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# 7

# Random Shock, Employment Variation, and Aggregation

## 7.1 HUMAN CAPITAL VERSUS RANDOM SHOCK MODELS

According to the foregoing analysis, the "residual," that is, within-group variation in earnings can be attributed to individual variation in returns to post-school investment, in rates of return, in quality of schooling, and to a variety of other factors which may be lumped together as the "unexplained" or, rather, "unmeasured" component $\epsilon_i$ (equation 5.5).

In stochastic theones of income distribution $\epsilon_t$ is interpreted as year-to-year individual fluctuation in earnings and the whole structure of earnings is explained by a stochastic process that is attributed to this "random shock" $\epsilon_t$. These models specify that:

$$v_t = \ln Y_t = \ln Y_0 + \sum_{j=1}^{t} \epsilon_j,$$

where the $\epsilon_j$ are homoscedastic and mutually independent. This leads to a monotonically increasing log variance as a function of $t$ (age or experience), and a positively skewed aggregate distribution (log-normal or Pareto, depending on differences in assumptions). But, as we have seen, the prediction that logarithmic variances of income grow monotonically and equally in all skill (schooling) groups is largely incorrect.

The greater and richer explanatory power of the human capital model need not preclude some validity in the random shock approach. Moreover, some of the predictions are similar: log variances of earnings do grow in some schooling groups and over certain phases of the working life. Even so, the same empirical phenomena are differently interpreted in the two models. In the stochastic models temporal variation in income is interpreted as chance variation. In contrast, in human capital models, much of the temporal variation in earnings is viewed as a systematic and persistent consequence of cumulative investment behavior. Discrimination between the two views can be sought in so-called panel correlations of earnings of the same cohort in two different time periods.

If we follow the earnings experience of a cohort *m* years after the initial year *t*, the random shock model implies that: (1) log variances will increase by the same amount $\sigma^2(\epsilon)$ each year, so that:

$$\sigma^2(\ln Y_{t+m}) = \sigma^2(\ln Y_t) + m\sigma^2(\epsilon); \qquad (7.1)$$

and (2) panel correlations, that is, correlations between $\ln Y_t$ and $\ln Y_{t+m}$, will decay continuously as the interval *m* is widened:

$$R^2(\ln Y_t, \ln Y_{t+m}) = \frac{\sigma^2(\ln Y_t)}{\sigma^2(\ln Y_{t+m})}, \qquad (7.2)$$

and

$$\frac{1}{R^2} = 1 + m\left[\frac{\sigma^2(\epsilon)}{\sigma^2(\ln Y_t)}\right]. \qquad (7.3)$$

According to the random shock model, both variances and the reciprocals of the coefficients of determination should increase linearly with the time interval *m*. We have already seen (Charts 6.2 and 6.3) a contradiction in that the profiles of variances are not linear. If it could be assumed that the profiles are linear, the steeper slope at the higher schooling level (Charts 6.2 and 6.3) implies a greater importance of random shock there, that is, a larger $\sigma^2(\epsilon)$, hence a more rapid decay of panel correlations in the higher schooling groups (since $\sigma^2(\epsilon)/\sigma^2(\ln Y_t)$ would be larger at higher schooling levels). Again, this implication is not substantiated in Table 7.1,

TABLE 7.1

PANEL CORRELATIONS OF MALE EARNINGS, BASED ON CONSUMERS UNION PANEL, 1959 SURVEY

| | Years of Schooling | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 12 or Less | | | 13–15 | | | 16 | | | 17 or More | | | All | | |
| Initial Year ($t$) | 2 | 7 | 11 | 2 | 7 | 11 | 2 | 7 | 11 | 2 | 7 | 11 | 2 | 7 | 11 |
| **Coefficients of Determination ($R^2$)** | | | | | | | | | | | | | | | |
| 4 | .989 | .227 | .312 | .911 | .444 | .518 | .854 | .302 | .376 | .803 | .441 | .316 | .822 | .388 | .430 |
| 7 | .951 | .220 | .268 | .852 | .324 | .265 | .691 | .383 | .381 | .760 | .430 | .388 | .752 | .426 | .348 |
| 9 | .711 | .491 | .279 | .800 | .396 | .483 | .712 | .598 | .527 | .800 | .461 | .381 | .785 | .503 | .453 |
| 12 | .837 | .654 | .498 | .907 | .648 | .616 | .889 | .581 | .552 | .897 | .528 | .679 | .878 | .578 | .586 |
| 15 | .846 | .520 | .412 | .816 | .684 | .507 | .932 | .538 | .615 | .873 | .555 | .608 | .824 | .630 | .608 |
| 18 | .818 | .588 | .399 | .898 | .604 | .591 | .918 | .652 | .662 | .887 | .652 | .739 | .898 | .681 | .714 |
| 21 | .899 | .483 | .498 | .839 | .699 | .643 | .874 | .771 | .755 | .925 | .771 | .596 | .871 | .716 | .658 |
| 24 | .828 | .419 | .403 | .931 | .764 | .688 | .966 | .768 | .715 | .908 | .868 | .637 | .930 | .788 | .648 |
| 27 | .902 | .682 | .744 | .935 | .801 | .860 | .955 | .765 | .757 | .982 | .794 | .419 | .952 | .793 | .781 |
| Average | .864 | .476 | .423 | .876 | .596 | .574 | .865 | .595 | .593 | .870 | .611 | .529 | .856 | .611 | .580 |
| **Reciprocals of $R^2$** | | | | | | | | | | | | | | | |
| Average of | | | | | | | | | | | | | | | |
| $t = 4, 7$ | 1.031 | 4.475 | 3.468 | 1.135 | 2.669 | 2.852 | 1.308 | 2.960 | 2.641 | 1.280 | 2.301 | 2.872 | 1.272 | 2.462 | 2.598 |
| All | 1.165 | 2.451 | 2.588 | 1.143 | 1.834 | 1.914 | 1.170 | 1.845 | 1.896 | 1.155 | 1.744 | 2.051 | 1.172 | 1.735 | 1.833 |
| $t = 12$ | 1.170 | 1.845 | 2.129 | 1.129 | 1.440 | 1.576 | 1.085 | 1.503 | 1.498 | 1.097 | 1.505 | 1.683 | 1.128 | 1.451 | 1.515 |

NOTE: Earnings at $t$ years of experience are correlated with earnings at $t + m$ years of experience; $t + m$ is in 1959 for each of the cohorts; $m = 2$, 7, or 11, as indicated in the column headings.

which is based on a 1959 survey of the Consumers Union Panel,[1] and contains panel correlations ($R^2$) and their inverses ($1/R^2$). Data on past earnings from which the correlations were calculated are based on recall of respondents. Recall data probably contain a great deal of error, which may affect the level and pattern of the coefficients of determination. In an attempt to minimize this error, correlations of earnings at $t$ and $t+m$ years of experience were observed only in those cohorts whose experience did not exceed $t+m$. Thus, only rows in Table 7.1 pertain to given cohorts. Years of experience were provided by respondents as time elapsed since they first entered full-time employment.

Despite the unpredictable effects of errors in such data, there are two features in the table that are noteworthy: (1) As the interval $m$ is widened from two to seven years, the correlation declines sharply when the panel base $t$ is in the first decade of experience. The decline is much milder thereafter. (2) When the interval $m$ is widened further, from seven to eleven years, the decline in correlation, if any, is negligible. The growth in $1/R^2$ is not linear, particularly over the earlier decades of experience. These findings are clearly inconsistent with the random shock model. They do seem reasonable in the light of the human capital model: panel correlations bracketing the overtaking stage would be expected to be relatively weak, but stronger thereafter.[2] The sharp deceleration or even halt in the decline of correlations beyond a seven-year span is not implausible: beyond overtaking, the ranking of individual earnings acquires a long-run stability, though disturbed by short-run, "transitory" fluctuations.

The panel correlations are consistent with a human capital model

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1. There were 4,191 usable responses in the recall data. Over half of the respondents were college graduates. For a detailed description of the data, see Juster (1964).

2. When the interval brackets the overtaking point, we are correlating

$$\ln E_s + \sum_{j=0}^{t-1} (rk_j - k_t)$$

with

$$\ln E_s + \sum_{j=1}^{t+m-1} (rk_j - k_{t+m}).$$

By definition, the post-school investment component of earnings is negative before overtaking and positive thereafter. The bracketing, therefore, introduces a negative correlation between the investment components of earnings, which weakens the panel correlation. Indeed, if $\sigma^2(\ln E_s)$ were zero, this correlation would be negative.

in which post-school investments and their ratios to earnings vary among individuals [$\sigma^2(k_t) > 0$]. In a model in which this variation is deemphasized but the variation in rates of return is stressed instead [$\sigma^2(r) > 0$], the implicit panel correlations would be high and independent of either the span of the panel interval $m$ or the stage in the working life. Since the current-investment component is, in that case, constant for all individuals, panel correlations of net earnings would be the same as panel correlations of gross earnings. It is precisely the difference between net and gross earnings that creates some of the indicated features of the observed panel correlations.

## 7.2 VARIATION IN EMPLOYMENT AS A FACTOR IN EARNINGS INEQUALITY

The finding that systematic investment components account for a large part of the temporal and individual variation in earnings does not preclude the existence of a random component $\epsilon_i$: panel correlations are certainly less than unity. But even a modest random component need not have the stochastic properties specified in the random shock models. Instead of being independent of the previous level of income, thereby creating an explosive variance, the random "transitory" component may be unrelated to a latent "permanent" level of income, so that the variance does not change much over time, if at all. Under this formulation, introduced by Friedman (1957), the contribution of the "transitory" component to total income inequality was estimated from income and consumption data to be about 20–30 per cent. This fraction is probably somewhat smaller in earnings than in total income,[3] and roughly compares in size to my estimates of the separate contributions of age variation and employment variation to total earnings inequality. The size of the log variance of earnings at the overtaking stage of the life cycle is about 25 per cent smaller than the aggregate variance, which may be viewed as a rough estimate of the contribution of age variation to total inequality. The contribution of employment variation, according to the regressions in Table 5.1, was also nearly one-fourth of total inequality.

3. "Transitory" variation in property and self-employment income is likely to be more pronounced than in earnings.

Which of the two factors should be considered transitory? Their joint contribution greatly exceeds the contribution of "transitories" as estimated from consumption data. The answer is that not all of the age variation can be considered transitory in the sense used in consumption studies: the consumption "horizon"[4] is short relative to the full length of the earnings profile. Similarly, not all of the employment variation, such as in weeks worked during the year, is transitory: some persons usually work less than others, some regularly experience greater turnover and unemployment than others.

Some of the "permanent" variation in weeks worked is an effect of human capital investments: larger investments by workers and employers tend to reduce worker turnover and unemployment (Becker, 1964, p. 18 ff.). Moreover, increased wages resulting from human capital investments may affect the labor supply. In either case, to the extent that employment during the year is an *effect* of human capital investments, and not an independent factor, the contribution of employment variation to earnings inequality should be credited to the distribution of human capital.

The theory of specific human capital (Becker, 1964) predicts an inverse relation between employment stability and the quantity of investment.[5] Assuming a positive correlation between specific and total post-school investments, as well as between schooling and job training—all measured in dollar costs—the empirical prediction is of a positive relation between schooling or age and the mean number of weeks worked in a group, as well as a negative relation between schooling or age and the standard deviation of weeks worked in the group. Table 7.2 shows that these relations do hold.

The fact that weeks worked and their dispersion are inversely associated across schooling and age groups[6] suggests that the employment factor represents a force in the direction of negative skewness of earnings. The incidence of underemployment is strongest at the lower levels of skill—a fact consistent with human capital theory. Yet for earnings distributions the employment implications of human

4. The "planning horizon" of the consumer may be measured by the inverse of the consumer discount rate.

5. Human capital investment is specific to a firm to the extent that it increases the marginal productivity of workers in the firm more than in other firms.

6. This negative correlation of means with variances produces negative skewness of the aggregate distribution of weeks worked.

TABLE 7.2
WEEKS WORKED IN 1959, BY AGE AND SCHOOLING
(white, nonfarm men)

| | Years of Schooling | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | 5–8 | | | 12 | | | 16 | | |
| Age | $\overline{W}$ | $\sigma(W)$ | $\frac{\sigma^2(W)}{\sigma^2(\ln Y)}$ | $\overline{W}$ | $\sigma(W)$ | $\frac{\sigma^2(W)}{\sigma^2(\ln Y)}$ | $\overline{W}$ | $\sigma(W)$ | $\frac{\sigma^2(W)}{\sigma^2(\ln Y)}$ |
| 20–24 | 43.5 | .288 | .692 | 45.0 | .209 | .518 | | | |
| 25–29 | 44.2 | .218 | .485 | 48.4 | .130 | .333 | 46.9 | .158 | .368 |
| 30–34 | 45.7 | .179 | .432 | 49.0 | .105 | .250 | 49.7 | .074 | .104 |
| 35–39 | 45.9 | .175 | .397 | 49.0 | .099 | .200 | 40.6 | .081 | .117 |
| 40–44 | 46.3 | .175 | .383 | 49.3 | .125 | .308 | 50.3 | .074 | .078 |
| 45–49 | 46.0 | .173 | .353 | 48.7 | .128 | .250 | 49.8 | .097 | .076 |
| 50–54 | 45.9 | .168 | .329 | 48.5 | .133 | .237 | 49.5 | .093 | .086 |
| 55–59 | 45.6 | .195 | .413 | 48.5 | .117 | .165 | 49.0 | .056 | .026 |
| 60–64 | 44.8 | .232 | .509 | 47.7 | .129 | .195 | 48.2 | .143 | .114 |

$\overline{W}$ = mean number of weeks.
$\sigma(W)$ = standard deviation of (logs of) weeks.
$\sigma^2(W)/\sigma^2(\ln Y)$ = ratio of variance of weeks to variance of earnings (in logs).

capital theory are the exact opposite of the direct productivity implications of the same theory. The latter produce a positive correlation between means and variances of subgroups, the former a negative correlation. Thus, the distribution of annual earnings shows more inequality and less positive skewness than the distribution of weekly, hourly, or full-time earnings (Mincer, 1957).[7]

## 7.3 FEMALE[8] AND FAMILY DISTRIBUTIONS

The relative contribution of employment dispersion to earnings inequality is fairly important in population groups with full and permanent labor force attachment, but it is much more important in

7. For an analysis of the effects of cyclical changes in employment on the distribution of earnings see Chiswick and Mincer (1972).

8. For a more intensive human capital analysis of earnings of women, see Mincer and Polachek (1974).

TABLE 7.3
EARNINGS PROFILES OF WOMEN AND MEN, BY SCHOOLING, 1959

| | Years of Schooling[a] | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Elementary | | High School | | College | | All | |
| Age | Women | Men | Women | Men | Women | Men | Women | Men |
| | | | **Hourly Wage Rates** | | | | | |
| 25–34 | 1.37 | 2.18 | 1.78 | 2.57 | 2.55 | 3.30 | 1.82 | 2.62 |
| 45–54 | 1.43 | 2.54 | 1.83 | 3.16 | 3.01 | 5.33 | 1.85 | 3.18 |
| All | 1.41 | 2.40 | 1.74 | 2.78 | 2.77 | 4.31 | 1.76 | 2.87 |
| | | | **Coefficients of Variation of Annual Earnings** | | | | | |
| 30–34 | | | | | | | | |
| All workers | .62 | .47 | .60 | .50 | .56 | .51 | .69 | .57 |
| Year-round | .41 | .42 | .38 | .46 | .41 | .48 | .49 | .52 |
| 50–54 | | | | | | | | |
| All workers | .65 | .52 | .62 | .64 | .56 | .67 | .68 | .73 |
| Year-round | .47 | .47 | .48 | .59 | .50 | .65 | .55 | .67 |
| 30–54 | | | | | | | | |
| All workers | .69 | .67 | .70 | .66 | .62 | .68 | .77 | .74 |
| Year-round | .49 | .59 | .48 | .58 | .50 | .62 | .57 | .67 |

SOURCE: Hourly wage rates: Fuchs (1967, Table A-1); coefficients: 1/1,000 sample of U.S. Census, 1960.

a. In upper panel, "elementary" refers to individuals with 5–8 years of schooling; "college," to those with 16 years or more. In lower panel, "elementary" refers to 8 years of schooling; "college," to 16 years. "High school" refers to 12 years of schooling in both panels.

groups whose attachment is weak. Men and women exemplify these differences in labor force behavior. The distribution of annual earnings of men is largely similar to the distribution of full-time male earnings. However, the earnings distribution of all women workers is quite different from the full-time distribution. The inequality in annual earnings of all women workers is larger than the inequality in the comparable male distribution, while the opposite is true of full-time earnings (Table 7.3).

Some of the differences between earnings distributions of men and women can be explained by the effects of labor supply behavior on human capital investment decisions. Individuals who expect to spend only a part of their adult lives in the labor force have weaker incentives to invest in forms of human capital which primarily enhance market productivities than persons who expect to be permanently attached to the labor force. Women are likely to invest less than men in vocational aspects of education, particularly in on-the-job training. This is reflected in the comparative (to males) structure of their *full-time earnings* by flatter age-earnings profiles (Table 7.3, upper panel), smaller variances within school and age classes, and less aggregate inequality of earnings (Table 7.3, lower panel).

The changes of relative inequality with age and schooling that we observed in the earnings structure of men are also less pronounced in the full-time earnings of women, and completely obscured in annual earnings (Table 7.3, lower panel).

Mean annual earnings of women are substantially lower than earnings of men. Sex differences in employment behavior and in human capital investment behavior are important causes of differences in means, as they are in affecting the variances and shapes of each of the distributions. An intensive analysis of these differences is outside the scope of the present study, as are comparisons of white, nonfarm men with other groups of men.

Given the greater variance and lower mean of earnings of female workers, a distribution of earnings of all workers, which includes both sexes, must show a greater inequality than the earnings of men alone,[9] as is clear from the aggregation formula (2.12):

$$\sigma_T^2 = \frac{1}{n} \Sigma n_i(\sigma_i^2 + d_i^2).$$

From many points of view, the "intensive" aggregation of male and female earnings within family units is of greater interest than the "extensive" aggregation of persons. Certainly, analyses of consumption behavior and notions of economic welfare are more closely linked to family than to personal distributions of income.

For simplicity, let us abstract from nonemployment income. Then, as a matter of arithmetic, dollar dispersion in family earnings is a positive function of the variances in earnings of family earners and of the correlation between these earnings:

$$\sigma^2(Y_T) = \sigma^2(Y_M) + \sigma^2(Y_F) + 2 \text{ Cov } (Y_M, Y_F); \tag{7.4}$$

where $Y_M = L_M W_M$; $Y_F = L_F W_F$. Here $T$ denotes family; $M$, husband; $F$, wife; $L$, hours of work; and $W$, wage rate. The sign of the covariance

9. This is confirmed by the data shown in Schultz (1971, Table 2).

depends partly on the correlation between the earning power (wage rates) of family members, and partly on their labor supply functions. The correlation between earning power, which is positive (classified by education for example), tends to impart a positive sign to the covariance; however, the income effect in the labor supply relations tends to influence the covariance in the opposite direction.

It is perhaps easiest to explain these tendencies if we consider the sign of Cov ($\ln Y_M$, $\ln Y_F$) which, on the assumption of monotonicity, is the same as the sign of Cov ($Y_M$, $Y_F$):

Let the labor supply function be:

$$\ln L_F = \alpha + \beta \ln Y_M + \gamma \ln W_F. \tag{7.5}$$

By (7.5):

$$\ln Y_F = \alpha + \beta \ln Y_M + (1 + \gamma) \ln W_F. \tag{7.6}$$

If $\ln Y_F$ is regressed on $\ln Y_M$, the observed slope is:

$$\beta' = \beta + (1 + \gamma) b_{W_F Y_M}, \tag{7.7}$$

where $b_{W_F Y_M}$ is the slope of the regression of wives' wage rates on husbands' earnings, in logs.

$$\beta' \gtreqless 0 \text{ as } b_{W_F Y_M} \gtreqless \frac{\beta}{1 + \gamma}. \tag{7.8}$$

Empirical work on labor supply functions (cf. Mincer, 1962; Cain, 1965; Bowen and Finegan, 1969) of married women suggests that $\beta'$ is close to zero; hence Cov ($\ln Y_M$, $\ln Y_F$) is in the neighborhood of zero. Since $b_{W_F Y_M}$ is smaller when $Y_M$ contains more of the transitory components, the covariance tends to a smaller positive or larger negative size in such groups.

When relative variances are considered, it is convenient to use the expression:

$$Y_T = Y_M(1 + R_F), \tag{7.9}$$

where $R_F = Y_F/Y_M$. The covariance $\ln Y_M$, $\ln (1 + R_F)$ is of the same sign as

$$\begin{aligned} \text{Cov}(\ln Y_M, \ln R_F) &= \text{Cov}(\ln Y_M, \ln Y_F - \ln Y_M) \\ &= \text{Cov}(\ln Y_M, \ln Y_F) - \sigma^2(\ln Y_M). \end{aligned} \tag{7.10}$$

Clearly if the first term on the right in equation (7.10) is close to zero, as seems to be the case, the covariance on the left must be large and negative. Again, it is stronger when $Y_M$ contains transitory elements than otherwise.

The conclusion that the correlation of components of family income, Cov $(Y_M, Y_F)$, is likely to be small, and even smaller when the earnings of heads of household contain transitory elements, implies that *dollar variances* of family earnings exceed those of husbands' earnings, and more so in families where husbands work full time.

Similarly, the conclusion that Cov $(\ln Y_M, \ln R_F)$ is large and negative suggests that *relative variances* of family income tend to be smaller than the inequality of the separate earnings of husbands or of wives, though this is less likely in distributions restricted to full-time working husbands.

These implications are empirically verified in Table 7.4 (page 126, below) based on the 1/1,000 sample of 1959 Census data, as they were previously in the 1950 BLS Survey of Consumer Expenditures.[10] Growth of the female labor force, while increasing the earnings inequality among all persons, has actually been a factor in the mild reduction of money income inequality among families.[11]

## 7.4 AGGREGATION OF OMITTED GROUPS

The population group of white, nonfarm men, the major empirical focus of this study, represented about 70 per cent of all male earners in 1959. Omitted are all nonwhite men, as well as white men who are students, men over 65, farm workers, and the self-employed. These omitted groups of male whites are characterized by highly dispersed, fluctuating, and often intermittent earnings. Analysis of their earnings distributions is outside the scope of this study. This is not to say that human capital analysis is not applicable to these groups. It is true, however, that employment variation, which is treated in a largely ad hoc manner in this study, must receive a great deal of attention in the analysis of such groups.

As far as overall inequality (measured in variances of logs) is concerned, the addition of a comparable nonwhite group to the white group (nonstudent, nonfarm, less than 65 years of age) in-

10. Cf. Mincer (1960, Table 4). Both tables show family incomes rather than earnings, a source of rather slight inaccuracy.

11. Cf. findings of D. Metcalf (1971) for the United States, and of H. Lydall (1959) for Britain.

TABLE 7.4
HUSBANDS' EARNINGS ($Y_H$) AND FAMILY INCOME ($Y_T$), 1959

| | $\overline{Y}_H$ | $\overline{Y}_T$ | $\sigma(Y_H)$ | $\sigma(Y_T)$ | $\sigma(\ln Y_H)$ | $\sigma(\ln Y_T)$ |
|---|---|---|---|---|---|---|
| **All Families, Wife Present** | | | | | | |
| Age | | | | | | |
| 15–24 | 3,560 | 5,180 | 2,080 | 3,310 | 0.695 | .616 |
| 25–34 | 5,510 | 6,830 | 2,850 | 3,780 | 0.557 | .511 |
| 35–44 | 6,610 | 8,454 | 4,210 | 5,520 | 0.586 | .547 |
| 45–54 | 6,520 | 9,100 | 5,100 | 6,520 | 0.656 | .612 |
| 55–64 | 5,970 | 8,620 | 5,200 | 6,790 | 0.754 | .683 |
| 65 and over | 4,310 | 7,140 | 5,430 | 6,690 | 1.046 | .750 |
| Schooling | | | | | | |
| 5–8 | 4,690 | 6,610 | 3,040 | 4,230 | 0.697 | .610 |
| 12 | 6,060 | 7,960 | 3,790 | 5,070 | 0.678 | .600 |
| 16 | 9,000 | 11,210 | 6,950 | 8,450 | 0.678 | .600 |
| All | 5,890 | 7,530 | 4,330 | 5,580 | 0.692 | .628 |
| **Husbands Working Year-round** | | | | | | |
| Age | | | | | | |
| 15–24 | 4,070 | 5,530 | 2,070 | 3,290 | 0.527 | .518 |
| 25–34 | 5,880 | 7,140 | 2,840 | 3,770 | 0.453 | .451 |
| 35–44 | 7,040 | 8,880 | 4,250 | 5,650 | 0.488 | .490 |
| 45–54 | 7,110 | 9,710 | 5,340 | 6,720 | 0.534 | .538 |
| 55–64 | 6,660 | 9,310 | 5,490 | 7,030 | 0.612 | .610 |
| 65 and over | 6,140 | 8,980 | 6,390 | 7,740 | 0.782 | .639 |
| Schooling | | | | | | |
| 5–8 | 5,300 | 7,180 | 3,120 | 4,280 | 0.497 | .508 |
| 12 | 6,370 | 8,220 | 3,790 | 5,100 | 0.476 | .483 |
| 16 | 9,550 | 11,750 | 7,060 | 8,660 | 0.593 | .575 |
| All | 6,490 | 8,460 | 4,460 | 5,800 | 0.540 | .536 |

SOURCE: 1/1,000 sample of U.S. Census, 1960.

creases inequality by no more than 2 percentage points. This is because the nonwhite group is relatively small, and its relative variance is not larger than that of the white group. The small effect is due almost entirely to the differences in means of the two groups.

When all male wage and salary earners are compared with the more homogeneous subgroup we studied, the (log) variance of annual earnings rises to 0.78 from 0.67. Finally, inclusion of self-employed and nonemployment income raises aggregate inequality in male annual earnings to 0.92.[12]

It is worth noting, though without elaboration at this point, that whether we move toward a more inclusive ("extensive") aggregation of population groups, as described here, or an "intensive" aggregation of income into a larger recipient unit, as described in the comparison of husbands' and family income, the characteristic age-schooling structure of income which we observed in earnings of white men remains very similar. Thus, the empirical "predictions" of human capital analysis are not fatally obscured by differences in concepts of population, recipient unit, or even (to some extent) income.[13]

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12. This is probably an understatement, as nonemployment income is underestimated in the Census.

13. This despite the different effects on inequality that are produced by "extensive" and "intensive" aggregation. My examples of each suggest that extensive aggregation tends to widen inequality (relative dispersion), while intensive aggregation tends to narrow it. A more rigorous statement is that an extensive aggregation of components produces an aggregate relative dispersion which *exceeds* the weighted average of component dispersions, while intensive aggregation produces a smaller than average inequality. The tendency to widen inequality by extensive aggregation is simply due to the existence of differences among means of components $d_i^2 > 0$, in aggregation formula (6.5). The opposite tendency in intensive aggregation is best viewed in terms of the coefficient of variation: given components of earnings, $Y_c$ with mean $\bar{Y}$ and variance $\sigma_c^2$, mean of total earnings $\bar{Y}_T = \Sigma_c \bar{Y}_c$, and $\sigma(Y_T) = \sigma(\Sigma_c Y_c) \leq \Sigma_c \sigma_c$. Only if the components are pairwise positively and perfectly correlated is the standard deviation of a sum equal to the sum of standard deviations. Hence the aggregate coefficient of variation

$$CV_T = \frac{\sigma(Y_T)}{\bar{Y}_T} < \frac{\sum_c \sigma_c}{\sum_c Y_c} = \sum_c \frac{\bar{Y}_c}{\bar{Y}_T} CV_c.$$

In the special case, where all $CV_c$ are the same, aggregate inequality $CV_T$ is necessarily less than the component inequality $CV_c$.