Comparing Inequalities Using Earnings Equations

by

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July 1, 2001

Abstract

We unify the decomposition methodologies of Juhn, Murphy, and Pierce (1993) and Fields (1999) for differences in inequalities across countries/groups/times using earnings equations. We demonstrate the unified methodology in a study of changes in earnings inequality in America during the late 1990s.

JEL codes: D30, J30

Keywords: decomposition analysis of inequality, earnings equation, coefficients (price) effect, characteristics (quantity) effect, residuals effect

The author wishes to thank James Davies, Gary Fields, Ira Gang and Mark Killingsworth. The author's work was supported by the CIBC Program in Human Capital and Productivity, Department of Economics, University of Western Ontario. Part of work was done while the author visited Department of Economics, Rutgers University.

1 Introduction

Juhn, Murphy, and Pierce (1993), below JMP (1993), is one of the most influential papers on earnings (wage) inequality. One of the merits of the paper is that it provides a very simple method for decomposing the differences in earnings inequality across countries/groups/times using earnings equations. At an aggregate level, the differences in earnings inequality may be decomposed into a part explained by the differences in the OLS estimates of the coefficients of earnings equations (coefficients effect or price effect), a part explained by the differences in observable quantities (characteristics effect or quantity effect), and a part explained by the differences in distribution of unobservables (residuals effects).[1] The JMP method reflects the preferences of many labor economists who want to analyze the changes or differences in earnings inequality in terms of differences in prices and quantities.

On the other hand, Fields (1999) provides another simple decomposition methodology which uses the information contained in the earnings equation. Fields' method is, however, focused on the contribution of each factor (e.g., age, education) in the earnings equation to earnings inequality. Using Fields' method, we can find how much each factor contributes to the differences in earnings inequality across countries/groups/times.

The JMP method is similar to the Blinder-Oaxaca type decomposition analysis of wage differentials, since the Blinder-Oaxaca type decomposition analysis also decomposes wage differentials into a coefficients effect (usually labeled as discrimination), a characteristics effect, and

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[1] The residuals effect is usually interpreted as the effect of differences in unmeasured characteristics and returns. However, it should be borne in mind that, as in all regression-based models, the residuals pick up all of the omitted variables, mismeasured ones, and the like.

a residuals effect (see Yun (2000) for details). However, unlike the Blinder-Oaxaca type decomposition analysis of wage differentials, the JMP method provides coefficients and characteristics effects only at an aggregate level. On the other hand, the Fields method provides the contributions of each factor to the differences in earnings inequality without further decomposing the contribution into coefficients and characteristics effects. By unifying the two methods, we are able to provide the coefficients and characteristics effects of each factor. This paper shows a way to unify the JMP and Fields methods in order to provide a decomposition of differences in earnings inequality at the individual factor as well as at the aggregate level. Using the unified method, we are able to directly answer the following types of questions, "How much do changes in educational attainments contribute to the changes in earnings inequality?" and "How much do changes in returns to educational attainments contribute to the changes in earnings inequality?".

The synthesis of the two methods is derived in section 2 and will be demonstrated by applying it to the study of changes in earnings inequality in America in the late 1990s. Section 4 concludes.

2. Synthesis of Fields and JMP methods

Our task is to compare earnings inequality between countries/groups/times A and B. The earnings inequality index is defined as follows,

$$I_A = I_A(Y_{1A}, Y_{2A}, \cdots, Y_{MA}), \text{ and } I_B = I_B(Y_{1B}, Y_{2B}, \cdots, Y_{NB})$$

where Y_{it} is the earnings of individual i in the country/group/time t, and $t = A, B$.

Let earnings be generated from the following regression equations (earnings equations)

$$y_A = \beta_{0A} + \sum_{k=1}^{k=K-1} \beta_{kA} x_{kA} + e_A \text{ and}$$

$$y_B = \beta_{0B} + \sum_{k=1}^{k=K-1} \beta_{kB} x_{kB} + e_B, \tag{1}$$

where $y_t = \log(Y_t)$, and x_{kt}, e_t are the k th exogenous variable and residuals, respectively, and $t = A, B$.

2.1. JMP method

JMP (1993) use earnings equations (1) to decompose the differences in earnings inequality. The decomposition is not unique. One possible decomposition sequence is as follows. Starting with the earnings equation of country/group/time A (y_A), first, replace the coefficients of the earnings equation of country/group/time A (β_{kA}) with those of country/group/time B (β_{kB}), while keeping the individual characteristics and residuals unchanged. The auxiliary earnings equation after changing coefficients is

$$y^* = \beta_{0B} + \sum_{k=1}^{k=K-1} \beta_{kB} x_{kA} + e_A. \tag{2}$$

Second, replace the individual characteristics of country/group/time A (x_{kA}) with those of country/group/time B (x_{kB}).[2] Compute another auxiliary earnings equation,

[2]In practice, the auxiliary earnings equation (y^{**}) may be obtained by replacing the residuals of the earnings equation of country/group/time B (y_B) with those of the earnings equation of country/group/time A (y_A). JMP (1993) used the cumulative density functions of the residuals of the earnings equations A and B in order to find corresponding residuals between the two earnings

$$y^{**} = \beta_{0B} + \sum_{k=1}^{k=K-1} \beta_{kB} x_{kB} + e_A. \tag{3}$$

Finally, replace the residuals of country/group/time A (e_A) with those of country/group/time of B (e_B). This results in exactly the earnings of country/group/time B (y_B). By using earnings generated from the four earnings equations, y_A, y^*, y^{**}, and y_B, we may measure earnings inequality corresponding to each earnings equation, denoted as I_{y_A}, I_{y^*}, $I_{y^{**}}$, and I_{y_B}, respectively. Note, first, that any inequality index may be used in the JMP method; second, if the index is based on level earnings, not log-earnings, then level earnings corresponding y^* and y^{**} should be computed.

The differences in earnings inequality between countries/groups/times A and B are decomposed as follows;

$$I_{y_A} - I_{y_B} = (I_{y_A} - I_{y^*}) + (I_{y^*} - I_{y^{**}}) + (I_{y^{**}} - I_{y_B}), \tag{4}$$

where the first, second and last components of right hand side represent, respectively, the effects of differences in coefficients (coefficients effect), the effects of differences in individual characteristics (characteristics effect), and the effects of differences in the distribution of unobservables (residuals effect). The decomposition into three effects is done only at an aggregate level. The JMP method does not allow an analysis at the individual characteristics level. Below we show that an analysis at the individual characteristics level may be achieved by combining the JMP method with the Fields (1999) method.

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equations (y_A, y_B).

2.2. Fields method

Fields (1999) uses the earnings equations (1) to answer the different question of how much of the differences in earnings inequality is attributable to individual factors.[3] In order to answer this question, first Fields devises a "relative factor inequality weight" of a factor k (s_k) which indicates the percentage of earnings inequality that is accounted for by the factor k.[4]

The relative factor inequality weight for a factor k may be derived by manipulating the earnings equation in terms of deviations from the mean;

$$y - \bar{y} = \sum_{k=1}^{K-1} \beta_k (x_k - \bar{x}_k) + (e - \bar{e}), \tag{5}$$

where $\bar{y}$, $\bar{x}_k$, and $\bar{e}$ are average earnings, an average value of factor k, and average residuals (zero by the assumption of OLS), respectively. By multiplying both sides of equation (5) by $(y - \bar{y})$, we obtain,

$$\sigma_y^2 = \sum_{k=1}^{K-1} \sigma_{\beta_k x_k, y} + \sigma_{e, y}, \tag{6}$$

where σ_y^2, $\sigma_{\beta_k x_k, y}$ and $\sigma_{e, y}$ are, respectively, the variance of log-earnings, the covariance of $\beta_k x_k$ and y and the covariance of the residuals (e) and y. Note that $\sigma_{e, y} = \sigma_e^2$ since $\sigma_{e, x_k} = 0$ by the

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[3] For applications of the Fields decomposition methodology, see Kattuman and Redmond (1997), Fields and Mitchell (1999), Fields and Yoo (2000), and Yun (2001).

[4] The use of relative factor inequality weights for decomposing inequality value by sources of income (e.g., labor income, capital income) was originally developed by Shorrocks (1982). A factor with a large relative factor inequality weight (s_k) contributes more to earnings inequality than do factors with smaller weights. Factors with negative weights contribute to reducing earnings inequality.

assumptions of OLS, where $k = 1, \cdots, K-1$.

Fields defines the relative factor inequality weight for a factor *k* using the OLS estimate of the coefficient of the earnings equation as

$$s_k = \frac{\sigma_{\beta_k x_k, y}}{\sigma_y^2} = \frac{\beta_k \cdot \sigma_{x_k} \cdot \rho_{x_k, y}}{\sigma_y}, \tag{7}$$

where σ_{x_k} is the standard deviation of x_k and $\rho_{x_k, y} = \frac{\sigma_{x_k, y}}{\sigma_{x_k}\sigma_y}$.

Fields (1999) argues that the relative contribution of a factor to overall inequality is invariant to the choice of inequality measure under six axioms proposed by Shorrocks (1982). Hence, the contribution of an individual factor to earnings inequality is simply $s_k \cdot I$. The residuals are also treated as another factor whose coefficient is one. Since the constant does not contribute to the earnings inequality, it is excluded from the analysis. Hence, factors are composed of residuals (*K* th factor) and (*K-1*) exogenous variables in equation (1).

Fields uses the relative factor inequality weight (s_k) to compute the contribution of an individual factor to the difference in earnings inequality between countries/groups/times *A* and *B*. The share of the contribution of a factor *k* to the difference in inequality between countries/groups/times *A* and *B* is defined as:

$$\Pi_k = \frac{s_{kA} \cdot I_A - s_{kB} \cdot I_B}{I_A - I_B}, \tag{8}$$

where $s_{k\,t}$ is, for $t = A$ and B, the relative factor inequality weight of factor k.[5] A positive (negative) value means that the factor contributes to increasing (leveling) earnings inequality in country/group/time A relative to country/group/time B.

As shown above, the Fields method shows the contributions of a factor k to the differences in earnings inequality ($s_{kA} \cdot I_A - s_{kB} \cdot I_B$), but it does not decompose the contributions into coefficients and characteristics effects. Instead, Fields (1999) focuses on the differences in s_k between countries/groups/times A and B. He provides an approximation for the differences in s_k in terms of percentage changes ($\%\,\Delta$). It is as follows;[6]

$$\%\,\Delta\,(s_k) \approx \%\,\Delta\,(\beta_k) + \%\,\Delta\,(\sigma_{x_k}) + \%\,\Delta\,(\rho_{x_k, y}) - \%\,\Delta\,(\sigma_y).$$

2.3. Unifying Fields and JMP methods

As shown above, the JMP method provides coefficients and characteristics effects only at the aggregate level, while the Fields method provides contributions of individual factors to the differences in earnings inequality without decomposing them into the coefficients and characteristics

[5] Note that the value of Π_k depends on the choice of inequality measure unlike the relative factor inequality weight (s_k).

[6] Fields (1999) also provides another approximation for the percentage changes in s_k;
$$\%\,\Delta\,(s_k) \approx 2 * \%\,\Delta\,(\beta_k) + 2 * \%\,\Delta\,(\sigma_{x_k}) - 2 * \%\,\Delta\,(\sigma_y).$$

effects.

We now unify the two approaches. The synthesis is remarkably simple. Let the variance of log-earnings be the earnings inequality measure. By computing the variance of log-earnings and relative factor inequality weight (s_k) for the earnings equations (1), y_A and y_B , and an auxiliary earnings equation (2), y^*, we may decompose the differences in variance of log-earnings between country/group/time A and country/group/time B as follows;

$$\begin{aligned}
\sigma^2_{y_A} - \sigma^2_{y_B} &= (\sigma^2_{y_A} - \sigma^2_{y^*}) + (\sigma^2_{y^*} - \sigma^2_{y_B}) \\
&= \sum_{k=1}^{k=K} (s_{ky_A}\cdot\sigma^2_{y_A} - s_{ky^*}\cdot\sigma^2_{y^*}) + \sum_{k=1}^{k=K} (s_{ky^*}\cdot\sigma^2_{y^*} - s_{ky_B}\cdot\sigma^2_{y_B}) \\
&= \sum_{k=1}^{k=K} (\beta_{kA}\cdot\sigma_{x_{kA}}\cdot\rho_{x_{kA},y_A}\cdot\sigma_{y_A} - \beta_{kB}\cdot\sigma_{x_{kA}}\cdot\rho_{x_{kA},y^*}\cdot\sigma_{y^*}) \\
&+ \sum_{k=1}^{k=K} (\beta_{kB}\cdot\sigma_{x_{kA}}\cdot\rho_{x_{kA},y^*}\cdot\sigma_{y^*} - \beta_{kB}\cdot\sigma_{x_{kB}}\cdot\rho_{x_{kB},y_B}\cdot\sigma_{y_B}),
\end{aligned} \tag{9}$$

where the first (K-1) factors are the exogenous variables in the earnings equations and K th factor is the residual with its coefficient of one (i.e., $\beta_{KA} = \beta_{KB} = 1$). The JMP method is used to derive the first line of equation (9), $(\sigma^2_{y_A} - \sigma^2_{y^*}) + (\sigma^2_{y^*} - \sigma^2_{y_B})$. The Fields method is used to derive the remaining lines of the equation (9).

Unlike the JMP method, the synthesis does not need to compute y^{**} and corresponding $\sigma^2_{y^{**}}$ in order to isolate the residuals effect. This is because the residuals effect is readily measured by $s_{Ky_A}\cdot\sigma^2_{y_A} - s_{Ky_B}\cdot\sigma^2_{y_B}$, which is equal to $s_{Ky^*}\cdot\sigma^2_{y^*} - s_{Ky_B}\cdot\sigma^2_{y_B}$. The residuals effect does not include $s_{Ky_A} \cdot \sigma^2_{y_A} - s_{Ky^*} \cdot \sigma^2_{y^*}$ because this equals zero.[7]

As noted previously, the JMP and Fields methods work with most inequality measures. Our synthesis uses the variance of log-earnings. This has the advantage over other inequality measures in that there is no change in the contributions of the residuals between the two earnings inequalities, I_{y_A} and I_{y^*} (i.e., $s_{Ky_A} \cdot \sigma^2_{y_A} = s_{Ky^*} \cdot \sigma^2_{y^*}$). This is because the coefficients of the residuals are one for both earnings equations (y_A , y_B) following the Fields method (i.e., $\beta_{KA} = \beta_{KB} = 1$).[8] Except for the variance of log-earnings, other inequality indices show changes in the contributions of the residuals between I_{y_A} and I_{y^*}.[9]

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[7] The fact that $s_{Ky_A} \cdot \sigma^2_{y_A} = \sigma_{e_A, y_A} = \sigma^2_{e_A} = \sigma_{e_A, y^*} = s_{Ky^*} \cdot \sigma^2_{y^*}$ can be easily proven using the assumption of OLS that $\sigma_{e_A, x_{kA}} = 0$ for $k = 1, ..., K$-1.

[8] One caveat is that choosing the variance of log-earnings as the inequality measure does not guarantee that $s_{ky_A} \cdot \sigma^2_{y_A}$ and $s_{ky^*} \cdot \sigma^2_{y^*}$ are the same even if coefficients of earnings equations *A* and *B* for factor *k* are the same except for residuals (i.e., $k \neq K$). We may obtain the identical values of $s_{ky_A} \cdot \sigma^2_{y_A}$ and $s_{ky^*} \cdot \sigma^2_{y^*}$ only when factors are independently distributed, i.e., $\sigma_{x_k, x_l} = 0$ for $k \neq l$

[9] Fields's relative factor inequality weight (s_k) was initially developed by using the variance of log-earnings and was applied to other indices under the six axioms proposed by Shorrocks (1982). The Gini coefficients, a version of Theil's index, earnings (level and log) differences between 90 percentile and 10 percentiles, and coefficient of variations are examined whether the contributions of residuals between I_{y_A} and I_{y^*} are changed. In a limited Monte Carlo study, Theil's index works reasonably well relative to others. Theil's index uses an equation of $\sum_{i=1}^{n} \frac{Y_i}{n\mu_Y} \log\left(\frac{Y_i}{\mu_Y}\right)$, where Y, μ_Y, and n are, respectively, earnings (level), mean earnings, and number of observations.

Finally, OLS estimates of earnings equations may be biased due to self-selection, simultaneity, etc. Several estimation methods (e.g., maximum likelihood estimation) may be used instead of OLS in order to obtain consistent estimates of earnings equations. It is possible to decompose the differences in earnings inequality by substituting the consistent estimates for the OLS estimates in equations (1), (2), and the unified decomposition equation (9). The contribution of the residuals to $\sigma^2_{y_A}$ and $\sigma^2_{y^*}$ may be identical if the estimation methods assume residuals are independent of exogenous variables.[10]

In this section, we have proposed a method by which we can decompose the differences in earnings inequality into coefficients and characteristics effects of individual factor by unifying the JMP (1993) and Fields (1999) methods. In the next section, we will demonstrate how we can apply our synthesis by studying changes in earnings inequality in America during late 1990s.

3. Empirical Example: Changes in Earnings Inequality, 1994 - 1999

We employ the unified method to the study of changes in earnings inequality in America during late 1990s using the March annual demographic micro data files from the current population survey (CPS). Our sample consists of wage/salary earning workers aged 18-65 with positive wage or salary in the year prior to the survey. The sample excludes the self-employed and people working

[10] The residuals computed using the consistent estimates of earnings equation are sometimes called the generalized residuals (Gourieroux, Monfort, Renault, and Trognon (1987)). The fact that the average of the generalized residuals may not be necessarily zero does not affect the decomposition results of the unified methodology.

in agriculture. To avoid the top-coding problem, the top 3 percent of the sample was truncated. The individual earnings are defined as annual wage or salary income in constant dollars (1982-84 = 100).[11]

Figure 1 shows the inequality of earnings trend from 1961-1999 (survey year, 1962-2000), measured by the ratio of mean earnings of top decile to bottom decile (Top/Bottom), coefficient of variations (CV), Gini coefficient, a version of Theil index, and variance of log-earnings (VLOG). For comparison purposes, the indices are standardized (with 1969 equal to 100) as in Karoly (1992). As Karoly (1992, p. 107) points out, we may draw quite different conclusions depending on the choice of inequality measure; CV, Theil and Gini show earnings inequality higher than the base year (1969) inequality level, though recently the Theil shows lower than the base year inequality level. On the other hand, VLOG and Top/Bottom show lower than the base year inequality levels except for the early 1970s and 1980s. Table 1 shows real values of these inequality indices for selected years.[12] Figure 2 shows the Lorenz curves for years of 1961, 1979 and 1999. As the diverse patterns of trend of inequality measured by various inequality indices suggest, the Lorenz curves are crossing.

Our empirical example will focus on changes in earnings inequality in recent years, the late 1990s. There are numerous papers on increases in earnings inequality during 1980s (e.g., Karoly (1992), JMP (1993)). It is interesting to investigate why the earnings inequality declined during the late 1990s as shown in the Figure 1. We choose the period 1994 to 1999 for our study. Table 2

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[11] Consumer price index - all urban consumers (series id: CUUR0000SA0 from web site of Bureau of Labor Statistics) is used to compute the earnings in constant dollars.

[12] The inequality indices are calculated using weights provided by the CPS.

shows mean characteristics of the samples in 1994 and 1999. The Lorenz curves at the Figure 3 show that the earnings distribution becomes more equitable between 1994 and 1999. In order to decompose the differences in earnings inequality between 1994 and 1999, we estimate earnings equations for both years using OLS. Table 3 reports the earnings equation estimates.

Using the estimates of earning equations in 1994 and 1999, first, the Fields method is applied to find the contributions of individual factors. The results are reported in the first and second columns of Table 4. The last two columns of Table 4 show the results of decomposing the differences in earnings inequality between the two years using the unified method.

In total, the coefficients, characteristics and residuals effects are, respectively, 24.1%, -7.7%, and 83.6% of the differences in variance of log-earnings between two years (0.13).[13] This means that earnings inequality in 1994 was higher than in 1999 due to differences in the coefficients of the earnings equation by 24.1%, due to differences in the characteristics of wage/salary earners by "negative" 7.7%, and due to differences in the distribution of residuals by 83.6%. In other words, the changes in wage structure (changes in coefficients) between 1994 and 1999 contributed to leveling the earnings inequality by 24.1%. The changes in individual characteristics, such as education, age, and industrial and occupational composition, contributed to increasing earnings inequality by 7.7%, that is, ceteris paribus, the earnings inequality would increase by 7.7% due to the changes in the characteristics. However, the main source of the change comes from changes in the dispersion of the residuals between two years.[14]

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[13]The characteristics effect is computed as 75.9% minus 83.6%, where 83.6% is the residuals effect.

[14]Many papers including JMP (1993) interpret the residuals as the product of unobserved characteristics and the returns to them. Using this kind of interpretation, the results imply that the

Now, let's look at contributions to the changes in earnings inequality by individual variables.[15] From the last two columns in the Table 4, we easily find that the composition of industry and industrial wage differentials played a major role in the changes in the earnings inequality among observed factors. The gross effects of industry variables are 8.6% of the changes in earnings inequality. Between the coefficients and characteristics effects, the coefficients effects have played more important role in reducing the earnings inequality, that is, changes in industrial wage differentials rather than changes in industrial composition contributed more to the leveling of earnings inequality. In addition to the industry variables, age variables also have played important role in the changes in earnings inequality. However, the regional variables have played only a small role in the leveling of earnings inequality. Another interesting fact is that the coefficients effect of educational variables (changes in education premium) contributed to decreasing inequality in the late 1990s, but the characteristics effect (the compositional changes in education) have dominated and contributed to making the earnings distribution less equitable.

As our empirical example above demonstrates, the coefficients effect, characteristics effect and residuals effect at the aggregate level across all the variables can be obtained using the JMP method. The gross effects of an individual variable are obtained from the Fields method for comparing earnings distributions. Our unified inequality decomposition method shows that the gross effects of an individual variable may be decomposed further into the coefficients effect and characteristics effect. Hence, we can systematically obtain the coefficients and characteristics effects

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returns (price) to unobserved characteristics have been lowered between 1994 and 1999.

[15] The effects of categorical variables (e.g., industry) or very closely related variables (e.g., age and age squares in hundreds) are computed as aggregating the effects of each variable.

at both the aggregate and individual variable levels.

4. Conclusion

JMP (1993) provides a simple method for decomposing the differences in earnings inequality across countries/groups/times. However, using the JMP decomposition one can only decompose at an aggregate level. This leaves very important questions unanswered. Questions we cannot answer using the JMP method include, for example, "How much do changes in educational attainments contribute to the changes in earnings inequality?" and "How much do changes in returns to educational attainments contribute to the changes in earnings inequality?".

This paper synthesizes the JMP (1993) method with the Fields (1999) method. This is, in reality, a reinterpretation of the Fields method in terms of price and quantity in order to find the coefficients and characteristics effects of individual factors. Though the choice of inequality measure is limited to the variance of log-earnings, the new method is very easy to implement, and it is easy to interpret each component (coefficients and characteristics effects).

An example of the unified method is provided by studying changes in the earnings inequality in America during late 1990s using the March CPS. During this period earnings inequality decline. One interesting finding is that changes in the premium to educational attainments have contributed to leveling earnings inequality. Taking this together with the role of residuals effect, one may wonder whether there was a reversal of the "skill-biased" technological changes which were supposed to cause the increase in earnings inequality during late 1970s and 1980s (JMP (1993), Katz and Auto (1999)). Skill-biased technological changes are believed to increase premium to education since the new technology demands more skilled, more educated workers. The decrease in earnings inequality and the role of education in this leveling is a quite interesting research topic.

The unified decomposition method developed in this paper may help us find the anwer the question above. It may shed new light on studies of earnings inequality by providing systematic comparisons of earnings inequalities in terms of the coefficients and characteristics effects, not only at an aggregate level, but also for each factor.

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Table 1. Earnings Inequality Measures

	Top/Bottom	CV	Gini	Theil	VLOG
1961	32.965	0.655	0.373	0.239	1.261
1964	32.760	0.662	0.377	0.242	1.258
1969	37.652	0.696	0.394	0.262	1.358
1974	38.861	0.715	0.403	0.272	1.371
1979	35.914	0.710	0.400	0.267	1.338
1984	40.281	0.731	0.410	0.280	1.407
1989	34.068	0.716	0.401	0.267	1.263
1994	34.953	0.738	0.408	0.276	1.247
1995	34.421	0.726	0.403	0.269	1.227
1996	32.158	0.722	0.400	0.265	1.197
1997	31.613	0.721	0.399	0.264	1.184
1998	29.131	0.711	0.393	0.256	1.118
1999	29.797	0.721	0.397	0.261	1.122

Source: Current Population Survey, various years, author's own calculation.

1. Tom/Bottom, CV, Gini, Theil, and VLOG are mean earnings ratio between top 10% and bottom 10%, coefficient of variation, the Gini coefficient, a version of Theil index, and variance of log-earnings, respectively. Theil's index uses an equation of $\sum_{i=1}^{n} \frac{Y_i}{n\mu_Y} \log\left(\frac{Y_i}{\mu_Y}\right)$, where Y, μ_Y, and n are, respectively, earnings (level), mean earnings, and number of observations.

Table 2. Sample Means

	1994		1999	
Annual Earnings (constant $)	14894.31	(10987.67)	16495.06	(11895.33)
Age	37.242	(11.816)	38.072	(12.051)
Education (year)	13.139	(2.569)	13.263	(2.564)
High School Dropout*	0.119	(0.324)	0.115	(0.319)
High School Graduate	0.340	(0.474)	0.326	(0.469)
Some College	0.308	(0.462)	0.307	(0.461)
College Graduate or More	0.232	(0.422)	0.252	(0.434)
Industry				
Construction	0.057	(0.232)	0.062	(0.241)
Manufacturing	0.179	(0.383)	0.168	(0.374)
Public Utilities	0.073	(0.260)	0.075	(0.263)
Trade (Sales)	0.216	(0.411)	0.215	(0.411)
Finance	0.061	(0.239)	0.061	(0.239)
Service	0.108	(0.311)	0.116	(0.321)
Professional Service	0.252	(0.434)	0.255	(0.436)
Public Administration*	0.055	(0.227)	0.049	(0.215)
Occupation				
Manager and Professional	0.291	(0.454)	0.314	(0.464)
Sales	0.114	(0.317)	0.115	(0.319)
Craft, Laborer	0.276	(0.447)	0.262	(0.440)
Service	0.153	(0.360)	0.151	(0.358)
Clerical*	0.177	(0.373)	0.159	(0.365)
Regions				
Midwest	0.245	(0.430)	0.245	(0.430)
South	0.350	(0.477)	0.348	(0.476)
West	0.210	(0.408)	0.218	(0.423)
Northeast*	0.195	(0.396)	0.188	(0.391)
MSA	0.635	(0.481)	0.684	(0.465)
Male	0.499	(0.500)	0.494	(0.500)
White (race)	0.834	(0.372)	0.823	(0.381)
Sample Size	61200		57008	

Standard deviations are reported in parentheses.

* indicates a reference group in the regression analysis.

Table 3. Regression Results of Earnings Equations

	1994		1999	
Constant	5.510**	(0.046)	5.804**	(0.044)
Age	0.156**	(0.002)	0.147**	(0.002)
Age^2 / 100	-0.172**	(0.003)	-0.161**	(0.002)
Education				
High School Graduate	0.394**	(0.013)	0.327*	(0.013)
Some College	0.399**	(0.013)	0.376**	(0.013)
College Graduate or More	0.639**	(0.015)	0.616**	(0.015)
Industry				
Construction	-0.223**	(0.024)	-0.210**	(0.023)
Manufacturing	-0.039**	(0.019)	-0.070**	(0.019)
Public Utilities	-0.036*	(0.021)	-0.051**	(0.021)
Trade (Sales)	-0.440**	(0.019)	-0.447**	(0.019)
Finance	-0.095**	(0.022)	-0.075**	(0.022)
Service	-0.573**	(0.020)	-0.470**	(0.020)
Professional Service	-0.379**	(0.018)	-0.403**	(0.018)
Occupation				
Manager and Professional	0.334**	(0.013)	0.356**	(0.012)
Sales	0.024	(0.016)	0.046**	(0.015)
Craft, Laborer	-0.066**	(0.014)	-0.018	(0.014)
Service	-0.288**	(0.014)	-0.251**	(0.014)
Regions				
Midwest	-0.044**	(0.011)	-0.021*	(0.011)
South	-0.053**	(0.011)	-0.039**	(0.010)
West	-0.040**	(0.012)	-0.031**	(0.011)
MSA	0.126**	(0.008)	0.125**	(0.008)
Male	0.454**	(0.008)	0.438**	(0.008)
White (race)	0.105**	(0.010)	0.072**	(0.010)
Adjusted R^2	0.332		0.350	
F Value	1381.23		1398.35	
Sample Size	61200		57008	

1. Standard errors are reported in parentheses, and ** and * mean statistically significant at 5% and 10%, respectively.

2. Reference groups are high school dropouts for education, public administration for industry, clerical workers for occupation, and northeast for region.

Table 4. Decomposition of Differences in Inequality

	Earning Inequality [a]				Decomposition [b]			
	1994		1999		Coefficients Effect		Characteristics Effect	
Total	1.247	(100.0)	1.122	(100.0)	0.030	(24.1)	0.095	(75.9)
Age, Age^2 /100	0.159	(12.7)	0.154	(13.7)	0.011	(9.0)	-0.007	(-5.3)
Age	0.554	(44.5)	0.553	(49.3)	0.040	(31.9)	-0.038	(-30.6)
Age^2 /100	-0.396	(-31.7)	-0.399	(-35.5)	-0.029	(-22.8)	0.032	(25.3)
Education	0.058	(4.7)	0.059	(5.2)	0.002	(2.2)	-0.004	(-2.8)
HS Grad.	-0.010	(-0.8)	-0.011	(-1.0)	0.001	(1.1)	0.000	(0.0)
College	-0.008	(-0.6)	-0.007	(-0.6)	-0.002	(-1.4)	0.001	(0.4)
College Grad.+	0.076	(6.1)	0.077	(6.9)	0.003	(2.6)	-0.004	(-3.3)
Industry	0.060	(4.8)	0.050	(4.5)	0.009	(7.3)	0.001	(1.0)
Construction	-0.001	(-0.1)	-0.001	(-0.1)	0.000	(0.1)	0.000	(0.0)
Manufacturing	-0.002	(-0.2)	-0.004	(-0.3)	0.001	(1.1)	0.000	(0.1)
Public Utilities	-0.001	(-0.1)	-0.001	(-0.1)	0.000	(0.3)	-0.000	(-0.0)
Trade (Sales)	0.040	(3.2)	0.040	(3.6)	-0.001	(-0.8)	0.001	(0.7)
Finance	-0.002	(-0.1)	-0.001	(-0.1)	-0.000	(-0.2)	0.000	(0.0)
Service	0.029	(2.3)	0.018	(1.6)	0.011	(8.6)	0.001	(0.8)
Prof. Service	-0.003	(-0.2)	0.000	(0.0)	-0.002	(-1.7)	-0.001	(-0.5)
Occupation	0.076	(6.1)	0.074	(6.6)	0.003	(2.6)	-0.001	(-0.9)
Manager	0.047	(3.8)	0.051	(4.5)	-0.002	(-1.7)	-0.001	(-1.0)
Sales	-0.001	(-0.1)	-0.001	(-0.1)	0.001	(0.5)	0.000	(0.0)
Craft, Laborer	-0.000	(-0.0)	-0.000	(-0.0)	-0.000	(-0.2)	0.000	(0.0)
Service	0.029	(2.4)	0.024	(2.2)	0.005	(4.0)	0.000	(0.0)
Regions	0.001	(0.1)	0.000	(0.0)	0.000	(0.3)	0.000	(0.0)
Midwest	0.000	(0.0)	-0.000	(-0.0)	0.000	(0.0)	0.000	(0.1)
South	0.001	(0.1)	0.001	(0.0)	0.000	(0.3)	0.000	(0.1)
West	-0.000	(-0.0)	0.000	(0.0)	-0.000	(-0.0)	-0.000	(-0.1)
MSA	0.004	(0.3)	0.004	(0.4)	-0.000	(-0.1)	-0.000	(-0.1)
Male	0.053	(4.3)	0.051	(4.5)	0.002	(1.7)	0.000	(0.4)
White (race)	0.003	(0.2)	0.001	(0.1)	0.001	(1.0)	0.000	(0.1)
Residuals	0.833	(66.8)	0.728	(64.9)			0.105	(83.6)

a. Shares of VLOG in 1994 (1.247) and 1999 (1.122) are reported in parentheses.

b. Share of differences in VLOG between 1994 and 1999 (0.125) are reported in parentheses.

Figure 1. Standardized Inequality Indices: 1961 to 1999 (1969 = 100)

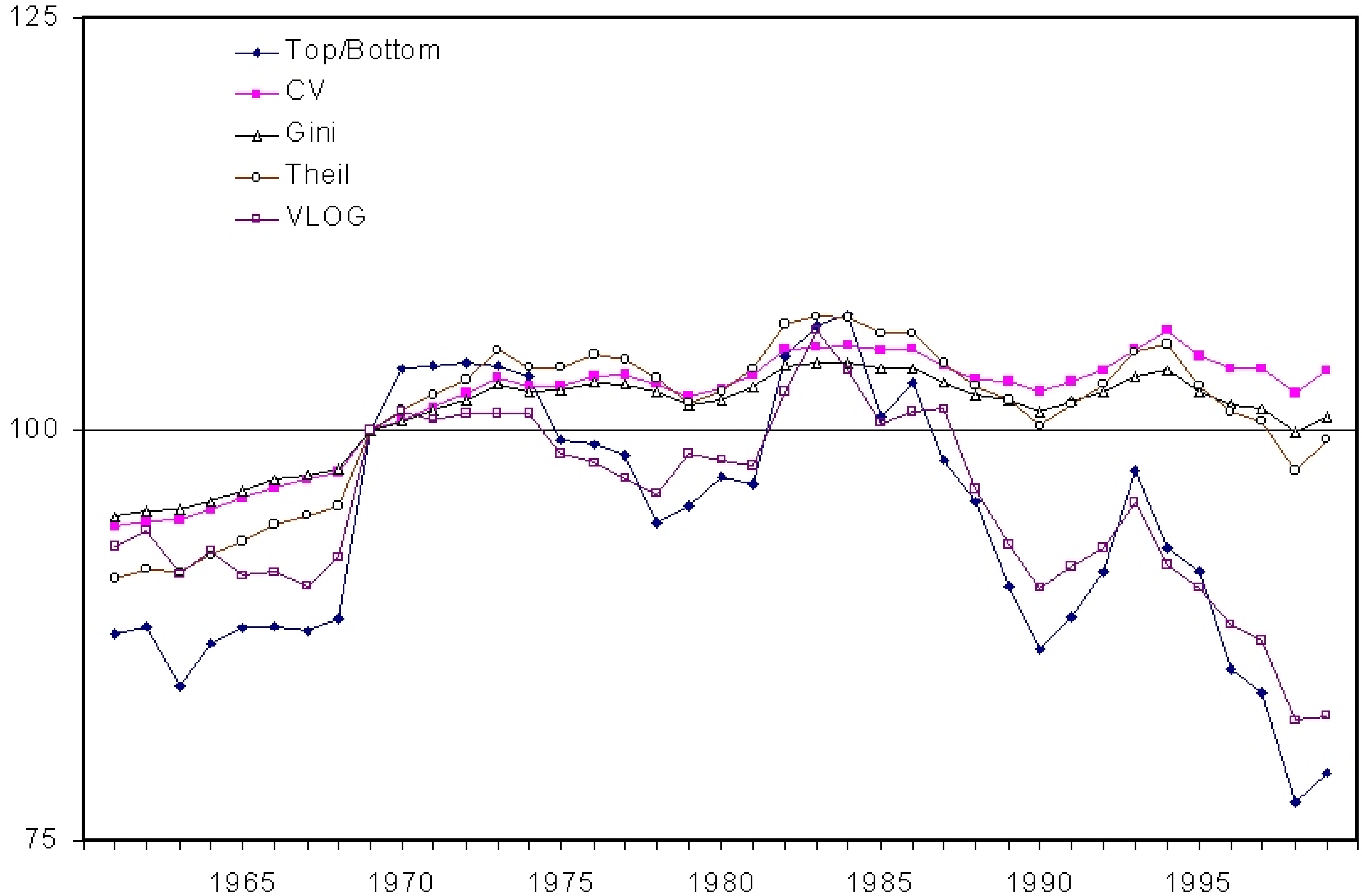

Figure 2. Lorenz Curves (1961, 1979, 1999)

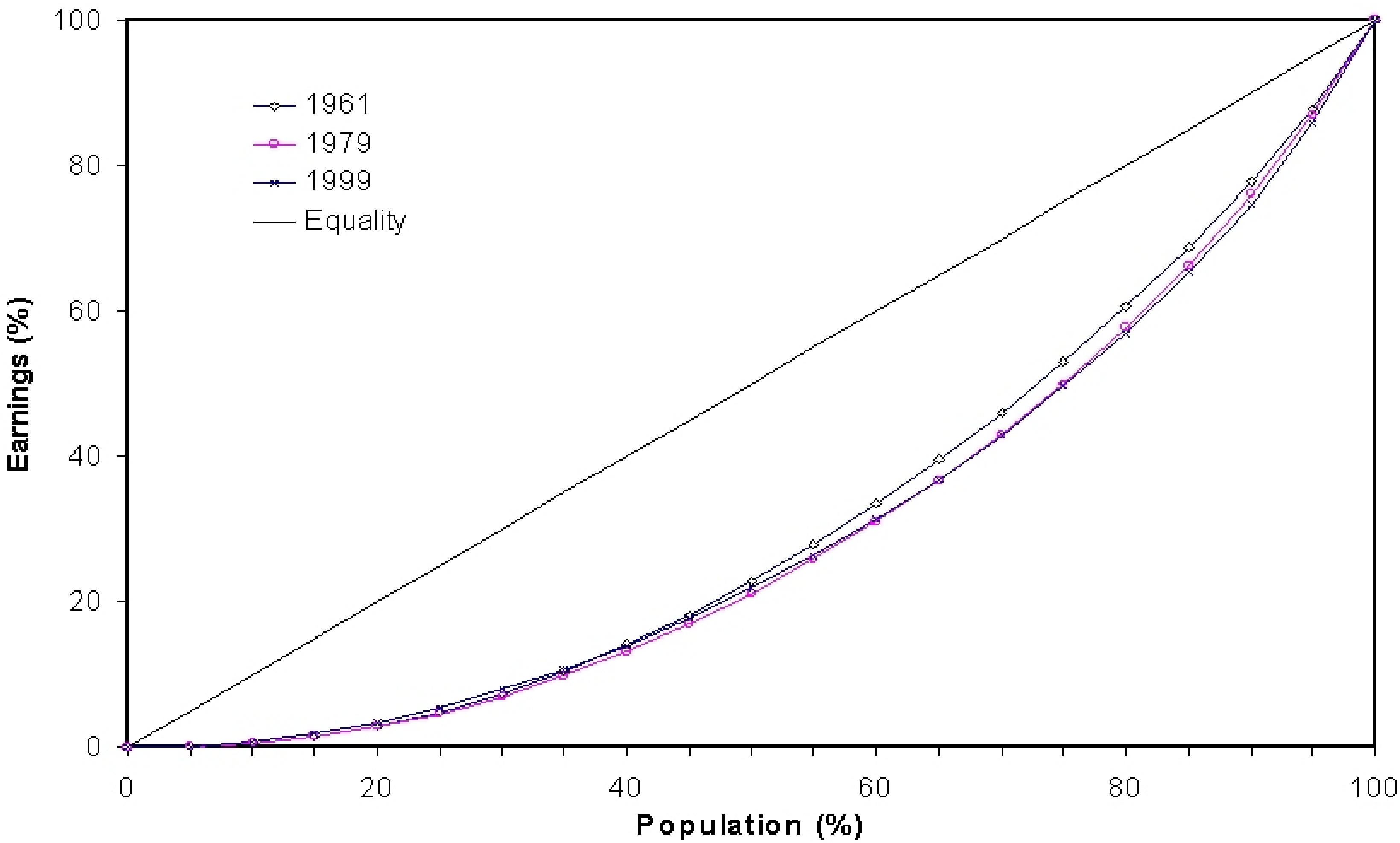

Figure 3. Lorenz Curves (1994, 1999)