# EARNINGS INEQUALITY IN USA, 1969–99: COMPARING INEQUALITY USING EARNINGS EQUATIONS

#### by Myeong-Su Yun\*

#### Tulane University, New Orleans

A simple decomposition method using an earnings equation is proposed by synthesizing two decomposition methodologies, those of Juhn, Murphy, and Pierce (1993) and Fields (2003), in order to study changes in earnings inequality in America during the last three decades in the 20th century. The proposed method enables us to compute both aggregate and detailed decompositions of changes in earnings inequality. The decomposition of earnings inequality change during the last three decades in 20th century shows that the increase in earnings inequality in America was caused by changes in the wage structure and the distribution of unobservables. The premium to education contributes substantially to the widening of earnings inequality during the 1980s and 1990s. A decreasing male wage premium contributes to leveling earnings inequality.

#### 1. INTRODUCTION

We have witnessed an explosion in the literature on earnings (wage) inequality during the last two decades (see Katz and Autor (1999) for summary of the studies). It is now believed that the economy experienced skill-biased technological changes since late the 1970s and early 1980s, which contributed to widening earnings inequality during last two decades of the 20th century.<sup>1</sup> The main evidence for this explanation comes from the increase in the premium to observed and unobserved skills, that is, increases in the wage premium for education, experience and unobserved skills.<sup>2</sup>

In order to understand the sources of increasing earnings inequality, we may want answers to the 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?". We propose a simple inequality decomposition method which can answer these questions by comprehensively evaluating the contribution of various individual factors to changes in earnings inequality. This new method is a synthesis of two existing methods; both are based on the earnings equation—one by Juhn, Murphy, and Pierce (JMP) (1993), and the other by Fields (2003).

*Note*: The author wishes to thank James Davies, Gary Fields, Ira Gang, the participants in seminars at University of Munich, IZA, and the Southern Economic Association (2001) and two anonymous referees. Special thanks to the editors, Bart van Ark and Stephan Klasen, who provided encouragement and showed great patience. Part of the work was done while the author visited the Department of Economics, Rutgers University.

\*Correspondence to: Myeong-Su Yun, Department of Economics, Tulane University, 206 Tilton Hall, New Orleans, LA 70118, USA (msyun@tulane.edu).

<sup>1</sup>See Card and DiNardo (2002) for a critical review of explanations of increasing wage inequality based on skill-biased technological changes. Bound and Johnson (1992) develop a theoretical model to evaluate various competing explanations of changes in earnings inequality.

<sup>2</sup>The increase in the wage premium for unobserved skills is sometimes referred to as an increase in "within group" inequality.

JMP (1993) shows that the differences in earnings inequality may be decomposed into a part explained by the differences in the coefficients of earnings equations (coefficients or price effect), a part explained by the differences in observable quantities (characteristics or quantity effect), and a part explained by the differences in distribution of unobservables (residuals effect).<sup>3</sup> The JMP method is similar to Oaxaca type decomposition analysis of wage differentials, since Oaxaca type decomposition analysis also decomposes wage differentials into a coefficients effect (usually labeled as discrimination), a characteristics effect, and a residuals effect. However, unlike Oaxaca type decomposition analysis of wage differentials, the JMP method provides coefficients and characteristics effects only at an aggregate level. Due to this shortcoming, the JMP method cannot directly answer interesting questions related to individual variables (so-called detailed decomposition), e.g., "How much do changes in returns to educational attainments contribute to the changes in earnings inequality?".

On the other hand, the literature on inequality has been interested in decomposing inequality by factors, that is, decomposing income inequality into the contributions of labor income, capital income, and government transfers. Fields (2003) points out that exogenous variables in the earnings equation can be treated the same as factors in the inequality literature, and proposes a simple decomposition methodology using the information contained in the earnings equation. Fields' method is focussed on the contribution of each factor (e.g. 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. While the Fields method provides the gross contributions of each factor to the differences in earnings inequality, it does not decompose the gross contribution into coefficients (price) and characteristics (quantity) effects.

By drawing on the strengths of the JMP and Fields decomposition methods, both based on the earnings equation, it is not hard to imagine that we may be able to study the coefficients and characteristic effects of each factor by weaving the two methods together. We show a way to unify the JMP and the Fields methods and use the unified method for studying the contribution of factors, not only at aggregate level (overall decomposition) but also at "individual" variable level (detailed decomposition), to changes in earnings inequality in America, 1969–99.

# 2. Synthesis of Fields and JMP Methods

Our task is to compare earnings inequality between time periods A and B<sup>4</sup>. The earnings inequality index is defined as follows,

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

where  $Y_{it}$  is the earnings of individual *i* in time period *t*, and t = A, *B*. For ease of presentation, we suppress individual subscripts in the equations.

<sup>&</sup>lt;sup>3</sup>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.

<sup>&</sup>lt;sup>4</sup>Time periods A and B may also be read as groups or countries A and B.

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

(1) 
$$y_{A} = \beta_{0A} + \sum_{k=1}^{k=K-1} \beta_{kA} x_{kA} + e_{A}, \text{ and} y_{B} = \beta_{0B} + \sum_{k=1}^{k=K-1} \beta_{kB} x_{kB} + e_{B},$$

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

### 2.1. JMP Method

The JMP (1993) method can be constructed as follows. Start with the earnings equation of time period  $A(y_A)$ . First, replace the coefficients of the earnings equation of time period  $A(\beta_{kA})$  with those of time period  $B(\beta_{kB})$ , while keeping the individual characteristics and residuals unchanged. The auxiliary earnings equation after changing coefficients is:

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

Second, replace the individual characteristics of time period  $A(x_{kA})$  with those of time period  $(x_{kB})$ .<sup>5</sup> Compute another auxiliary earnings equation:

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

Finally, replace the residuals from time period  $A(e_A)$  with those from time period  $B(e_B)$ . This results in exactly the earnings of time period  $B(y_B)$ . 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 that any inequality index may be used in the JMP method.

The differences in earnings inequality between time periods A and B are decomposed as follows:

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

where the first, second and last components of the right hand side represent, respectively, the effects of differences in coefficients (coefficients or price effect), the effects of differences in individual characteristics (characteristics or quantity effect), and the effects of differences in the distribution of unobservables (residuals effect). Note that the decomposition into three effects is done only at an aggregate level, not at an individual variable level.

<sup>&</sup>lt;sup>5</sup>In practice, the auxiliary earnings equation  $(y^{**})$  can be obtained by replacing the residuals of the earnings equation from time period  $B(y_B)$  with those of the earnings equation from time period  $A(y_A)$ . JMP (1993) uses the cumulative density functions of the residuals from the earnings equations A and B in order to find corresponding residuals between the two earnings equations  $(y_A, y_B)$ .

# 2.2. Fields Method

Fields (2003) uses the earnings equations (1) to find out how much of the difference in earnings inequality is attributable to individual factors.<sup>6</sup> His method consists of two steps. First, decompose inequality into contributions of individual factors at a point in time (levels question). Second, compare inequalities across time using the results of the first step (differences question).

At the first step (levels question), 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.<sup>7</sup> The relative factor inequality weight for a factor k may be derived by using following identity,

(5) 
$$\sigma_y^2 = \sum_{k=1}^{K-1} \sigma_{\beta_k x_k, y} + \sigma_{e, y},$$

where  $\sigma_y^2$ ,  $\sigma_{\beta_k x_k, y}$ , 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 construction of OLS, where k = 1, ..., 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

(6) 
$$s_k = \sigma_{\beta_k x_{k,y}} / \sigma_y^2 = (\beta_k \cdot \sigma_{x_k} \cdot \rho_{x_{k,y}}) / \sigma_y.$$

where  $\sigma_{x_k}$  is the standard deviation of  $x_k$  and  $\rho_{x_{k,y}} = \sigma_{x_{k,y}} / \sigma_{x_k} \sigma_y$ .

Fields (2003) 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 ( $\beta_K = 1$ ).<sup>8</sup> Factors are composed of residuals (*K*-th factor) and (*K* – 1) exogenous variables excluding constant in equation (1).

At the second step (differences question), the share of the contribution of a factor k to the difference in inequality between time periods A and B is defined as:

(7) 
$$\prod_{k} = (s_{kA} \cdot I_A - s_{kB} \cdot I_B)/(I_A - I_B),$$

where  $s_{kt}$  is, for t = A and B, the relative factor inequality weight of factor k.<sup>9</sup> A positive (negative) value means that the factor contributes to increasing (leveling) earnings inequality in time period A relative to time period B when  $I_A > I_B$ .

<sup>6</sup>For applications of the Fields decomposition methodology, see Fields and Mitchell (1999), Fields and Yoo (2000), and Gindling and Trejos (2005).

<sup>9</sup>Note that the value of  $\Pi_k$  depends on the choice of inequality measure, unlike the relative factor inequality weight (*s<sub>k</sub>*).

<sup>&</sup>lt;sup>7</sup>The use of relative factor inequality weights for decomposing the inequality value by income source (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.

<sup>&</sup>lt;sup>8</sup>The residuals may be further specified as a product of the standard deviation and the standardized residuals with mean zero and variance one, i.e.,  $e = \sigma_e \theta$  where  $\theta = e/\sigma_e$  (Juhn *et al.*, 1991). The standard deviation of residuals and the standardized residuals may be considered as the coefficient and characteristic of unobserved skills, respectively, that is,  $\beta_K = \sigma_e$  and  $x_K = \theta$ . Obviously, this specification does not change the relative factor inequality weight of the residuals.

As shown above, the Fields method shows the gross 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.<sup>10</sup>

# 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 coefficients and characteristics effects. Both methods try to investigate the changes in inequality based on the earnings equation but provide only a partial picture of the changes in earnings inequality. It is not hard envisioning synthesizing them into a unified method since the two methods complement each other.

The synthesis is remarkably simple. Let the variance of log-earnings be the earnings inequality measure.<sup>11</sup> 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 the variance of log-earnings between time periods A and B into the coefficients and characteristics (including residuals) effects as follows:

(8) 
$$\sigma_{y_{A}}^{2} - \sigma_{y_{B}}^{2} = (\sigma_{y_{A}}^{2} - \sigma_{y^{*}}^{2}) + (\sigma_{y^{*}}^{2} - \sigma_{y_{B}}^{2})$$
$$= \sum_{k=1}^{k=K} (s_{ky_{A}} \cdot \sigma_{y_{A}}^{2} - s_{ky^{*}} \cdot \sigma_{y^{*}}^{2}) + \sum_{k=1}^{k=K} (s_{ky^{*}} \cdot \sigma_{y^{*}}^{2} - s_{ky_{B}} \cdot \sigma_{y_{B}}^{2}),$$

where the first (K - 1) factors are the exogenous variables in the earnings equations and the *K*-th factor is the residual with its coefficient of one (i.e.  $\beta_{KA} = \beta_{KB} = 1$ ).<sup>12</sup> The first line in equation (8) is derived using the JMP method while the second line is derived using the Fields method.

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

<sup>10</sup>Instead, Fields (2003) focuses on the differences in  $s_k$  between time periods A and B. He provides two ways of approximating the differences in  $s_k$  in terms of percentage changes (% $\Delta$ ). They are:

$$\%\Delta(s_k) \approx \%\Delta(\beta_k) + \%\Delta(\sigma_{x_k}) + \%\Delta(\rho_{x_k,y}) - \%\Delta(\sigma_y), \text{ and}$$
  
$$\%\Delta(s_k) \approx 2*\%\Delta(\beta_k) + 2*\%\Delta(\sigma_{x_k}) - 2*\%\Delta(\sigma_y).$$

<sup>11</sup>A shortcoming of the unified method is that it is limited to the variance of log-earnings as the inequality index. This method cannot be applied to percentile differences in log-earnings, e.g. 90–10, 90–50, and 50–10, used in JMP (1993) or various other inequality indices used in Fields (2003).

<sup>12</sup>Equation (8) can be written as:

$$\sigma_{y_{A}}^{2} - \sigma_{y_{B}}^{2} = \sum_{k=1}^{k=K} (\beta_{k_{A}} \cdot \sigma_{x_{kA}} \cdot \rho_{x_{kA,y_{A}}} \cdot \sigma_{y_{A}} - \beta_{kB} \cdot \sigma_{x_{kA}} \cdot \rho_{x_{kA,y^{*}}} \cdot \sigma_{y^{*}})$$
$$+ \sum_{k=1}^{k=K} (\beta_{k_{B}} \cdot \sigma_{x_{kA}} \cdot \rho_{x_{kA,y^{*}}} \cdot \sigma_{y^{*}} - \beta_{kB} \cdot \sigma_{x_{kB}} \cdot \rho_{x_{kB,y_{B}}} \cdot \sigma_{y_{B}}).$$

because this equals zero.<sup>13</sup> This property seems to be a mixed blessing; on the one hand it helps us reduce burden of constructing  $y^{**}$  via tedious matching, but on the other hand, it says there is no way to distinguish price and quantity effects of residuals (unobserved skills).<sup>14</sup>

Equation (8) may be modified to easily identify the characteristics, coefficients and residuals effects, as follows:

(8') 
$$\sigma_{y_{A}}^{2} - \sigma_{y_{B}}^{2} = \sum_{k=1}^{k=K-1} (s_{ky^{*}} \cdot \sigma_{y^{*}}^{2} - s_{ky_{B}} \cdot \sigma_{y_{B}}^{2}) + \sum_{k=1}^{k=K-1} (s_{ky_{A}} \cdot \sigma_{y_{A}}^{2} - s_{ky^{*}} \cdot \sigma_{y^{*}}^{2}) + (\sigma_{e_{A}}^{2} - \sigma_{e_{B}}^{2}),$$

where the first, second and third components represent, respectively, characteristics, coefficients and residuals effects. Note that the order of the equation (8) was coefficients and then the characteristics (including residuals) effects.

### 3. Changes in Earnings Inequality, 1969–99

The previous section proposed a simple and new decomposition method for differences in earnings inequality by unifying the JMP (1993) and Fields (2003) methods. We employ the unified method to comprehensively evaluate the price and quantity effects of various factors to changes in earnings inequality in America during the last three decades in the 20th century (1969–99).

# 3.1. Data and Overall Trend

For the purpose of studying changes in earnings inequality over time, the Current Population Survey (CPS) is widely used. We also draw data from the March annual demographic micro data files of the CPS. The sample selection criteria are similar to those of JMP (1993). Our sample consists of wage/salary earning workers aged 18–65 who worked at least 14 weeks in the year prior to the

<sup>&</sup>lt;sup>13</sup>Due to the construction of OLS,  $\sigma_{e_A,x_{kA}} = 0$  for k = 1, ..., K-1, and hence it can be easily shown that  $s_{K_{YA}} \cdot \sigma_{Y_A}^2 = \sigma_{e_A,y^A} = \sigma_{e_q}^2 = \sigma_{e_A,y^*} = s_{Ky^*} \cdot \sigma_{y^*}^2$ . This is a desirable property since the coefficient of residuals is one for both earnings equations. From a limited Monte Carlo study, we find that the contribution of residuals changes between the earnings inequality,  $I_{Y_A}$  and  $I_{y^*}$ , when inequality indices other than variance of log-earnings are used, which is the main reason why we use the variance of log-earnings as the inequality measure in proposed unified method. Choosing the variance of log-earnings as the inequality measure does not necessarily guarantee that  $s_{ky_A} \cdot \sigma_{y_A}^2$  and  $s_{ky^*} \cdot \sigma_{y^*}^2$  are the same even if the coefficients of earnings equations A and B for factor k are the same except for the residuals (i.e.,  $k \neq K$ ). We can obtain the identical values of  $s_{ky_A} \cdot \sigma_{y_A}^2$  and  $s_{ky_*} \cdot \sigma_{y^*}^2$  only when factors are independently distributed, i.e.  $\sigma_{x_k,x_l} = 0$  for  $k \neq l$ .

<sup>&</sup>lt;sup>14</sup>One may ask whether the price and quantity effects can be separately identified if the coefficients of the residuals are assumed to be the standard deviations of residuals (i.e.,  $\beta_{KI} = \sigma_{e_r}$ , see footnote 8) rather than one (i.e.,  $\beta_{KA} = \beta_{KB} = 1$ ). This refinement of the price and quantity of the residuals does not help to separately identify the price and quantity effects of residuals; it only shifts the residuals effect from being measured as a characteristics effect to being measured as a coefficients effect. The inability to divide the price and quantity effects of residuals may not be a major shortcoming. First, decomposing the residuals into the standard deviation of residuals and standardized residuals is problematic since the two measures are not necessarily independent (Suen, 1997). Second, defining the inequality measure itself as the price of unobserved skills does not provide much insight to why inequality increases. It says that earnings inequality increases because "within group" inequality increases, which can be said without further specifying the price and quantity of the residuals.



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

survey and earn a minimum of \$67 per week in constant dollar (1982-84 = 100).<sup>15</sup> The sample excludes the self-employed and people working in agriculture. To avoid the top-coding problem, the top 3 percent of the sample was truncated.<sup>16</sup> Individual earnings are defined as weekly wage or salary income in constant dollars (1982-84 = 100).

Figure 1 shows the trend of earnings inequality in America, 1969–99 (survey year, 1970–2000), measured by the ninetieth-tenth percentile log wage differential (Log Diff), 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). Though the magnitude

<sup>15</sup>The weekly wage rate is computed by dividing yearly earnings with number of weeks worked during last year. Note that the number of weeks worked last year was reported in brackets until 1974 and as actual weeks since 1975. The consumer price index–all urban consumers (series id: CUUR0000SA0 from the website of the Bureau of Labor Statistics, http://stats.bls.gov/cpi/home.htm) is used to compute earnings in constant dollars. \$67 is equal to one-half of the 1982 real minimum wage based on a 40 hour week with the hourly minimum wage of \$3.35. The truncation of the lower tail of distribution is often intended to eliminate the measurement error associated with erroneous income codes.

<sup>16</sup>Some papers instead impute the income of the top-coded by multiplying a certain number. For example, JMP (1993) imputes weekly earnings for workers top coded as 1.33 times the top-coded number. We opt to truncate the top 3 percent of the sample since the value of the top-code itself and the proportion of top-coded earnings are changing over the years. It should be borne in mind that the truncation causes earnings inequality to be underestimated.

	Log Diff	CV	Gini	Theil	VLOG
All					
1969	1.336	0.475	0.264	0.110	0.260
1979	1.333	0.487	0.270	0.115	0.259
1989	1.435	0.524	0.289	0.132	0.301
1999	1.529	0.567	0.307	0.149	0.331
Men					
1969	1.130	0.400	0.223	0.081	0.199
1979	1.212	0.427	0.242	0.093	0.231
1989	1.406	0.488	0.273	0.118	0.287
1999	1.482	0.539	0.296	0.139	0.323
Women					
1969	1.153	0.459	0.244	0.097	0.204
1979	1.128	0.464	0.245	0.098	0.197
1989	1.366	0.526	0.283	0.127	0.272
1999	1.466	0.573	0.303	0.148	0.307

TABLE 1 Earnings Inequality Measures

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

*Notes*: Log Diff, CV, Gini, Theil, and VLOG are log-wage differentials 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  $\sum_{i=1}^{n} (Y_i/(n\mu_Y))\log(Y_i/\mu_Y)$ , where Y,  $\mu_Y$  and n are, respectively, earnings (level), mean earnings, and number of observations.

of increases is different, Figure 1 clearly shows an increase in earnings inequality during this period regardless of inequality measures. This is somewhat surprising since some studies (e.g. Karoly (1992) for a study of yearly earnings) point out that it is possible to draw quite different conclusions about trend in earnings inequality depending on the choice of inequality measure. Figure 1 also shows that earnings inequality was stable until 1980, steadily increased from 1980 to 1986, was stable again from 1987 to 1992, and increased thereafter.<sup>17</sup> Table 1 shows real values of these inequality indices for selected years.<sup>18</sup>

Figures 2 and 3 show earnings inequality by gender. It is clear from the figures that men's earnings inequality increased more than women's earnings inequality relative to their levels in 1969. Figure 3 shows that the trend of inequality indices for women has a pattern similar to the overall trend (Figure 1): stable during 1970s and increasing during 1980s and 1990s. Figure 2 shows that the trend of men's earnings inequality was a little different: stable during the 1970s but higher than the 1969 level, and increasing during the 1980s and 1990s.

# 3.2. Decomposing Changes in Inequality with the Unified Method

We apply the unified decomposition method to compare earnings inequality by decade, i.e. 1969, 1979, 1989 and 1999. Table 2 shows the mean characteristics of the samples in these years. In order to decompose the changes in earnings inequality, we estimate parsimonious earnings equations for the four years using OLS. Table 3 reports the earnings equation estimates.

<sup>&</sup>lt;sup>17</sup>It is not clear how much of the increase in earnings inequality during the 1990s is due to changes in the CPS questionnaire in 1994.

<sup>&</sup>lt;sup>18</sup>The inequality indices are calculated using weights provided by the CPS.





Figure 3. Standardized Inequality Indices for Women: 1969 to 1999 (1969 = 100)

		1969	1	979	1	989		999
All								
Weekly earnings	373.474	(177.371)	365.485	(177.847)	370.217	(193.938)	390.988	(221.883)
Age	39.190	(12.920)	36.851	(12.605)	37.338	(11.350)	39.221	(11.254)
Experience	21.587	(13.823)	18.331	(13.301)	18.268	(11.733)	19.854	(11.436)
Education	11.604	(2.952)	12.521	(2.733)	13.071	(2.650)	13.369	(2.616)
Region								
Midwest	0.280	(0.449)	0.272	(0.445)	0.246	(0.431)	0.243	(0.429)
South	0.298	(0.457)	0.316	(0.465)	0.341	(0.474)	0.357	(0.479)
West	0.163	(0.369)	0.184	(0.388)	0.199	(0.399)	0.215	(0.411)
Northeast*	0.258	(0.438)	0.227	(0.419)	0.214	(0.410)	0.186	(0.389)
MSA	0.690	(0.463)	0.664	(0.472)	0.648	(0.477)	0.688	(0.463)
Whites (race)	0.887	(0.317)	0.873	(0.333)	0.848	(0.359)	0.821	(0.383)
Male	0.632	(0.482)	0.588	(0.492)	0.555	(0.497)	0.542	(0.498)
Sample size	40,116		54,747		50,582		45,323	
Men								
Weekly earnings	436.285	(174.386)	426.023	(182.048)	416.719	(203.265)	433.655	(233.900)
Age	39.684	(12.553)	37.143	(12.604)	37.340	(11.356)	38.977	(11.240)
Experience	22.227	(13.588)	18.718	(13.358)	18.392	(11.710)	19.749	(11.371)
Education	11.458	(3.112)	12.426	(2.879)	12.949	(2.764)	13.229	(2.696)
Region								
Midwest	0.289	(0.453)	0.279	(0.449)	0.253	(0.435)	0.248	(0.432)
South	0.287	(0.452)	0.309	(0.462)	0.327	(0.469)	0.348	(0.476)
West	0.161	(0.368)	0.180	(0.384)	0.199	(0.400)	0.219	(0.414)
Northeast*	0.264	(0.441)	0.231	(0.422)	0.220	(0.414)	0.184	(0.388)
MSA	0.690	(0.463)	0.660	(0.474)	0.646	(0.478)	0.687	(0.464)
Whites (race)	0.895	(0.307)	0.884	(0.321)	0.863	(0.344)	0.841	(0.366)
Sample size	25,219		31,862		27,824		24,509	
Women								
Weekly earnings	265.797	(122.078)	278.926	(129.363)	312.104	(164.021)	340.422	(195.004)
Age	38.343	(13.484)	36.434	(12.595)	37.336	(11.343)	39.511	(11.264)
Experience	20.491	(14.151)	17.778	(13.201)	18.113	(11.761)	19.979	(11.512)
Education	11.854	(2.636)	12.657	(2.502)	13.225	(2.491)	13.534	(2.508)
Region								
Midwest	0.267	(0.442)	0.262	(0.440)	0.236	(0.425)	0.236	(0.425)
South	0.317	(0.465)	0.326	(0.469)	0.358	(0.480)	0.367	(0.482)
West	0.167	(0.373)	0.190	(0.392)	0.199	(0.399)	0.209	(0.407)
Northeast*	0.249	(0.433)	0.221	(0.415)	0.206	(0.405)	0.188	(0.391)
MSA	0.690	(0.463)	0.669	(0.470)	0.652	(0.476)	0.689	(0.463)
Whites (race)	0.874	(0.332)	0.858	(0.349)	0.830	(0.376)	0.798	(0.401)
Sample size	14,897		22,885		22,758		20,814	

TABLE 2 SAMPLE MEANS

*Notes*: Standard deviations are reported in parentheses. \*Indicates a reference group in the regression analysis. Weekly earnings are in constant dollars (1982–1984 = 100).

$\begin{array}{c ccccccccccccccccccccccccccccccccccc$						<u> </u>			
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		19	969	19	979	19	89	19	999
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	All								
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Constant	4.343*	(0.013)	4.279*	(0.012)	3.984*	(0.014)	3.794*	(0.016)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Experience	0.027*	(0.001)	0.033*	(0.000)	0.035*	(0.001)	0.035*	(0.001)
Education $0.054^*$ $(0.001)$ $0.061^*$ $(0.001)$ $0.086^*$ $(0.001)$ $0.099^*$ $(0.001)$ RegionMidwest $0.024^*$ $(0.005)$ $-0.056^*$ $(0.005)$ $-0.080^*$ $(0.006)$ $-0.015^*$ $(0.006)$ South $-0.091^*$ $(0.005)$ $-0.056^*$ $(0.005)$ $-0.124^*$ $(0.006)$ $-0.066^*$ $(0.000)$ West $-0.028^*$ $(0.006)$ $0.028^*$ $(0.004)$ $0.121^*$ $(0.004)$ $0.115^*$ $(0.000)$ MSA $0.122^*$ $(0.004)$ $0.098^*$ $(0.004)$ $0.121^*$ $(0.004)$ $0.115^*$ $(0.000)$ Whites (race) $0.174^*$ $(0.006)$ $0.110^*$ $(0.004)$ $0.318^*$ $(0.004)$ $0.269^*$ $(0.004)$ Male $0.499^*$ $(0.004)$ $0.418^*$ $(0.004)$ $0.333^*$ $(0.004)$ $0.269^*$ $(0.000)$ Adjusted R <sup>2</sup> $0.406$ $0.349$ $0.323$ $0.321$ $0.321$ $0.321$ $0.321$ $0.321$ F value $3,052.18^*$ $3,268.12^*$ $2,676.81^*$ $2,379.18^*$ $Men$ Constant $4.806^*$ $(0.011)$ $0.042^*$ $(0.001)$ $0.041^*$ $(0.000)$ Experience <sup>2</sup> /100 $-0.058^*$ $(0.001)$ $-0.066^*$ $(0.001)$ $-0.062^*$ $(0.002)$ Education $0.046^*$ $(0.001)$ $0.072^*$ $(0.007)$ $-0.055^*$ $(0.008)$ $-0.044^*$ $(0.007)$ Ment $0.053^*$ $(0.007)$ $-0.055^*$ $(0.008)$ $-0.04$	Experience <sup>2</sup> /100	-0.044*	(0.001)	-0.052*	(0.001)	-0.053*	(0.001)	-0.054*	(0.002)
Region Midwest $0.024^*$ $(0.005)$ $0.045^*$ $(0.005)$ $-0.080^*$ $(0.006)$ $-0.015^*$ $(0.006)$ South $-0.091^*$ $(0.005)$ $-0.056^*$ $(0.005)$ $-0.124^*$ $(0.006)$ $-0.066^*$ $(0.006)$ West $-0.028^*$ $(0.006)$ $0.028^*$ $(0.006)$ $-0.061^*$ $(0.006)$ $-0.024^*$ $(0.006)$ MSA $0.122^*$ $(0.004)$ $0.098^*$ $(0.004)$ $0.121^*$ $(0.004)$ $0.115^*$ $(0.006)$ Whites (race) $0.174^*$ $(0.006)$ $0.110^*$ $(0.004)$ $0.121^*$ $(0.004)$ $0.164^*$ $(0.006)$ Male $0.499^*$ $(0.004)$ $0.418^*$ $(0.004)$ $0.333^*$ $(0.004)$ $0.269^*$ $(0.006)$ Adjusted R <sup>2</sup> $0.406$ $0.349$ $0.323$ $0.321$ $0.321$ $0.321$ $0.321$ $0.321$ F value $3,052.18^*$ $3,268.12^*$ $2,676.81^*$ $2,379.18^*$ $Men$ Constant $4.806^*$ $(0.011)$ $0.042^*$ $(0.001)$ $0.041^*$ $(0.000)$ Experience $0.035^*$ $(0.001)$ $-0.066^*$ $(0.001)$ $-0.062^*$ $(0.002)$ Education $0.046^*$ $(0.001)$ $0.076^*$ $(0.001)$ $0.090^*$ $(0.000)$ RegionMidwest $0.070^*$ $(0.007)$ $-0.045^*$ $(0.007)$ $-0.055^*$ $(0.008)$ $-0.044^*$ $(0.007)$ West $0.052^*$ $(0.008)$ $-0.048^*$ $(0.007)$ $-0.068^*$ $(0.001)$ $-$	Education	0.054*	(0.001)	0.061*	(0.001)	0.086*	(0.001)	0.099*	(0.001)
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	Region						, í		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Midwest	0.024*	(0.005)	0.045*	(0.005)	-0.080*	(0.006)	-0.015*	(0.007)
West $-0.028^*$ $(0.006)$ $0.028^*$ $(0.006)$ $-0.061^*$ $(0.006)$ $-0.024^*$ $(0.006)$ MSA $0.122^*$ $(0.004)$ $0.098^*$ $(0.004)$ $0.121^*$ $(0.004)$ $0.115^*$ $(0.006)$ Whites (race) $0.174^*$ $(0.006)$ $0.110^*$ $(0.005)$ $0.118^*$ $(0.006)$ $0.104^*$ $(0.006)$ Male $0.499^*$ $(0.004)$ $0.418^*$ $(0.004)$ $0.303^*$ $(0.004)$ $0.269^*$ $(0.004)$ Adjusted R <sup>2</sup> $0.406$ $0.349$ $0.323$ $0.321$ $0.321$ $0.321$ F value $3.052.18^*$ $3.268.12^*$ $2.676.81^*$ $2.379.18^*$ MenConstant $4.806^*$ $(0.016)$ $4.642^*$ $(0.015)$ $4.278^*$ $(0.018)$ $4.083^*$ $(0.02)$ Experience $0.035^*$ $(0.001)$ $0.042^*$ $(0.001)$ $0.041^*$ $(0.000)$ Experience²/100 $-0.058^*$ $(0.001)$ $-0.066^*$ $(0.001)$ $-0.062^*$ $(0.002)$ $-0.062^*$ $(0.000)$ RegionMidwest $0.070^*$ $(0.007)$ $0.072^*$ $(0.007)$ $-0.055^*$ $(0.008)$ $-0.044^*$ $(0.007)$ West $0.070^*$ $(0.007)$ $-0.045^*$ $(0.007)$ $-0.062^*$ $(0.008)$ $-0.044^*$ $(0.007)$	South	-0.091*	(0.005)	-0.056*	(0.005)	-0.124*	(0.006)	-0.066*	(0.006)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	West	-0.028*	(0.006)	0.028*	(0.006)	-0.061*	(0.006)	-0.024*	(0.007)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	MSA	0.122*	(0.004)	0.098*	(0.004)	0.121*	(0.004)	0.115*	(0.005)
Male $0.499*$ $(0.004)$ $0.418*$ $(0.004)$ $0.303*$ $(0.004)$ $0.269*$ $(0.004)$ Adjusted R <sup>2</sup> $0.406$ $0.349$ $0.323$ $0.321$ $0.321$ $0.321$ F value $3,052.18*$ $3,268.12*$ $2,676.81*$ $2,379.18*$ Men       Constant $4.806*$ $(0.016)$ $4.642*$ $(0.015)$ $4.278*$ $(0.018)$ $4.083*$ $(0.02)$ Experience $0.035*$ $(0.001)$ $0.042*$ $(0.001)$ $0.041*$ $(0.000)$ $0.041*$ $(0.001)$ $0.041*$ $(0.001)$ $0.041*$ $(0.001)$ $0.041*$ $(0.001)$ $0.041*$ $(0.001)$ $0.042*$ $(0.001)$ $0.041*$ $(0.001)$ $0.041*$ $(0.001)$ $0.041*$ $(0.001)$ $0.041*$ $(0.001)$ $0.090*$ $(0.001)$ $0.090*$ $(0.001)$ $0.090*$ $(0.001)$ $0.090*$ $(0.001)$ $0.090*$ $(0.001)$ $0.090*$ $(0.000)$ $0.042*$ $(0.001)$ $0.090*$ $(0.000)$ $0.004*$ $(0.000)$ $0.001*$ $0.0000*$ $0.000*$ $0.000*$ <	Whites (race)	0.174*	(0.006)	0.110*	(0.005)	0.118*	(0.006)	0.104*	(0.006)
Adjusted $\mathbb{R}^2$ 0.406       0.349       0.323       0.321         F value       3,052.18*       3,268.12*       2,676.81*       2,379.18*         Men       Constant       4.806*       (0.016)       4.642*       (0.015)       4.278*       (0.018)       4.083*       (0.02         Experience       0.035*       (0.001)       0.042*       (0.001)       0.042*       (0.001)       0.041*       (0.00         Experience²/100       -0.058*       (0.001)       -0.066*       (0.001)       -0.062*       (0.002)       -0.062*       (0.001)       0.090*       (0.000)         Education       0.046*       (0.001)       0.053*       (0.001)       0.076*       (0.001)       0.090*       (0.000)         Region       Midwest       0.070*       (0.007)       -0.045*       (0.007)       -0.019*       (0.008)       -0.044*       (0.000)         South       -0.084*       (0.007)       -0.045*       (0.007)       -0.065*       (0.008)       -0.044*       (0.007)	Male	0.499*	(0.004)	0.418*	(0.004)	0.303*	(0.004)	0.269*	(0.004)
F value $3,052.18^*$ $3,268.12^*$ $2,676.81^*$ $2,379.18^*$ Men         Constant $4.806^*$ $(0.016)$ $4.642^*$ $(0.015)$ $4.278^*$ $(0.018)$ $4.083^*$ $(0.02)$ Experience $0.035^*$ $(0.001)$ $0.042^*$ $(0.001)$ $0.041^*$ $(0.001)$ Experience <sup>2</sup> /100 $-0.058^*$ $(0.001)$ $-0.066^*$ $(0.001)$ $-0.062^*$ $(0.002)$ $-0.062^*$ $(0.000)$ Education $0.046^*$ $(0.001)$ $0.053^*$ $(0.001)$ $0.076^*$ $(0.001)$ $0.090^*$ $(0.000)$ Region         Midwest $0.070^*$ $(0.007)$ $-0.045^*$ $(0.007)$ $-0.055^*$ $(0.008)$ $-0.044^*$ $(0.007)$ South $-0.084^*$ $(0.007)$ $-0.065^*$ $(0.008)$ $-0.044^*$ $(0.007)$ $-0.065^*$ $(0.008)$ $-0.044^*$ $(0.007)$	Adjusted R <sup>2</sup>	0.406	` ´	0.349		0.323	Ì.	0.321	Ì,
	F value	3,052.18*		3,268.12*		2,676.81*		2,379.18*	
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Mon								
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Constant	4 806*	(0.016)	4 642*	(0.015)	4 278*	(0.018)	4 083*	(0.021)
Experience <sup>2</sup> /100 $-0.058^*$ $(0.001)$ $-0.066^*$ $(0.001)$ $-0.062^*$ $(0.002)$ $-0.062^*$ $(0.001)$ Education $0.046^*$ $(0.001)$ $-0.053^*$ $(0.001)$ $-0.062^*$ $(0.001)$ $0.090^*$ $(0.001)$ Region       Midwest $0.070^*$ $(0.007)$ $0.072^*$ $(0.007)$ $-0.055^*$ $(0.008)$ $0.019^*$ $(0.008)$ South $-0.084^*$ $(0.007)$ $-0.045^*$ $(0.007)$ $-0.045^*$ $(0.008)$ $-0.044^*$ $(0.001)$	Experience	0.035*	(0.001)	0.042*	(0.001)	0.042*	(0.001)	0.041*	(0.001)
Education $0.046*$ $(0.001)$ $0.053*$ $(0.001)$ $0.022*$ $(0.002)$ $0.002*$ $(0.002)$ Region       Midwest $0.070*$ $(0.007)$ $0.072*$ $(0.007)$ $-0.055*$ $(0.008)$ $0.019*$ $(0.008)$ South $-0.084*$ $(0.007)$ $-0.045*$ $(0.007)$ $-0.045*$ $(0.007)$ $-0.044*$ $(0.007)$ West $0.052*$ $(0.008)$ $-0.044*$ $(0.007)$ $-0.055*$ $(0.008)$ $-0.044*$ $(0.007)$	Experience <sup>2</sup> /100	-0.058*	(0.001)	-0.066*	(0.001)	-0.062*	(0.001)	-0.062*	(0.001)
Region         (0.007) $0.072^*$ (0.007) $-0.055^*$ (0.008) $0.019^*$ (0.008)           Midwest $0.070^*$ $(0.007)$ $0.072^*$ $(0.007)$ $-0.055^*$ $(0.008)$ $0.019^*$ $(0.008)$ South $-0.084^*$ $(0.007)$ $-0.045^*$ $(0.007)$ $-0.019^*$ $(0.008)$ West $0.052^*$ $(0.008)$ $0.031^*$ $(0.007)$ $-0.065^*$ $(0.008)$ $-0.018$ $(0.016)^*$	Education	0.046*	(0.001)	0.053*	(0.001)	0.076*	(0.001)	0.090*	(0.001)
Midwest $0.070^*$ $(0.007)$ $0.072^*$ $(0.007)$ $-0.055^*$ $(0.008)$ $0.019^*$ $(0.000)$ South $-0.084^*$ $(0.007)$ $-0.045^*$ $(0.007)$ $-0.119^*$ $(0.008)$ $-0.044^*$ $(0.000)$ West $0.055^*$ $(0.008)$ $-0.018$ $(0.017)$ $-0.065^*$ $(0.008)$ $-0.018$ $(0.011)^*$	Region	01010	(0.001)	01000	(01001)	01070	(01001)	01090	(0.001)
South $-0.084^{*}$ (0.007) $-0.045^{*}$ (0.007) $-0.119^{*}$ (0.008) $-0.044^{*}$ (0.00 West $0.055^{*}$ (0.008) $0.031^{*}$ (0.007) $-0.055^{*}$ (0.008) $-0.018$ (0.01	Midwest	0.070*	(0.007)	0.072*	(0.007)	-0.055*	(0,008)	0.019*	(0, 009)
West $0.052*$ (0.008) $0.031*$ (0.007) $-0.065*$ (0.008) $-0.018$ (0.01	South	-0.084*	(0.007)	-0.045*	(0.007)	-0.119*	(0.008)	-0.044*	(0.009)
(1,0) $(1,0)$ $(1,0)$ $(1,0)$ $(1,0)$ $(1,0)$ $(1,0)$ $(1,0)$ $(1,0)$	West	0.052*	(0.008)	0.031*	(0.007)	-0.065*	(0.008)	-0.018	(0.010)
MSA 0.121* (0.005) 0.084* (0.005) 0.096* (0.006) 0.089* (0.00	MSA	0.121*	(0.005)	0.084*	(0.005)	0.096*	(0.006)	0.089*	(0.007)
Whites (race) 0.217* (0.008) 0.174* (0.007) 0.179* (0.008) 0.140* (0.00	Whites (race)	0.217*	(0.008)	0.174*	(0.007)	0.179*	(0.008)	0.140*	(0.009)
Adjusted $\mathbb{R}^2$ 0.257 0.253 0.288 0.286	Adjusted R <sup>2</sup>	0.257	()	0.253	()	0.288	()	0.286	()
F value 1.093.31* 1.347.75* 1.406.19* 1.224.93*	F value	1.093.31*		1.347.75*		1,406.19*		1.224.93*	
Wanan	Woman	ŕ				,		ŕ	
Constant $4.290^{*}$ (0.022) $4.275^{*}$ (0.018) $3.937^{*}$ (0.021) $3.729^{*}$ (0.02	Constant	4 290*	(0, 022)	4 275*	(0.018)	3 937*	(0, 021)	3 720*	(0, 023)
$\begin{array}{cccc} (0.021) & (0.021$	Experience	0.017*	(0.022)	0.023*	(0.010)	0.029*	(0.021)	0.029*	(0.023)
Experience <sup>2</sup> /100 $-0.025^{*}$ (0.001) $-0.037^{*}$ (0.002) $-0.048^{*}$ (0.002) $-0.045^{*}$ (0.002)	Experience <sup>2</sup> /100	_0.025*	(0.001)	-0.037*	(0.001)	-0.048*	(0.001)	-0.045*	(0.001)
Experience $(100 - 0.023 - (0.002) - 0.037 - (0.002) - 0.045 - (0$	Education	0.023	(0.002)	0.074*	(0.002)	0.090*	(0.002)	0.112*	(0.002)
Region	Region	0.075	(0.001)	0.074	(0.001)	0.077	(0.001)	0.112	(0.001)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Midwest	-0.062*	(0, 0.09)	0.008	(0, 007)	_0 112*	(0, 0.09)	-0.055*	(0.010)
South $-0.06^{\circ}$ (0.007) $-0.70^{\circ}$ (0.007) $-0.13^{\circ}$ (0.008) $-0.090^{\circ}$ (0.007)	South	-0.106*	(0.009)	-0.070*	(0.007)	_0.133*	(0.009)	_0.090*	(0.010)
$W_{\text{est}} = -0.166  (0.007)  0.073  (0.007)  0.155  (0.009)  -0.020  (0.010)  0.023  (0.010)  0.055  (0.009)  -0.020  (0.010)  0.020  (0.010)  0.055  (0.009)  -0.020  (0.010)  0.020  (0.010)  0.055  (0.009)  -0.020  (0.010)  0.020  (0.010)  0.055  (0.009)  -0.020  (0.010)  (0.010)  0.020  (0.010) $	West	-0.016	(0.007)	0.073*	(0.007)	-0.055*	(0.000)	-0.029*	(0.00)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	MSA	0.121*	(0.010)	0.119*	(0.000)	0.151*	(0.007)	0.146*	(0.010)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	Whites (race)	0.111*	(0.007)	0.035*	(0.000)	0.051*	(0.000)	0.069*	(0.007)
$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	Adjusted $\mathbb{R}^2$	0 229	(0.010)	0.224	(0.000)	0.286	(0.000)	0.312	(0.000)
F value 554 51* 824 22* 1 139 83* 1 182 89*	F value	554 51*		824 22*		1.139.83*		1 182 89*	

TABLE 3 **REGRESSION RESULTS OF EARNINGS EQUATIONS** 

*Notes*: Standard errors are reported in parentheses. \*Indicates statistically significant at 5%.

	1	969	19	979	19	89	1	999
All								
VLOG	0.260	(100.0)	0.259	(100.0)	0.301	(100.0)	0.331	(100.0)
Experience and Experience <sup>2</sup> /100	0.013	(4.9)	0.020	(7.7)	0.021	(7.0)	0.020	(6.2)
Education	0.021	(8.1)	0.021	(8.3)	0.045	(15.0)	0.063	(19.0)
Region	0.004	(1.7)	0.002	(1.0)	0.003	(1.0)	0.001	(0.4)
MŠA	0.004	(1.5)	0.003	(1.0)	0.004	(1.2)	0.003	(1.0)
Whites (race)	0.005	(1.8)	0.002	(0.8)	0.002	(0.8)	0.002	(0.6)
Male	0.059	(22.6)	0.042	(16.3)	0.022	(7.2)	0.016	(4.9)
Residuals	0.154	(59.4)	0.168	(65.0)	0.204	(67.7)	0.224	(67.9)
Men								
VLOG	0.199	(100.0)	0.231	(100.0)	0.287	(100.0)	0.323	(100.0)
Experience and Experience <sup>2</sup> /100	0.016	(7.9)	0.031	(13.5)	0.034	(11.7)	0.030	(9.3)
Education	0.019	(9.8)	0.019	(8.1)	0.040	(13.8)	0.056	(17.5)
Region	0.006	(2.9)	0.003	(1.2)	0.003	(1.0)	0.001	(0.4)
MŠA	0.004	(2.1)	0.002	(0.8)	0.002	(0.8)	0.002	(0.6)
Whites (race)	0.006	(3.1)	0.004	(1.7)	0.004	(1.5)	0.003	(0.9)
Residuals	0.148	(74.2)	0.172	(74.7)	0.204	(71.2)	0.231	(71.4)
Women								
VLOG	0.204	(100.0)	0.197	(100.0)	0.272	(100.0)	0.307	(100.0)
Experience and Experience <sup>2</sup> /100	0.005	(2.3)	0.007	(3.6)	0.010	(3.8)	0.019	(3.9)
Education	0.034	(16.4)	0.031	(15.7)	0.057	(21.0)	0.076	(24.7)
Region	0.003	(1.4)	0.002	(1.1)	0.004	(1.3)	0.002	(0.6)
MŠA	0.004	(1.9)	0.004	(1.9)	0.006	(2.3)	0.005	(1.8)
Whites (race)	0.002	(0.9)	0.000	(0.1)	0.000	(0.2)	0.001	(0.3)
Residuals	0.157	(77.0)	0.153	(77.6)	0.194	(71.4)	0.211	(68.7)

TABLE 4 Decomposition of Inequality

Note: Shares of VLOG (variance of log-earnings) in terms of percentage are reported in parentheses.

Using the estimates of earning equations, the Fields method is applied to find the contributions of individual factors. The results are reported in Table 4.<sup>19</sup> Tables 5, 6 and 7 show the results of decomposing the differences in earnings inequality between the two years using the unified method summarized in equation (8') for both genders, men and women, respectively.

As Table 5 shows, over the three decades, 1969–99, earnings inequality measured by the variance of log-earnings has increased by about 27 percent from 0.260 to 0.331. In total, the characteristics, coefficients and residuals effects are, respectively, -4.2 percent, 4.5 percent and 99.6 percent. This means that virtually all increase in earnings inequality over the three decades can be explained by the residuals effect, and the decrease and increase of inequality due to characteristics and coefficients effects, respectively, are cancelled out. When we look at the increase in earnings inequality between 1979 and 1999 (since there was virtually no change during 1970s), the characteristics, coefficients and residuals effects are, respectively,

<sup>&</sup>lt;sup>19</sup>The effects of categorical variables (e.g. regions) or very closely related variables (e.g. experience and experience squares in hundreds) are computed as aggregating the effects of each variable in Tables 4 and 5–7.

Diff in VLOG	1999 v 0.070	s. 1969 (100.0)	1999 vs 0.072 (	. 1979 100.0)	1979 v -0.001	s. 1969 (100.0)	1989 vs. 0.042 (1	. 1979 100.0)	1999 - 0.029	's. 1989 (100.0)
Decomposition	Char	Coeff	Char	Coeff	Char	Coeff	Char	Coeff	Char	Coeff
Aggregate	-0.003	0.003	-0.001	0.017	-0.003	-0.013	-0.002	0.00	0.002	0.007
	(-4.2)	(4.5)	(-2.0)	(23.7)	(194.6)	(960.8)	(-5.2)	(20.9)	(5.8)	(24.5)
Experience and	-0.001	0.00	-0.002	0.002	-0.000	0.007	-0.002	0.004	0.002	-0.003
Exprience <sup>2</sup> /100	(-2.1)	(12.8)	(-2.5)	(3.2)	(26.9)	(-556.4)	(-5.6)	(8.9)	(5.6)	(-8.6)
Education	-0.004	0.045	0.000	0.041	-0.003	0.003	-0.000	0.024	0.001	0.017
	(-5.0)	(64.5)	(0.0)	(57.3)	(219.6)	(-250.0)	(-0.2)	(56.1)	(2.8)	(57.8)
Region	-0.000	-0.003	0.000	-0.001	-0.000	-0.001	0.000	0.001	-0.000	-0.002
1	(-0.4)	(-4.0)	(0.1)	(-1.7)	(35.8)	(110.8)	(0.2)	(1.3)	(-0.6)	(-5.4)
MSA	-0.001	-0.000	-0.000	0.001	-0.000	-0.001	-0.000	0.001	-0.000	-0.000
	(-0.9)	(-0.1)	(-0.4)	(1.5)	(21.2)	(94.2)	(-0.3)	(3.2)	(-0.7)	(-0.8)
Whites (race)	0.001	-0.004	0.000	-0.000	-0.000	-0.002	0.000	0.000	0.000	-0.001
	(1.2)	(-5.0)	(0.0)	(-0.6)	(22.3)	(182.7)	(0.4)	(0.4)	(0.7)	(-1.8)
Male	0.002	-0.045	-0.000	-0.026	0.002	-0.018	0.000	-0.021	-0.001	-0.005
	(3.1)	(-63.6)	(-0.5)	(-35.9)	(-131.2)	(1379.5)	(0.3)	(-49.0)	(-2.0)	(-16.8)
Residuals	0	020	0.0	56	0.0	14	0.0	135	0	021
	6)	9.6)	(78	3)	(-1, 0)	55.4)	(84	1.3)	U	(7.6
<i>Notes</i> : Share of Char and Coeff	differences in are, respectiv	a VLOG in tern velv. characteris	is of percentage tics and coeffici	are reported i ents effects.	n parentheses.					
	-									

TABLE 5 Decomposition of Differences in Informative (A11)

						~				
Diff in VLOG	1999 vs 0.124 (	s. 1969 100.0)	1999 vs 0.092 (1	. 1979 (00.0)	1979 v 0.032	s. 1969 (100.0)	1989 vs 0.056 (	s. 1979 100.0)	1999 - 0.036	vs. 1989 (100.0)
Decomposition	Char	Coeff	Char	Coeff	Char	Coeff	Char	Coeff	Char	Coeff
Aggregate	-0.003	0.044	-0.000	0.034	-0.002	0.00	-0.003	0.027	0.003	0.007
Experience and	0.002	(35.1) 0.012	(c.u–) –0.001	(5.7.3) 0.000	(c.c–) 0.003	(27.9) 0.013	(c.4-) -0.003	(4/.8) 0.005	(c.8) 0.003	(18.2) -0.006
Exprience <sup>2</sup> /100	(1.9)	(9.6)	(-1.5)	(0.1)	(0.0)	(39.4)	(-5.4)	(9.6)	(7.8)	(-17.7)
Education	-0.004	0.041	0.001	0.037	-0.003	0.003	0.001	0.020	0.000	0.017
	(-3.3)	(33.2)	(0.7)	(40.2)	(-10.7)	(8.4)	(0.0)	(36.5)	(0.4)	(45.9)
Region	-0.000	-0.004	0.000	-0.002	-0.000	-0.003	0.000	0.000	0.000	-0.002
)	(-0.2)	(-3.5)	(0.1)	(-1.8)	(-1.4)	(-8.0)	(0.0)	(0.0)	(0.2)	(-4.6)
MSA	-0.001	-0.001	-0.000	0.000	-0.000	-0.002	-0.000	0.001	-0.000	-0.000
	(-0.7)	(-1.1)	(-0.4)	(0.4)	(-0.8)	(-6.1)	(-0.5)	(1.1)	(-0.3)	(-0.6)
Whites (race)	0.000	-0.004	0.000	-0.002	-0.001	-0.002	0.000	0.000	0.000	-0.002
	(0.3)	(-3.1)	(0.5)	(-1.7)	(-1.7)	(-5.8)	(0.4)	(0.5)	(0.4)	(-4.7)
Residuals	0.0	83	0.0	58	0.0	025	0.0	132	0	027
	(66	(6)	(63	.2)	(7)	7.6)	(56	(8)	()	3.2)
Notes: Share of	differences in	1 VLOG in terr	ns of percentag	e are reported	in parentheses.					

DECOMPOSITION OF DIFFERENCES IN INEQUALITY (MEN) TABLE 6

140

Char and Coeff are, respectively, characteristics and coefficients effects.

Diff in VLOG	1999 vs 0.103 (	s. 1969 100.0)	sv 9991 ) 111.0	. 1979 100.0)	1979 v -0.008	s. 1969 (100.0)	1989 vs 0.075 (	s. 1979 100.0)	1999 v 0.035	's. 1989 (100.0)
Decomposition	Char	Coeff	Char	Coeff	Char	Coeff	Char	Coeff	Char	Coeff
Aggregate	-0.001	0.050	0.003	0.049	-0.004	0.001	0.001	0.033	0.004	0.014
	(-0.9)	(48.6)	(2.7)	(44.3)	(56.6)	(-18.7)	(0.7)	(44.2)	(11.5)	(40.1)
Experience and	0.000	0.007	0.000	0.005	-0.000	0.003	-0.001	0.004	0.002	0.000
Exprience <sup>2</sup> /100	(0.2)	(6.7)	(0.2)	(4.1)	(5.1)	(-36.5)	(-0.8)	(5.0)	(4.5)	(0.2)
Education	-0.001	0.043	0.003	0.042	-0.004	0.001	0.001	0.025	0.003	0.016
	(-1.0)	(42.1)	(2.6)	(38.2)	(46.7)	(-10.5)	(1.3)	(33.7)	(8.4)	(44.5)
Region	-0.000	-0.001	0.000	-0.000	-0.000	-0.001	-0.000	0.002	-0.000	-0.002
)	(-0.2)	(-7.2)	(0.0)	(-0.2)	(2.8)	(7.9)	(-0.0)	(2.1)	(-0.3)	(-4.6)
MSA	-0.000	0.002	-0.000	0.002	0.000	-0.001	0.000	0.002	-0.000	-0.000
	(-0.2)	(1.8)	(-0.1)	(1.6)	(-0.0)	(1.4)	(0.2)	(3.1)	(-1.2)	(-1.1)
Whites (race)	0.000	-0.001	0.000	0.001	-0.000	-0.001	0.000	0.000	0.000	0.000
	(0.2)	(-1.2)	(0.1)	(0.6)	(3.0)	(19.1)	(0.1)	(0.3)	(0.1)	(1.1)
Residuals	0.0	)54	0	159	0-	005	0.0	42	0.0	117
	(52	3)	(5)	3.0)	(9)	2.1)	(55	.1)	(4)	3.4)
Notes: Share o	f differences in	n VLOG in teri	ns of percentag	e are reported i	in parentheses.					
Char and Coet	f are, respectiv	ely, characteris	tics and coeffici	ents effects.						

TABLE 7 DECOMPOSITION OF DIFFERENCES IN INEQUALITY (WOMEN)

141

-2.0 percent, 23.7 percent and 78.3 percent.<sup>20</sup> Both decomposition results show the importance of the residuals effect.

As Table 6 shows, between 1969 and 1999, about 67 percent of the increase in earnings inequality of men can be explained by the residuals effect while 35 percent of the increase can be explained by the coefficients effect; the characteristics effect only plays a very small role. The importance of the residuals effect, still the largest, decreases in explaining the increase in earnings inequality among women as Table 7 shows. The coefficients effect plays a more important role in decomposition analysis for women than for men or everyone together.

The factors (variables) used in the decomposition may be grouped as experience, education, region and Metropolitan Statistical Area (MSA), gender, race, and residuals. As Tables 5–7 show, the residuals have played the major role in increasing earnings inequality as we have discussed above. Judging from the gross effects of factors (= sum of coefficients and characteristics effects), factors related to education and, to a much less degree, experience, contribute to widening earnings inequality while gender contributes to leveling earnings inequality.

The findings from the decomposition analysis using the unified methodology developed in this paper may be summarized as follows. First, the education variable, especially its coefficient effect, has played a major role in increasing inequality, particularly during the 1980s and 1990s, while during the 1970s, the coefficients effect of education is small. However, the change in educational attainment does not contribute much to changes in earnings inequality.

Second, overall experience also contributes to increasing inequality. Experience was the major disequalizing factor during the 1970s. Surprisingly, the importance of contribution of the experience factor to increasing earnings inequality almost disappears during the 1980s and 1990s. Indeed, the coefficients effect of factors related to experience contributes to equalizing during the 1990s. The changes in returns to education and experience have been considered as major evidence for the skill-biased technological change (JMP, 1993). Though it is true that education is the most important factor in disequalizing the distribution of earnings, experience is not one of the major factors in contributing to an increase in earnings inequality.

Third, gender plays a significant role in reducing earning inequality. Gender is the most important equalizing factor via its coefficients effect throughout the three decades as shown in Table 5. Race is also a factor in equalizing the earnings distribution, though the impact is very small. It is possible that anti-discrimination policy has contributed to leveling earnings inequality via equalizing over gender.

#### 4. CONCLUSION

The goal of this paper was to study changes in earnings inequality by comprehensively evaluating contributions of various factors on changes in earnings

<sup>&</sup>lt;sup>20</sup>In other words, during the 1980s and 1990s the changes in individual characteristics, such as education and experience, contributed to lowering earnings inequality by 2.0 percent; the changes in wage structure (changes in coefficients) between 1979 and 1999 contributed to increasing the earnings inequality by 23.7 percent; the remaining 78.3 percent of changes in equality is the residuals effect.

inequality using the earnings equation. To do so, this paper proposes a simple and new decomposition method by synthesizing the JMP (1993) and Fields (2003) decomposition methods. JMP (1993) provides a baseline for the synthesis; they show that the differences in inequality may be explained by the difference in coefficients, characteristics and residuals. However, using the JMP decomposition one can only decompose at an aggregate level. This does not provide much insight into how to analyze the contribution of individual variables. By applying Fields' method, the contributions of individual factors are decomposed into a part explained in terms of price and a part explained by quantity. 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 of the decomposition equation (coefficients and characteristics effects). This may argue that the unified decomposition method is to earnings inequality what Oaxaca decomposition is to wage differentials. This synthesized decomposition method is potentially a basic tool for studying earnings inequality.

The unified method is applied to studying changes in the earnings inequality in America (1969–99) using the March CPS. During this period, education contributes to widening earnings inequality while gender contributes to leveling earnings inequality. Usually the coefficients effects of individual factors dominate their characteristics effects. The implications of the findings on earnings inequality using the unified decomposition methodology regarding the practice of the literature seem to be mixed. On the one hand, focusing on education, experience and residuals seems to be justified since the residuals effect is the largest and education is the most important disequalizing factor among observed factors. However, experience turns out to be almost a non-factor during the skyrocketing increase in earnings inequality since 1980.

#### References

- Bound, John and George Johnson, "Changes in the Structure of Wages in the 1980s: An Evaluation of Alternative Explanations," *American Economic Review*, 82(3), 371–92, June 1992.
- Card, David and John E. DiNardo, "Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles," *Journal of Labor Economics*, 20(4), 733–83, October 2002.
- Fields, Gary S., "Accounting for Income Inequality and its Change: A New Method with Application to U.S. Earnings Inequality," in Solomon W. Polacheck (ed.), *Research in Labor Economics, Vol* 22: Worker Well-Being and Public Policy, JAI, Oxford, 1–38, 2003.
- Fields, Gary S. and Jennifer C. O'Hara Mitchell, "Changing Income Inequality in Taiwan: A Decomposition Analysis," in Gary R. Saxonhouse and T. N. Srinivasan (eds), *Development, Duality, and the International Economic Regime: Essays in Honor of Gustav Ranis*, University of Michigan Press, Ann Arbor, 130–51, 1999.
- Fields, Gary S. and Gyeongjoon Yoo, "Falling Labor Income Inequality in Korea's Economic Growth: Patterns and Underlying Causes," *Review of Income and Wealth*, 46(2), 139–59, June 2000.
- Gindling, T. H. and Juan Diego Trejos, "Accounting for Changing Earnings Inequality in Costa Rica, 1980–1999," *Journal of Development Studies*, 41(5), 898–926, July 2005.
- Juhn, Chinhui, Kevin M. Murphy, and Brooks Pierce, "Accounting for the Slowdown in Black-White Wage Convergence," in Marvin H. Kosters (ed.), Workers and Their Wages: Changing Patterns in the United States, AEI Press, Washington, D.C., 107–43, 1991.
  - —, "Wage Inequality and the Rise in Returns to Skill," *Journal of Political Economy*, 101(3), 410–42, June 1993.
- Karoly, Lynn A., "Changes in the Distribution of Individual Earnings in the United States: 1967–1986," *Review of Economics and Statistics*, 74(1), 107–15, February 1992.

- Katz, Lawrence F. and David H. Autor, "Changes in the Wage Structure and Earnings Inequality," in Orley Ashenfelter and David Card (eds), *Handbook of Labor Economics*, Volume 3A, Elsevier Science B.V., Amsterdam, 1463–555, 1999.
- Shorrocks, Anthony F., "Inequality Decomposition by Factor Components," *Econometrica*, 50(1), 193–211, January 1982.
- Suen, Wing, "Decomposing Wage Residuals: Unmeasured Skill or Statistical Artifact?," Journal of Labor Economics, 15(3), 555–66, July 1997.