Earnings Inequality within and Between Levels of Responsibility in Engineering

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Department of Economics

Christopher B. Ellis

Levels of Responsibility in Planning and Planning Inequality: Within and Between

Table 4.4: Fit of the Singh-Maddala Distribution Versus an Unrestricted Multinomial Model (By Year and Level)

<table>
<thead>
<tr>
<th>Level</th>
<th>Year</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
<th>Level 4</th>
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<tbody>
<tr>
<td></td>
<td>1970</td>
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<td></td>
<td>1977</td>
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</tbody>
</table>

Summary of fit for the maximum likelihood estimates reported in Table 7:

- The likelihood ratio for the restricted model is significant at the 0.01 level.
- The likelihood ratio for the unrestricted model is significant at the 0.01 level.
- The overall fit of the Singh-Maddala distribution is significantly better than the multinomial model.
I. Introduction

A number of recent studies have documented the dramatic rise in wage inequality in the U.S. over the last 30 years. These changes are broad and fundamental, and it is clear that a variety of forces are behind them. There is a limit, however, to what can be learned from studying the whole labor market. The variables in the Current Population Survey, the main source of data in this literature, do not fully describe either workers or their jobs. Davis and Haltiwanger (1990) provide evidence that over the same period firms have resized their wage dispersion is not well understood.

This paper documents the aggregate relationship between salaries and rank within firms using data for a single occupation—engineering. Engineering was chosen because it is a large, well-defined profession, in which responsibility varies greatly across jobs.

The data come from two sources. The first is male engineers in the CPS for the years 1989 to 1991. The second source is a little-known survey conducted by the Bureau of Labor Statistics since 1981. The Professional Administratives, Technical and Clerical Pay Survey (henceforth PATC), reports the distribution of monthly salaries for various white-collar occupations by level of responsibility. The next section and Appendix A describes the survey in detail, but several features should be noted here:

- It reports the size distribution of monthly salaries for small, medium, and large firms.
- It gives the mean monthly salary for each ranked salary of responsibility level.
- It classifies jobs within plants by by occupation, and by level of responsibility within the occupation, for male engineers. The definitions of levels are specific to each occupation, and the detailed classification is given in Appendix A. A synopsis appears in Appendix A.
- The survey remained virtually the same from 1981 through 1986, which is the last year used in this study.

Overall earnings inequality for engineering jobs rose during this period, the early 1970s and 1980s. Before 1970 inequality was falling, although the pattern was sensitive to the definition of inequality. These two episodes of increased salary dispersion were distinct.
null
the entry of young workers into the profession. The evidence then suggests that technology plays a secondary role, and has not been the dominant force behind changes in responsibility assignment.

To help understand the wage structure, the data must measure the concept of responsibility not only at a point in time but across a period of dramatic technological change. The next section describes the PATC survey in some detail, and argues that it is up to this task.

II. The PATC Measure of Responsibility

Since Adam Smith (1976 p.204) included it in his list of five causes for equilibrium wage differentials, responsibility has played an important role in labor market theories. Yet it eludes a simple and non-empty definition. Clearly responsibility is an aggregate of many duties. It can be identified with rank in an organization or the number of workers an individual supervises, but these definitions only partially measure responsibility. They also make it difficult to compare responsibility across different sized firms.

To be more accurate, yet still specific, we can think of responsibility as a balance of two other abstract quantities: scale and scope. Scale defines the amount of resources, human and physical, which a worker controls. The human resources include the worker’s skills and the skills of those she supervises. Scope, on the other hand, defines how much the worker can affect the product flowing from this capital.

For example, compare a truck driver’s truck and a doctor’s education. The two assets might represent similar amounts of capital, but the doctor clearly has more scope in using her capital. And within firms a manager tends to have greater scope than her subordinates. Scope, however, is not synonymous with management level and responsibility is not inherent within rank. An auditor may have a smaller staff but greater responsibility than a middle manager.

The long literature on hierarchies within firms provides theories of responsibility assignment that correspond to this view. The literature’s implications for aggregate distri

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4 “Fourthly, the wages of labour vary accordingly to the small or great trust which must be reposed in the workmen,” Smith (1978 p. 207)
5 For example Tuck (1954), Mayer (1960), Lucas (1978), Rosen (1982) and Waldman
III. Task Assignment and Wage Distributions

Combine the distribution of only data through 1966 are used.

After 1966 the changes were split into two main stages. Changes have been attempted to
be surveyed. Until 1966 these changes are implemented for the first time, but
the survey does not. These changes are implemented for the first time, but
about the survey design:

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national statistics. According to the job descriptions appeared in Appendix 1 to
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The description of each level the final results of the survey.

TABLE 2

Simple Correlations Between Employment Shares

<table>
<thead>
<tr>
<th>Level</th>
<th>Share</th>
<th>Share</th>
<th>Average</th>
<th>Minimum</th>
<th>Maximum</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>0.49</td>
<td>0.98</td>
<td>0.83</td>
<td>0.66</td>
<td>0.94</td>
</tr>
<tr>
<td>II</td>
<td>0.27</td>
<td>0.67</td>
<td>0.27</td>
<td>0.13</td>
<td>0.35</td>
</tr>
<tr>
<td>III</td>
<td>0.12</td>
<td>0.39</td>
<td>0.45</td>
<td>0.25</td>
<td>0.69</td>
</tr>
<tr>
<td>IV</td>
<td>0.09</td>
<td>0.24</td>
<td>0.22</td>
<td>0.12</td>
<td>0.40</td>
</tr>
</tbody>
</table>

Summary of the Data

The percentage of engineers assigned to each level is summarized in Table 1 and Figure 1.1. Once the first three levels are combined to form I*, the employment shares form a pyramid. That is, in each year more engineers work in I* than II* and so on. Employment at level I* steadily fell until the mid 1970s and then rose until 1986. In the 1960s, the share of engineers in the other levels rose in response, although the top three levels grew faster than the middle levels. In a sense, the profession became increasingly top heavy. Between 1976 and 1986 the previous pattern was reversed as employment shifted back into the lowest level. The negative correlations in Table 2 confirm that employment at level I* moves counter to higher levels. Finally, note that total employment of engineers grew steadily except during the sluggish 1970s (Figure 1.2). 

Besides reporting employment by level, the PATC survey reports salary distributions by reporting the percentage of engineers whose monthly salaries fall into one of roughly 50 intervals. When the percentage at the upper and lower tails drops below 1% of total employment in the level, the intervals beyond that point are combined. The tail categories therefore differ across levels.

To make the form of the data clear, Figure 3 shows the densities of real salaries by level for 1986. Each point in the graph lies above the midpoint of a salary interval, converted to 1982 dollars. The height of the point is the percentage of engineers in the interval divided by its width. Only the inside salary categories for each level are shown, because the midpoints of the tail categories are unknown. The share of employment in the level is roughly the area under its density in Figure 3.

Figure 4 shows that the overall shapes of the salary distributions have not changed a great deal. (The graphs are made by smoothing the data in the same form as Figure 3.) The shifts out of and then back into level I* can be seen by the size of its curve relative to the others. Shifts in the relative locations of distributions can also be discerned in Figure 4, but Figure 5 illustrates this better.

Figure 5 shows that median wages followed the pattern of total employment in Figure 1.2. Median wages rose steadily in all levels during the 1960s and 1980s, but they stagnated in the 1970s. Wage growth in the 1980s was fastest in the top three levels, IV* to VI*,

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7 Although changes in the survey's coverage occurred in 1966 and 1986, employment figures do not jump in these years. This is because the changes only lowered the minimum establishment size, and engineers are concentrated in large establishments.
To illustrate, let's consider the distribution for income between family heads, which amounts to a positive definite distribution. The distribution can be approximated using the lognormal distribution. The lognormal distribution is a flexible model that allows for a wide range of shapes. It is often used to model income distributions because it can capture the skewness and kurtosis present in real-world data.

**Figure 8:**
Earnings Inequality Within and Between Levels

The lognormal distribution is characterized by two parameters: the mean (μ) and the variance (σ^2). The probability density function of the lognormal distribution is given by:

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\frac{1}{\sigma \sqrt{2\pi}} \exp\left(-\frac{(\ln(x) - \mu)^2}{2\sigma^2}\right)
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where \( x \) is the income, \( \mu \) is the mean, and \( \sigma \) is the standard deviation. The lognormal distribution is often used because it can model the skewness and kurtosis present in income distributions.

The mean and median incomes are reported in Table 8 of Appendix B. It is important to note that the lognormal distribution is not the same as the normal distribution. The lognormal distribution is skewed to the right, while the normal distribution is symmetric. The lognormal distribution is often used to model income distributions because it can capture the skewness and kurtosis present in real-world data.
The Singh-Maddala distribution does well, but assessing the fit is not straightforward. The problem lies in the fact that the PATC survey is based upon a stratified sample of firms rather than jobs or workers. So the number of engineers sampled is not known. The employment levels shown in Figure 1.2 are estimates for the whole population of jobs, and because the sample is stratified the actual number of jobs contacted in each category is not proportionate to the reported levels. Nonetheless, the sample of engineering jobs actually surveyed is large, at least 50,000 in each year.9

One way to measure fit when the cell probabilities are known but the sample size is not is to compute the minimum sample size that causes a likelihood ratio test to reject the Singh-Maddala distribution in favor of the multinomial when using, say, a .01 significance level. This critical sample size is summarized in Table 4 and fully reported in Table 6. The sizes are fairly large; for all levels the average is above 1000 across years. In 1971 and level III*, for instance, the fit is so close that the discrepancies would cause rejection of Singh-Maddala only if based on a sample of 20,967 or more. In only one case—level VI* in 1986—does the value fall below 1000. The fit is best in the middle levels and worse in level I* and level VI*.

At first these sample sizes look small quite small to a true sample of 50,000 or more. However, all the estimates are conditional on employment in a level and the sample in each level is a fraction of the overall sample. Because employment is quite small in the upper levels (see Table 1), the lower critical sample sizes here are not a serious indication of a bad fit. Finally, Figure 5 shows how good the fit is for the best and worst cases. The larger discrepancy in the worst case is due to raggedness in the data (see Figure 2) caused by a smaller sample size at upper levels and rounding in the original PATC tables.

Aggregate and Within-Level Earnings Inequality

The estimates are used to construct the aggregate salary distribution, the mixture or pooling of distributions within hierarchy levels (see Appendix B for details). These estimates are then used to compute measures of earnings inequality within engineering in each year.

The two most common measures of earnings inequality are the Gini coefficient and

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9 Officials at the BLS suggested in conversations that firms employing roughly one in three workers are contacted each year. Compared to the levels of employment, the figure of 50,000 in the text is conservative.
WHEN-DEPRENTropy contributes directly to aggregate entropy, the decrease in

Inequality in real GDP, which increases with non-monotonic process, becomes some-

measure of overall earnings inequality. Figure 6.

Figure 6.

Measures of Overall Earnings Inequality

gini coefficient

Year

0.04
0.05
0.06
0.07
0.08
0.09
0.1
0.11
0.12
0.13
0.14
0.15
0.16
0.17
0.18
0.19
0.2
and the share of employment at different levels. Figure 8 shows how within- and between-inequality differed. Changes in entropy between levels contributed to all changes in overall entropy. In particular, Figure 8 confirms what Figure 4 hinted at: inequality between levels rose sharply in the 1980s. During the early 1960s the drop in within-level inequality occurred while the overall value held steady. Since 1976 within-level entropy has fallen, so the rise in inequality during the early 1970s was fueled by both within- and between-inequality. The rise in the 1980s, on the other hand, was fueled exclusively by a widening gap between responsibility levels.

Entropy and employment within levels do not relate in any obvious way. Inequality fell in all levels before 1976 and after 1976, periods in which employment shares within levels moved in opposite directions. If employment in level I* fell before 1976 simply because workers were being promoted out of it more quickly, then earnings differentials within the level should have fallen, and at least the primary effect should have been a drop in wage dispersion. The patterns so far suggest that many of the changes relate to demographic shifts within engineering.

The Experience Distribution in Engineering

Table 4 summarizes the information on male engineers appearing in the CPS from 1969 to 1991. (Appendix A describes the sample.) Since only men were available, column (2) shows for certain years the overall percentage of female engineers in the U.S. Although the growth of young women entering the profession alters the overall experience distribution, their numbers in the profession are still relatively small. Including them would only accentuate the shift toward an inexperienced stock of workers.

Figure 9 shows the change in three segments of the experience distribution: below fifteen years, between fifteen and thirty, and above thirty years. The 90% confidence intervals are also shown. The share of young workers fell slightly in the early 1970s and then started to rise significantly in 1976. In 1985, this baby-boom in engineering had peaked as early entrants started to hit mid-career. Prior to that, the share of engineers between fifteen and thirty years experience fell continuously from 1969. At the other end of the spectrum, the number of older engineers rose until 1980, at which time the retirement of the post-war cohorts and the influx of the baby-boom began.11

11 There is some evidence (Dalton and Thompson 1971) that engineers peak in performance by age 45, or approximately 25 years experience. Coincidentally, Dalton and Thompson’s study appeared in the year when the post-War cohort reached its professional
introduction

experience distribution among firms to better sort workers between levels, creating less within-firm inequality and more between.

FIGURE 4. Median Wages and Percentile Overlap

The early 1970s occur when the experience distribution is only changing gradually. The early 1990s occur when the experience distribution is only changing gradually. The early 1970s occur when the experience distribution is only changing gradually. The early 1970s occur when the experience distribution is only changing gradually.
deals with tasks varying greatly in size and complexity. While the share of employment in upper ranks has fallen since 1976, relative earnings in those ranks rose. Thus the shift in supply, caused by the drop in highly experienced engineers, appears to dominate this type of technology bias, although the impact of this bias may not have been felt before 1986.

The unique way in which the PATC survey documents aggregate changes in firm organization leads to several open questions. For instance, Freeman (1977) has put forth the active labor market idea: young workers should feel more sharply the effects of labor demand conditions. The same principle may operate for firms. If experienced workers are in short supply, growing firms may be slower to adopt large vertical hierarchies. Firms with stable control structures may find it more costly to respond since they have explicit and implicit contracts with workers. To what extent are changes in rank assignment due to firms actually re-organizing versus new firms adapting to current conditions? More generally, accounting for theories of the firm may refine current explanations for changes in the wage structure that focus on labor supply and labor demand factors.

IV. Conclusion

Responsibility is a scarce resource—we can’t all be chiefs. And a major role of firms is to organize interaction between workers at different ranks. It is not surprising then that the distribution of experience within an occupation affects the value and assignment of responsibility. The PATC data on job rank confirm that this effect is real, and that much remains to be known about the aggregate implications of job placement within firms.

If past trends are any guide the rise in inequality in engineering may have slowed in the late 1980s. The baby boom entered mid-career and the post-war cohort began to retire, compressing the experience distribution. This should narrow the wage gaps between ranks since worker skills are less varied. Indeed, the wage data on engineers from the CPS (Table 4) suggest that inequality leveled off after 1985. On the other hand, since the supply of relatively inexperienced workers is falling, firms may find it more difficult to allocate responsibility to workers efficiently, in turn leading to greater inequality within job ranks.
Appendix A: Details of the Data
Excluded from the survey are:

1. Engineers in charge of programs so extensive and complex that one or more subordinate supervisory engineers are performing at level VIII.
2. Individuals whose decisions have direct and substantial effect on setting policy for the organization (beyond engineering programs).
3. Individual researchers recognized as national or international authorities.

The universe for the PATC survey consists of establishments in the continental U.S. and above a minimum total size of employment. Utilities and firms in the service sector are included, but educational and government institutions are not. The minimum size depends on industry, and it has remained nearly constant between 1962 and 1986. Prior to 1966 the minimum establishment size was 250 employees in all industries. In 1966 the minimum was lowered to 100 in transportation, communication, public utilities, and wholesale trade and was lowered to 50 in services and FIRE. In 1986 the minimum was lowered to 50 in all industries. These changes appear to have had little impact on the distributions for engineers because their employment is concentrated in much larger plants. For instance, in 1970 roughly 60% of engineers in the survey worked in establishments with more than 2500 workers.

The survey covers workers employed during the month of the interview rather than the whole year. Interview dates occurred within four month periods centered in March for years before 1969 and after 1971. In the years 1969-1971 the average date was June.

The Current Population Survey

The CPS sample is drawn from the March tape. It includes males between the ages of 16-64 not in the armed forces who worked 40 or more weeks during the previous year and who report their occupation as engineer. The derived occupation code for engineers is used in all years except until 1982, when marine and naval architects included with engineers were dropped.

The weekly wage is the sum of yearly wage and self-employment income divided by the number of weeks worked, expressed in 1982 dollars. Out of 18,980 observations meeting these criteria, a total of 199 had topcoded self-employment or wage income. Earnings for these records were multiplied by 1.3. Records with allocated earnings flags were dropped.
\[ (\mathbf{1} - \mathbf{1}^T \mathbf{1}^T)^{-1} \mathbf{1}^T \mathbf{1} = \mathbf{1} \mathbf{1}^T (\mathbf{1} \mathbf{1}^T)^{-1} \]

and the density is

\[ f(x) = (x \mathbf{1}^T)^{-\frac{1}{2}} e^{\mathbf{x}^T \mathbf{1} \mathbf{1}^T} \]

where \( f(x) \) is the density distribution of \( x \).

The distribution of \( x \) is a mixture of the distributions of each entry, weighted by the corresponding coefficient. The MLE of \( \theta \) is given by

\[ \hat{\theta} = \arg \max_{\theta} \prod_{i=1}^{n} f(x_i | \theta) \]

where \( f(x_i | \theta) \) is the density of \( x_i \) given \( \theta \).

The appendix B, Statistical Appendix, provides further details and derivations for the above results.
In turn, let $\Phi_t(x)$ denote the share of total earnings made by engineers making less than $x$:

$$\Phi_t(x) = \frac{1}{\mu_t} \int_0^x g_t(y)dy.$$ 

Then the aggregate Gini coefficient in year $t$ is:

$$\gamma_t = \int_0^1 [z - \Phi_t(G_t^{-1}(z))]dz$$

$G_t$ must be inverted numerically. Computation of $G_t^{-1}$ and the maximum likelihood estimates was done in Gauss386, using its BFGS routine. The numerical integration required to compute $\gamma_t$ used Romberg's method. No problems in reaching convergence were encountered.

References


