Adjusted Gini Coefficients with Quantile Regression

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M.S. Research Paper
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Under the Supervision of Dr. John A. Bishop
July, 2003

Abstract: In the paper, we apply the Gini adjustment procedure developed Bishop, Formby, and Smith (1997) to investigate the effects of demographic factors on earnings inequality in Taiwan. We advance their method using quantile regression to control for demographic factors between 1978 and 1999 base on the subsample of workers conducted by the DGBAS. It is found that the marginal impact effects of female on earnings inequality are generally larger than the effects of years of schooling and experience. Hence, our findings indicate that gender gap has the most significant impact on earnings inequality in Taiwan. Finally, the policy implications from our study are that controlling for gender gaps could reduce earnings inequality. In particular, adoption of an affirmative action policy for women may successfully reduce the overall level of earnings inequality in Taiwan.

I. Introduction

Taiwan's "economic miracle" of the 1970's was largely due to fundamental economic reform in the 1950's and stunning economic growth in the 1960's. Throughout its economic progress, Taiwan maintained a relatively equitable distribution of income and was accordingly identified as an example of successful growth with equity. However, earnings inequality has increased since the mid-1980s.

It is widely accepted that the "gender gap" has a significant impact on earnings inequality and considered pervasive across occupations. Occupational segregation by gender is detrimental to women because it usually has a negative effect on female-male pay differentials. The Directorate-General of Budget, Accounting and Statistics (DGBAS), Executive Yuan reports that the average monthly wage and salary of a female is 73.9% of a male's in 2000. This ratio was 65.2% one decade ago.

Concerning wage inequality in general, Mincer (1974) and Becker (1964) argued that human capital is an important factor for explaining the wage gap. To the extent that males invest more human capital than females, the gender gap results. Following up the human capital model, the returns to education and labor market experience changed enormously from the 1960's to mid 1970's, and played a major role in widening the wage inequality (Moshe Buchinsky, 1994). The changes in wage structure have also been attributed to an increase in the number of "more-educated" workers (Blackburn, Bloom, and Freeman (1991), Card and Krueger (1992). Furthermore, Katz and Murphy (1992) concluded that labor supply fluctuations combined with stable demand growth explain much, but not all, of the change in education and wage differentials.

In the case of Taiwan, Parich and Willis (1993) provide evidence supporting the above point and speculate that it might result from culture and family structure. On the other hand, Averitt (1966) divided the economy into core industries and peripheral industries where the former pays more than the latter. Moreover, Coverdill (1988) gave possible explanations of why females tend to work in the peripheral industries. Bergmann (1974) proposed the crowding hypothesis. Her arguments lead to occupation segregation. Sorensen (1990) confirmed the crowding hypothesis. Becker (1985) and Polacheck, et.al. (1976) argued that child care and housework will lead married women to seek less demanding jobs, resulting in earnings and occupational difference between men and women. Baxter (1991) confirmed that housework does have a negative impact on female’s wage and salary.

In this paper, we apply the Gini adjustment procedure developed by Bishop, Formby, and Smith (1997) to investigate the effects of demographic factors on earnings inequality in Taiwan. Bishop, Formby, and Smith noted that the favored approach for measuring the impact of a variable on levels of inequality is to use a “decomposable” inequality index. One potentially critical constraint of using a decomposing method is that it can only capture a single characteristic like gender; thereby ignoring possible covariance among other variables such as gender, schooling, and experience.

We advance the decomposing method using quantile regression (Koenker and Bassett, 1978) to control for demographic factors between 1978 and 1999. As a matter of fact, a major difference between OLS and quantile regression is that the OLS characterizes a distribution only at the mean of the distribution whereas the quantile regression focuses on the median or other quantiles. Further, quantile regression estimates separate means for grouped data. Therefore, we are able to analyze the marginal effects of earnings changes to each quantile group. This represents the precise estimate of the outlying points potentially unobtainable from OLS estimation.

Finally, we compare the demographic effects on earnings inequality individually across different time periods. By comparing the marginal effects of demographic factors on Gini coefficient, we find that gender has the largest effect on the distribution of earnings across time. It is believed that our results can fully explain that the gender differential constitutes a significant impact on earnings inequality in Taiwan.

The reminder of this paper is organized as follows: Section II presents the data and its sources, as well as its limitations. Section III discusses the measurement of variables, outlines the quantile regression model and develops the adjusted-Gini to explain the influence of demographic factors on earnings inequality. Section IV provides descriptive statistics along with OLS results. Section V reports the empirical findings on quantile regression and adjusted-Gini. Section VI concludes.

II. Data

Our analysis is based upon the subsample of workers in the "Household Income and Expenditure Survey", a series of country-wide surveys conducted by the Directorate-General of Budget, Accounting and Statistics, Executive Yuan, R.O.C. (DGBAS). Interviews and account keeping are used to collect data in the survey. Households to be interviewed are drawn from the population by the stratified random sampling method.

The DGBAS annually provides detailed income information for individuals in a large number of representative households. Microdata are available since 1976. The sample rate of households was 0.3% for 1975-1977 and 0.4% for 1978-1983. However, we focus our study on 1978 and later for two reasons: First, the DGBAS does not provide the weighting information for 1976 and 1977; Second, Taiwan's income inequality began to soar after 1978.

Occupations in the dataset are classified according to the International Standard Classification Occupation of the United Nations (UN). The UN revised occupation determinations in 1958, 1968, and 1988. The DGBAS revised its occupation classification in 1992.

There are a number of limitations to the data associated with DGBAS surveys. For example, a major difficulty is how to ascribe and achieve characteristics in the determination of an individual's earnings? Additionally, since women's labor market behavior is largely constrained by their familial responsibilities and activities, their processes of economic achievements are more intricate than men's. A comparison of gender differences in earnings determination is of interest in its own right.

The present analysis focuses on individual annual earnings and the differentials on years of 1978, 1985, 1992, and 1999, with sample sizes of 15,798, 20,022, 21,246, and 17,394 respectively.

III. Methodologies

Human capital theory provides the conceptual economic apparatus for this paper (Becker, 1957, 1964, 1965). The resources of an individual are regarded as a stock of capital that determines the individual’s productivity and hence his or her earnings. By adopting the human capital model (Mincer, 1974), we can analyze the differential earnings that result the differences in investment of education.

We extend the standard human capital model and specify the following earnings equation to analyze the earnings differentials:

$$Log(Earnings) = \beta_0 + \beta_1 Years\ of\ Schooling + \beta_2 Experience + \beta_3 Experience\ Squared$$

$$\beta_4 Occupation + \beta_5 Occupation/Female + \mu$$

where *Log(Earnings)* is the natural logarithm of the earnings; *Years Of Schooling* is the rate of return to schooling; *Experience* is the work experience throughout an individual’s life cycle, measured as “age minus years of schooling minus six”; *Experience Squared* shows the effect of experience on earnings should be curvilinear; *Occupation* is the functional differentiation of positions from a technical division of labor; *Occupation/Female* is the occupational premium that depends on gender.

It is expected that gender gap will have an impact on the earnings inequality and be pervasive across occupations. Individuals with different levels of education will work in different occupation. However, the extension has been accompanied by occupational variables and interaction term of occupation with female. Therefore, occupational segregation by gender is detrimental to women. It usually has a negative effect on female-male pay differentials. To address this issue, we also follow the "Occupational Segregation Model" by introducing the gender effects as a set of occupational interaction terms-----*Occupation/Female.*

(i) Quantile Regression

OLS is the most common approach to estimating the earnings distribution. Because OLS characterizes the mean of a distribution and does not explain the tails very well, we adopt the Quantile Regression to more accurately represent the outlying areas of a distribution.

Given a dependent variable, y_t, is distributed as

$$\mathrm{Prob}(y_t < \tau \mid x_t) = F_y(\tau \mid x), \qquad y_t : t = 1, 2, \cdots, T$$

where x is an independent variable and τ is a critical value. Let $\{ y_t : t = 1, 2, \cdots, T \}$ be a random sample on a random variable *Y* having distribution function *F*, and $x_t^{'}\beta_\theta$ be the θth quantile i.e.,

$$\theta = \int_{-\infty}^{x_t^{'}\beta_\theta} f_y(s \mid x_t)ds \qquad 0 < \theta < 1$$

Instead of minimizing the sum of squared residuals as is usual with the classical linear regression, Koenker and Bassett (1978) minimize the following objective function:

$$\min_{\mathrm{b}} \left\{ \sum_{t \in \{t: y_t > b\}} \theta |y_t - b| + \sum_{t \in \{t_t: y_t < b\}} (1-\theta) |y_t - b| \right\}$$

In sum, *Quantile Regression* seeks to extend these ideas (quintiles, deciles, percentiles, and occasionally fractiles etc.) to the estimation of *conditional quantile functions*---models in which quantiles of the conditional distribution of the response variable are expressed as functions of observed covariates (Koenker and Hallock, 2001). The regression divides the population into five segments, or quantiles at .10, .25, .50, .75, and .90 of the reference population in each segment, and estimates separate means for each quantile. Therefore, we are able to analyze the marginal effects of earnings changes in each quantile group. This represents the precise estimate of the outlying points potentially unobtainable from OLS estimation.

(ii) Measuring the Effect of Gender Gap on Earnings Inequality

To illustrate the influence of gender gap on earnings inequality we specify the “Gini Adjustment Method”, which uses quantile regression to isolate the effects of demographic factors on the distribution of earnings. In some respects our approach harks back to Bishop, Formby, and Smith’s paper, which uses quantile regression instead of OLS to address the demographic effects on income distribution.

We advance their method by constructing a vector for (log) adjusted income given by,

$$InY^* = InY - \beta * Female$$

where β is the regression coefficient of "female effects" on the income distribution; the standard Gini coefficient is based on unadjusted income (*Y*) and adjusted Gini coefficient is based on the female-adjusted income vector (Y^*).

We then construct the absolute measure of marginal impact effects on inequality-----the difference between the adjusted and unadjusted Gini coefficients to represent an estimate of the influence of demographic factors on income inequality. In addition, the percent of the unadjusted Gini is reported in our paper to provide a normalized measure.

$$\textit{Marginal Impact Effects on Inequality} = Gy^* - Gy$$

We repeat the estimation procedure for other factors by comparing the standard Gini coefficient in a particular year to estimates of the years of schooling and experience Gini coefficients. The Gini coefficients are presented from both quantile regression and OLS estimation.

IV. Descriptive Statistics

Table I presents the mean and standard deviation values for annual years of schooling, worker's age, female participation rate, and the percentage of females in an occupation group, along with the number and percentage of cases, for 1978, 1985, 1992, and 1999. Because of the different classification over various periods, we separate the data into two subgroups: panel (a) includes the data for 1978 and 1985, and panel (b) includes data for 1992 and 1999.

Percentages of workers that are female in specified occupations are distributed across the eight broad categories in each year. In general, the female participation rate is fairly low, 27.33 percent in 1978 and 33.20 percent in 1985. The distributions for the 1978 and 1985 panel (a) show that women tended to be concentrated in supervisor and production occupations. In 1978, 62.48 percent of all women workers were in these two categories, compared to 64.17 percent in 1985. Production occupations are the strong-holds of skilled blue-collar workers and include automobile mechanics and repairers. Before 1992, women were less likely to be administrators and associate managers or transport and equipment operators. Less than 2 percent of female workers are in these two categories. The occupational concentration for female workers corresponds to fewer years of schooling, which on average is about 11 years for both time periods considered.

Due to increased investment in education, the average years of schooling increased to 11.87 years in 1992 and 12.63 years in 1999; represented in panel (b). Female workers tend to shift from labor intensive occupations into more capital intensive occupations, such as clerical and sales jobs. Clerical jobs include secretary, file clerk etc. The sales category is classified as service workers, shop and market sales workers, including a variety of private household workers, waitress, and so on. These two categories represent 46.24 percent of all the female occupations in 1999, and 42.16 percent in 1992. Still, women were less likely to be managers in both years. The average years schooling for 1992 is 11.87 years and 12.63 in 1999 (which are higher than the previous years). Female participation rates increase to 36.45 percent and 37.77 percent, respectively.

Table II presents the OLS results. We may observe that experience and years of schooling gradually increase across time. In 1999, an additional year of experience will increase a worker's average earnings by 4%, as well as an additional year of schooling increases a worker's average earnings by 5%. This finding provides weak evidence for the application of human capital theory in Taiwan. Our estimation indicates that there is a penalty associated with being a female: female workers earn

35% less across all occupations than their male counterparts in 1999. Compared to the higher inequality levels seen in earlier years (1978, 1985, and 1992), this suggests that the gender gap issue is diminishing.

An individual's earnings are determined by their occupations. Although there are different occupation determinations across time periods, professional workers, managers, and administrators earn much more than other occupations (shown in Table II). According to the findings in Table I, female workers were substantially less concentrated in the high-paying occupations. To some extent, these differences in distribution by occupation simply reflect gender differences in occupations. Occupational segregation can be explained for gender difference associated with earnings difference.

V. Empirical Findings

(i) Quantile Regression

The quantile regression results for 1978, 1985, 1992, and 1999 are presented in Table III. In addition to the explanatory variables found in Table II, we specify an occupation/ female interaction term in the quantile regression model to investigate the existence of a gender gap phenomenon in Taiwan. Since the occupation dummies already exist in the regression model, negative occupation/female coefficients can be interpreted as the percentage that females earn less than males in a particular occupation, i.e. occupational segregation and gender gap. This evidence supports our hypothesis that gender gap phenomenon is pervasive across occupations and different time periods.

Examining the occupation/female coefficients across quantiles, a pattern of low quantile high gender gap can be found except for professional workers. For those female professional workers, gender gaps follow a U-shape distribution across time. As the results in Table III-1999 show, the lowest and the highest 10 percent quantiles of female professional workers have the greater penalties while the middle quantile group has the least penalty. The same pattern occurs throughout different time periods. In contrast, OLS estimates indicate female professionals overall earn 21.97% less than their male counterparts. Relatively speaking, quantile regression provides a more precise estimation of the earnings distribution of the occupation group.

In general the gender gaps are shrinking uniformly for the period 1992-1999 as we trace the change of occupation/female coefficients across time and quantile for each occupation. In contrast to the 78.97% earnings penalty for the bottom 10% quantile of female laborers in 1978, the penalty for the same group in 1999 declines to 20.47%. However, for the period 1978-1985, administrator, sales workers, and production workers are enjoying the shrinking gender gap across quantiles while supervisor and service workers are suffering an enlarging gender gap across quantiles.

For operators and laborers, the patterns are mixed in that gender gaps of low quantile operators are increasing while gaps in the high quantile are decreasing. The pattern for laborers is the opposite of operators.

Again, the empirical results indicate that the OLS estimates are not sufficient to provide a comprehensive description of the gender gap issue in Taiwan. The range estimate is preferred because it captures the variation of the earnings distribution rather than just the point estimate. For example, OLS estimates that the average marginal effect on female manager is -15%. Quantile regression yields estimates that differ substantially from the OLS estimates and provide a broader understanding of the issue: The marginal effect on female manager varies from -4.17% to -17.2% across quantiles; the magnitude of the effect is broadly distributed.

(ii) Adjusted Gini Coefficient

Table IV reports OLS results for the standard (unadjusted) Gini coefficients (column 1) and an individual's years of schooling, work experience, and female indicator Gini coefficients (column 2-4). The absolute differences of the marginal impact effects are shown in columns 5-7. The Gini coefficients of each demographic factor are independent across years; that is, each estimated Gini coefficient corresponds with a particular year. In other words, we individually estimate adjusted Gini coefficients in a certain year, and assume that there is no simultaneous effect on coefficients across different time periods. The Gini coefficients reported by quantile regression shown in Table V. follow the same ideas the OLS specification.

In Tables IV and V, the female-adjusted Gini coefficients are shown in column 2, and column 5 provides measures of the marginal effects of female on income inequality across time. The standard Gini coefficients indicate the female effects are the smallest in 1992 and the greatest in 1985. This is consistent with both OLS and quantile regression. With quantile regression the difference between the standard Gini and the female-adjusted Gini range from a low of 0.0263 to 0.413. With OLS they range from a low of 0.0282 to 0.0388. Generally, adjusting for female effects reduces inequality from 16.3% to 10.8% in OLS, and from 16.3% to 9.9% in quantile regression.

Columns 3 and 4 show the adjusted Gini coefficients obtained from the vector of schooling-adjusted and experience-adjusted incomes that are interpreted in the same manner as the female-adjusted Ginis in column 2. Interestingly, the experience effects are only larger than schooling effects in the earlier year. After 1978, investing in education has a greater impact on reducing earnings inequality than work experience. For instance, the marginal effect of schooling in 1999 is 7.3%, comparatively greater than the marginal impact effect of experience at 5.6% (using quantile regression).

Comparison of adjusted Gini coefficients in Table IV and V, the results reveal that the marginal effects of female on earnings inequality is generally larger than the effects of schooling and experience. Adjusting for female effects reduces inequality from 16.3% to 9.9%; schooling effects reduces inequality from 7.3% to 3.1%; experience effects reduce inequality from 5.6% to 4.1%.

VII. Conclusions

The Taiwan Economy experienced a significant increase in the breadth of earnings inequality over the past two decades. Quantile regression coefficients demonstrate greatest variance across quantiles for occupation/female interaction terms. This finding indicates that gender gap has a huge impact on earnings inequality in Taiwan.

Using the Gini adjustment procedure developed by Bishop, Formby, and Smith, we investigate the effects of gender, schooling, and experience on the distribution of individual earnings by developing a new technique---quantile regression methodology. However, adjusted Ginis are not sensitive to this regression method because Gini is heavily weighted by the mean rather than the tails. A comparison of OLS and quantile regression estimations are quite consistent over time.

Over the period studied we find that gender has the greatest influence on the overall size distribution on earnings. Schooling effects are expected to have a significant influence on earnings distribution though this is not substantiated by our results. In sum, adjusting for female effects reduces inequality from 16.3% to 9.9%; schooling effects reduce inequality from 7.3% to 3.1%; and experience effects reduce inequality form 5.6% to 4.1%. Finally, the policy implications from our study are that controlling for gender differences could reduce earnings inequality. Adoption of an affirmative action policy for women may successfully reduce the overall level of earnings inequality in Taiwan.

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Table I. Summary Statistics

Panel (a). 1978, 1985

Variable	1978	Std Error	1985	Std Error
Years of Schooling	10.9973	.0248	11.1641	.0215
Age	35.6807	.0828	35.7075	.0712
Female	27.33%	.0035	33.20%	.0034
Professional Female[1]	12.41%	.0053	9.14%	.0037
Administrator Female[2]	1.19%	.0017	.99%	.0012
Supervisor Female	29.29%	.0079	25.07%	.0059
Sales Female	11.42%	.0051	11.22%	.0040
Service Female	8.25%	.0043	11.77%	.0041
Production Female	33.19%	.0084	39.10%	.0072
Operator Female[3]	.25%	.0008	.17%	.0005
Laborer Female	4.07%	.0031	2.53%	.0019
Total Employed	100%		100%	

[1]professional, technical and related workers

[2]administrators and associate managers

[3]transport and equipment operators

Panel (b). 1992, 1999

Variable	1992	Std Error	1999	Std Error
Years of Schooling	11.8667	.0208	12.6230	.0226
Age	36.4482	.0646	37.7690	.0734
Female	36.01%	.0033	39.76%	.0037
Manager Female[4]	1.68%	.0015	2.31%	.0018
Professional Female	9.15%	.0034	8.75%	.0035
Technician Female[5]	11.55%	.0038	16.28%	.0047
Clerk Female	22.83%	.0052	25.03%	.0057
Sales Female[6]	19.33%	.0048	21.21%	.0053
Craft Female	14.29%	.0042	2.44%	.0019
Operator Female[7]	12.90%	.0040	16.52%	.0047
Laborer Female	8.30%	.0032	7.38%	.0032
Total Employed	100%		100%	

[4]legislators, government administrators, business executives and managers

[5]technicians and associate professionals

[6]service workers, shop and market sales workers

[7]plant and machine operators laborers and assemblers

Table II. OLS

Variable	1978	1985	1992	1999
Experience	.0417 (.0308)	.0417 (.0011)	.0449 (.0009)	.0424 (.0010)
Experience Square	-.0008 (.00003)	-.0007 (.00002)	-.0008 (.00002)	-.0007 (.00002)
Years of Schooling	.0379 (.0018)	.0547 (.0014)	.0548 (.0014)	.0594 (.0016)
Female	-.4956 (.0090)	-.4933 (.0065)	-.4603 (.0059)	-.3558 (.0067)
Professional	.5277 (.0226)	.4218 (.0199)	.5626 (.0161)	.6383 (.0186)
Manager	---	---	.6401 (.0156)	.7559 (.0182)
Administrator	.7333 (.0253)	.6149 (.0214)	---	---
Technician	---	---	.3558 (.0139)	.4315 (.0153)
Supervisor	.3932 (.0198)	.2795 (.0176)	---	---
Sales Worker	.4033 (.0194)	.2223 (.0171)	.2183 (.0123)	.2400 (.0143)
Clerk	---	---	.2979 (.0138)	.3371 (.0158)
Service Worker	.2480 (.0218)	.1104 (.0182)	---	---
Production	.1125 (.0180)	.0199 (.0160)	---	---
Craft	---	---	.1585 (.0119)	2264 (.0150)
Operator	.3533 (.3533)	.1913 (.0199)	.1270 (.0126)	.2204 (.0142)
R-Square	.3919	.4832	.5050	.4721
Adj R-Sq	.3915	.4829	.5047	.4718
Number of Obs	15798	20022	21246	17394

Note: Omitted occupational group is laborer.

Table III. (a)Quantile Regression--1978

Variable	OLS	.10 Qnt.	.25 Qnt.	.50 Qnt.	.75 Qnt.	.90 Qnt.
Intercept	10.3684	9.6436	10.0846	10.4854	10.7376	10.9377
Experience	.0445	.0575	.0484	.0392	.0375	.0384
Experience Squared	-.0008	-.0011	-.0009	-.0007	-.0007	-.0007
Years of Schooling	.0384	.0473	.0438	.0372	.0355	.0344
Professional*Female	-.3132	-.4110	-.2313	-.1897	-.2776	-.4039
Administrator*Female	-.1781	-.2768	-.1858	-.2283	-.2268	.0187
Supervisor*Female	-.3525	-.3821	-.3740	-.3378	-.3295	-.3215
Sales*Female	-.6375	-.8075	-.7036	-.6687	-.6067	-.4650
Service*Female	-.5289	-.7060	-.5911	-.5246	-.4660	-.4029
Production*Female	-.5987	-.7376	-.6155	-.5841	-.5469	-.5608
Operator*Female	-.6464	-.6959	-.8638	-.6650	-.1959	-.0975
Laborer*Female	-.5501	-.7897	-.6532	-.5828	-.4966	-.3813
Professional	.4581	.5872	.4405	.3603	.3432	.3885
Administrator	.6949	.7257	.6110	.6407	.6804	.7091
Supervisor	.3317	.4761	.3316	.2883	.2811	.2826
Sales Worker	.4225	.3581	.3451	.3831	.4446	.5260
Service Worker	.2480	.2643	.2016	.2344	.2223	.2194
Production Worker	.1322	.1970	.1293	.1081	.0835	.0908
Operator	.3425	.4863	.3689	.2989	.2599	.2297

Table III. (b)Quantile Regression--1985

Variable	OLS	.10 Qnt.	.25 Qnt.	.50 Qnt.	.75 Qnt.	.90 Qnt.
Intercept	11.0278	10.4820	10.7992	11.0805	11.3134	11.4697
Experience	.0435	.0524	.0453	.0418	.0396	.0414
Experience Squared	-.0008	-.0010	-.0008	-.0007	-.0006	-.0007
Years of Schooling	.0552	.0589	.0579	.0547	.0531	.0524
Professional*Female	-.3165	-.3913	-.2719	-.2354	-.2713	-.3666
Administrator*Female	-.1610	-.2694	-.0988	-.1700	-.1184	-.0690
Supervisor*Female	-.3660	-.3844	-.3770	-.3781	-.3338	-.3070
Sales*Female	-.5550	-.6471	-.6195	-.5378	-.5155	-.4172
Service*Female	-.5796	-.7330	-.6975	-.5559	-.4872	-.4120
Production*Female	-.5553	-.7119	-.5502	-.5179	-.5145	-.5160
Operator*Female	-.5067	-.5957	-.7854	-.2967	-.3592	-.4658
Laborer*Female	-.5929	-.7595	-.6112	-.5811	-.5967	-.6058
Professional	.3329	.3696	.3115	.2854	.2766	.3413
Administrator	.5617	.5232	.4689	.5154	.5790	.6277
Supervisor	.1994	.2451	.1897	.1722	.1544	.1806
Sales Worker	.2145	.0728	.1207	.1873	.2849	.3335
Service Worker	.1268	.0832	.1111	.1019	.1167	.1604
Production Worker	.0191	.0255	-.0031	.0019	.0101	.0224
Operator	.1669	.2064	.1869	.1526	.1150	.1051

Table III. (c)Quantile Regression--1992

Variable	OLS	.10 Qnt.	.25 Qnt.	.50 Qnt.	.75 Qnt.	.90 Qnt.
Intercept	11.5588	11.0428	11.3523	11.6082	11.8145	11.9898
Experience	.0469	.0563	.0483	.0454	.0440	.0427
Experience Squared	-.0008	-.0011	-.0009	-.0008	-.0007	-.0007
Years of Schooling	.0543	.0589	.0555	.0528	.0516	.0526
Manager*Female	-.3067	-.2678	-.2844	-.2937	-.3341	-.3177
Professional*Female	-.2328	-.3002	-.2032	-.1600	-.1924	-.3156
Technician*Female	-.2762	-.3661	-.3263	-.2645	-.2238	-.1726
Clerk*Female	-.3073	-.3155	-.3384	-.3446	-.3114	-.2581
Sales*Female	-.5440	-.6957	-.5915	-.5326	-.4979	-.4156
Craft*Female	-.6189	-.7299	-.6211	-.5981	-.5880	-.5720
Operator*Female	-.5860	-.6832	-.6000	-.5603	-.5455	-.5407
Laborer*Female	-.4433	-.5859	-.4970	-.4293	-.3838	-.3721
Manager	.6355	.5621	.5676	.5790	.6387	.7325
Professional	.4749	.5150	.4901	.4438	.4317	.4748
Technician	.3084	.3425	.3100	.2962	.3054	.2776
Clerk	.2084	.2130	.2218	.2240	.2234	.1723
Sales	.2625	.1539	.2156	.2617	.3238	.3485
Craft	.2022	.1877	.1944	.1918	.2060	.1884
Operator	.1771	.1974	.1918	.1631	.1534	.1510

Table III. (d)Quantile Regression--1999

Variable	OLS	.10 Qnt.	.25 Qnt.	.50 Qnt.	.75 Qnt.	.90 Qnt.
Intercept	11.6403	11.1146	11.4536	11.6839	11.8444	12.0622
Experience	.0431	.0468	.0400	.0410	.0451	.0470
Experience Squared	-.0070	-.0009	-.0007	-.0006	-.0007	-.0007
Years of Schooling	.0579	.0555	.0576	.0611	.0616	.0587
Manager*Female	-.1466	-.1720	-.1686	-.1288	-.1624	-.0417
Professional*Female	-.2197	-.3282	-.1960	-.1334	-.1620	-.2825
Technician*Female	-.2220	-.2696	-.2381	-.2261	-.1751	-.1267
Clerk*Female	-.2714	-.2812	-.2982	-.2619	-.2277	-.2227
Sales*Female	-.4915	-.5637	-.5019	-.4613	-.4782	-.4618
Craft*Female	-.5175	-.6685	-.5675	-.4908	-.3973	-.3567
Operator*Female	-.4898	-.5357	-.4498	-.4646	-.4819	-.4717
Laborer*Female	-.2617	-.2047	-.2268	-.3182	-.2880	-.3111
Manager	.7774	.8787	.7484	.6601	.6953	.7788
Professional	.6307	.8285	.6749	.5248	.4907	.5394
Technician	.4372	.6145	.4681	.3561	.3397	.3245
Clerk	.3265	.5044	.3809	.2521	.2135	.1809
Sales	.3572	.3682	.3132	.2934	.3773	.4009
Craft	.2865	.4130	.3124	.2357	.2099	.2095
Operator	.3151	.5045	.3484	.2510	.2254	.1938

Table IV. Gini Coefficient--OLS

Year	Standard Gini Coefficient (1)	Adjusted Gini Coefficient: Female (2)	Adjusted Gini Coefficient: Schooling[1] (3)	Adjusted Gini Coefficient: Experience[2] (4)	Marginal Impact Effects on Inequality: Female (5)	Marginal Impact Effects on Inequality: Schooling[1] (6)	Marginal Impact Effects on Inequality: Experience[2] (7)
1978	.2886 (.0026)	.2561 (.0025)	.2797 (.0027)	.2768 (.0025)	.0325 12.7%	.0089 3.2%	.0118 4.3%
1985	.2947 (.0019)	.2559 (.0018)	.2803 (.0018)	.2818 (.0019)	.0388 16.3%	.0145 5.1%	.0129 4.6%
1992	.2851 (.0019)	.2477 (.0018)	.2664 (.0018)	.2734 (.0018)	.0374 15.1%	.0187 7.0%	.0116 4.3%
1999	.2897 (.0023)	.2615 (.0022)	.2697 (.0022)	.2773 (.0022)	.0282 10.8%	.0200 7.4%	.0124 4.5%

[1]Years of Schooling = 12
[2]Experience = 0

Table V. Gini Coefficients--Quantile Regression

Year	Standard Gini Coefficient (1)	Adjusted Gini Coefficient: Female (2)	Adjusted Gini Coefficient: Schooling[1] (3)	Adjusted Gini Coefficient: Experience[2] (4)	Marginal Impact Effects on Inequality: Female (5)	Marginal Impact Effects on Inequality: Schooling[1] (6)	Marginal Impact Effects on Inequality: Experience[2] (7)
1978	.2886 (.0026)	.2561 (.0025)	.2800 (.0027)	.2772 (.0025)	.0325 12.7%	.0086 3.1%	.0114 4.1%
1985	.2947 (.0019)	.2534 (.0018)	.2805 (.0018)	.2817 (.0019)	.0413 16.3%	.0143 5.1%	.0131 4.6%
1992	.2851 (.0019)	.2462 (.0018)	.2663 (.0018)	.2711 (.0018)	.0389 15.8%	.0188 7.1%	.0140 5.2%
1999	.2897 (.0023)	.2635 (.0022)	.2699 (.0022)	.2744 (.0022)	.0263 9.9%	.0198 7.3%	.0153 5.6%

[1]Years of Schooling = 12
[2]Experience = 0

Appendix.

Occupation	1978	1985	1995	1999
Laborer	√	√	√	√
Clerk/Administrator	√	√	√	√
Operator	√	√	√	√
Production/Craft	√	√	√	√
Sale/Service Worker			√	√
Sales Worker	√	√		
Service Worker	√	√		
Technician			√	√
Manager			√	√
Professional			√	√
Professional/Manager	√	√		
Supervisor	√	√		