the effect of changes in the number of workers among jobs.

The increased dispersion in the fourth column could simply reflect the possibility that the survey now includes more diverse occupations and employers than previously. The results in the last columns of Tables 2A and B use a rolling sample (described above) to control for sample changes. The column presents three-year moving averages, to smooth the noise from occasional small samples and to interpolate missing years in the CSS.

The results controlling for changes in the occupational mix also reflect growing inequality. Although wage inequality rose in each of the decades covered, the growth wage concentrated in the 1970s and 1980 with no significant rise in the 1990s in either dataset.

b. Trends in variance components. .

In this section we examine the separate contributions of occupation, employer and internal structure differentials to widening inequality. Then we examine the role of occupation-employer covariance and of individual wage variation within a job cell.

Components of inequality between firms, occupations, and job cells.

Figures 1A and 1B show how the three between-cell components of wage dispersion contributed to widening wage dispersion in the CSS from 1956 through 1996 and in the NY Survey from 1980 to 1999. The graph shows the trends in the standard deviations of firm effects and occupation effects; a similar graph in variances would show the variance components adding up to the total variance of wages, as in equation (9). (Recall that the dispersion of internal structures is the standard deviation or variance of the residual in equation (8).)

The figures show that main reason for the recent widening wage inequality in these large firms is widening occupation differentials. From 1970 to the end of the surveys the standard deviation of occupational premiums rose from 27 percent to 40 percent in the CSS and were roughly constant during the 1990s near 37 percent in the NY Survey.

Employer differentials are large. Wage differentials among CSS employers widened dramatically in the late 1970s; the standard deviation of the employer effects rose from 9 percent in 1970 to 15 percent in 1980. In contrast, these differentials showed little change in the 1960s, 1980s, and 1990s in both the CSS and the NY Survey. The importance of employer differentials is a bit lower in New York than the Midwest.

In the CSS the standard deviation of internal structure differentials increased from 11 percent to 15 percent during the 1960s and the 1970s. However, this form of wage variation held steady during the 1980s or 1990s. Given the rising inequality among occupations, the relative importance of firm effects and internal wage structures fell since 1980, even as their absolute importance remained steady. Internal wage structures are similar in magnitude in the NY and CSS surveys, and also show no strong trend in the 1990s.

Sorting of skills among employers

The Kremer and Maskin theory suggests that rising returns to skill will lead to increased sorting of skills among employers. They show that the R^2 of the regression of wages on a set of employer-specific dummies is a theoretically appropriate means of summarizing this sorting.

The results from the Cleveland Salary Survey provide slight support for the hypothesis that rising returns to skill correlate with increased sorting. Using 1979 as the (somewhat arbitrary) starting point for the rising return to skill, the trend in R^2 is an increase of a paltry 0.0024 increase per year ($t = 2.81$, $P < .05$). A visual inspect of the explanatory power of employer effects shows no increase from 1979 to 1993, but a rapid rise from 1993 to 1999. This pattern is the opposite of the returns to skill during these decades.

In the shorter time series of the NY salary survey the R^2 of the employer effects entered alone rises from .097 in 1989 to .114 by 2000. Thus, there is a similar rise of 0.20 percent per year, although the effect is not statistically significant ($t = 1.47$).

Variation within employer-occupation job cells.

The data allow investigation of wage variation within job-cell only during the 1980s and 1990s. In 1989 a supplemental question was added to the CSS asking managers whether they had modified their pay-for-performance programs over the 1980s. About four-fifths of the employers in this sample reported that they implemented or strengthened their merit raise and pay-for-performance programs in the preceding decade. Thus, if these schemes affect the dispersion of wages within a job title, we should see an increase in variation due to this component in the 1980s or 1990s.

Table 3 shows a decomposition of wage variation into the portions between and within job cells in the CSS from 1980 to 1996. In each year, the standard deviation of wages within job-cell is low, as found in BLS Industry and Area Wage Surveys (Groshen 1991b, 1989). There is only a slight upward trend in the standard deviation of cash compensation within a cell. The rise is from near eight percent in the early 1980s to near nine percent by the mid-1990s in the CSS.[3]

Although similar data were not available in the NY survey, we were able to replicate this analysis using data from a third wage survey, that of Hay Associates.[4] The survey covered managers and professionals for large industrial companies. We matched responses from 39 employers in 1986 and 1992, and we examined job cells with at least four incumbents. There were 4,351 job cells in 1986 and 3,921 in 1992. The data set and the matching process are described further in O'Shaughnessey, Levine, and Cappelli (2001).

Consistent with results in the CSS, the typical (median) standard deviation in total cash compensation within a job cell had a standard deviation of total pay of 7.0 percent in 1986 and 7.5 percent in 1992. All job levels experienced an increase in the standard deviation of total compensation, but it was larger for first-line supervisors (rising from 7.3 to 8.0 percent) and smaller for professionals (6.9 to 7.0 percent).[5] The standard deviation of wages within a job cell grew less rapidly (the 0.5 percentage point change equals about an 8 percent increase) than the standard deviation of wages in the entire sample (which rose by 11 percent).

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[3] Regressing the standard deviation of wages within job-cell against time yields a coefficient of 0.00062 per year (SE = 0.00024, $P < 0.05$), implying a 0.6 percentage point rise in within-cell inequality per decade.

[4] We thank K.C. O?Shaughnessey for performing these analyses.

[5] The mean and median number of incumbents in each job cell (that is, with identical function, employer

A second dimension of within-cell inequality can be individualized bonuses. Thirty-two percent of employees in the Hay sample received a positive bonus in 1992, up from 19.6 percent in 1986.

This calculation understates the extent of bonuses because not all employees who were eligible for bonuses necessarily received payment. If we instead estimate the percentage of job cells where bonuses were received, the percentage rose from 27 to 47 percent over the same period. In 1986, bonus variation within job cells was on average a small part of total pay. The mean standard deviation of bonus/(base+bonus) within job cell was 0.75%. That is, bonuses increased pay variation only modestly among people in the same job cell.

At the same time, the proportion of pay at risk in our data set as measured by the size of the bonus payments rose from 0.75 percent in 1986 to 1.03 percent in 1992. While the absolute level of these payments is low, the increase in level is particularly impressive given that 1992 was a year of low corporate profits. Assuming that bonus pools are related to corporate performance, the 1992 figures are an understatement of the true rise in the importance of bonuses.[6]

These results suggest that adoption of individual (as opposed to group-based) pay-for-performance or incentive schemes has widened wage inequality only slightly in the CSS and the Hay data sets. If such schemes are now a substantially larger source of wage variation than before, they must have largely replaced the variation from other wage-setting practices (such as seniority). Similarly, if such schemes were applied to groups rather than individuals (for example, with team-based pay or gainsharing), then they must have replaced a previous source of variation, because neither employer nor internal structure components increased variation in the 1980s.

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and skill points) were similar in both years (approximately 10 and 4).

[6] The mean variation within a job cell of pay attributable to bonuses was driven down because many jobs offered no bonus. For job cells with some non-zero bonuses, the mean standard deviation of %bonus within a job cell was 2.9% in 1986 and 2.7% in 1992. This decline is misleading, however, because (as noted in the text) the total fraction of job cells with a positive bonus rose rapidly. The small but rising importance of bonuses is better measured by the calculation in the text.

c. Persistence of wage components

We begin by comparing the overall persistence of occupational, employer, and internal structure differentials over spans of one to fifteen years. In Figure 3, the vertical axis measures the correlation of estimated differentials in one year with estimates from another year. The horizontal axis indicates the number of years spanned. All possible spans in the data are combined to construct the correlations. For example, the one-year employer correlations are calculated over coefficients from every two consecutive years from each respondent firm.

Overall, estimated CSS occupational differentials have a correlation of 0.99 with the same occupation one year earlier. The autocorrelation of occupation effects declines to 0.90 when measured fifteen years apart.

Although employer differentials show less stability than occupational premia (starting at 0.93 for one-year autocorrelations and declining to 0.62 over fifteen years), nevertheless they suggest a high degree of permanence in employers? wage strategies – as would be expected under an internal labor market, and has been found in other studies. The fifteen-year correlations suggest that workers can expect that, if they join a high-wage firm in the middle of their career, it will still be a fairly high-wage firm when they are nearing retirement.

In the CSS the autocorrelations of internal structure differentials start at 0.76 one year apart and decline to 0.24 over fifteen years. New York autocorrelations are similar (though we stop at 7-year autocorrelation, due to the short time span).

Each job-cell has far fewer observations than does an entire firm or occupation, making it more sensitive to moves of a small number of individuals. Thus, we expect these differentials to be less stable than employer and occupation differentials. Nevertheless, they are strongly positive, indicating fairly stable divergences from market means, particularly over one- to five-year spans. That is, employers with lower relative wages for secretaries than for other employees in one year will probably have low relative wages for many years to come.

d. Trends in persistence

Do the autocorrelations indicative that employer wage structures have become less or more stable over the last two decades? To answer this, we graph the autocorrelations plotted in figure 3 separately depending on the end year of the span. If employer and internal structure differentials have become less stable, we should see a downward drift in autocorrelations.

Figures 4A and B shows one-, five-, and ten-year (CSS) or seven-year (NYSS) autocorrelations for occupational wage differentials arranged by the end-year of the span. Discontinuities in the lines reflect missing data for the end year.

Autocorrelations in the CSS over one- and five-year periods were very high in late 1960s (0.99), then fell in late 1970s to 0.94. We then see a slow recovery through 1982-83 recession to 0.96-.98 and continued growth, back to very high levels near 0.98. Ten-year autocorrelations fell from late 1960s to a minimum near 1979, and have risen steadily since. Their quick recovery implies that some of the late 1970s drop was transitory changes from persistent differentials (that is, differentials returned to long-term patterns). If occupational wage relativities were becoming less stable (because occupational wages now less protected from shocks, or shocks were larger), these autocorrelations would drift down over the 1980s and 1990s. Although there is some evidence of reordering during the late 1970s (as would be expected during high inflation if wages are rigid – see Groshen and Schweitzer 1996), there is no evidence of a similar decline in stability recently.[7] In fact, ten-year autocorrelations have been rising recently at a statistically significant pace.[8]

In the New York Salary Survey occupational autocorrelations were similarly high and stable.

Figures 5A and B repeats the exercise for employer differential autocorrelations. The very early years of the CSS show evidence of strengthening of the persistence of employer wage effects, as described in "golden age" descriptions of industrial relations. Again, the 1970s saw some restructuring of employer wage relativities, with recovery of stability in the 1980s and 1990s. One-year autocorrelations are remarkably constant. They drift upward slightly ($P < .05$), which is certainly not

[7] Alternatively, this instability may reflect a data issue. Only job-cell means, not medians are available for the 1970s. Sample means are more sensitive to outliers, so their presence may explain the apparent reduced stability for these years.

[8] $P < .05$ in a quadratic of time for the entire series, or for a linear term in time for a sample restricted to the 1980s and 1990s.

what we would expect if employer wage structures were becoming less important or undergoing a major reordering. Similarly, the longer-span autocorrelations drift upward slightly (again, statistically significantly)— reinforcing the conclusion that employer wage differences remain as stable now (if not more so) as they were during the 1960s.

In the New York Salary Survey employer autocorrelations were similarly high and stable (Figure 5B).

Figures 6A and B plot trends in internal structure persistence. Focusing on the one-year autocorrelations in the CSS, again there is no evidence of a recent decline in the persistence of wage structures. The persistence is hump-shaped with slow decline since the late-1960s peak. Fitting a quadratic in time to the series of autocorrelations is not statistically significant; thus, neither the hump nor the slow decline is statistically significant. During the shorter time period of the New York Salary Survey, autocorrelations of the internal wage structures are roughly as high and show no important trend (Figure 6B).

Finally, note that the patterns over time of the variance and persistence of employer and internal structure differentials differ from each other and from that for occupation differentials. The variety of patterns calls into question any assumption that all of the differentials measure labor market returns to a single set of skill factors.

We performed several checks on the robustness of these results. These autocorrelations can be biased down due to measurement error in the internal structure effects estimated in our data. We replicated some of the longer-term autocorrelations using three-year centered moving averages. That is, instead of correlating the 1970 and the 1980 internal wage structures, we correlated 1969-1971 average internal structures with their 1979-1981 counterparts. Autocorrelations of such moving averages are smoother over time, but otherwise very similar in their level and changes over time to those calculated without averaging.

As a check to ensure outliers do not drive the results, we reran the main analyses using rank (rather than standard) autocorrelations. Again, results were very similar. There may also be measurement error because we have a sample of occupations, not all of those in an employer. In this case, although measurement error might bias down all of the autocorrelations, there is no reason to expect this bias to have changed over time.

4. Summary, Caveats, and Conclusions

We observed the wage structures of a sample of employers before and after they were shocked by a general increase in the returns to skills during the 1980s. The main results by decade are:

1. The 1960s saw a strengthening of employer wage structures, as measured by the size and persistence of employer and internal wage structure differentials.
2. During the early 1970s, the permanence of internal structure differentials peaked. Then they gradually became more flexible. Employer differentials were reordered and magnified in the late 1970s.
3. Occupational wage differentials were magnified during the 1980s and early 1990s, but were no less persistent. Employer and internal structure differentials maintained their size and persistence. Within-job-cell wage dispersion remained small throughout this period, but increased slightly.

In sum, capitalizing on the perspective provided by our long time period, we can only characterize the changes we detect in employer structures since 1980 as minor, contradicting the pure human capital explanation of employer wage structures.

Our results also provide strong evidence against the possibility that employer wage variations are temporary or random. High-wage employers pay high wages for a decade or more. Internal wage structures show more movement, but still have high persistence over many years. Moreover, the persistence of wage levels and structures has not declined over time.

This historical perspective is missing from many analyses of recent labor market changes—such as those based on the Displaced Worker Survey—which unavoidably begin in 1980. Ironically, economic theorists were just beginning to grapple with employer wage structures when the management press proclaimed their demise. Our results, taken in concert with findings of only modest changes in job stability, suggest that the announced death of rigid wage structures may be premature, giving the theorists some more time. Nevertheless, both careers and personnel practices are evolving, even if not in the dramatic way that some observers suggest. Our findings suggest a need for novel data sets and theory to understand this evolution.

Caveats

Our results show very cleanly that a rising skill differential did not lead to a proportional rise in employer wage differentials among important types of US employers for non-production workers. However, more work will need to see if other parts of the labor market reacted differently. In particular, small or new or southern or western employers, or those that refuse to participate in salary surveys remain to be studied. In addition, our data miss changes in some elements of compensation that are large (for example, benefits) or growing in importance (for example, stock options for mid-level managers). Furthermore, our data covers staff occupations, not core employees who do production work (such as assembly line workers, waiters, or bank tellers) or their direct supervisors. To the extent our data contains benchmark jobs (that is, the jobs most likely to be found at many employers), pay at these jobs is likely to be tied most closely to the market. Thus, results with these data may understate the importance of idiosyncratic employer wage structures.

Implications

With these caveats in mind, these results are inconsistent with the prediction of pure human capital theory that employer and internal structure differentials rose in tandem with occupational differentials during the 1980s and 1990s. Thus, if these differentials represent returns to unmeasured ability, those returns did not keep pace with returns to measured ability during the 1980s and 1990s. Alternatively, these differentials may reflect other factors in addition to unmeasured human capital.

More complex versions of human capital theory can have many forms of unmeasured skills, some of which are correlated with occupation, others with employer, and yet others with rank in the wage distribution within a job title. Such theories are not testable with our (or any other) data.

Nevertheless, our results are inconsistent with mainstream interpretations that use human capital theory as a unifying framework for understanding rising inequality. Several widely cited papers have used rising returns to being white (Juhn, Murphy and Pierce 1993) and to plant size in manufacturing (Haltiwanger and Davis 1991) as evidence that these differentials represent unmeasured skills whose returns is rising along with returns to measured human capital. On the other hand, these results are consistent with the findings of Abowd, et al. (2001), who (extending their work in Abowd, et al. (1999)) find that about half of raw employer differentials cannot be explained by fixed individual characteristics. If economists use human capital theory to explain increases in wage differentials that occur when returns to measured skill rise, they should also confront wage differentials that remain constant or barely rise (as we find) or that decline (e.g., the gender differential—see Blau and Kahn 1997).

There is, however, some support for the hypothesis that sorting by ability has increased. The correlation between the average wage of the occupations employed at a firm and the firm?s average pay rose meaningfully, but from a very low base. This increase supports certain theories of human capital and sorting (e.g., Kremer and Maskin 1995). This result is also consistent with a theory of social comparison that claims widening differentials among occupations worsen perceived internal equity, and lead to outsourcing. An important avenue for further research involves testing for whether outsourcing is a substantial force in weakening wage structures and their rigidity.

In the future, it is important to unify studies of wage structures with studies of job stability and tenure. Both sides are important to both employees and employers, and the two can have important interactions. To understand the evolution of the labor market, the price (wage) side of the equation is as important as the much-studied quantity (tenure) side. Moreover, these studies will need to consider possible shifts in the boundaries of organizations; as noted above, such shifts can permit rigid structures for an organization coupled with less rigidity for a career.

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Table 1A
Occupations in the Cleveland Community Salary Survey (1955 - 1996)
(Not all occupations were present all years.)

Account Executive	Clerk Typist C	IBM Unit Head	Press Operator I
Accounting Clerk I	Clerk Typist II	Information Processor II	Press Operator II
Accounting Clerk II	Comp & Benefits Admin.	Information Security Analyst	Programmer I
Accounting Manager	Comp & Benefits Manager	Internal Audit Manager	Programmer II
Accounting Supervisor	Comp Analyst	Inventory Control Clerk	Programmer/Analyst III
Accounts Payable Clerk	Computer Operations	Job Analyst	Proof Clerk
Addressograph Operator	Computer Operns.	Junior Auditor	Proof Machine Checker
Administrative Asst I	Computer Operator I	Junior Computer Operator	Proof Machine Operator
Administrative Asst II	Computer Operator II	Junior Economist	Protection Manager
Administrative Asst III	Console Operator	Junior Stenographer	Public Relations Specialist
Administrative Secretary	Contracts Administrator	Lead Carpenter	Purchasing Agent
Analyst Programmer I	Correspondence Clerk	Lead Check Processor	Purchasing Clerk
Analyst Programmer II	Custodian	Lead Computer Operator	Receptionist
Asst. Analyst Programmer	Custodian	Lead Mail Clerk	Receptionist Clerk
Asst. Console Operator	Custodian II	Lead Painter	Records/Files Clerk
Asst. Dept. Manager	Data Entry Operator	Lead Programmer	Registered Nurse

Attorney	Data Processing Manager	Lead Stock Clerk	Research Statistician
Attorney II	Data Processing Supervisor	Librarian	Secretary to Adm. Officer
Audit Analyst I	Dayporter	Mail Clerk	Secretary to CEO
Audit Analyst II	Department PC Specialist	Mail Clerk I	Securities Proc. Clerk
Audit Analyst III	Dept. Manager	Mail Supervisor	Security Guard
Audit Clerk	Dept. Manager	Maintenance Mechanic I	Sen. Proof Machine
Audit Manager	Dept. Manager II	Maintenance Mechanic II	Senior Attorney
Audit Team Manager	Dept. Secretary	Mechanic I	Sergeant of the Guard
Bookkeeping Machine	Dept. Secretary II	Mechanic II	Sr. Audit Clerk
Budget Analyst	Division Head	Messenger	Sr. Budget Clerk
Budget Manager	Duplicating Operator	Methods Analyst I	Sr. Functional Expense
Building Engineer I	Economic Advisor	Methods Analyst II	Sr. Keypunch Operator
Building Engineer II	Economist	Multilith Operator	Sr. Stenographer
Building Equipment	Economist II	Night Cleaner - Male	Sr. Supervisor
Building Manager	Editor	Office Equipment Mechanic I	Sr. Systems Analyst
Camera Operator	Editor House Publications	Office Equipment Mechanic II	Statistical Clerk
Captain of the Porters	EDP Audit Analyst I	Offset Pressman	Statistical Clerk I
Carpenter	EDP Audit Analyst II	Operating Engineer	Stenographer
Charwoman	Electrician	Operating Engineer	Stock Clerk
Charwoman-Night	Employee Benefits	Operations Research Anlst. I	Supervisor
Check Adjustment Clerk	Employee Benefits Specialist	Operations Research Anlst. II	Systems Analyst
Check Adjustment Clerk II	Employment Interviewer	Org. Development Specialist	Systems Consulting
Check Processing Clerk I	Employment Supervisor	Painter	Systems Project Manger
Check Processing Clerk II	Executive Secretary	Paymaster	Tabulating Operator
Check Processing Clerk III	File Clerk	Payroll Clerk I	Tape Librarian
Check Processing	File Clerk A	Payroll Clerk II	Telephone Operator
Chief Building Engineer	Forms Designer	Payroll Supervisor	Trainee Keypunch
Chief Electrician	General Clerk C	Personal Interviewer	Training Coordinator
Chief Maintenance	General Ledger Bookkeeper	Personnel Clerk	Unit Head
Chief Mechanic	Graphics Illustrator	Personnel Interviewer	Washroom Maid
Clerk Typist	Guard Supervisor	Personnel Manager	Word Processor
	Head Telephone Operator	Personnel Receptionist	

Table 1B: Occupations in the New York Salary Survey (1989-2000)

(Not all occupations were present all years.)

- Accounting Clerk A
- Accounting Clerk B
- Air Conditioning Engineer A
- Air Conditioning Engineer B
- Assistant Bank Examiner A
- Assistant Bank Examiner B
- Assistant Financial Analyst A
- Assistant Financial Analyst B
- Assistant Staff Director - Computer Operations
- Associate System Programmer
- Attorney
- Audit Project Director
- Auditor A
- Auditor Analyst A
- Auditor B
- Bank Examiner A
- Bank Examiner B
- Budget Analyst A
- Budget Analyst B
- Carpenter
- Chef
- Chief - Building Services
- Chief - Funds Transfer
- Chief - Protection Operations
- Chief Electrician
- Compensation Analyst A
- Compensation Analyst B
- Compensation Specialist
- Computer Network Operator
- Cook A
- Counter Server B
- Data Entry Operator A
- Data Entry Operator B
- Data Processing Operations Analyst A
- Data Processing Operations Analyst C
- Department Utility Assistant
- Dining Room Attendant
- Director of Employee Relations
- Economist A
- Economist B
- Economist C
- Electronic Data Processing Auditor A
- Electronic Data Processing Auditor B
- Electrician
- Electrician's Helper
- Elevator Operator
- Employee Interviewer A
- Executive Chef
- Financial Analyst A
- Financial Analyst B
- Financial Specialist
- Financial Specialist A
- Financial Specialist B
- Funds Transfer Clerk A
- Funds Transfer Clerk B
- Funds Transfer Clerk C
- General Clerk
- Guard
- Junior General Clerk
- Junior Paralegal
- Kitchen Cleaner A
- LAN Administrator
- Legal Stenographer
- Librarian
- Mail Clerk B
- Mason
- Nurse Practitioner
- Office Designer
- Office Designer A
- Office Messenger
- Operations Support Analyst A
- Operations Support Analyst B
- Operations Support Analyst C
- Painter
- Payroll Control Clerk A
- Payroll Control Clerk B
- Plumber
- Print/Address Services Clerk A
- Printing Services Clerk
- Professional Recruiter
- Programmer
- Programmer Trainee
- Project Director - Applications Programming
- Receptionist
- Secretary I
- Secretary II
- Secretary III
- Secretary IV
- Secretary V
- Securities Processing Clerk B
- Securities Processing Clerk C
- Securities Processing Teller
- Senior Accounting Clerk
- Senior Attorney
- Senior Audit Projector Director
- Senior Auditor A
- Senior Auditor B
- Senior Bank Examiner
- Senior Budget Analyst
- Senior Compensation Analyst B
- Senior Computer Network Operator
- Senior Data Processing Operations Analyst
- Senior Economist
- Senior Electronic Data Processing Auditor
- Senior Employee Relations Representative
- Senior Financial Analyst
- Senior Financial Analyst B
- Senior General Clerk
- Senior Librarian
- Senior Mail Clerk
- Senior Nurse
- Senior Office Designer
- Senior Paralegal
- Senior Programmer Analyst
- Senior Stock Transfer Checker
- Senior Systems Programmer
- Senior Tape Librarian
- Senior Telephone Operator
- Senior Trainer
- Senior Unit Teller
- Senior Word Processing Operator
- Sergeant
- Service Assistant
- Special Project Director - Applications Programming
- Staff Director - Accounting
- Staff Director - Budget Analyst
- Staff Director - Computer Operations
- Staff Director - Systems Programming
- Staff Director - Training
- Staff Nurse
- Stenographer A
- Stock Transfer Checker
- Supervising Examiner
- Supervisor - Accounting
- Supervisor - Building Cleaning
- Supervisor - Computer Operations
- Supervisor - Operations
- Supervisor - Payroll
- Supervisor - Post Office
- Supervisor - Reproduction
- Supervisor - Telephone
- Systems Programmer
- Technical Specialist
- Telephone Operator
- Trainer
- Training Assistant
- Training Specialist
- Typist A
- Typist B
- Unit Teller
- Unit Teller Trainee
- Utility Service Assistant
- Warehouse Supply Clerk A
- Watch Engineer
- Word Processing Operator A
- Word Processing Operator B
- Word Processing Operator Trainee

Table 2a: Characteristics of CSS Data Set, 1956-1996

Year	Total Number of:			Std. Dev.(Log Wage) Among Job-Cells*	
	Job-Cells	Occupations	Employers	Total Sample	Rolling Sample (Smoothed)
1956	1,473	44	77	.314	.304
1957	1,737	47	87	.310	.300
1958	1,737	43	88	.299	.297
1959	1,749	43	88	.296	.297
1960	1,749	43	87	.303	.298
1961	1,993	50	96	.305	.302
1962	1,978	53	94	.311	.304
1963	2,122	53	99	.313	.308
1964	2,250	53	95	.318	.311
1965	2,279	53	97	.323	.315
1966	missing				.317
1967	2,224	53	94	.321	.315
1968	2,383	55	96	.332	.315
1969	2,426	53	97	.333	.316
1970	missing				.319
1971	1,460	66	41	.340	.319
1972	954	66	61	.340	.322
1973	1,048	66	66	.342	.326
1974	1,504	40	80	.331	.333
1975	1,215	42	50	.345	.338
1976	1,466	42	75	.344	.345
1977	2,240	72	73	.411	.352
1978	2,635	92	70	.417	.363
1979	3,048	100	83	.425	.367
1980	3,370	100	90	.412	.370
1981	2,477	68	86	.419	.366
1982	2,316	67	84	.417	.365
1983	2,493	76	84	.422	.365
1984	2,748	76	86	.425	.368
1985	2,736	75	88	.417	.370
1986	2,851	76	91	.435	.373
1987	2,742	76	85	.440	.379
1988	2,668	76	84	.447	.383
1989	2,701	76	83	.446	.388
1990	2,931	75	96	.445	.390
1991	2,711	76	90	.451	.395
1992	2,512	75	89	.456	.400
1993	2,488	75	85	.451	.405
1994	2,500	83	84	.458	.406
1995	1,967	83	66	.457	.403
1996	1,694	83	57	.441	.397
TOTAL	87,575	106 (ever)	228 (ever)		

*Log wage point units. Weight: one observation per job-cell.

Table 2B: Characteristics of NYSS Data Set, 1989-2000

	Total Number of:			Std. Dev. (Log Wage) Among Job-Cells*	
Year	Job-Cells	Occupations	Employers	Total Sample	Rolling Sample (Smoothed)
1989	919	102	23	.415	.430
1990	956	102	24	.414	.434
1991	1,056	122	25	.429	.437
1992	1,091	122	25	.439	.440
1993	1,017	122	26	.435	.440
1994	987	126	24	.442	.439
1995	839	126	22	.422	.438
1996	605	85	24	.429	.435
1997	601	93	21	.415	.432
1998	671	93	23	.415	.429
1999	602	93	22	.414	.431
2000	530	92	18	.430	.434
TOTAL	9,874	180 (ever)	42 (ever)		

* Log wage point units. Weight: one observation per job-cell.

Table 3

Wage Dispersion Within CSS Job-Cell During the 1980s and 1990s

		Standard Deviation of Log Wages*		
Year	**Number of Observations**	**Total**	**Between Job Cells**	**Within Job Cells**
1980	23,475	0.353	0.342	0.086
1981	19,753	0.355	0.344	0.088
1982	18,302	0.347	0.339	0.077
1983	19,336	0.352	0.344	0.078
1984	19,379	0.355	0.345	0.082
1985	20,101	0.362	0.353	0.080
1986	20,893	0.378	0.369	0.083
1987	21,552	0.384	0.375	0.081
1988	20,293	0.397	0.388	0.088
1989	21,613	0.384	0.375	0.084
1990	22,327	0.388	0.379	0.086
1991	21,945	0.389	0.378	0.088
1992	8,769	0.368	0.352	0.099
1993	20,870	0.399	0.388	0.092
1994	18,487	0.415	0.405	0.088
1995	14,351	0.413	0.405	0.082
1996	10,932	0.418	0.408	0.093

*In log-wage-point units.

Appendix 1: How Representative is the CSS?

This section examines whether the CSS wage patterns are similar to those of the CPS, and whether CSS employers are similar to matched employers in Compustat. See Groshen (1996) for more detail on salary surveys in general and the CSS in particular.

In general, Cleveland, Cincinnati, and Pittsburgh are more urban, have more cyclically sensitive employment, and have undergone more industrial restructuring than the nation as a whole. Prior to the 1980s, wages in these three cities were higher than the national average. Now, they are approximately average for the country.

A1.1 Comparisons with other data on employees

The CSS is not a random sample either of occupations or employers; thus, it is important to place our results in context of the US economy. In particular, the CSS covers common nonproduction occupations in large employers in three Midwestern cities. Table A1 compares some features of the CSS to the 1995 Current Population Survey (CPS) Outgoing Rotation File. The CPS is the broadest and most-studied household survey, and we used the most recent survey at the time we wrote this appendix. The top panel compares weekly wage statistics in the CSS with those of the CPS and three subsets. The first subset selects the 44 2-digit CPS occupations into which the (more narrow) CSS occupations would fall. The second subset is the states of the East North Central census region (which includes Ohio). The final subset is the most exclusive: CSS occupations in the East North Central region.

As expected, weekly earnings in the CSS sample exceed those of the average US worker. The contrast between overall CPS wage levels and those in CSS occupations suggests that much of this difference is due to the occupations surveyed in the CSS. Restricting the CPS sample to Midwestern states does not noticeably narrow the gap. Remaining differences in wage levels probably reflect the fact that CSS respondents are urban and large; these characteristics correlate with high wages (Brown and Medoff 1989).

Wage variation is considerably lower in the CSS. In this case, restricting the CPS samples to CSS occupations does not improve the correspondence. This result is consistent with the CSS pulling less than the full range of narrow occupations within each 2-digit CPS occupational code. In addition, the concentration of large employers in the CSS would also have this effect, because wage variation between large and small firms is omitted.

Nevertheless, the lower panel shows that the occupational relative wage structure of the CSS closely follows that in the CPS. Standard and rank-order correlation coefficients are shown for the whole US and for the East North Central. The first three rows show that occupations mean and median wages across the two samples have correlation coefficients of almost 0.8. The bottom row shows that this correspondence also holds for within-occupation wage dispersion.

Similar comparisons between the CSS and published occupational means in Bureau of Labor Statistics Area Wage Surveys (AWS) for Cleveland, Cincinnati and Pittsburgh for the late 1970s and early 1980s yielded correlations in the range of 0.9 and above. The AWS also oversampled large employers. Movements of mean wages for similar occupations were highly correlated across the two surveys, and levels were usually within 5 percent of each other. CSS respondents appear representative of the broader AWS samples in the three cities.

These comparisons increase our confidence that the findings in the CSS sample are indicative of national conditions for non-production employees of large US firms.

A1.2 Comparisons with other data on employers

Table A2 reports on several tests of whether CSS members are representative of similar-sized firms in their industries. In the first year that an employer appears in both the CSS and Compustat, we matched it to the Compustat company in the same 2-digit SIC code that is closest in log(sales). We then compared the CSS and matched firms on a variety of accounting measures. We followed the two firms until the end of the sample (1996) or until one of the firms dropped out of Compustat**?** typically due to a merger or acquisition. Our samples for these analyses was reduced to only 52 companies because many employers**?** such as those that are privately-held or in the nonprofit and public sectors**?** could not be matched to Compustat.

Based on a simple t-test, none of the differences between the two samples was statistically significant. For example, the difference in median return on assets in the first year of each match is small: 17.3 percent for CSS versus 16.3 percent for Compustat. Similarly, the two samples both have median debt-to-equity ratios of about 22 percent in the first year of the match. Growth rates of sales and the above ratios are also very similar between the samples.

Survival in the Compustat database mainly measures avoidance of bankruptcy, merger, or acquisition. We cannot measure the mix of reasons that companies dropped out of either database. However, a merger or acquisition need not lead to attrition from the CSS if participation continued under the new ownership. This may explain why employers in the CSS sample exit slightly less often than the matched sample (37 percent versus 48 percent, respectively), although the difference is not statistically significant. Median lifetimes in the sample (33 years for CSS, 31 for matches) were similar. A variety of tests for differences in survival times (Wilxocon-

Gehan, Mantel-Haenszel, and log-rank) could not reject equal probabilities. (These tests all adjust for censoring of still-living companies [Stata 1995: 202].)

Thus, the CSS sample looks reasonably representative of Compustat firms of the same industry and size.

A1.3 Tests for CSS effects on wage structures

It is possible that information from the CSS could be a key component in employers**?** maintenance of rigid ILMs. If so, respondents who do not maintain ILMs will not join the CSS, while those who decide to weaken their internal labor markets will drop out of the CSS. In either case, employers outside the CSS would have very different wage structures than those inside the survey. Our investigations reveal little evidence of such differences.

First, evidence was presented above that the occupational wage structure (in means and standard deviations) in the CSS matches US patterns (as measured by the CPS and AWS) reasonably well. In addition, comparisons with matched Compustat firms are similarly reassuring. Moreover, in a supplement added to the CSS in 1989, few participants reported that they used the CSS as their main source of wage-setting information.

To explore further this possibility, we took advantage of the entry and exit of firms from the sample. We isolated the behavior of firms in the years immediately after they joined the CSS and before they left it. If participants in the CSS were markedly different from the rest of the market, then new entrants would have had differing wage structures that then converged to the rest of the CSS as participation continued. In addition, respondents that were about to drop out would have shown signs of divergence or reordering in the years preceding their departure from the sample.

One-year employer autocorrelations for entrants in their first year participating in the CSS are negligibly lower than for the whole CSS population sample (0.92, compared to 0.93), while those about to exit show no difference at all. In wage level, new entrants pay an average of 4% below the sample mean in their first year. Those about to exit pay about 2% above the CSS mean in the last year before they leave the sample. Both of these wage-level differences dissipate in the years further from entry or exit.

Internal structure wage differentials are again slightly less persistent for newcomers**?** first years (0.72) as compared to the rest of the sample (0.76). This result is consistent with some reordering--but not major realignment, since the difference is small and occurs only in the first year. Companies that are about to exit the sample do not have noticeably different autocorrelations from stayers in the years just prior to exit.

These probes suggest that it is unlikely that CSS respondents are extremely different from the rest of the market. Nevertheless, some of the results are consistent with a mild conforming influence of participation in the CSS. And some changes could take place in the years before entry or after exit. However, the 2% wage premium associated with immanent exit is inconsistent with a characterization of leavers as those who are reverting to a low-wage, spot-market employment strategy.

Table A1

Comparison of Weekly Earnings in the 1995 CSS
With the 1995 CPS Outgoing Rotation File

A. Means, Medians and Standard Deviations of Weekly Earnings

	CSS	Current Population Survey			
		Whole Sample	CSS Occupations Only	East North Central Region	CSS Occs. in East North Central
Mean	646	500	614	511	616
Median	577	403	504	423	520
Log median	6.36	6.00	6.22	6.05	6.25
Std. Deviation	280	365	415	369	412
Std. Dev. of log	0.413	0.817	0.773	0.839	0.793
Number of observations	14,351	169,781	40,230	27,544	6,316

B. CSS - CPS Correlations of Occupational Wage Structure

	CPS: All US		CPS: East North Central	
	Pearson Correlation	Spearman (Rank Order)	Pearson Correlation	Spearman (Rank Order)
Mean	0.790	0.798	0.785	0.796
Median	0.757	0.783	0.750	0.765
Log Median	0.787	0.783	0.766	0.765
Std. Deviation	0.776	0.779	0.708	0.772

Notes: In the top panel, “CSS occupations” denotes observations in the 44 2-digit CPS occupational codes corresponding to occupations in the CSS. For the correlations, in the CSS data, the 83 occupations were aggregated into 44 occupational groups corresponding to the 2-digit CPS codes. All correlations are statistically significant at above the .1% level.

Source: Authors’ calculations from the Federal Reserve Bank of Cleveland Community Salary Survey and the Current Population Survey Outgoing Rotation File, 1995.

Table A2

Comparisons of CSS and Matched Compustat Employers

	Sample Medians		Test for Hypothesis That Median Difference = 0	
	CSS Employers	**Compustat Matches**	**Statistic**	**Value**
Sales (millions of 1966 dollars)	649	632	Not applicable[a]	--
Change in log sales	+4.6	+3.0	t-statistic	1.56
Percent return on assets (ROA)	17.3	16.3	t-statistic	0.64
Change in ROA	-0.14	-0.07	t-statistic	-0.51
Debt/equity (percent)	21.7	22.4	t-statistic	-1.26
Change in debt/equity	+0.4	+0.2	t-statistic	1.36
Percent of sample that survived until sample end (1996)	62	53	Z-statistic[b]	-1.2
			P-value	0.23

Notes: The first year the firm entered the Cleveland Salary Survey we identified the best match (based on sales) in Compustat and measured all levels. Changes were measured to last year that both firms were in Compustat.
[a] Samples were matched on log(sales).
[b] Z-statistic and associated P-value of the Gehan generalization of the Wilcoxon-Mann-Whitney test for differences in survival times in the Compustat database between CSS and matched firms (Stata 1995). This test adjusts for censoring of the data by the end of the sample in 1996.
No t statistics were statistically significantly different from zero at the 5 percent level.