NBER WORKING PAPER SERIES

WAGE COMPARISONS - A SELECTIVITY BIAS

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Working Paper No. 13

NATIONAL BUREAU OF ECONOMIC RESEARCH, INC.
261 Madison Avenue
New York, N.Y. 10016

October, 1973

Preliminary; Not for Quotation

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The economics of information have been established by now as an integral part of economic analysis. The effect of the scarcity of information on the dispersion of prices and wages, the quality of goods, frictional unemployment and the microeconomics of inflation have been widely discussed in the literature.[1] However, surprisingly little has been written on the implications of search (and in particular, job search) for the estimation of the wage function and its ramifications in such cases as the estimation of the determinants of labor force participation, age-earning profiles, rates of return and rates of depreciation of human capital, degree of discrimation, etc.[2]

Given a wage offer distribution, the parameters of the observed wage distribution depend on the intensity of search. The lower a person's wage demands the greater the chance of his finding an acceptable job, but the lower the wage he expects to receive and the wider the dispersion of acceptable wages around their mean. On the other hand, the job seeker may opt for a more ambitious search strategy, raising his minimum wage demand and consequently increasing the risk of remaining unemployed, but also increasing the expected wage and decreasing the dispersion of the acceptable offers.

Much of the discussion in labor economics concerning labor force participation, wages, and earnings centers on the wage offer distribution. However, the empirical validation of the theory is based on the observed wage distribution. The implicit identification of wage offers with observed wages is particularly suspect when those employed constitute only a fraction of the total population. In this case, the observed distribution represents only one part of the wage offer distribution, the other part being rejected by the job seekers as unacceptable. Thus, the traditional estimation procedures may involve certain biases when applied to the secondary labor groups-- married women, teenagers, and the aged.

This paper attempts to point out some of these biases and suggests a method for their correction. In the next section we outline a simplified search model. The implications of this model for the investigation of labor force participation, discrimination, and the rates of return and rates of depreciation of human capital are discussed in the third section. In the fourth section I describe an estimation procedure for the wage-offer distribution using a simplified set of assumptions. The paper closes with a discussion of some results obtained using the new method.

Correcting for what I call the selectivity bias I show that traditional measures underestimate the rate of return to human capital and its rate of depreciation when they are applied to married women. These measures tend to overstate the white/non-white wage differential, but to understate the wage offer differentials between males and females and between women with and without young children. The use of data on the average wage of working women yields upward biased estimates of the effect of wages on the labor force participation of married women, as well as overestimates (in absolute terms) of the age and education effects.

The Search Model

Economic literature contains a large variety of search models. These models vary in their description of the search behavior and their assumptions about the job seeker's time horizon and his prior knowledge of market conditions. Some authors assume that the job seeker decides ahead of time on the number of searches he will undertake while others adopt a sequential search model. Some assume that the wage-offer distribution is well known, while others postulate that the job seeker revises his assumptions about the distribution as a consequence of the search. Some allow for an infinite time horizon while others restrict the time horizon.

For simplicity let us assume that the job seeker is unemployed, that he adopts a sequential search strategy, that he has perfect knowledge on the job-offer distribution (but that he does not know what is the wage associated with any specific vacancy), that he has an infinite time horizon, and that job-hopping is prohibitively expensive.[3] The job seeker is faced by a stream of job offers. Let it be assumed, for simplicity, that these offers arrive at a uniform rate, and let us define the time interval in such a way that the job seeker samples one offer per period. Firms differ in their search costs (e.g. the cost of ascertaining the worker's marginal productivity) and consequently may offer different wages W to the same job seeker, where W consists of non-pecuniary as well as pecuniary returns. Let f(W) denote the density function of W.

The job hunter decides on a wage W_n^* to distinguish between those wage offers which he deems acceptable and those which he rejects. The search process ends as soon as the job seeker receives an offer that exceeds W_n^*. Let W^0 denote the job seeker's price of time at home; then he accepts no wage offer that falls short of W^0, i.e. $W_n^* \geq W^0$. In general, the job seeker determines W_n^* so that any acceptable job offer will assure him of an income stream not inferior to the one he expects if he continues his search. Let R_n denote the present value of a one dollar wage offer accepted in period n

$$R_n = \sum_{t=n+1}^{\infty} (1 + r)^{-t} = (1 + r)^{-n}/r \ , \qquad (1)$$

where it is assumed that the rate of discount r is constant. Let I_n be the present value of the income stream the job seeker expects to receive if he continues his search beyond period n (both R_n and I_n are discounted to period 0); then $R_n W_n^* \geq I_n$, i.e. $W_n^* \geq I_n/R_n$.

Assuming decisions are made at the end of the period [i.e. offers accepted in period n start yielding returns only in period (n + 1)], the job seeker enjoys in period n an income of $W^0 - C$, where C denotes the costs of search which include both direct costs (e.g. advertisement, employment-agency fees, transportation) and indirect ones (e.g. the value of leisure forgone owing to the search).

Given the wage offer distribution f(W) and the asking wage W_n^*, there exists a probability of P_n that the job seeker will accept a job in period n, where

$$P_n = \text{Prob}(W_n \geq W_n^*) = \int_{W_n^*}^{\infty} f(W)dW. \quad (2)$$

An acceptable job will yield on the average a wage of E_n, where

$$E_n = E(W_n | W_n \geq W_n^*) = \frac{1}{P_n} \int_{W_n^*}^{\infty} Wf(W)dW. \quad (3)$$

If the offer received in period n is found to be unacceptable [an event whose assigned probability is $(1 - P_n)$] the job seeker can still look forward to an expected income stream of I_n. A job seeker embarking on search in period n can, therefore, expect an income stream of

$$I_{n-1} = (1 + r)^{-n}(W^0 - C) + P_n R_n E_n + (1 - P_n)I_n, \quad (4)$$

where r is the rate of discount. Given the infinite time horizon, the constant rate of discount, constant costs of search (C), constant current earnings (W^0) and a constant wage-offer distribution [f(W)], the job seeker in period n + 1 is faced by the same conditions facing the job seeker in period n. Hence, the same optimum strategy that was employed in period n will be adopted in period (n + 1), i.e. $W_n^* = W_{n+1}^* = W^*$.[4] Consequently, the present value of the returns to search in period n (discounted to period n) should equal the present value of the returns to search in period (n + 1) [discounted to period (n + 1)]. Put differently,

$$I_{n-1} = (R_{n-1}/R_n)I_n = (1 + r)I_n. \quad (5)$$

Moreover, the probability of acceptance (P_n) and the average acceptable wage (E_n) remain constant over time.

Inserting equations (5) and (1) in equation (4) and given that $W^*_n = W^*$, $P_n = P$, and $E_n = E$ for every n, the asking wage equals[5]

$$W^* = \frac{1}{r + P} [r(W^0 - C) + PE]. \tag{6}$$

In other words, the minimum acceptable wage will be such as to equate the cost of search plus forgone earnings with the net returns from search

$$C + (W^* - W^0) = P\frac{E - W^*}{r}. \tag{7}$$

The lower boundary of W^* is W^0. Let P^0 be the probability that the wage offer exceeds W^0 and E^0, the average acceptable wage when the job seeker's wage demands are confined to W^0. The job seeker quits his search when $W^0 > I_n/R_n$, i.e. when

$$C > P^0 \frac{E^0 - W^0}{r}. \tag{8}$$

For example, in the case of married women, when their price of time in home activities is sufficiently high relative to their market productivity (i.e. if $W^0 > E^0 - rC/P^0$), the woman will decide to stay out of the labor force altogether.

Other things being equal, an increase in the job seeker's price of time (W^0) reduces the forgone earnings associated with the rejection of any wage offer ($W^* - W^0$) and thus increases the job seeker's wage demands, though at a lower rate than the increase in the price of time

$$dW^* = \frac{r}{r + P} dW^0 \leq dW^0. \tag{9}$$

The increase in wage demands reduces the probability of employment

$$dP = -f(W^*)dW^* = -\frac{r}{r + P} f(W^*)dW^0 < 0 , \tag{10}$$

but increases the average acceptable wage

$$dE = \frac{f(W^*)}{P} (E - W^*)dW^* = \frac{r}{r + P} \frac{f(W^*)}{P} (E - W^*)dW^0 > 0 . \tag{11}$$

Moreover, since the returns to entry into the labor force [i.e. $P^0(E^0 - W^0)/r$] are a diminishing function of W^0, and since the cost of search (C) may increase with W^0, this change increases the tendency to abstain from entering the labor market.

Given W^0, an upward shift in the wage offer distribution, i.e. an increase in the mean wage offer distribution μ_W [other parameters of f(W) remaining constant], increases the returns to search and hence the probability of labor force participation and wage demands. However, the adjustment in wage demands lags behind the shift in f(W)

$$dW^* = \frac{P}{r + P} d\mu_W \tag{12}$$

resulting in an increase in the probability of employment

$$dP = f(W^*)(d\mu_W - dW^*) = \frac{r}{r + P} d\mu_W > 0 . \tag{13}$$

The increase in the wage demands intensifies the effect of the shift of f(W) on the expected acceptable wage offer. The average acceptable wage increases, though at a slower rate than the shift in μ_W

$$dE = d\mu_W + \frac{f(W^*)}{P}(E - W^*)(dW^* - d\mu_W) = [1 - \frac{r}{r + P}\frac{f(W^*)}{P}(E - W^*)]d\mu_W. \tag{14}$$

When the shift in the wage-offer distribution is accompanied by an increase in the price of time the tendency to enter the labor force increases as long as $d\mu_W > dW^0$. Both the shift in f(W) and the increase in W^0 tend to increase wage demands. Assuming $dW^0 < d\mu_W$, wage demands increase at a slower rate than the shift in $\mu_W (dW^* < d\mu_W)$, resulting in both an increase in the probability of employment and an increase in the average acceptable wage (the latter however changing more slowly than μ_W).

The Wage Offer Distribution versus The Observed Wage Distribution: The Selectivity Bias

The model described in the previous section analyzes the job seeker's search strategy. One can design a somewhat similar model to describe the employer's search policy. There are still some unresolved problems: how do the two strategies interact and what is the process that determines simultaneously the rate of unemployment, the vacancy rate, and the distribution of wages. The formulation of such a model is clearly beyond the scope of this paper. At the risk of being unrigorous I shall therefore adopt a partial-equilibrium approach. I assume that the wage-offer distribution is given and is not affected by the job seeker's strategy.[6] Under this strong assumption, the observed wage distribution is a subset of the wage-offer distribution, i.e. that part of the distribution which is acceptable to the job seeker.

Wage data constitute a prime source of information for the estimation of labor supply and demand, the determinants and the effects of the investment in human capital (e.g. schooling, on-the-job training, health, migration) and the analysis of occupational choice. Objections have been raised to the indiscriminate use of such data which usually reflect only the average pecuniary returns to a person's labor before the deduction of taxes. Hence they do not allow a distinction between the marginal wage and the average wage, do not account for non-pecuniary returns (i.e. psychic income) and the value of on-the-job training, and are overstated to the extent that work involves direct costs (e.g. commuting) and that the supply of labor is affected by after-tax wages. Several ingenious methods have been devised to overcome these shortcomings.

One bias that seems to have escaped economists' attention is that introduced by the search process. Given the wage-offer distribution, the bolder a person's search strategy (i.e. the higher one's asking wage W*) the higher the wage he expects to accept. Thus, the observed wage distribution has to be adjusted for differences in the search policy.

Nowhere is this bias more serious than in the case of the secondary labor-force groups. These groups are characterized by partial participation in the labor force, indicating that portions of the wage offer distribution faced by these groups are considered too low to be acceptable. The observed wage distribution is a truncated section of the wage-offer distribution and its parameters depend on the parameters of f(W) as well as on the truncation point W*. Unless variations in W* are corrected for one is bound to obtain biased estimates of the parameters of $f(W)$.

Let us consider two groups of women who face the same wage-offer distribution, $f(W)$, have the same costs of search, C, and the same discount rate. Let it also be assumed that both groups have the same price-of-time distribution except that the mean price of time (μ_{W^0}) of one group is higher than that of the second [let these distributions be denoted by $g(W^0 - K)$, where $K_1 > K_2 > 0$ and $d\mu_{W^0} = dK$]. Since both groups face the same opportunities $f(W)$ and have the same costs of search, they have the same critical price of time, i.e. the price that distinguishes between women who participate and those who do not participate in the labor force [$\overline{W}^0 = E^0 - (rC/P^0)$]. Their labor force participation rate θ equals

$$\theta = \text{Prob}(W^0 < \overline{W}^0) = \int_{-\infty}^{\overline{W}^0} g(W^0 - K)dW^0 \ . \tag{15}$$

This rate is inversely related to the mean price of time (and to K)

$$d\theta = -g(\overline{W}^0)d\mu_{W^0}. \tag{16}$$

Given the wage-offer distribution, the price of time W_i^0 determines the asking wage W_i^*, which in turn determines the average acceptable wage E_i. Given a sufficiently long period of search (a large enough n), the average wage of the labor force participants in a certain group equals

$$\overline{E} = E(E|W^0 < \overline{W}^0) = \frac{1}{\theta}\int_{-\infty}^{\overline{W}^0} Eg(W^0 - K)dW^0 \ . \tag{17}$$

It can be shown that when $g(W^0)$ is log-convex (a property which holds for most functions which we have in mind) a leftward shift in the price-of-time distribution (i.e. a decline in K) results in a reduction of the wage demands and the average wage,[7] $d\bar{\varepsilon}/d\mu_{W0} > 0$.

For example, let us assume two groups of married women, say whites and non-whites, with the same market characteristics (e.g. education and work experience). If there were no discrimination, and ignoring differences in psychic incomes, both groups should face the same wage offer distribution f(W) (Figure 1). But, if an average white woman places on her time at home a higher value (W^0) than an average non-white because of her husband's higher earnings and the existence of other sources of income, her wage demands (W^*) will be higher, and her realized average wage (E) will be higher, though the probability that she participates in the labor force may be lower. A comparison of the average wages of working women belonging to the two groups ($\bar{E}_W$ and $\bar{E}_N$) may lead to the conclusion that non-white women are discriminated against, while in effect discrimination is non-existent.

On the other hand, if the two groups have the same price-of-time distribution, the same C and r, and the same wage-offer distribution except for a shift factor, then by (11) and (14) the difference in the critical price of time ($\bar{W}^0$) between the two groups is equal to the difference between their mean wage offers. We shall expect the group with the higher mean wage offer to have the higher participation rate $[d\theta/d\mu_W = d\theta/d\bar{W}^0 = g(\bar{W}^0) > 0]$. The increase in the average wage however falls short of the increase in the mean wage offer, $d\bar{E} = [1 - (d\bar{E}/d\mu_{W0})]d\mu_W < d\mu_W$.

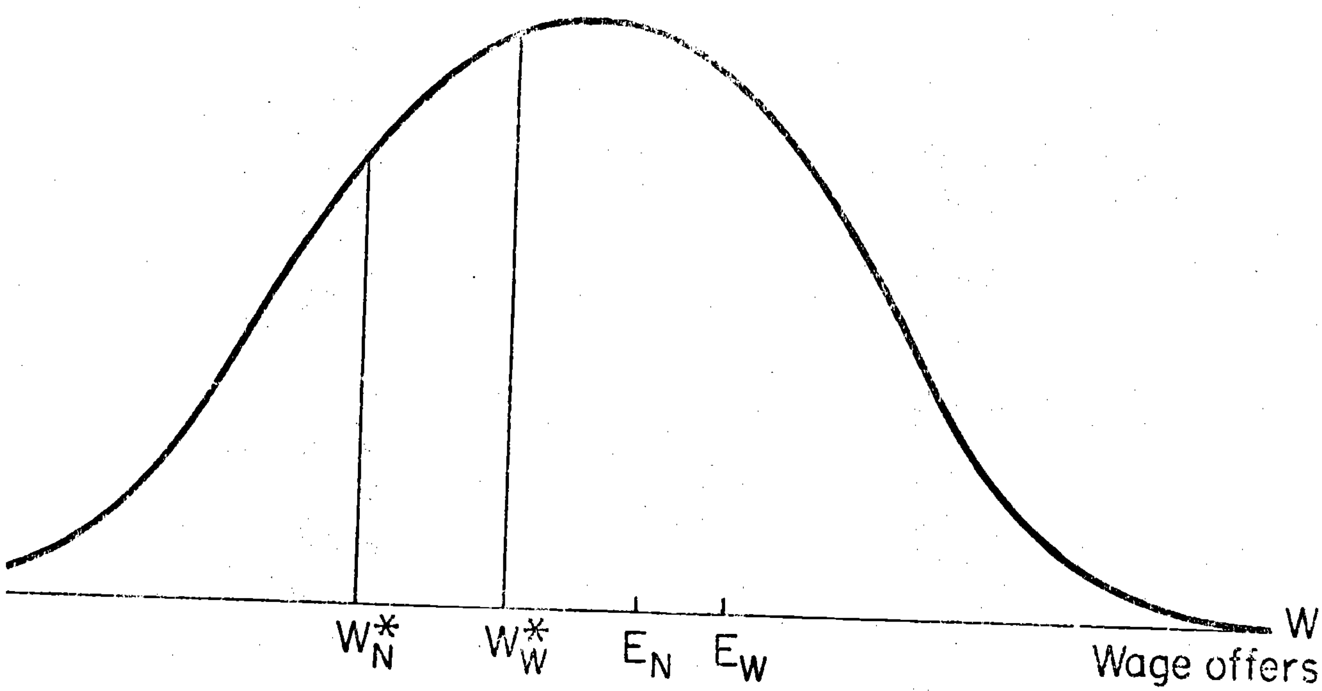


Figure 1

Thus, if it is assumed that education affects market productivity (and hence the wage-offer distribution) but does not affect non-market productivity and the price of time, women with higher education are expected to have a higher participation rate. The average wage of these women however increases more slowly than their mean wage offers. These conclusions will hold even if we remove the assumption that education does not affect non-market productivity as long as it is assumed that its effect on market productivity exceeds that of non-market productivity (see Figure 2).

Wage comparisons of whites and non-whites and of women with different levels of education are two of the cases that may be affected by what may be called the "selectivity bias." In the remaining part of this section I shall discuss a few other cases where this kind of bias may be prevalent.

Male-female wage differentials: Over 95 percent of males in the prime age groups (25-55) participate in the labor force (U.S. Statistical Abstract 1971, p. 21), while the rate of participation of females, and in particular married women, almost never exceeds 55 percent (ibid., p. 24). The difference in participation can be explained by the lower wage-offer distribution facing women, and probably by their higher value of time in the absence of market opportunities. Both factors tend to increase the difference between the average acceptable wage and the mean wage offer.

It has been estimated (Fuchs, 1971) that female average hourly earnings adjusted for color, schooling, age, city size, marital status, class of worker, and length of work-trip constituted in 1959 only two thirds of the hourly earnings of non-farm males. Given the "selectivity

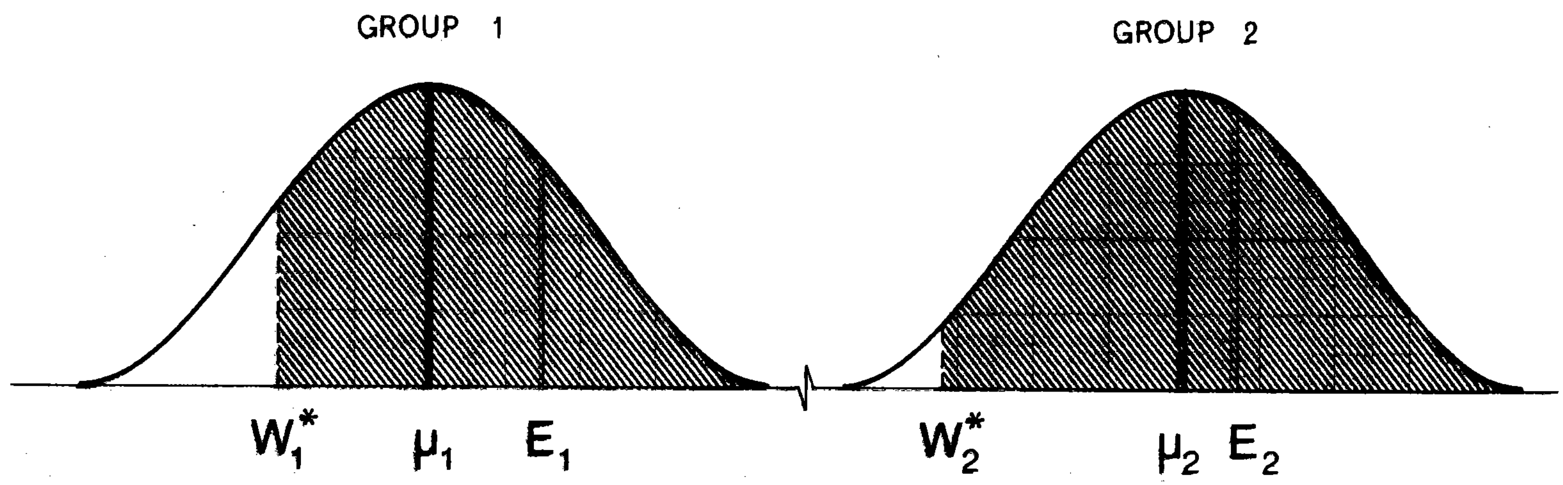


FIGURE 2

bias" it seems that this figure underestimates the "true" male-female wage differentials.

Age-wage profiles: Labor force participation rates of males vary very little in the 25-54 age-groups, decline somewhat (to a level of about 80 percent) in the 55-64 group and fall very steeply (to 25 percent) thereafter. Female participation rates have a bimodal distribution with peaks in the 20-24 and 45-54 age groups (U.S. Statistical Abstract 1971, p. 24). These variations in the participation rates may bias the estimates of the age-wage profiles.

Age-wage profiles (or age-earning profiles) are used frequently to estimate the rate of depreciation of human capital (Rosen, 1972) and the rates of return to education and on-the-job training. Retirement may introduce a bias in the estimate of the rate of depreciation and obsolescence of human capital. The direction of the bias is however indeterminate. It depends on who is the first to retire, those with the high wage offers or those with the low wage offers. The increase in non-human capital with age may increase the shadow price of time, which will rise more for those who benefited over time from the higher wage offers, so that they will be the first to retire. On the other hand, the margin between the market wage and the home wage is smallest for those at the lower tail of the wage distribution. Any deterioriation in wage offers may therefore make them leave the labor force.

Likewise, as argued above, inter-educational variations in the participation rates may bias the estimated rate of return on investment in human capital of women. It is well established that women's labor force participation increases with education. Put differently, an increase in education shifts the wage-offer distribution by more than it increases the woman's price of time at home (the latter increases either because of the effect education may have on her home productivity and/or because of the increased probability that she is married to a man with higher earnings). Ignoring the effect education may have on the dispersion of the wage-offer distribution, the difference between the observed average wage rate (E) and the mean wage-offer distribution shrinks with education.[8] The difference between the observed wages of working women in two education groups therefore tends to understate the difference between their mean wage offers and the estimated rate of return to education.

It has been argued (Michael and Lazear, 1971) that the woman's wage rate may be affected by the number and age composition of her children. The existence of young children increases the demand for the wife's time at home and her price of time and reduces her tendency to participate in the labor force. Leaving the labor market may accelerate the depreciation of the woman's market-oriented skills and shift her wage-offer distribution downward. However, the decline in the wage-offer distribution does not necessarily result in a decline in the observed wage of working mothers. If the increase in these women's wage demands is sufficiently large it will offset the decline in the wage offers and result in an increase in the observed average wage.[9]

<u>The determinants of labor force participation:</u> Labor force participation increases with the mean of the wage-offer distribution and declines with W^0. A prerequisite for the estimation of the determinants of participation is knowledge of the distribution of the

price of time at home (Ben-Porath, 1973; Gronau, 1973b; Lewis, 1971). However, this information is insufficient unless supplemented by knowledge of the mean wage offer. Replacing the latter by the average observed wage yields only imperfect estimates of the parameters of the labor force participation function, unless one knows the relationship between the average wage and the mean wage offer $(d\bar{E}/d\mu_W)$.

It was shown that an increase in the mean wage offer (μ_W) leads to an increase in the observed wage (E), but that this increase is smaller than the original shift in μ_W. Differences in the observed wages of different, say, education groups therefore tend to understate the difference between the mean wage offers and to overstate the sensitivity of participation rates of changes in wages. Furthermore, since the correlation between μ_W and E is not perfect, the misspecification of the wage variable introduces errors of measurement into the equation which may also bias the other estimates of the determinants of labor force participation.

The Estimation of the Wage Offer Distribution

The observed wage distribution is only one section of the wage-offer distribution, namely those wages that exceed the asking wage W* where the price of time of the job seeker falls short of $\overline{W}^0$. To prevent the kind of selectivity bias discussed in the preceding section the original wage-offer distribution must be generated. The derivation of the wage-offer distribution from the truncated observed distribution is a difficult task even if the point of truncation (i.e. W*) is known, and it verges on the impossible when W* and its determinants, i.e. the price of time, the costs of search, and the rate of discount are not known. In the following section I adopt an oversimplified version of the search model. This section is therefore merely illustrative, serving, it is hoped, as a base point for future research.

Let it be assumed that the job seeker is aware of the best offer he can attain[10] W and let his policy be to stay out the labor force if his price of time W^0 exceeds his best offer W and otherwise to accept the wage offer W. Given these oversimplified assumptions the participation rate is

$$\theta = \text{Prob}(W > W^0) = \text{Prob}(w = W - W^0 > 0) = \int_0^\infty g(w)dw, \quad (18)$$

where g(w) is the density function of the differential $w = W - W^0$. The average wage of working women is

$$E = E(W|W > W^0) = \frac{1}{\theta} \int_{-\infty}^{\infty} \int_{W^0}^{\infty} Wh(W,W^0)dWdW^0, \quad (19)$$

where $h(W,W^0)$ denotes the joint density distribution of W and W^0.

Let it be assumed that $h(W,W^0)$ is a bivariate normal density function

$$h(W,W\ ) = [2\pi\sigma_W\sigma_{W0}\sqrt{1 - \rho^2}]^{-1} \exp\{-\frac{1}{2(1 - \rho^2)} [X^2 - 2\rho XY + Y^2]\}, \quad (20)$$

where $X = (W - \mu_W)/\sigma_W$, $Y = (W^0 - \mu_{W0})/\sigma_{W0}$ and ρ is the correlation coefficient between W and W^0. The differential w has a normal distribution $w \sim N(\mu,\sigma^2)$ where $\mu = \mu_W - \mu_{W0}$ and $\sigma^2 = \sigma_W^2 + \sigma_{W0}^2 - 2\rho\sigma_W\sigma_{W0}$. The participation rate is

$$\theta = (2\pi\sigma^2)^{-1/2} \int_0^\infty \exp[-\frac{1}{2} \frac{w - \mu}{\sigma}^2]dw = (2\pi)^{-1/2} \int_{-\mu/\sigma}^{\infty} \exp[-\frac{1}{2}Z^2]dX; \quad (21)$$

where Z is a standardized normal variable $Z = (w - \mu)/\sigma$. The average wage is[11]

$$E = \mu_W + \overline{X}(\sigma_W^2/\sigma)|1 - \beta| \ , \tag{22}$$

where β is the regression coefficient of W^0 on W $(=\rho\sigma_{W0}/\sigma_W)$ and

$$\overline{X} = g(Z = -\mu/\sigma)/\theta \ . \tag{23}$$

Let it be assumed that the (best) wage offers depend on the woman's race, age, education, and number of children but not on her husband's income.[12] The sample can be classified by race, age, education, number of children, and husband's income. Given the rate of participation θ in each cell, the value of the ratio $-(\mu/\sigma)$, i.e. the value satisfying $\text{Prob}(Z > -\mu/\sigma) = \theta$,can be generated from the normal tables.[13] Given the value of $-(\mu/\sigma)$ one can use the same tables to derive the value of $g(Z = -\mu/\sigma)$, and hence the value of $\overline{X}$. Assuming that σ_{W0} does not change with income, one can regress within a race/age/education-number-of-children group j for different income groups

$$E = a_{0j} + a_{1j}\overline{X} \ , \tag{24}$$

where $a_{0j} = \text{est}(\mu_{Wj})$ and $a_{1j} = \textbf{est}|1 - \beta|(\sigma_{Wj}^2/\sigma_j)$. Moreover if one adopts the stronger assumption that σ_W^2 does not vary with race, age, education and number of children (i.e. that σ is constant) one can estimate for the whole sample

$$E = \Sigma a_{0j}D_j + a_1\overline{X} \ , \tag{25}$$

where D_j is a dummy variable representing race/age/education/number-of-children group j, and where $a_{0j} = est(\mu_{Wj})$.

The Data and the Results

To estimate the wage-offer distribution I used the 1960 Census 1/1000 sample. I focused on married women, the sample consisting of 26,530 women belonging to urban primary families, spouse present. Assuming that the mean of the wage-offer distribution is a function of race, age, education, and number of children, the data were subclassified by these characteristics: 2 race groups (white, negro) × 4 age groups (below 30, 30-39, 40-49, 50+) × 4 education groups (elementary school, high school, college, and graduate studies)× 3 groups for number of children below the age of 6 (0,1,2+). Since it was assumed that the wife's price of time in the absence of market opportunities is, in addition to these factors, a function of income, the data were further divided by income excluding wife's earnings (12 groups: less than $2,000, 2,000-2,999, 3,000-3,999,...,9,000-9,999, 10,000-14,999, 15,000-19,999, and 20,000+).[14] This subclassification yielded 1,152 cells which are the basic observations of my sample.

For each cell I computed two statistics: (a) the labor force participation rate of women belonging to the cell (i.e. the percentage of women working or looking for work during the week preceding the census), and (b) the average hourly wage rate of working women belonging to the cell. The 1960 census did not contain any direct evidence on the hourly wage rate and I had to do with an imperfect substitute, defining the hourly wage as the ratio of the woman's 1959 earnings divided by the product of the number of weeks she worked in

1959 and the number of hours she worked during the week preceding the census. Finally, to rule out the possibility of negative mean wage offers, the assumption of bivariate normality was replaced by the assumption of bivariate log-normality. Thus, instead of computing the usual arithmetic mean wage rate I computed the arithmetic mean of the natural logarithm of the wage rates. The dependent variable E in equation (25) therefore denotes the natural logarithm of the geometric mean of the hourly wage rates.

Equation (25) was estimated for 4 groups: whites with no children under 6 years old, whites with one child under 6, whites with two or more children under 6 and non-whites with no children under 6 (the other two groups are too small to allow estimation). The results are presented in Table 1.[15] All the regressions are significant and all the coefficients of $\overline{X}$ are positive as expected (they are significant in three out of the four cases, the exception being the regression for non-whites).

Given the estimates of a_{0j} one can compute the median of the log-normal best-wage-offer distribution $[\mu_{Wj} = \exp(a_{0j})]$. These estimates are presented in Table 2 and Figure 3 for the group of white women with no young children, together with the original data of the geometric means of the hourly wage rates.

Figure 3 demonstrates two of the salient features of the age-wage profiles of married women. The first of these, often discussed in the literature, is their flatness. Thus, except for the wages of women graduates, there is very little change in the average wage of working married women over their life cycle.[16] The second feature, one rarely

TABLE 1

The Estimation of the Mean Wage Offer

$$E = a_{0j}D_j + a_1\overline{X}$$

:ducation and age	Whites						Nonwhites	
	Children under 6:						0 children under 6	
	0		1		2+			
	a	t	a	t	a	t	a	t
) - 8 years of schooling								
: 30	-0.2163	3.29	-0.2265	1.35	-0.4656	0.24	0.2939	1.28
ı0 - 39	0.0019	2.51	-0.0585	0.55	-0.2939	0.48	-0.3852	3.16
ı0 - 49	-0.0364	4.13	-0.1458	0.65	*		-0.4815	3.91
ı0+	-0.1935	5.82	*		*		-0.3720	2.50
) - 12 years of schooling								
: 30	0.1344	0.31	-0.0589	1.01	-0.4223	0.05	0.0619	0.20
ı0 - 39	0.1466	2.74	0.0307	1.34	-0.4158	2.45	0.0325	0.24
ı0 - 49	0.1211	0.77	0.2494	1.04	*		-0.0785	0.83
ı0+	0.0212	2.71	*		*		-0.3953	2.27
.3 - 16 years of schooling								
: 30	0.4930	5.81	0.1436	0.86	-0.0510	2.01	0.5857	1.90
ı0 - 39	0.3566	3.69	0.2283	1.31	0.0733	2.14	0.6204	2.61
ı0 - 49	0.4695	6.57	0.1426	0.36	*		0.6077	2.30
ı0+	0.3998	4.22	*		*		0.5211	1.65
.7+ years of schooling								
: 30	0.7761	3.63	0.6084	1.54	*		1.3195	1.51
ı0 - 39	0.9313	5.39	0.5642	1.37	*		1.2525	2.41
.0 - 49	0.8078	6.38	*		*		1.6895	4.47
0+	0.9054	5.43	*		*		0.9645	2.10
	0.3577	6.01	0.3150	1.91	0.4539	2.05	0.1300	0.70
dj R^2		0.60		0.05		0.14		0.47

No observations in the cell.

TABLE 2

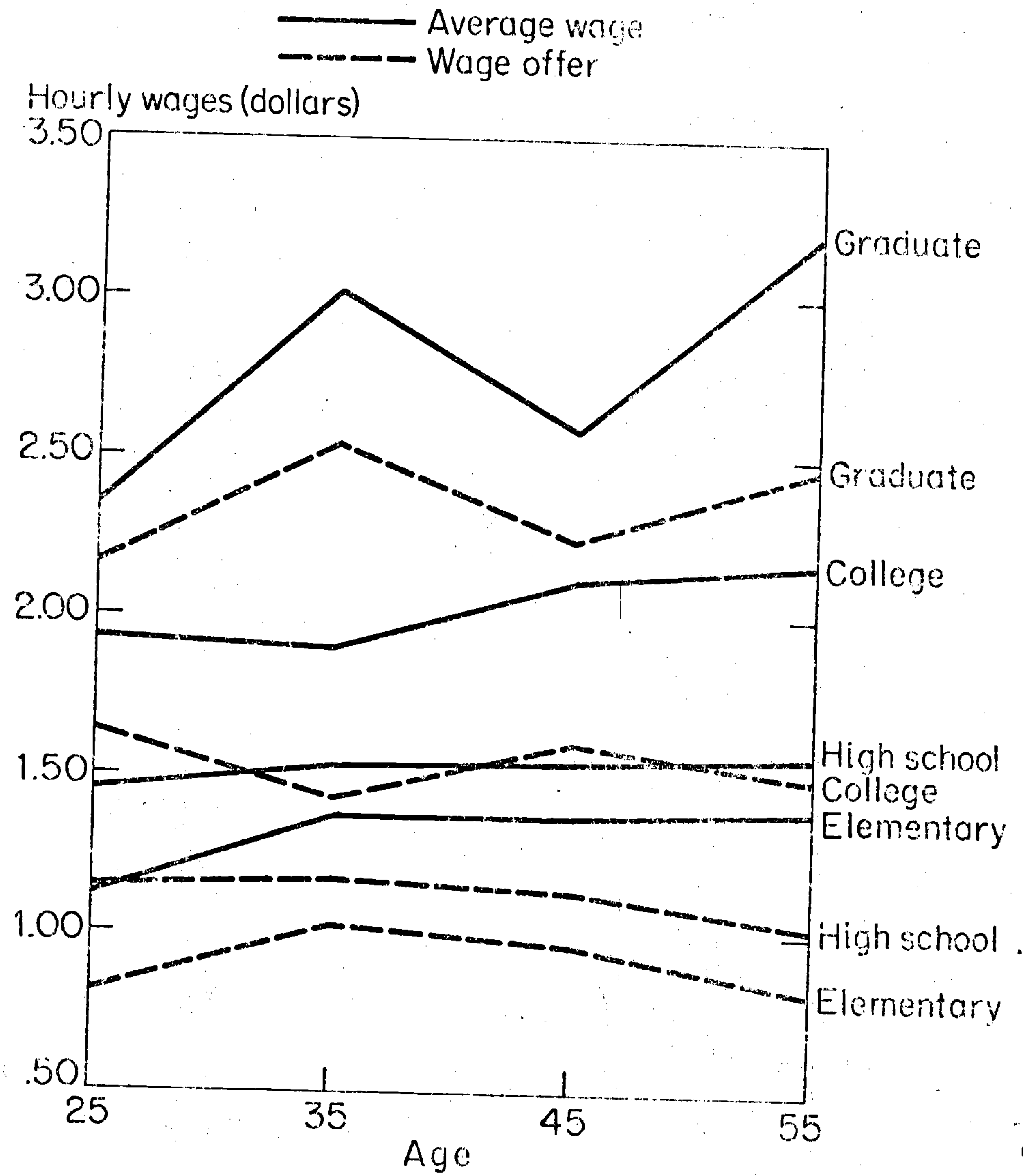
The Geometric Average Wage And the Median Wage Offer by Age and Education: White Married Women With No Young Children

Age	Elementary school	High school	College	Post-graduate
Geometric average wage				
< 30	1.12	1.45	1.93	2.35
30-39	1.37	1.53	1.90	3.02
40-49	1.37	1.54	2.11	2.59
50+	1.39	1.56	2.17	3.20
Median wage offer				
< 30	0.81	1.14	1.64	2.17
30-39	1.02	1.16	1.43	2.54
40-49	0.96	1.13	1.60	2.24
50+	0.82	1.02	1.49	2.47

Figure 3

The Geometric Average Wage and the Median Wage Offer by Age and Education

White Married Women with No Young Children



commented on, is the fact that the profiles show no tendency to slope downward as a result of negative net investment in human capital.[17]

The replacement of the average wage of working women by the imputed median wage offers has very little effect on the slope of the early parts of the age profiles, but reverses the slope of the later segment (the exception again being the graduate group). It seems that a married woman faces her peak wage offer at the age of 30-40 when she has elementary or high school education, and at the age of 40-50 when she is a graduate.[18]

Sixteen observations are too small a sample to derive any strong conclusions. Still, at the risk of seeming foolhardy, I could not resist the temptation to apply to the observations in Table 2 some of the techniques devised and applied with such success by Jacob Mincer (1972) to earnings of prime-age males. Assuming that schooling and on-the-job training involve no direct costs, and that the ratio of "time-equivalent" investment in on-the-job training declines linearly with age (Mincer, 1972, Ch. 3) I estimated the function

$$E = b_0 + b_1 S + b_2 T + b_3 T^2, \qquad (26)$$

where S denotes the number of years of schooling (it was assumed that these are 8, 12, 15 and 18 for the four education groups, respectively), and T denotes the number of years of working experience (defined[19] as $T = \text{age} - S - 8$). To correct for heteroscedasticity each of the observations was weighted by the number of working women belonging to that age-education group.[20] The results of equation (26) are compared with the estimates of a similar regression equation in which the estimated median wage offer is the dependent variable (see Table 3).

The strong multicollinearity between the variable T and its square (the simple correlation coefficient is 0.97) undermines the reliability of the estimated effect of market experience.[21] Keeping the shakiness of the evidence in mind, it is still interesting to compare the coefficients of T and T^2. Thus, while the coefficients of both T and T^2 in the regression of the average wage rate are positive, implying an upward sloping age-wage profile, the coefficient of T^2 is negative when the dependent variable is the imputed wage offers, as one would expect. The wage offers increase at an ever diminishing rate, reflecting the decline in investment in human capital over the life cycle. An absolute decline in wage offers sets in after 25-30 years of experience ($-b_2/b_3 = 27$).

Assuming that education has the same effect on the productivity of time in all its uses (e.g. work in the market, work at home, education and leisure) the coefficient of years of schooling in equation (26) measures the rate of return to formal education (Mincer, 1972, Ch. 3). The comparison of the coefficient of S in the regression of the wage rate with that of the mean wage offer confirms our prior expectations. The use of the observed wage rather than the imputed wage offer tends to bias downward the estimated rate of return to schooling. The extent of the bias increases when the experience variables (T and T^2) are omitted from the regression.

The data on the average wage rates in the other three groups (white women with young children and non-whites with no young children),and consequently the other three regressions,show no clear systematic pattern

TABLE 3

The Estimation of the Rate of Return to Education and the Effect of Work Experience*

Dependent variable		Intercept	Explanatory variable S	T	T^2	Adjusted R^2
Average wage rate (E)						
Regression (1):	b	-0.3901	0.0655	0.3048	0.2256	0.80
	t	2.97	7.72	0.42	0.13	
Regression (2):	b	-0.2273	0.0584			0.76
	t	2.26	7.01			
Median wage offer (μ_W)						
Regression (1):	b	-0.7429	0.0748	0.4356	-0.1587	0.83
	t	4.79	7.46	0.51	0.80	
Regression (2):	b	-0.7986	0.0797			0.84
	t	7.35	8.86			

* T is measured in 100-year units.

of behavior, and I have not attempted to apply equation (26) to these groups,[22] but have made do with a comparison of the average wage and wage offers of the women belonging to these groups. This comparison is contained in Table 4.

The first line of Table 4 describes the (geometric) average wage of working women belonging to the four groups investigated in our study. There are only slight differences in average wages between the three groups of white women, regardless of the number of young children, and there exists a substantial gap between the wage enjoyed by white women and that of non-whites, the latter being less than two thirds of the former. As the second line of this table indicates, this pattern is little affected by using as weights the total number of women belonging to a cell rather than the number of the working women belonging to the cell.

The average wage of each group naturally depends on its age and educational composition. To standardize for differences in composition one has to use a uniform weighting scheme. The weights used to compute the "standardized potential wage rate" (line 3) are the number of white women without young children belonging to the age and education group. The isolation of the age and education effect only slightly reduces the white non-white differential (from 0.61 to 0.65) but changes the wage hierarchy of the white women. Thus, while the unstandardized figures give an edge to women without young children (the wage of women with 2 young children being 87 percent of the wage of women without young children) this relationship is reversed when one accounts for age and education differences between the groups (the ratio becoming 1.07).

TABLE 4

The Geometric Average Wage and the Median
Wage Offer by Race and Number of Young Children

	Whites: Children under 6: 0	Whites: Children under 6: 1	Whites: Children under 6: 2+	Non-whites 0 children under 6
1. Average wage of working woman				
$	1.59	1.53	1.46	1.00
Relative*	1.00	0.96	0.92	0.63
2. Average potential wage rate				
$	1.56	1.53	1.36	0.95
Relative*	1.00	0.98	0.87	0.61
3. Standardized potential wage rate				
$	1.56	1.81	1.67	1.02
Relative*	1.00	1.16	1.07	0.65
4. Standardized median wage offer				
$	1.09	1.08	0.72	0.93
Relative*	1.00	0.99	0.66	0.85

* The relative wage is the wage of group i divided by the corresponding wage of white women with no young children.

These figures thus appear to contradict the hypothesis that children result in accelerated depreciation of the mother's market skills.[23]

The replacement of the average wage by the standardized imputed median wage offer (line 4) leads to significant changes in the observed wage pattern. The effect of children on the mother's wage offers turns out to be a prominent feature of the wage structure. The wage a white mother with two young children can expect to get in the market is only two thirds of that of a woman belonging to the same age-education group who does not have young children. (On the other hand, one young child does not seem to affect his mother's wage offers.) Furthermore, the removal of the selectivity bias seems to remove over one half of the white/non-white differential (non-whites' wage offers being 85 percent of those of whites), calling for major revisions in the evaluation of the importance of discrimination as a factor affecting the wage structure of non-white women.

On the other hand, it seems that the estimate of the male-female differential must be revised upwards. The median wage offer of married women is only about 70 percent of the standardized average wage. Since the male labor-force participation rate is close to 100 percent, the data on their wages is hardly affected by the selectivity bias ($\bar{X}$ being very close to zero). The comparison of wage offers of males and females would therefore show a substantially larger differential than the 3:2 ratio quoted earlier in this paper.

Finally, it has been argued (Lewis, 1971) that using the average wage of working women rather than their mean wage offer results in an upward bias in the estimated effect of wages on labor force participation.

I have elsewhere (Gronau, 1973a) used the results presented in Table 2 to estimate the price-of-time distribution and the implicit participation function of American married women. Employing probit analysis I examined the effect of the woman's and her husband's age and education, family income, and the number and age composition of the children on her price of time, i.e. her labor force participation (I allowed the effect of children to differ according to their mother's education). The results of this analysis are reproduced in Table 5, where one regression contains the (geometric) average wage rate of working women as an explanatory variable, and the other regression uses our estimate of μ_W.

These results clearly confirm our expectations. The introduction of the wage offers as an explanatory variable considerably reduces the estimated wage effect. The misspecification of the wage variable also affects the estimated effects of other variables, notably the wife's age and education.[24] We have seen earlier that the observed wage of working women belonging to the 50+ age group considerably overstates the wage offers faced by their non-working counterparts. The decline in labor force participation witnessed in that group is therefore attributed to age, while essentially it is merely a wage effect. Likewise, changes in the observed wage tend to understate the changes in the wage offers associated with an increase in education. Using the average wage of working women tends to overplay the direct effect of education on labor force participation.[25]

The data on the hourly wage rate used in our estimates are far from perfect. One might prefer a long term measure of participation, say, BLE 5. The Determinants of Housewives' Value of Time: An Interaction Model

natory bles	Potential wage = average wage			Potential wage = median wage offer		
	Probit coeffi- cients	t scores	Marginal effect on μ_{W0}	Probit coeffi cients	t scores	Marginal effect on μ_{W0}
ant	-1.894	1.58		0.870	1.44	
l income**	-0.850	3.91	9.5	-0.823	3.86	17.1
0	0.159	0.46	-1.8	-0.346	1.18	7.1
0	-0.870	3.24	9.7	-0.249	0.85	5.1
tion*						
nentary	0.081	0.19	-0.9	-0.072	0.18	1.5
lege	-2.138	2.43	23.8	-1.135	1.82	23.3
nd's age***	-0.296	2.60	3.3	-0.206	1.84	4.2
nd's education*						
nentary	0.418	2.10	-4.6	0.410	2.08	-8.4
lege	-0.126	0.58	1.4	-0.128	0.59	2.6
r of children < 3						
nentary	-0.861	1.31	9.6	-0.868	1.32	17.8
n school	-1.077	4.20	12.0	-1.071	4.20	22.0
lege	-1.880	3.49	20.9	-2.012	3.71	41.4
r of children 3 - 5						
nentary	0.114	0.20	-1.3	0.106	0.18	-2.2
n school	-0.768	3.53	8.5	-0.783	3.61	16.1
lege	-0.443	0.99	4.9	-0.536	1.19	11.0
r of children 6 - 11						
nentary	-0.186	0.79	2.1	-0.215	0.92	4.4
n school	-0.382	2.71	4.3	-0.389	0.28	8.0
lege	-0.364	1.22	4.0	-0.390	1.32	8.0
r of children 12 - 17						
nentary	0.275	1.05	-3.1	0.235	0.88	-4.8
n school	-0.291	1.78	3.2	-0.256	1.58	5.3
lege	0.337	0.96	-3.8	0.369	1.06	-7.6
tial hourly wage ($)	8.982	3.35		4.866	3.29	
yhood ratio test	169.0			165.0		
es of freedom	21			21		

ny variable. ** $10,000. *** 10 years.

Source: R. Gronau, "The Effect of Children on the Housewife's Value of Time," al of Political Economy, 73(No. 2, part II, March/April 1973), S168 - S199.

annual rather than weekly participation. Data problems are enhanced by a set of admittedly very strong assumptions, notably the assumption of homoscedasticity of the price of time and the wage-offer distribution. Finally, the estimation model is based on a search model that is clearly sub-optimal. Thus one should regard the results of this section as no more than an empirical exercise. One should strive to overcome these shortcomings by using a better suited body of data, by assuming a different joint distribution of W and W^0 that calls for weaker assumptions, or by focusing on a different statistic (e.g. the standard deviation of the wage of working women).[26] Nevertheless, it seems, at least to me, that the evidence collected here is a strong enough warning that comparisons of wage data should take selectivity bias into account.

APPENDIX*

Let

$$X = (W - \mu_W)/\sigma_W, \qquad Y = (W^0 - \mu_{W0})/\sigma_{W0}, \qquad w = W - W^0,$$

$$\mu = \mu_W - \mu_{W0} \qquad \sigma^2 = \sigma_W^2 + \sigma_{W0}^2 - 2\rho\sigma_W\sigma_{W0},$$

$$Z = (w - \mu)/\sigma \qquad \text{and } Z_0 = -(\mu/\sigma).$$

Define

$$\varepsilon = (W^0 - \mu_{W0}) - \beta(W - \mu_W) = \sigma_{W0}(Y - \rho X),$$

where $\beta = \rho(\sigma_{W0}/\sigma_W)$ is the regression coefficient of W^0 on W. The mean value of ε is zero and its variance is $\sigma^2 = \sigma_{W0}^2(1 - \rho^2)$. Define the standardized variable $\lambda = \varepsilon/\sigma_\varepsilon$, and let

$$\lambda^* = (\varepsilon - \mu)/(1 - \beta)\sigma_W = (\lambda\sigma_\varepsilon - \mu)/\sqrt{(\sigma^2 - \sigma_\varepsilon)} = A + B\lambda,$$

where $A = -\mu/\sqrt{(\sigma^2 - \sigma_\varepsilon^2)}$ and $B = \sigma_\varepsilon/\sqrt{(\sigma^2 - \sigma_\varepsilon^2)}$.

When $\beta < 1$

$$\theta = \text{Prob}(W > W^0)$$

$$= \text{Prob}\{\frac{1}{(1 - \beta)\sigma_W}[\beta(W - \mu_W) + (1 - \beta)(W - \mu_W) - (W^0 - \mu_{W0}) + \mu] > 0\}$$

$$= \text{Prob}\{\frac{(1 - \beta)(W - \mu_W)}{(1 - \beta)\sigma_W} > \frac{[(W^0 - \mu_{W0}) - \beta(W - \mu_W)] - \mu}{(1 - \beta)\sigma_W}\}$$

$$= \text{Prob}\{X > (\varepsilon - \mu)/(1 - \beta)\sigma_W = \lambda^*\}.$$

The conditional expectation

$$E = E(W|W > W^0)$$

$$= E(\mu_W + X\sigma_W|W > W^0) = \mu_W + \sigma_W E(X|X > \lambda^*) = \mu_W + \overline{X}'\sigma_W.$$

---

* This appendix is based on the extensive comments of Gregg H. Lewis.

Since X and Y are normally distributed, ε and λ which are linear combinations of X and Y are normally distributed. Furthermore, by definition X and ε and, in turn, X and λ are orthogonal. Hence

$$h'(X,\lambda) = (2\pi)^{-1} \exp[-\tfrac{1}{2}(X^2 + \lambda^2)].$$

Thus

$$\overline{X}' = E(X|X > \lambda^*) = (2\pi\theta)^{-1} \int_{-\infty}^{\infty} \int_{\lambda^*}^{\infty} X \exp[-\tfrac{1}{2}(X^2 + \lambda^2)]dXd\lambda$$

$$= (2\pi\theta)^{-1} \int_{-\infty}^{\infty} \exp[-\tfrac{1}{2}(\lambda^2 + \lambda^{*2})]d\lambda$$

$$= (2\pi\theta)^{-1} \int_{-\infty}^{\infty} \exp\{-\tfrac{1}{2}[A^2 + 2AB\lambda + (1 + B^2)\lambda^2]\}d\lambda$$

$$= (2\pi\theta)^{-1} \int_{-\infty}^{\infty} \exp\{-\tfrac{1}{2}[(1 + B^2)(\lambda + \frac{AB}{1 + B^2})]^2 + (A^2 - \frac{(AB)^2}{1 + B^2})]\}d\lambda$$

$$= (2\pi\theta)^{-1} \exp(-\frac{1}{2}\frac{A^2}{1 + B^2}) \int_{-\infty}^{\infty} \exp[-\tfrac{1}{2}(1 + B^2)(\lambda + \frac{AB}{1 + B^2})^2]d\lambda$$

$$= \frac{1}{\theta\sqrt{[2\pi(1 + B^2)]}} \exp(-\frac{1}{2}\frac{A^2}{1 + B^2}).$$

Inserting $1 + B^2 = \sigma^2/(\sigma^2 - \sigma_\varepsilon^2) = \sigma^2/(1 - \beta)^2\sigma_W^2$

and $A^2/(1 + B^2) = (-\mu/\sigma)^2 = Z_0^2$ it is found that

$$\overline{X}' = [(1 - \beta)\sigma_W/\sigma][\exp(-\tfrac{1}{2}Z_0^2)/\theta\sqrt{(2\pi)}] = [(1 - \beta)\sigma_W/\sigma]\overline{X},$$

where $\overline{X} = \exp(-\tfrac{1}{2}Z_0^2)/\theta\sqrt{(2\pi)} = g(Z_0)/\theta.$

When $\beta > 1$

$$\theta = \text{Prob}(W > W^0) = \text{Prob}(X < \lambda^*)$$

$$\overline{X}'' = E(X|X < \lambda^*) = -\overline{X}' = [(\beta - 1)\sigma_W/\sigma]\overline{X}.$$

Hence, in general

$$E = \mu_W + |1 - \beta|(\sigma_W^2/\sigma)\overline{X}.$$

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Footnotes

*This study is part of the NBER's project on Economic and Social Measurement funded by National Science Foundation. The paper has not undergone the full critical review accorded the National Bureau's studies. I am greatly indebted to Gregg H. Lewis and Robert T. Michael for their extensive notes. I benefited from the suggestions of Gary Becker, Stanley Diller, Victor Fuchs, James Heckman, Thomas Juster and Esther Samuel. Finally, I would like to thank Margo Faier for her devoted research assistance.

[1]The economics of information date back to Stigler's seminal papers (1961, 1962) in the early 1960's. The theory gained renewed popularity in the early 1970's in the context of the microeconomic analysis of the Phillips curve (Gronau 1971, McCall 1970, Mortensen 1970, Phelps 1970). For other applications and a survey of the theory see Nelson, 1970 and Rothschild, 1971.

[2]One of the few exceptions is Lewis (1971).

[3]Thus, I rule out a search strategy that calls for the job seeker to accept the first job offered, continue his search while on the job, and switch to a better job as soon as it becomes available. This kind of strategy is inconsistent with voluntary unemployment.

Admittedly, this model, first proposed in the literature by McCall (1970) and Mortensen (1970), is based on somewhat simplified assumptions. The use of a more sophisticated approach would not have affected our major conclusion that there is a positive correlation between the initial wage demands and the accepted wage.

[4]For a more rigorous proof of this statement see McCall (1970) and Mortensen (1970). This conclusion does not hold if the job seeker's time horizon is finite, if imperfections in the capital market result in an increase in r as the search proceeds, if there are increasing costs of search, if current earnings (e.g. marginal utility of leisure) diminish, or if the job seeker changes his evaluation of f(W) as the result of the search (see Gronau, 1971).

[5]Inserting (5) and (1) in (4)

$$W^*_n = I_n/R_n =$$

$$= r(1 + r)^n[(1 + r)^{-(n+1)}(W^0 - C) + P_{n+1}R_{n+1}E_{n+1} + (1 - P_{n+1})I_{n+1}].$$

Since $W^*_n = W^*_{n+1} = W^*$, $P_n = P_{n+1} = P$, $E_n = E_{n+1} = E$

$$W^* = (1 + r)^{-1}[r(W^0 - C) + PE + (1 - P)(I_{n+1}/R_{n+1})]$$

$$= (1 + r)^{-1}[r(W^0 - C) + PE + (1 - P)W^*]$$

Rearranging terms, one obtains equation (6).

[6]Thus, I rule out the possibility that the employer is aware of the job seeker's search strategy and adapts his wage offer accordingly.

[7]Let us define the density function

$$h_K(W^0) = \begin{cases} g(W^0 - K)/\theta_K & \text{where } W^0 \leq \overline{W}^0 \\ 0 & \text{where } W^0 > \overline{W}^0 \end{cases},$$

where $\theta_K = \text{Prob}(W^0 \leq \overline{W}^0)$. The likelihood ratio of $h_K(W^0)$ depends solely on the likelihood ratio of $g(W^0 - K)$:

$$h_{K_1}(W^0)/h_{K_2}(W^0) = (\theta_{K_2}/\theta_{K_1})[g(W^0 - K_1)/g(W^0 - K_2)],$$

since $(\theta_{K_2}/\theta_{K_1})$ is a constant which is independent of W^0 (it depends on $\overline{W}^0$, K_1 and K_2). Thus $h_K(W^0)$ has a monotone likelihood ratio if $g(W^0 - K)$ has one, a necessary and sufficient condition for which is that -log g is convex (Lehman 1959, p. 330).

Since E has been shown to be a nondecreasing function of W^0, and if $h_K(W^0)$ has a monotone likelihood ratio in W^0

$$\overline{E} = \int_{-\infty}^{\infty} E h_K(W^0) dW^0$$

is a nondecreasing function of K (ibid., p. 74).

[8] An increase in the standard deviation of the wage-offer distribution leads to an increase in wage demands

$$dW^* = \frac{P}{r + P} \overline{X} d\sigma_W > 0 \qquad \text{where} \qquad \overline{X} = (E - \mu_W)/\sigma_W.$$

Its effect on the probility of acceptance and the average acceptable wage seems, however, to be indeterminate

$$dP = \frac{r}{r + P} f(W^*)[W^0 - (\mu_W + C)] \frac{d\sigma_W}{\sigma_W}$$

$$dE = [\overline{X} - \frac{f(W^*)}{P} (X^* - \frac{P}{r + P} \overline{X})(E - W^*)] d\sigma_W ,$$

where $X^* = (W^* - \mu_W)/\sigma_W$.

[9] By equations (11) and (14) the average acceptable wage increases if

$$dW^0 > [1 - \frac{r + P}{r} \frac{P}{f(W^*)} \frac{1}{E - W^*}] d\mu_W.$$

[10] Note that from this point on W denotes the best wage offer and f(W) denotes the best-wage-offer distribution rather than the wage-offer distribution.

[11]See appendix.

[12]I ignore the possible correlation between the husband's income and the wife's wage offers which may arise because of the positive correlation in their natural ability.

[13]For example if $\theta = 0.16 \Rightarrow -\mu/\sigma = 1$, $\theta = 0.50 \Rightarrow -\mu/\sigma = 0$, $\theta = 0.84 \Rightarrow -\mu/\sigma = -1$.

[14]This classification is very similar but not identical to the one I used before (Gronau, 1973b).

[15]Instead of equation (25) I estimated

$$\overline{X} = a'_{00} + \sum_{j=1}^{15} a'_{0j} D_j + a_1 \overline{X} , \tag{25'}$$

where the basic group (i.e. the subscript 00) is the group of women 30-39 years old with high school education. To derive the estimators of the mean wage offers [a_{0j} in equation (25)] one has to compute $a_{0j} = a'_{00} + a'_{0j}$. These estimates are presented in Table 1.

However, I have not recalculated the t coefficients. Thus, the t_j coefficients ($j = 1,\ldots,15$) presented in Table 1 reflect the significance of the differential between the mean wage offers of the j-th group and the base group (i.e. they serve to test the hypotheses $H_0 : \mu_{Wj} = \mu_{W_0}$), while the t coefficient for the base group measures how significantly different is the mean wage offer of this group from zero (i.e. $H_j : \mu_{W_0} = 0$).

[16]This flatness may be partly due to a cohort effect, and does not necessarily imply that women entering the labor force now can expect no increase in their wage rates.

[17] Of course, this may be merely due to the crude aggregation of the wage data. The expected downward sloping portion of the age-wage profile might have emerged had I used a more refined age classification. However, it is noteworthy that Arleen Leibowitz, who fitted a quadratic function to data of weekly wages of married women who are full time workers, found that the wage rates tend to decrease only after 43 years of experience when the woman is a high school graduate, and after 60 years of experience when she has 13 years of schooling or more (Leibowitz 1972, p. 43). This would imply that the peak of the age-wage profile is reached at the age of 61 if the woman is a high school graduate and at the age of 83 if she finished college (the regression coefficients in the case of elementary school are insignificant).

[18] The negatively sloping portion of the wage-offer profiles may, of course, be due purely to inter-cohort differences.

[19] Age is assumed to be 26, 35, 45 and 55 in the four age groups, respectively.

[20] The major conclusions of this analysis would not have changed had I used a different weighting scheme, e.g. estimating an unweighted regression or weighting each observation by the total number of women belonging to that group.

[21] One should not conclude from the low t-values associated with T and T^2 that length of work experience does not play any role in the determination of wage rates of married women. The omission of T^2 from equation (26) results in the coefficient of T becoming significantly different from zero (see also Leibowitz 1972, p. 43).

[22]Any attempt of this kind in the case of white women with young children would have proved futile in the face of the large number of empty cells in these groups.

[23]This statement has to be qualified since the results presented in Table 4 are not standardized for the number of children older than six.

[24]I owe this point to Robert E. Hall. Note that the effect of the misspecification of the wage wariable on the estimated effect of any variable on the housewife's price of time is indeterminate. This effect is measured as the ratio of the probit coefficients of that variable and the coefficient of the wage variable. The effect of the misspecification in this case therefore depends on the direction and magnitude of the bias in both probit coefficients. For example, though the education coefficient is biased (in absolute terms) upward, the effect of education on the woman's price of time remains unchanged when E is replaced by μ_W.

[25]Let the "true" function be

$$\theta = \delta_0 + \delta_1\mu_W + \delta_2 S \qquad \delta_1 > 0, \quad \delta_2 < 0$$

where S denotes education. The replacement of μ_W by E

$$\theta = C_0 + C_1 E + C_2 S$$

results in biased estimators of δ_i

$$\text{Plim}(C_1) = \delta_1 \cdot \delta_{\mu E \cdot S}$$

$$\text{Plim}(C_2) = \delta_2 + \delta_1 \cdot \delta_{\mu S \cdot E} .$$

If, as was claimed, $\delta_{\mu E \cdot S} > 1$ and $\delta_{\mu S \cdot E} < 0$

$$\text{Plim}\ (C_1) > \delta_1 \quad \text{and} \quad |\text{Plim}(C_2)| > |\delta_2| .$$

[26]A set of data that seems very alluring in this context is the National Longitudinal Survey: Survey of Work Experience of Females 30-44 (the "Ohio Survey") which contains information on the asking wage of non-working women.

Analysis of the variance of the observed wage distribution (S_W^2) may yield further insights into the problems discussed above, since it can be shown that if W and W^0 are normally distributed

$$S_W^2 = \sigma_W^2 \; [1 - \beta)^2(\sigma_W^2/\sigma^2)(\overline{X} + Z)\overline{X}].$$

Assuming σ_W and σ_{W0} are constant one can regress S_W^2 on $\overline{X}(\overline{X} + \overline{Z})$ to obtain independent estimates of these parameters.