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A Theoretical and Empirical Study of Occupational Choice under Uncertainty

Abstract
This paper will present a model of occupational choice in which the agents are uncertain about their wage within the occupation. Agents are assumed to know their own stock of human capital and the distribution of wages per unit of human capital in the occupation at the time of initial labor market entry. The agents decide which occupation to select based on their expected utility from each occupation, given the tastes for future consumption, the available stock of human capital, the tastes for the occupation, the costs of entry into the occupation, the assets available for consumption, the tastes for risk, and the distribution of wages within each occupation. By specifying the form of the utility function, we can derive estimable equations relating the probability of choosing an occupation, i, to the moments of the distribution of wages and the past accumulations of human capital. By imposing appropriate restrictions on the parameters of the model, both within equations and across equations, all the parameters of the structural model underlying the occupational choice may be derived.

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A Theoretical and Empirical Study of Occupational Choice under Uncertainty

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human capital. By imposing appropriate restrictions on the parameters of
the model, both within equations and across equations, all the parameters of
the structural model underlying the occupational choice may be derived.

An empirically estimable occupational choice equation is derived
directly from the theoretical model. This equation is estimated using an
interesting and unique data set which summarizes the occupational choice of
high school graduates in each of the 23 county-level school districts in
Maryland annually from 1951 through 1969. In addition to occupational
choice, these data provide information on county school characteristics and
on the wealth of the county population. Data on the wage distribution by
occupation are compiled by the U.S. Bureau of the Census for the nation.
Preliminary regression results are reported in the last two sections of this paper.

I. Previous Research

There are two major categories of research papers which relate to occupational choice: (1) studies which try to explain occupational choice using statistical "logit models", and (2) studies which are primarily concerned with the impact of intermittent work by women on female occupational choice - and often use "logit" methods.

Two papers by Schmidt and Strauss [1975] and Boskin [1974] attempt to explain occupational choice using "logit models". Schmidt and Strauss use a largely descriptive approach in explaining worker choice among five occupational groups. Their explanatory variables are educational attainment, work experience, race, and sex which are introduced with little theoretical foundation. One might question whether education and work experience truly are exogenous variables or whether they are choice variables (along with occupational choice). They conclude that there are substantial differences between the sexes and races using the 1960 and 1970 Public Use Samples and the 1967 Survey of Economic Opportunity.

Boskin provides a better theoretical foundation. He argues that people will invest in an occupation if the benefits exceed the costs. He notes that imperfect capital markets may alter one's investment decision. In his empirical work, the probability of entering one of eleven occupations depends on the present value of lifetime earnings, the ratio of training costs to household wealth (the "financing" variable), and the present value of expected losses of income due to unemployment in the occupation. He
finds the expected signs (lifetime earnings is positive while the other two variables are negative) but concludes that magnitudes and significance vary substantially by race.

Like Boskin, we consider the level of earnings in an occupation. But whereas Boskin assumes that wages are received with certainty, we assume that there is uncertainty - a person does not know if he will end up above, equal to, or below the mean of the occupation's distribution.

A second set of papers has focused on the intermittent work life of females. Polachek [1981] has been a leading advocate of the idea that women are less likely to enter occupations which have a large payoff to stable and continuous participation. Like Boskin, Polachek builds a human capital foundation. He assumes that people maximize lifetime income which equals years in the labor force times the rental rate on human capital times the lifetime amount of human capital. Human capital is viewed as being heterogeneous and varies with years of schooling and with years out of the labor force.

Like Schmidt and Strauss, Polachek estimates a multiple logit model. Choice among eight occupational categories are explained in terms of marital status, years of schooling, potential lifetime working years, and home work years. He finds that women having more home work years are less likely to enter professional and managerial occupations, as compared to other occupational groups (for which continuous work is presumably less important). It should be noted that McDowell [1982] and Polachek [1978] have published related studies on the impact of intermittent work on the selection of college major.
Intermittent work is a less important phenomenon for males as compared to females. Since this paper focuses on male occupational choice, Polachek's work is of less relevance. However, if we study females in the future, we must surely consider these effects.

II. The Model

To begin, we assume that individuals live for two periods. In the first period, an individual accumulates human capital by investing time in schooling, nonschool training, or both. The production of human capital is characterized as

\[ h_1 = h_1^S(I_1, S_1) + h_1^J(1-I_1) + h_1^H(A_1) \]

where \( h_1 \) is human capital produced in period 1, \( h_1^S \) is human capital produced in school, \( I_1 \) is the proportion of time invested in a school of quality \( S_1 \), \( h_1^J \) is human capital from non-school training, and \( h_1^H \) is human capital produced in the household which is a function of household wealth, \( A_1 \). Normalizing total time at 1, we assume that all period 1 time is divided between schooling or working, where working is considered nonschool training. Leisure time is exogenous. Letting \( L_1 \) be hours of work in period 1, we have \( I_1 + L_1 = 1 \) so that \( L_1 = 1 - I_1 \). Household wealth is assumed to be equally productive, whether the individual is in school or out of school.

Utility depends upon consumption in periods 1 and 2. The agent's problem is to maximize lifetime utility

\[ E(U) = E[U(C_1, C_2)] \]

where \( C_1 \) is equal consumption in period 1, subject to (1) and the lifetime budget constraint
where \( \rho \) is the discount factor, \( W_1 \) is the wage faced by the individual in period 1, assumed to be an unskilled wage, and \( W_{21}h_1 \) is the earnings per unit of human capital in period 2 in occupation 1. Period 2 consumption will be a function of available assets and earned income, so that

\[
C_2 = \frac{A_1 + W_1(1-I_1) - C_1}{\rho} + W_{21}h_1
\]

Substituting (3) into (2), we can write the period 1 maximization problem as

\[
\max E\left[ U \left( C_1, \frac{A_1 + W_1(1-I_1) - C_1}{\rho} + W_{21}h_1 \right) \right]
\]

with respect to the decision variables \( C_1 \) and \( I_1 \).

In period 2, however, \( C_1 \) and \( I_1 \) are fixed at their period 1 optimal levels \( C_1^* \) and \( I_1^* \). If we also assume utility is additively separable in \( C_1 \) and \( C_2 \), the period 2 maximization problem may be written

\[
\max U_1(C_1^*) + E[U_2(I_1^* + h_1^*W_{21})];
\]

\[
Y_1^* = \frac{A_1 + W_1(1-I_1^*) - C_1^*}{\rho}
\]

where \( U_1 \) and \( U_{21} \) are independent functions, \( U_{21} \) being the utility obtained from choosing occupation 1. Maximizing utility requires choosing occupation 1 so as to maximize the second term of (5), regardless of the optimum levels of \( I_1^* \) and \( C_1^* \) chosen in period 1. We can therefore concentrate on the choice process underlying the maximization of the second term in (5).

We also allow the human capital produced in period 1 to vary by occupation. Thus, the knowledge obtained in period 1 may have occupation-specific as well as general components. Designating the occupation 1
specific human capital as $h_i^*$, the objective becomes to select occupation $i$ so as to maximize $E[U_{2i}(Y_i^* + h_i^*W_{2i})]$ across all occupations.

We specify the expected utility in period 2 for occupation $i$ as

\[ E(U_{2i}) = E[\alpha_i - \beta \exp(-\gamma h_i^*W_{2i} - Y_i^*)] \]

where $\alpha_i$ is a taste parameter for occupation $i$, $\beta$ is a taste parameter for period 2 consumption, and $\gamma$ is a measure of absolute risk aversion. Both $\beta$ and $\gamma$ are assumed to be positive. Agents know $Y_i^*$ with certainty, and so $Y_i^*$ is not interacted with the risk-aversion parameter. On the other hand, $W_{2i}$ is stochastic, meaning that the allocation of the human capital stock $h_i^*$ to occupation $i$ will be subject to risk-averse behavior.

Because $Y_i^*$ is known with certainty and will be equal across all occupational choices, and because $\alpha_i$ is a known parameter (to the individual), we may write (6) as

\[ E(U_{2i}) = \alpha_i + E[-\beta \exp(-\gamma h_i^*W_{2i})] \]

where $\beta_i = \beta \exp(-Y_i^*)$.

Taking the Maclaurin series expansion about $-\gamma h_i^*$ in the stochastic part of (7), and assuming the distribution of $W_{2i}$ has at least $m$ moments, we may approximate the expected utility of selecting occupation $i$ as

\[ E(U_{2i}) = \alpha_i - \beta_i [1 + E(W_{2i})(-\gamma h_i^*) + \frac{E(W_{2i}^2)}{2} (-\gamma h_i^*)^2 + \ldots] \]

\[ = \alpha_i - \beta_i - \beta_i \sum_{k=1}^{m} \frac{(-\gamma h_i^*)^k}{k!} E(W_{2i}^k) + \beta_i \xi_i \]

where $\xi_i$ is an error term representing the difference between our approximation and the actual expected utility.
Notice that in this formulation, the mean of the distribution of wages per unit of human capital serves to increase expected utility of selecting occupation $i$. The second moment of the distribution decreases expected utility. A positive (negative) third moment of the distribution increases (decreases) expected utility, and so on.

The agent wants to pick the occupation $i$ which will maximize his expected utility in period 2. Thus, the probability of choosing occupation $i$ over occupation $j$, may be written $P_i = \text{Pr}[E(U_{2i}) > E(U_{2j})]$. Since $\beta_1$ is deterministic and equal across all occupations, this can be rewritten as

$$P_i = \text{Pr}\left\{ \frac{E(U_{2i})}{\beta_1} > \frac{E(U_{2j})}{\beta_1} \right\},$$
or

$$P_i = \text{Pr}\left\{ \frac{(a_i - a_j)}{\beta_1} - \sum_{k=1}^{m} \frac{(-\gamma h_i^*)^k}{k!} E(W_{2i}^k) \right\} > (-\xi_i + \xi_j)$$

If we also assume that the occupation-specific approximation errors $\xi_i$ and $\xi_j$ have independent Weibull distributions, (9) may be written

$$P_i = \frac{\exp(E(U_{2i}) - \xi_i)}{\sum_{j=1}^{n}(\exp(E(U_{2j}) - \xi_j)}$$

where $n$ is the number of available occupations.

We can thus write a system of estimable equations for occupations 1, 2, ..., $n-1$, such that

$$\log\left(\frac{P_i}{P_n}\right) = \sum_{k=1}^{m} \frac{(-\gamma h_i^*)^k}{k!} E(W_{2i}^k) - \frac{(\gamma h_i^*)^k}{k!} E(W_{2i}^k) + \frac{(a_i - a_n)}{\beta_1}$$

for $i = 1, 2, \ldots, n-1$. Equation (11) shows that the log of the odds of choosing occupation $i$ over occupation $n$ is a function of the differences
between the first through $m^{th}$ moments of the wage distributions for occupations $i$ and $n$ and the difference in taste between the occupations $i$ and $n$.

While individuals know the taste parameters $\alpha_i$ and $\alpha_n$, they are not known by the econometrician. To obtain an estimable version of (11), we assume that the utility obtained by selecting occupation $i$ over occupation $n$ varies over time. We decompose the taste parameters into two components so that $\frac{1}{\beta_i}(\alpha_i - \alpha_n) = \bar{e}_i + \epsilon_i$, where $\bar{e}_i$ is the mean preference for occupation $i$ over occupation $n$, and $\epsilon_i$ is some time-specific positive or negative increment in the taste for occupation $i$ over occupation $n$. We can thus rewrite (11) as

$$\log \left( \frac{p_i}{p_n} \right) = \sum_{k=1}^{n} \left[ \frac{(-h_{11}^*)^k}{k!} E(w_{11}^k) - \frac{(h_{11}^*)^k}{k!} E(w_{11}^k) \right] + \bar{e}_i + \epsilon_i$$

If $h_{11}^*$ and the moments of the distribution of wages per unit of human capital may be observed empirically, the structural parameter $\gamma$ may be identified from the restrictions implied by (11'). To see this, suppose that only the first two moments of each wage distribution exists, and let $u_i$ represent the first moment of the wage distribution for occupation $i$ and $\sigma_i$ represent the second moment of the wage distribution for occupation $i$. (11') becomes:

$$\log \left( \frac{p_i}{p_n} \right) = a_1(h_{11}^*u_i - h_{11}^*u_n) - a_2(h_{11}^*\sigma_i - h_{11}^*\sigma_n) + \bar{e}_i + \epsilon_i$$

Where $a_1 = \gamma$

$$a_2 = \gamma^2/2$$

Obviously, $\gamma$ is overidentified in this system. Notice that as higher moments of the distribution of wages are added to (12), $\gamma$ becomes even more overidentified.
Unfortunately, the stock of human capital is not observed directly. However, inputs into the production of human capital (school quality, school attendance and family assets) are observable. Thus, we can impose a human capital production function of the form

\[ h_i = \delta_{0i} + \delta_{1i} I_1 S_1 + \delta_{2i} A_1 \]

where as before, \( S_1 \) is a vector of school characteristics, \( I_1 \) is proportion of time invested in school and \( A_1 \) is a vector of relevant family assets.

Provided \( h_i \) is linear in parameters, the production function may contain any number of interaction terms and quadratic forms of the inputs, so that the production function can be quite general.\(^6\)

Inserting (13) into (12), we have

\[
\begin{align*}
\log \left( \frac{p_i}{p_n} \right) & = \gamma \left[ (\delta_{0i} + \delta_{1i} I_1 S_1 + \delta_{2i} A_1) \mu_i \right] - (\delta_{0n} + \delta_{1n} I_1 S_1) \\
& + \delta_{2n} A_1 \] \left[ \left( \delta_{0i} + \delta_{1i} I_1 S_1 + \delta_{2i} A_1 \right)^2 (\sigma_i) \right] \\
& - (\delta_{0n} + \delta_{1n} I_1 S_1 + \delta_{2n} A_1)^2 (\sigma_n) ] + \epsilon_i + \epsilon_1 \\
\end{align*}
\]

Whose estimable form is

\[
\begin{align*}
\log \left( \frac{p_i}{p_n} \right) & = (b_1 + b_2 I_1 S_1 + b_3 A_1) \mu_i - (b_4 + b_5 I_1 S_1 + b_6 A_1) \mu_n \\
& - (b_7 + b_8 (I_1 S_1)^2 + b_9 (A_1^2) + b_{10} (I_1 S_1) + b_{11} A_1 \\
& + b_{12} (I_1 S_1 A_1) \sigma_i + (b_{13} + b_{14} (I_1 S_1)^2 + b_{15} (A_1^2) \\
& + b_{16} (I_1 S_1) + b_{17} A_1 + b_{18} (I_1 S_1 A_1) \sigma_n + \bar{\epsilon}_i + \epsilon_1 \\
\end{align*}
\]
Because of the nonlinear dependence between these restrictions, we have only 6 independent equations in 7 structural parameters. Furthermore, even if the number of moments of the wage distribution were to be increased, we would not obtain additional identifying restrictions. In order to identify the structural parameters, \( \gamma, \delta_{01}, \delta_{11}, \delta_{21}, \delta_{0n}, \delta_{1n} \) and \( \delta_{2n} \), we must obtain one additional restriction. We propose fixing \( \gamma \), since we know it must be positive, and since changing its value scales the production parameters up or down by the same factor. Once \( \gamma \) is set to some value \( \overline{\gamma} \), we can identify all other parameters in the model. Notice that because the production parameters can be obtained from one occupational choice equation, the model allows inferences to be drawn on the effects of school quality and household wealth on the productivity of human capital within a given occupation. Thus, we may test for the equality of production parameters, \( \delta_{ij} \), across all occupations, \( j = 1, \ldots, n \). The results will show if human
capital is equally valuable in all occupations or if general training is more valuable in some occupations than others.

III. Empirical Strategies

The relevant distribution of wages within an occupation will undoubtedly differ across individuals because of differences in human capital accumulation in period 1. Unfortunately, we do not observe different distributions of wages for individuals, only a distribution of wages for the entire occupation. It is important, therefore, to derive individual wage distributions from available information on the national market for labor within the occupation and the characteristics of the individual's human capital investment.

We begin by assuming that the distribution of earnings per unit of human capital within an occupation is independent of the distribution of human capital within the occupation. This assumption is equivalent to one in which returns per asset are independent of the distribution of asset holdings among individuals. Mathematically, our independence assumption implies

\[ f(W, h) = f_1(W) f_2(h) \]

where we have dropped the subscript \( i \) for ease of exposition. (16) shows that the joint density function of wages per unit of human capital and human capital in an occupation is equal to the product of the marginal densities of \( W \) and \( h \). This property implies that for an individual with human capital stock \( \bar{h} \), the conditional distribution of wages per unit of human capital is
(17) \[ f(W_2 | h) = \frac{f_1(W_2)f_h(h)}{f_h(h)} = f_1(W_2) \]

so that the distribution of wages per unit of human capital for any individual is the same, regardless of the individual's holding of human capital. This property allows us to characterize the individual's period 2 earnings as \( \bar{W}_2 \), the formulation imposed in the analysis above.

The assumption of independent density functions for \( W_2 \) and \( h \) also allows a convenient transformation of available data to arrive at estimates of the moments of the distribution for \( W_2 \). We observe the distribution of \( hW_2 \) in an occupation. Provided the distributions of \( W_2 \) and \( h \) have moment generating functions, the joint density of \( W_2 \) and \( h \) is

(18) \[ M(W_2, h) = M(W_2, 0)M(0, h) \]

This implies that

(19) \[ \mu_{W_2, h} = \frac{\mu_{W_2, h}}{\mu_h} \]

(20) \[ \sigma_{W_2, h} = \frac{\sigma_{W_2, h}}{\sigma_h} \]

where \( \mu_j \) is the first moment, and \( \sigma_j \) is the second moment of the variable \( j \). Thus, if we can obtain the distribution of human capital within an occupation as well as the joint distribution of human capital and earnings per unit of human capital in the occupation, we may derive the moments of the distribution function for \( W_2 \).

The empirical constraint is that we would like to have data on \( \mu_W \) and \( \sigma_{W_2} \), but they are not directly available. We do have data on the right-hand-side variables of equations 19-20. In order to estimate \( \mu_{W_2} \) and \( \sigma_{W_2} \),
we take logarithms of equations 19-20 and rearrange. For example, from equation 19 we get:

\[(21) \ln \mu_{W_2,h} = \ln \mu_h + \ln \mu_{W_2} .\]

This form suggests estimating \( \mu_{W_2} \) as the anti-logarithm of the residuals from a regression of \( \ln \mu_{W_2,h} \) on \( \ln \mu_h \). The empirical implementation of this strategy is discussed more fully in the next section.

Thus far, we have treated period two as a single year. In actuality, period two should be composed of \( T \) subperiods, where \( T \) is the length of time in the workforce. The relevant moments of the earnings distribution will no longer be only the current moments, but the expected path of future moments as well.

Let \( \mu_{W_t} \) and \( \sigma_{W_t} \) be, respectively, the first and second moments of the distribution of earnings per unit of human capital in period \( t \). Furthermore, let \( \mu_{W_t} \) and \( \sigma_{W_t} \) both be stationary stochastic processes. Finally, we assume that the laws of motion for the distribution of earnings per unit of human capital are autoregressive processes such that

\[
\mu_{W_t} = \alpha_1 \mu_{W_{t-1}} + \alpha_2 \mu_{W_{t-2}} + \ldots + \alpha_q \mu_{W_{t-q}} + \nu_{t}^\mu
\]

\[
\sigma_{W_t} = \delta_1 \sigma_{W_{t-1}} + \delta_2 \sigma_{W_{t-2}} + \ldots + \delta_p \sigma_{W_{t-p}} + \nu_{t}^\sigma
\]

which can be rewritten

\[
\alpha(L) \mu_{W_t} = \nu_{t}^\mu, \quad \alpha(L) = 1 - \alpha_1 L - \alpha_2 L^2 - \ldots - \alpha_q L^q
\]

\[
\delta(L) \sigma_{W_t} = \nu_{t}^\sigma, \quad \delta(L) = 1 - \delta_1 L - \delta_2 L^2 - \ldots - \delta_p L^p
\]

where \( L \) is the lag operator.
We assume that the relevant measure of the period 2 first and second movements is the discounted sum of current and expected future moments. Thus, following Hansen and Sargent (1980), we can write the first and second moments for period 2 as

\[
\begin{align*}
\mu_{t+2} &= \sum_{j=0}^{T} \rho^j E_t(\mu_{t+j}) = \sum_{j=0}^{T} \rho^j \left[ \alpha(L)^{-1} \right] + \nu^\mu_t \\
\sigma_{t+2} &= \sum_{j=0}^{T} \rho^j E_t(\sigma_{t+j}) = \sum_{j=0}^{T} \rho^j \left[ \delta(L)^{-1} \right] + \nu^\sigma_t
\end{align*}
\]

where \( E_t(o) \) is the expectation operator conditional on information at time \( t \), and \([o]^+\) is the anihilation operator. In this manner, the agent's occupational choice can be formulated to depend not only on the current moments of the distribution of earnings in all occupations, but also on the rational forecasts of the future distributions of earnings in all occupations.
The empirical portion of this study utilizes a unique and rich source of data. Each year between 1947 and 1969 the Maryland State Board of Education has published data on the number of high school graduates broken down by their major type of activity in the year following graduation. The data indicate the proportion who continued their education as well as the proportion who took jobs (broken down by occupational group).

The data are also rich in that they are available by sex and by county-level school district. Differences among 23 counties together with changes over time should create sufficient variation to allow us to estimate the parameters of our own model. Separate data for boys allows us to abstract from the complications which intermittent work time may cause in a study of female occupational choice.

The Maryland survey categorized male workers into six broad occupational groups:¹¹

1. Farming, fishing, and lumbering
2. Operatives and laborers
3. Service workers
4. Craftsmen
5. Clerical and sales
6. Professionals and managers

These are the six occupational categories used in this study. Although slightly fewer groups are available to us as compared to Boskin and Polachek, our six categories span the universe and appear to be aggregated into reasonably homogeneous sets.
The Maryland State Board of Education provides several consistent series of school quality measures such as expenditures on teacher salaries, number and certification levels of teachers, textbooks and other instructional materials, and size of school enrollment. Average attendance figures are also available by school district. The measure of school quality used in this study is real instructional salaries per student enrolled, weighted by a school utilization ratio. To be more specific, we divided "Salaries and Wages for Instruction at the Secondary Level" by the number of students belonging (enrolled) to the school district and then expressed it in real dollars using the Consumer Price Index. This value was multiplied by a measure of the extent to which students utilize the schools (the ratio of students attending to students belonging). In order to take account of the fact that a student's schooling investment occurred over several years, a six-year moving average was computed. This variable was used as our proxy for "IS".

A measure of average county assets is also available from the Maryland State Board of Education. The Board reports the value of property which is assessable for tax purposes by county level school district. As with the school quality variable, we compute a six-year moving average of real property values per capita (deflating by the Consumer Price Index and by the total county population as interpolated from the Decennial Census of Population). This is our proxy for "A1".

Data on the earnings distribution by occupation are not available for individuals in Maryland. As a result, we were forced to use national income data from the U.S. Bureau of the Census [Series P-60]. Income distributions by discrete intervals have been published annually for males by major
From these distributions, we estimated the annual mean and the second moment of income (each expressed in real terms) for each of our six occupational groupings.

Unfortunately, these Census Bureau data do not hold constant the level of educational attainment within an occupation. As a consequence, an increase in the proportion who are college educated will tend to alter the published distribution of income, even though high school graduates taking jobs may have experienced no change in their actual income distribution. Ideally, we would like to purge the data of such changes in educational attainment. Fortunately, data have been available since the early 1950s on educational attainment (from the U.S. Bureau of Labor Statistics) which allow us to attempt some adjustments. Using these data, we computed the mean, variance, and skewness of educational attainment of males by occupation 1951-1970.

The method of purging the income distribution data of educational attainment effects was motivated by the analysis in the previous section. Equation 21 suggests regressing the logarithm of income on the logarithm of education, for each moment of their respective distributions. The antilogarithm of the residuals from such a regression should yield the corresponding income moment purged of the education effect. This, in fact, was done for each of the six occupational groups, although we modified the regression equation slightly by including an intercept. An intercept was included in order to account for other variables which determine income levels. In addition to education, age (or experience) is a major determinant of income. Since the age distribution within an occupation is expected
to change slowly, if at all, we simply treat it as a constant in our regression.\footnote{17}

This procedure yielded six time series, each of which varied around a mean of 1.0. The next step was to incorporate information about the relative magnitudes of income moments between occupations. Fortunately, distributions of male income for each occupation group were broken down by the level of educational attainment in the 1960 and the 1970 Census of Population. We computed the 1960 mean and variance of income for each occupation for males age 25–64 having exactly four years of high school education. Professionals/managers having the highest values were set equal to 1.0 in 1959. The ratio of each occupation to professionals/managers defines that occupation's relative mean or variance in 1959. A consistent time series was then constructed by multiplying this 1959 "relative" by the anti-log of the residuals for each series.

This procedure created several time series 1951–1969 which were devoid of any long-term trends in occupational means of variances. The next step was to build any such trends back into the data.

This was easily done for the 1959–1969 period since the Census of Population income distributions for high school graduates were published for both 1959 and 1969 incomes. We simply compared the 1959 and 1969 values and built that trend into the data.\footnote{18} Unfortunately, similar data disaggregated jointly by education and occupation were not published in the 1950 Census. In order to build in the 1950–1959 trend, we were forced to use a different procedure. In essence, the ratio of the income moment to the educational attainment moment was computed from each of the 1950, 1960, and 1970 Censuses of Population. After verifying that changes in these ratios
1959-1969 compared favorably to the "true" changes 1959-1969, we computed the 1950-1960 changes and used these to build in trends for the years 1951-1959.

The final step was to construct weighted averages of the occupational income series which better approximate the expectations of the agents. Two methods were used. First, a simple two-year moving average was computed. High school graduates in 1951, for instance, are observed in their occupational pursuits in fall 1951 and spring 1952. Hence, we felt that the appropriate income data should be an average of the 1951 and 1952 calendar-year values. These final constructed series are plotted in Figures 1 and 2 in the Appendix. Descriptive statistics and correlation coefficients are also reported in the appendix. Not surprising are the relatively high correlations among the occupational means. Only the pattern for farmers varies substantially from the other occupational means. There is, of course, more year-to-year and short-term variation among the groups. The correlations among the occupational variances are not as high.

The second method was to compute the present value of current and expected future moments as discussed. Initially, we computed first, second, and third-order autoregressive regressions for each of the occupational income time series. In a majority of cases, we did find evidence of a second-order autoregressive process, but we found no evidence of a third-order process. As shown in footnote 9, by imposing a second order autoregressive process, the present value of the expected path of a variable \( \mu \) converges to:

\[
\frac{1}{1-\rho \alpha_1 - \rho^2 \alpha_2} \mu_t + \frac{\alpha_2 \rho}{1-\rho \alpha_1 - \rho^2 \alpha_2} \mu_{t-1}
\]
where \( \rho \) is the discount factor (set equal to .9), and \( \alpha_1 \) and \( \alpha_2 \) are the autoregressive parameters computed from a regression.\(^{19}\)

V. ORDINARY LEAST SQUARES REGRESSIONS

Initially equation 15 was estimated separately for each occupation using ordinary least squares. This was done in order to hold down initial estimation costs and in order to consider the partial impacts of the explanatory variables. In the next section, nonlinear estimation methods are used in order to compute the structural parameters of equation 15.

The farmer/farm-laborer category was used as the reference group because there were virtually no counties or years in which there were no male farm workers. This was computationally convenient because we did not then have to worry about dividing by zero.\(^{20}\) The dependent variable was computed as the logarithm of the number in an occupation divided by the numbers of farmers. The problem of taking the log of zero still remained in some instances. In such cases, we set the numerator's zero value equal to 0.1.

In order to reduce the problem of collinearity, a modified form of equation 15 was estimated. Corresponding parameters were constrained to be equal (i.e., \( b_1 = b_4 \); \( b_2 = b_5 \); \( b_3 = b_6 \); \( b_7 = b_{13} \); etc.) so that regressions were run on \( (\mu_i - \mu_n) \) and \( (\sigma_i - \sigma_n) \) as well as their interaction terms with "I\( _1 S_1" \) and "A\( _1"\), for each occupational group \( i \).

An initial attempt was made to estimate equation 15 utilizing measures of skewness in addition to the mean and variance. This did not work well, so that the skewness variable and interaction terms were discarded. There
are several possible reasons for this poor performance. First, the measure of skewness which we used is itself a function of the mean and of the (square root of the) variance. The moments are not independent. Second, we had considerable difficulty adjusting our income skewness measure for changes in the skewness of educational attainment (see footnote 16). The data are not as consistent or as reliable as for the mean and variance. Third, estimation of higher moments is more subject to noise and peculiarities in the data when such moments must be estimated from categorical data. The problem is that only a relatively small number of income intervals (15-17) are provided each year. Fourth, the introduction of skewness adds nine interaction terms associated with assets and school quality. Because these two variables are themselves fairly highly correlated (and highly correlated with their squares, cubes and cross products), we simply get too much collinearity in such a regression. (See the appendix for the correlation coefficients.)

One additional modification was made to equation 15. A set of county dummy variables was added in order to control for county specific effects. These control for differences in the distribution of individuals (their tastes and families' backgrounds) between counties. Of course, such dummy variables also control for county differences in school quality and in assets. This may reduce the ability of our school quality (IS) and asset (A) variables to explain the cross-county variation in occupational choice. Nevertheless, we felt that the dummy variables controlled for several important effects for which we had no suitable proxy variables.
Tables I-III present our estimates using the simple two-year averages of the occupational income series. After discussing these results, Tables IV-VI replicate the first set of tables substituting the Hansen-Sargent weighted average series for the simple averages.

Table I reports our regression estimates of equation 15. Estimates were made using data over the 19-year period 1951-1969 and over the 23 Maryland counties for a total of 434 observations. The least squares results are quite good in general, with $R^2$'s varying between .54 and .71. Magnitudes of the regression coefficients and associated t-statistics are given at the top of the table. Although theory does not require that these individual coefficients have any necessary signs or magnitudes, it is interesting to note that they are reasonably consistent across equations (professional/managers differ the most).

Of greater interest are the summary statistics below the dashed line. We expect that an increase in mean own occupational income relative to farming income should increase the likelihood of being in that occupation. The slope with respect to $(\mu_i - \mu_r)$ is positive as expected in all cases and is statistically significant for professional/managers and clerical/sales.

The results for the occupational variances are not quite as good. We expect that an increase in the variance of own occupational wage per unit of human capital relative to farming wages should increase uncertainty and decrease the likelihood of being in the occupation. This was only true for three occupations, and of those, only the professional/manager slope is significantly different from zero. For the other four occupations, the variance slopes could reasonably be considered to be zero. Although
### TABLE I

<table>
<thead>
<tr>
<th></th>
<th>Professionals and Managers</th>
<th>Clerical and Sales</th>
<th>Craftsmen</th>
<th>Operatives and Laborers</th>
<th>Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>(\mu_1 - \mu_P)</td>
<td>13.07</td>
<td>-6.20</td>
<td>-9.93</td>
<td>-12.21</td>
<td>-15.60</td>
</tr>
<tr>
<td></td>
<td>(1.90)</td>
<td>(1.27)</td>
<td>(1.81)</td>
<td>(2.33)*</td>
<td>(1.32)</td>
</tr>
<tr>
<td>(\text{IS}*(\mu_1 - \mu_P))</td>
<td>-0.057</td>
<td>.035</td>
<td>.040</td>
<td>.041</td>
<td>.085</td>
</tr>
<tr>
<td></td>
<td>(2.35)*</td>
<td>(2.31)*</td>
<td>(2.58)*</td>
<td>(2.08)*</td>
<td>(1.65)</td>
</tr>
<tr>
<td>(A*(\mu_1 - \mu_P))</td>
<td>4.63</td>
<td>.54</td>
<td>1.19</td>
<td>.88</td>
<td>-.65</td>
</tr>
<tr>
<td></td>
<td>(2.56)*</td>
<td>(1.03)</td>
<td>(1.03)</td>
<td>(3.62)</td>
<td>(1.15)</td>
</tr>
<tr>
<td>(\sigma_1 - \sigma_P)</td>
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<td>3.59</td>
<td>14.11</td>
<td>15.64</td>
<td>16.47</td>
</tr>
<tr>
<td></td>
<td>(1.06)</td>
<td>(.56)</td>
<td>(2.36)*</td>
<td>(2.43)*</td>
<td>(2.43)*</td>
</tr>
<tr>
<td>(\text{IS}*(\sigma_1 - \sigma_P))</td>
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<td>-.029</td>
<td>-.064</td>
<td>-.107</td>
<td>-.097</td>
</tr>
<tr>
<td></td>
<td>(1.61)</td>
<td>(.67)</td>
<td>(1.68)</td>
<td>(4.03)*</td>
<td>(2.36)*</td>
</tr>
<tr>
<td>(\text{IS}^2*(\sigma_1 - \sigma_P))</td>
<td>.9x10^{-4}</td>
<td>.6x10^{-4}</td>
<td>.6x10^{-4}</td>
<td>1.7x10^{-4}</td>
<td>1.5x10^{-4}</td>
</tr>
<tr>
<td></td>
<td>(1.76)</td>
<td>(.73)</td>
<td>(.84)</td>
<td>(3.46)</td>
<td>(2.18)*</td>
</tr>
<tr>
<td>(A*(\sigma_1 - \sigma_P))</td>
<td>.67</td>
<td>-.34</td>
<td>-.40</td>
<td>-.26</td>
<td>.35</td>
</tr>
<tr>
<td></td>
<td>(.99)</td>
<td>(.17)</td>
<td>(1.12)</td>
<td>(.98)</td>
<td>(.12)</td>
</tr>
<tr>
<td>(\text{IS}^2*(\sigma_1 - \sigma_P))</td>
<td>.46</td>
<td>.26</td>
<td>.19</td>
<td>.19</td>
<td>.35</td>
</tr>
<tr>
<td></td>
<td>(1.58)</td>
<td>(.89)</td>
<td>(.72)</td>
<td>(.11)</td>
<td>(1.46)</td>
</tr>
<tr>
<td>(\text{IS}^2*(\sigma_1 - \sigma_P))</td>
<td>.0015</td>
<td>-.0029</td>
<td>.0045</td>
<td>-.0048</td>
<td>-.0065</td>
</tr>
<tr>
<td></td>
<td>(.26)</td>
<td>(.39)</td>
<td>(.67)</td>
<td>(1.14)</td>
<td>(1.04)</td>
</tr>
<tr>
<td>County Dummies Inc.</td>
<td>Inc. Inc. Inc. Inc. Inc.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>(F-statistic)</td>
<td>(20.56)*</td>
<td>(36.13)*</td>
<td>(18.66)*</td>
<td>(21.89)*</td>
<td>(17.08)*</td>
</tr>
<tr>
<td>R²</td>
<td>.618</td>
<td>.706</td>
<td>.616</td>
<td>.616</td>
<td>.537</td>
</tr>
</tbody>
</table>

Summary Statistics:

\[
\frac{\Delta Y}{\Delta (\mu_1 - \mu_P)} = \frac{\Delta Y}{\Delta (\sigma_1 - \sigma_P)} = \frac{\Delta Y}{\Delta A} = \frac{\Delta Y}{\Delta (IS)}
\]

\[
\begin{align*}
\Delta Y & = 9.66 & 4.02 & 3.04 & .16 & 4.32 \\
&(3.44)* & (1.87)* & (1.07) & (.07) & (1.10) \\
\Delta Y & = -2.25 & -.40 & .63 & 1.06 & -.26 \\
&(2.77)* & (.39) & (.51) & (.99) & (.16) \\
\Delta Y & = .94 & .13 & .15 & .05 & .16 \\
&(2.86)* & (.76) & (.68) & (.25) & (.62) \\
\Delta Y & = .0004 & .0057 & .0065 & .0063 & .0049 \\
&(1.12) & (3.09)* & (2.43)* & (2.51)* & (1.55) \\
\end{align*}
\]

(t-statistics in parentheses)

* significant at 5% level
**TABLE II**

<table>
<thead>
<tr>
<th>Professionals and Managers</th>
<th>Clerical and Sales</th>
<th>Craftsmen</th>
<th>Operatives and Laborers</th>
<th>Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>((\mu_1 - \mu_F))</td>
<td>13.25</td>
<td>-6.16</td>
<td>-10.25</td>
<td>-12.45</td>
</tr>
<tr>
<td>(\text{(1.94)})</td>
<td>(\text{(1.29)})</td>
<td>(\text{(1.89)})</td>
<td>(\text{(2.41)*})</td>
<td>(\text{(1.18)})</td>
</tr>
<tr>
<td>((\text{IS})^2(\mu_1 - \mu_F))</td>
<td>-0.016</td>
<td>-0.040</td>
<td>0.052</td>
<td>0.050</td>
</tr>
<tr>
<td>(\text{(0.87)})</td>
<td>(\text{(3.41)*})</td>
<td>(\text{(4.37)*})</td>
<td>(\text{(3.40)*})</td>
<td>(\text{(1.89)})</td>
</tr>
<tr>
<td>((\sigma_1 - \sigma_F))</td>
<td>-2.26</td>
<td>3.59</td>
<td>14.69</td>
<td>15.82</td>
</tr>
<tr>
<td>(\text{(1.00)})</td>
<td>(\text{(5.8)})</td>
<td>(\text{(2.48)*})</td>
<td>(\text{(3.50)*})</td>
<td>(\text{(2.09)*})</td>
</tr>
<tr>
<td>((\text{IS})^2(\sigma_1 - \sigma_F))</td>
<td>-0.016</td>
<td>-0.032</td>
<td>-0.089</td>
<td>-0.093</td>
</tr>
<tr>
<td>(\text{(1.36)})</td>
<td>(\text{(0.89)})</td>
<td>(\text{(2.86)*})</td>
<td>(\text{(4.28)*})</td>
<td>(\text{(2.81)*})</td>
</tr>
<tr>
<td>((\text{IS})^2(\text{IS} - \text{IS}))</td>
<td>(6 \times 10^{-4})</td>
<td>(6 \times 10^{-4})</td>
<td>(1.2 \times 10^{-4})</td>
<td>(1.3 \times 10^{-4})</td>
</tr>
<tr>
<td>(\text{(2.10)*})</td>
<td>(\text{(1.10)})</td>
<td>(\text{(2.86)*})</td>
<td>(\text{(4.41)*})</td>
<td>(\text{(2.89)*})</td>
</tr>
</tbody>
</table>

County Dummies

<table>
<thead>
<tr>
<th>County Dummies</th>
<th>(F-statistic)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Inc.</td>
</tr>
<tr>
<td></td>
<td>(\text{(21.60)*})</td>
</tr>
</tbody>
</table>

\(R^2\) \hspace{1cm} .608 \hspace{1cm} .704 \hspace{1cm} .613 \hspace{1cm} .612 \hspace{1cm} .529

**Summary Statistics:**

\[
\frac{\partial Y}{\partial (\mu_1 - \mu_F)} =
\begin{align*}
\text{9.19} & \quad \text{(3.25)*} \\
\text{4.08} & \quad \text{(1.93)*} \\
\text{2.90} & \quad \text{(1.02)} \\
\text{.28} & \quad \text{(.12)} \\
\text{16.04} & \quad \text{(1.89)*}
\end{align*}
\]

\[
\frac{\partial Y}{\partial (\sigma_1 - \sigma_F)} =
\begin{align*}
\text{-2.10} & \quad \text{(2.58)*} \\
\text{-38} & \quad \text{(0.38)} \\
\text{.76} & \quad \text{(.62)} \\
\text{1.06} & \quad \text{(1.00)} \\
\text{-.36} & \quad \text{(.22)}
\end{align*}
\]

\[
\frac{\partial Y}{\partial (\text{IS})} =
\begin{align*}
\text{.0072} & \quad \text{(4.16)*} \\
\text{.0069} & \quad \text{(5.76)*} \\
\text{.0077} & \quad \text{(3.83)*} \\
\text{.0070} & \quad \text{(3.35)*} \\
\text{.0054} & \quad \text{(2.04)*}
\end{align*}
\]

\((t\text{-statistics in parentheses})\)

* significant at 5% level
TABLE III

<p>| Professionals and | Clerical and |Operatives and | |</p>
<table>
<thead>
<tr>
<th>Managers</th>
<th>Sales</th>
<th>Craftsmen</th>
<th>Laborers</th>
<th>Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(\mu_1 - \mu_F)$</td>
<td>-0.57</td>
<td>-2.85</td>
<td>3.08</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>(0.12)</td>
<td>(1.30)</td>
<td>(1.02)</td>
<td>(0.12)</td>
</tr>
<tr>
<td>$A^*(\mu_1 - \mu_F)$</td>
<td>2.98</td>
<td>2.96</td>
<td>2.50</td>
<td>2.55</td>
</tr>
<tr>
<td></td>
<td>(2.25)*</td>
<td>(4.62)*</td>
<td>(3.13)*</td>
<td>(2.36)*</td>
</tr>
<tr>
<td>$(\sigma_1 - \sigma_F)$</td>
<td>-1.52</td>
<td>0.90</td>
<td>1.36</td>
<td>-0.08</td>
</tr>
<tr>
<td></td>
<td>(1.07)</td>
<td>(0.46)</td>
<td>(0.60)</td>
<td>(0.04)</td>
</tr>
<tr>
<td>$A^*(\sigma_1 - \sigma_F)$</td>
<td>0.21</td>
<td>-1.82</td>
<td>-2.81</td>
<td>-1.50</td>
</tr>
<tr>
<td></td>
<td>(0.37)</td>
<td>(1.42)</td>
<td>(2.08)*</td>
<td>(1.45)</td>
</tr>
<tr>
<td>$A^2*(\sigma_1 - \sigma_F)$</td>
<td>-0.15</td>
<td>0.37</td>
<td>0.47</td>
<td>0.24</td>
</tr>
<tr>
<td></td>
<td>(1.13)</td>
<td>(1.72)</td>
<td>(2.19)*</td>
<td>(1.59)</td>
</tr>
<tr>
<td>County Dummies</td>
<td>Inc.</td>
<td>Inc.</td>
<td>Inc.</td>
<td>Inc.</td>
</tr>
<tr>
<td>(F-statistic)</td>
<td>(21.20)*</td>
<td>(35.48)*</td>
<td>(18.72)*</td>
<td>(20.91)*</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.607</td>
<td>0.697</td>
<td>0.607</td>
<td>0.598</td>
</tr>
</tbody>
</table>

Summary Statistics:

| \[\frac{\partial y}{\partial (\mu_1 - \mu_F)}\] | 6.50 | 4.17 | 9.02 | 6.44 | 6.18 |
| | (2.74)* | (3.49)* | (5.55)* | (4.55)* | (2.59)* |
| \[\frac{\partial y}{\partial (\sigma_1 - \sigma_F)}\] | -1.95 | -1.09 | -2.36 | -2.13 | -1.84 |
| | (3.13)* | (2.56)* | (4.21)* | (4.62)* | (2.43)* |
| \[\frac{\partial y}{\partial A}\] | 0.85 | 0.56 | 0.44 | 0.26 | 0.40 |
| | (4.68)* | (5.17)* | (2.74)* | (1.81)* | (2.36)* |

(t-statistics in parentheses)

* significant at 5% level
disappointed in the results overall, we are pleased that the professional/
managerial slope was most negative. This occupation (together with farmers)
contains the greatest uncertainty of earning power.

Partial effects with respect to assets and school quality were also
computed. All of these slopes were positive. We interpret this to imply
that increasing wealth and school quality induce young men to enter all five
occupations at the expense of farming. One of the asset slopes and three
out of five school quality slopes were statistically significant.

The set of 22 county dummy variables were jointly significant in each
of the five equations. Although not shown in Table I, the orderings of the
individual county dummies were quite consistent across occupational groups.
As one would expect, most young men enter nonagricultural occupations in the
suburban Anne Arundel, Baltimore, Montgomery, and Prince George's counties.
Young men are more likely to enter agriculture in the rural Garret, Kent,
and Queen Anne's counties.

We were concerned that our results may have been clouded by intercor-
relation between assets and school quality. Although having only a .714
correlation themselves, we feared that the seven interaction terms shown in
Table I might be causing some of the same problems that we experienced when
we entered so many skewness terms. In order to test this, Table II presents
regression results when the asset variable was deleted. The school quality
variable is deleted in Table III.

The results in Table II do not differ greatly from Table I's results.
The mean and variance slopes are very similar in magnitude and significance.
However, the slopes with respect to "IS" do increase in magnitude and
significance. This appears to confirm that assets and school quality are competing with each other for explanatory power. The "IS" variable is statistically significant in all five equations, rather than three as in Table I.

The results in Table III are considerably better in the sense that the variance slope has the expected negative sign and is significant all five times. The slope with respect to mean income is positive and significant all five times. This formulation provides clear support for the hypothesis that variances (and uncertainty) do matter in occupational choices. It is less clear why we didn't get equally good results in Table II, if collinearity between assets and school quality was the culprit. As a final observation from Table III, we note that the slope with respect to assets was significant four out of five times.

The next step is to test the sensitivity of our results to the use of our more sophisticated occupational income expectations data. These Hansen-Sargent weighted average income series are substituted in Tables IV-VI for the simple averages of Tables I-III. No other changes in the regressions were introduced.

The results are very similar, although there is a slight deterioration in terms of consistency of signs and statistical significance. Only five out of the forty-six correct signs switched to an incorrect sign. In no case (for Tables I-VI) was an incorrect sign statistically significant. In Table VI, which controls only for assets, all slopes had the expected signs.
### TABLE IV

<table>
<thead>
<tr>
<th>Professionals and Managers</th>
<th>Clerical and Sales</th>
<th>Craftsmen</th>
<th>Laborers</th>
<th>Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>( (\mu_1 - \mu_p) )</td>
<td>.12</td>
<td>-1.60</td>
<td>.32</td>
<td>9.85</td>
</tr>
<tr>
<td></td>
<td>(.06)</td>
<td>(1.54)</td>
<td>(.22)</td>
<td>(2.45)*</td>
</tr>
<tr>
<td>( (IS)*(\mu_1 - \mu_p) )</td>
<td>-.001</td>
<td>.008</td>
<td>.003</td>
<td>-.044</td>
</tr>
<tr>
<td></td>
<td>(.12)</td>
<td>(1.54)</td>
<td>(.64)</td>
<td>(2.11)*</td>
</tr>
<tr>
<td>( A*(\mu_1 - \mu_p) )</td>
<td>.53</td>
<td>.35</td>
<td>.26</td>
<td>.32</td>
</tr>
<tr>
<td></td>
<td>(1.76)</td>
<td>(.94)</td>
<td>(.81)</td>
<td>(.20)</td>
</tr>
<tr>
<td>( (\sigma_1 - \sigma_p) )</td>
<td>2.37</td>
<td>.75</td>
<td>1.58</td>
<td>.02</td>
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<td>(.75)</td>
<td>(.94)</td>
<td>(1.51)</td>
<td>(.01)</td>
</tr>
<tr>
<td>( (IS)*(\sigma_1 - \sigma_p) )</td>
<td>-.013</td>
<td>-.002</td>
<td>-.004</td>
<td>.001</td>
</tr>
<tr>
<td></td>
<td>(1.51)</td>
<td>(.36)</td>
<td>(.58)</td>
<td>(.08)</td>
</tr>
<tr>
<td>( (IS)^2*(\sigma_1 - \sigma_p) )</td>
<td>2.3x10^-5</td>
<td>.5x10^-5</td>
<td>-2x10^-5</td>
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</tr>
<tr>
<td></td>
<td>(1.32)</td>
<td>(.64)</td>
<td>(.13)</td>
<td>(.22)</td>
</tr>
<tr>
<td>( A*(\sigma_1 - \sigma_p) )</td>
<td>-.198</td>
<td>-.44</td>
<td>-.66</td>
<td>-.28</td>
</tr>
<tr>
<td></td>
<td>(.38)</td>
<td>(1.58)</td>
<td>(1.72)</td>
<td>(.51)</td>
</tr>
<tr>
<td>( A^2*(\sigma_1 - \sigma_p) )</td>
<td>.088</td>
<td>.091</td>
<td>.046</td>
<td>.021</td>
</tr>
<tr>
<td></td>
<td>(1.53)</td>
<td>(3.19)*</td>
<td>(1.13)</td>
<td>(.66)</td>
</tr>
<tr>
<td>( (IS)<em>A</em>(\sigma_1 - \sigma_p) )</td>
<td>-.0011</td>
<td>-.0004</td>
<td>.0012</td>
<td>.0004</td>
</tr>
<tr>
<td></td>
<td>(.72)</td>
<td>(.57)</td>
<td>(1.23)</td>
<td>(.46)</td>
</tr>
<tr>
<td>County Dummies</td>
<td>Inc.</td>
<td>Inc.</td>
<td>Inc.</td>
<td>Inc.</td>
</tr>
<tr>
<td>(F-statistic)</td>
<td>(20.47)*</td>
<td>(37.89)*</td>
<td>(18.84)*</td>
<td>(22.48)*</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>.615</td>
<td>.716</td>
<td>.620</td>
<td>.631</td>
</tr>
</tbody>
</table>

**Summary statistics:**

\[
\frac{3\bar{Y}}{\sigma(\mu_1 - \mu_p)} = 1.23, \quad 1.17, \quad 1.66, \quad -.49, \quad 1.25
\]

\[
(1.06), \quad (1.62), \quad (1.92)*, \quad (.44), \quad (1.09)
\]

\[
\frac{3\bar{Y}}{\sigma(\sigma_1 - \sigma_p)} = -.055, \quad -.040, \quad .026, \quad .093, \quad .10
\]

\[
(.18), \quad (.23), \quad (.11), \quad (.38), \quad (.36)
\]

\[
\frac{3\bar{Y}}{A} = .59, \quad .34, \quad .32, \quad .00, \quad .38
\]

\[
(1.96)*, \quad (1.82)*, \quad (1.33), \quad (0.00), \quad (1.29)
\]

\[
\frac{3\bar{Y}}{\bar{A}(IS)} = -.0003, \quad .0035, \quad .0047, \quad .0074, \quad .0077
\]

\[
(.07), \quad (1.33), \quad (1.24), \quad (3.48)*, \quad (1.79)*
\]

*(t-statistics in parentheses)*

* significant at 5% level
<table>
<thead>
<tr>
<th></th>
<th>Professionals and Managers</th>
<th>Clerical and Sales</th>
<th>Craftsmen</th>
<th>Operatives and Laborers</th>
<th>Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>$(\mu_1 - \mu_F)$</td>
<td>.77</td>
<td>-1.47</td>
<td>.38</td>
<td>8.27</td>
<td>-3.08</td>
</tr>
<tr>
<td></td>
<td>(.38)</td>
<td>(1.42)</td>
<td>(.27)</td>
<td>(2.16)*</td>
<td>(.95)</td>
</tr>
<tr>
<td>$(IS)(\mu_1 - \mu_F)$</td>
<td>.0003</td>
<td>.011</td>
<td>.005</td>
<td>-.035</td>
<td>.017</td>
</tr>
<tr>
<td></td>
<td>(.74)</td>
<td>(2.95)*</td>
<td>(1.43)</td>
<td>(2.82)*</td>
<td>(1.47)</td>
</tr>
<tr>
<td>$(\sigma_1 - \sigma_F)$</td>
<td>1.98</td>
<td>.56</td>
<td>1.66</td>
<td>.49</td>
<td>2.16</td>
</tr>
<tr>
<td></td>
<td>(1.49)</td>
<td>(.72)</td>
<td>(1.62)</td>
<td>(.42)</td>
<td>(2.25)*</td>
</tr>
<tr>
<td>$(IS)(\sigma_1 - \sigma_F)$</td>
<td>-.013</td>
<td>-.004</td>
<td>-.010</td>
<td>-.004</td>
<td>-.013</td>
</tr>
<tr>
<td></td>
<td>(1.86)</td>
<td>(1.72)</td>
<td>(1.98)</td>
<td>(.76)</td>
<td>(3.03)</td>
</tr>
<tr>
<td>$(IS)^2(\sigma_1 - \sigma_F)$</td>
<td>1.8x10^-5</td>
<td>8x10^-5</td>
<td>1.4x10^-5</td>
<td>1.0x10^-5</td>
<td>1.6x10^-5</td>
</tr>
<tr>
<td></td>
<td>(1.76)</td>
<td>(1.56)</td>
<td>(2.02)*</td>
<td>(1.79)</td>
<td>(3.06)*</td>
</tr>
<tr>
<td>County Dummies</td>
<td>Inc.</td>
<td>Inc.</td>
<td>Inc.</td>
<td>Inc.</td>
<td>Inc.</td>
</tr>
<tr>
<td>(F-statistic)</td>
<td>(22.57)*</td>
<td>(39.69)*</td>
<td>(22.42)*</td>
<td>(23.30)*</td>
<td>(17.37)*</td>
</tr>
<tr>
<td>$R^2$</td>
<td>.609</td>
<td>.709</td>
<td>.615</td>
<td>.628</td>
<td>.538</td>
</tr>
</tbody>
</table>

Summary statistics:

$$\frac{3\gamma}{\delta(\mu_1 - \mu_F)}$$

1.54                      1.25                      1.60                      -.69                      4.36

(1.34)                     (1.74)*                    (1.87)*                    (.62)                     (1.47)

$$\frac{3\gamma}{\delta(\sigma_1 - \sigma_F)}$$

-.11                      -.04                      .06                       .16                       .05

(.39)                      (.25)                      (.24)                      (.67)                      (.18)

$$\frac{3\gamma}{\delta(IS)}$$

.0035                      .0059                      .0072                      .0077                      .0091

(.81)                      (2.53)*                    (2.14)*                    (4.17)*                    (2.47)*

(t-statistics in parentheses)

* significant at 5% level
TABLE VI

<table>
<thead>
<tr>
<th></th>
<th>Professionals and Managers</th>
<th>Clerical and Sales</th>
<th>Craftsmen</th>
<th>Operatives and Laborers</th>
<th>Service</th>
</tr>
</thead>
<tbody>
<tr>
<td>( (\mu_1 - \mu_F) )</td>
<td>.92</td>
<td>-.70</td>
<td>1.92</td>
<td>9.31</td>
<td>-.09</td>
</tr>
<tr>
<td></td>
<td>(.77)</td>
<td>(.93)</td>
<td>(2.19)*</td>
<td>(4.13)*</td>
<td>(.04)</td>
</tr>
<tr>
<td>( \Lambda^*(\mu_1 - \mu_F) )</td>
<td>.40</td>
<td>.75</td>
<td>.35</td>
<td>-3.46</td>
<td>.77</td>
</tr>
<tr>
<td></td>
<td>(1.60)</td>
<td>(2.95)*</td>
<td>(1.47)</td>
<td>(4.16)*</td>
<td>(.86)</td>
</tr>
<tr>
<td>( (\sigma_1 - \sigma_F) )</td>
<td>.69</td>
<td>.66</td>
<td>.22</td>
<td>-1.16</td>
<td>1.13</td>
</tr>
<tr>
<td></td>
<td>(1.32)</td>
<td>(2.08)*</td>
<td>(.51)</td>
<td>(2.22)*</td>
<td>(2.27)*</td>
</tr>
<tr>
<td>( \Lambda^*(\sigma_1 - \sigma_F) )</td>
<td>-.67</td>
<td>-.56</td>
<td>-.41</td>
<td>.28</td>
<td>-.86</td>
</tr>
<tr>
<td></td>
<td>(2.12)*</td>
<td>(3.17)*</td>
<td>(1.69)</td>
<td>(1.05)</td>
<td>(3.39)*</td>
</tr>
<tr>
<td>( \Lambda^2*(\sigma_1 - \sigma_F) )</td>
<td>.10</td>
<td>.09</td>
<td>.07</td>
<td>.02</td>
<td>.11</td>
</tr>
<tr>
<td></td>
<td>(1.98)*</td>
<td>(3.65)*</td>
<td>(1.97)*</td>
<td>(.75)</td>
<td>(3.22)*</td>
</tr>
<tr>
<td>County Dummies (F-statistic)</td>
<td>Inc.</td>
<td>Inc.</td>
<td>Inc.</td>
<td>Inc.</td>
<td>Inc.</td>
</tr>
<tr>
<td></td>
<td>(21.59)*</td>
<td>(38.90)*</td>
<td>(19.37)*</td>
<td>(21.63)*</td>
<td>(17.60)*</td>
</tr>
<tr>
<td>( R^2 )</td>
<td>.612</td>
<td>.713</td>
<td>.616</td>
<td>.610</td>
<td>.540</td>
</tr>
</tbody>
</table>

Summary statistics:

\[
\frac{3\bar{Y}}{3(\mu_1 - \mu_F)}
\]

1.87  1.09  2.75  1.10  1.74

\[
(2.41)* (2.44)* (5.30)* (1.45) (2.05)*
\]

\[
\frac{3\bar{Y}}{3(\sigma_1 - \sigma_F)}
\]

-.29  -.10  -.32  -.37  -.20

\[
(2.37)* (1.36) (3.35)* (3.27)* (1.56)
\]

\[
\frac{3\bar{Y}}{3\Lambda}
\]

.46  .55  .33  .26  .74

\[
(1.79)* (3.67)* (1.64) (2.42)* (3.11)*
\]

(t-statistics in parentheses)

* significant at 5% level
In Tables I-III, thirty-one slope coefficients were significant at the 5% level. Introduction of the Hansen-Sargent series created a net loss of nine significant slope coefficients. Despite this effect, eleven out of fifteen coefficients remained statistically significant in Table VI.

VI. Structural Estimation of the Occupational Choice Model

Recall that equation (14) is:

\[
(14) \log \left( \frac{p_i}{p_n} \right) = \gamma (\delta_0 + \delta_1 I_i S_1 + \delta_2 A_1) (u_i) - (\delta_0 + \delta_1 n I_i S_1 + \delta_2 A_1)(u_i)
\]

\[+ \delta_2 n A_1 (u_i) - \frac{\gamma^2}{2} [ (\delta_0 + \delta_1 I_i S_1 + \delta_2 A_1)^2 (\sigma_i) - (\delta_0 + \delta_1 I_i S_1 + \delta_2 n A_1)^2 (\sigma_i) ] + \epsilon_i + \xi_i \]

We assume that the \( \epsilon_i \) have a multivariate normal distribution with uncorrelated disturbances across time and space. The covariance matrix is specified as

\[E(\epsilon_i, \epsilon_j) = V \text{ for } i=j', \ t=t' \]

\[= 0 \text{ otherwise} \]

The log-likelihood function over \( T \) time periods, \( c \) counties and \( m \) equations is

\[
(22) \sum_{i=1}^{c} \log \left( \frac{L_i(\theta)}{2\pi} \right) = -\left( cmT/2 \right) \log(2\pi) - \left( cm/2 \right) \log \det (V)
\]

\[- \left( 1/2 \right) \text{Tr} \left( V^{-1} \sum_{i=1}^{c} M_i(\varepsilon) \right) \]

where \( M_i(\varepsilon) \) is the \( m \) by \( m \) moment matrix of errors for the individual \( i \) equal to \( \epsilon_{it} \epsilon_{it}' \), \( \theta \) is the vector of parameters \( (\gamma, \delta_0, \delta_1, \delta_2)' \), and \( V \) is the related covariance matrix of the errors. Following Bard (1974), we maximize (22) with respect to the unknown \( V \) to derive the maximum likelihood estimator of \( V \). The resulting estimated covariance matrix has the form
Replacing \( V \) with \( \tilde{V} \) in (22) yields the concentrated likelihood function

\[
L(\theta) = -(\ln Tc/2)[1 + \log(2\pi) - \log(Tc)] - (cT/2)\log \left| \sum_{i=1}^{n} M_i(\epsilon) \right|
\]

(23) may be maximized with respect to the vector of parameters to obtain the maximum likelihood estimates of the structural parameters.

The vector \( \theta \) can be specified in a number of ways. Since \( \gamma \) is positive if occupational choice is subject to risk-averse behavior, we fix it to equal .25. Other values of \( \gamma \) did not yield different values of the likelihood function, nor did they change the qualitative results for the other parameters. Once \( \gamma \) is fixed, we can identify the remaining parameters.

Our least restrictive parameter vector is thus \( \theta_1 = [\delta_{0i}, \delta_{1i}, \delta_{21}]'\), \( i = 1, 2, \ldots, 6 \). Recall that \( \delta_{0i} \) is the constant, occupation i-specific level of human capital, \( \delta_{1i} \) is the occupation i-specific level of human capital production parameter for school quality, and \( \delta_{21} \) is the occupation i-specific production parameter for family assets. To test if school quality and family assets have occupation-specific effects on human capital, we consider two subsets of \( \theta_1 \), \( \theta_2 = [\delta_{0i}, \bar{\delta}_1, \delta_{21}]' \) and \( \theta'_2 = [\delta_{0i}, \delta_{1i}, \bar{\delta}_2]' \), \( i = 1, 2, \ldots, 6 \). The first restricts that school quality have the same productivity across all occupations, and the second restricts that family assets have the same productivity across all occupations. Letting \( L(\cdot) \) be the likelihood value for the relevant parameter vector, \( 2(L(\theta_1) - L(\theta_2)) \) and \( 2(L(\theta_1) - L(\theta'_2)) \) will both be distributed chi-square with five degrees of freedom.
The maximum likelihood estimation was performed using the GQOPT2 program. The results from the least restrictive parameter set \( \theta_1 \) are contained in Table VII. Most of the production parameters are positive, indicating that school quality and assets are productive in producing occupation-specific human capital. The exception is in the farming occupation, where both family assets and school quality reduce human capital, and the professional occupation where school quality is unproductive. School quality is most productive for the operative occupation, followed by the craft, service and clerical occupations. Family assets are most productive for the service occupation, followed by the operative, clerical, professional and craft occupations. The null hypotheses that either school quality or family assets did not enter into the human capital production process were rejected at the .005 level of confidence.

Table VIII contains the results from the restricted parameter vectors \( \theta_2 \) and \( \theta'_2 \). The results are quite similar to those of Table VII, with the exception that only one production parameter, the effect of school quality in the farming occupation, remains negative. This result leads to the speculation that the negative signs in Table VII may result from the multicollinearity problems discussed above.

The estimated coefficients in Table VIII are quite similar across the two equations. The school quality and family asset equations have nearly identical effects. In both systems human capital inputs are most important in the service, craft, clerical and operative occupations with smaller effects in the professional occupation.

To test if school quality and family assets have occupation-specific effects as well as general effects, we compare the likelihood values in
<table>
<thead>
<tr>
<th>Parameter</th>
<th>Estimate</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\delta_0$ professional</td>
<td>-4.00</td>
</tr>
<tr>
<td>$\delta_0$ operative</td>
<td>-10.26</td>
</tr>
<tr>
<td>$\delta_0$ clerical</td>
<td>-3.93</td>
</tr>
<tr>
<td>$\delta_0$ craft</td>
<td>-4.41</td>
</tr>
<tr>
<td>$\delta_0$ service</td>
<td>-9.64</td>
</tr>
<tr>
<td>$\delta_0$ farming</td>
<td>1.88</td>
</tr>
<tr>
<td>$\delta_1$ professional</td>
<td>-0.556</td>
</tr>
<tr>
<td>$\delta_1$ operative</td>
<td>1.222</td>
</tr>
<tr>
<td>$\delta_1$ clerical</td>
<td>0.466</td>
</tr>
<tr>
<td>$\delta_1$ craft</td>
<td>0.776</td>
</tr>
<tr>
<td>$\delta_1$ service</td>
<td>0.660</td>
</tr>
<tr>
<td>$\delta_1$ farming</td>
<td>-0.310</td>
</tr>
<tr>
<td>$\delta_2$ professional</td>
<td>2.802</td>
</tr>
<tr>
<td>$\delta_2$ operative</td>
<td>3.157</td>
</tr>
<tr>
<td>$\delta_2$ clerical</td>
<td>2.966</td>
</tr>
<tr>
<td>$\delta_2$ craft</td>
<td>2.383</td>
</tr>
<tr>
<td>$\delta_2$ service</td>
<td>4.881</td>
</tr>
<tr>
<td>$\delta_2$ farming</td>
<td>-0.6834</td>
</tr>
<tr>
<td>$\gamma^*$</td>
<td>0.25</td>
</tr>
<tr>
<td>$L(\theta)$</td>
<td>-2954.299</td>
</tr>
</tbody>
</table>

*$\gamma$ is restricted to be .25 and is not estimated.
TABLE VIII

Maximum likelihood estimates of parameter vector $\theta_2$

<table>
<thead>
<tr>
<th>Category</th>
<th>Estimate $\delta_0$</th>
<th>Category</th>
<th>Estimate $\delta_0$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Professional</td>
<td>-5.443</td>
<td>Professional</td>
<td>-4.731</td>
</tr>
<tr>
<td>Operative</td>
<td>-10.08</td>
<td>Operative</td>
<td>-10.445</td>
</tr>
<tr>
<td>Clerical</td>
<td>-4.851</td>
<td>Clerical</td>
<td>-4.536</td>
</tr>
<tr>
<td>Craft</td>
<td>-4.878</td>
<td>Craft</td>
<td>-4.753</td>
</tr>
<tr>
<td>Service</td>
<td>-11.219</td>
<td>Service</td>
<td>-9.249</td>
</tr>
<tr>
<td>Farming</td>
<td>1.947</td>
<td>Farming</td>
<td>.0495</td>
</tr>
<tr>
<td>$\delta_1$ Professional</td>
<td>1.078</td>
<td>$\delta_2$ Professional</td>
<td>2.285</td>
</tr>
<tr>
<td>Operative</td>
<td>3.677</td>
<td>$\delta_2$ Operative</td>
<td>4.156</td>
</tr>
<tr>
<td>Clerical</td>
<td>2.994</td>
<td>$\delta_2$ Clerical</td>
<td>3.378</td>
</tr>
<tr>
<td>Craft</td>
<td>2.552</td>
<td>$\delta_2$ Craft</td>
<td>3.033</td>
</tr>
<tr>
<td>Service</td>
<td>5.177</td>
<td>$\delta_2$ Service</td>
<td>5.099</td>
</tr>
<tr>
<td>Farming</td>
<td>-.855</td>
<td>$\delta_2$ Farming</td>
<td>.738</td>
</tr>
<tr>
<td>$\gamma^*$</td>
<td>.205</td>
<td>$\gamma$</td>
<td>.092</td>
</tr>
</tbody>
</table>

$L(\theta_2) = -2966.843$  
$L(\theta_2) = -2964.005$

*$\gamma$ is restricted to .25 and is not estimated.
Table VIII with that of Table VII. The critical value of the test at the .005 level of confidence is $\chi^2(5) = 16.75$. The null hypothesis that family assets are equally productive across all occupations is rejected 

$\left(2(\mathcal{L}(\theta_1) - \mathcal{L}(\theta_2)) = 19.4\right)$. This result supports the conjecture that schools and family inputs may have specific as well as general training effects.

VI. Concluding Comments

The results are extremely promising. In particular, it seems apparent that this model successfully captures occupational choice behavior in a human capital framework where the valuation of human capital is uncertain. It also appears that, by placing structure on the human capital production process, we can draw inferences about the effect of school quality or family asset differences on occupational choice. Finally, by deriving the logit specification explicitly from a structural model, we are able to interpret our parameter estimates from this logit specification.

This model can be applied to a number of other applications involving human capital investment choices under uncertainty. In particular, migration and job turnover behavior would appear to be similar to the occupational choice behavior modeled herein.
Footnotes

1. \[
\frac{dU_2}{d(h_1^*w_{2i})} = \gamma \beta_1 \exp(-\gamma h_1^*w_{2i}) > 0, \quad \frac{d^2U_2}{d(h_1^*w_{2i})^2} = -\gamma^2 \beta_1 \exp(-\gamma h_1^*w_{2i}) < 0.
\]

2. The individual's earnings per unit of human capital are not known with certainty, since the number of hours worked in period 2 is uncertain. This uncertainty becomes unimportant under two circumstances. First, if \( h_1^* \) is zero, \( \gamma h_1^*w_{2i} \) is zero, and expected utility will vary across occupations solely on the basis of the taste parameter \( \alpha_i^* \). Second, as \( Y_i^* \) approaches infinity, \( \exp(-\gamma h_1^*w_{2i}) \) approaches zero, and once again expected utility will vary across occupations solely on the basis of taste. Therefore, taste will dictate choice of occupation to the greatest extent for either the least educated or the most wealthy segments of the population.

3. Because utility is ordinal rather than cardinal, we can expand the Taylor series about any point, \(-\gamma h_1^*\). If \( E(U_{2i}) > E(U_{2j}) \), \( i \neq j \), evaluated at a point \(-\gamma h_1^*\), then \( E(U_{2i}) > E(U_{2j}) \) evaluated at any point \( \{-\gamma h_1^*\} \neq \{-\gamma h_1^*\} \).

We are implicitly assuming that whatever the distribution of the wage per unit of human capital in occupation \( i \), the distribution is such that it has a moment generating function.

4. Although our economic agent observes all moments of the distribution, in practice, the econometrician may only observe some finite number of these moments. Thus, the econometrician can only approximate the agent's expected
utility with error. We assume that this approximation error is random across time and space.

For a description of the properties of the Weibull distribution, see Domencich and McFadden (1975).

In fact, $h_1$ can be specified as $\log(h_1)$ or $\exp(h_1)$, so long as the measure of human capital is linear in the parameters of the production function.

See, for example, Hogg and Craig (1970), p. 80.

This assumption allows us to introduce the expected future path of the distribution of earnings per unit of human capital into the occupational choice decision. Thus, expected future moments are included as well as current moments.

We found that most of the time paths of the first and second moments were characterized by second-order autoregressive processes. Thus, the values for $\mu_{w_2}$ and $\sigma_{w_2}$ converge to

$$\mu_{w_2} = \frac{1}{1 - \rho \alpha_1 - \rho^2 \alpha_2} \mu_t + \frac{\alpha_2 \rho}{1 - \rho \alpha_1 - \rho^2 \alpha_2} \mu_{t-1}$$

$$\sigma_{w_2} = \frac{1}{1 - \rho \delta_1 - \rho^2 \delta_2} \sigma_t + \frac{\delta_2 \rho}{1 - \rho \delta_1 - \rho^2 \delta_2} \sigma_{t-1}$$

as $T$ gets very large.

The anihilation operator restricts the powers of $L$ to be positive.

A seventh category in the published data is titled "Protective Service Workers Including Armed Forces." A substantial number of young men are in this classification, especially during the Korean War years and the late 1950s. Some decline in the early 1960s and a rise in the late 1960s suggests that variation in this category is largely exogenous, changing with
national defense requirements and draft calls. Hence, we exclude these men from our data set. Our employed population is best interpreted as the employed civilian population.

12 An alternative measure was computed dividing by the number "attending" rather than "belonging". The two proxies had a correlation of .996 and made little difference in our results.

13 The data relate to total income from all sources of males age 14 and over having some work experience during the calendar year. Some small but unavoidable distortion in the distribution of sales, service, and agricultural incomes (occupations where teens are concentrated) may result from the inclusion of teenagers working part-year and part-time.

14 Midpoints of each interval were used in conjunction with the interval frequencies. The open-ended upper tail interval of those earning more than $25,000 was set at $30,000 throughout the period. Although this may slightly bias down the estimated moments, any error is believed to be minor in that such a small proportion of men earned more than $25,000 during this period. Fortunately, the other published intervals were highly consistent 1951-1970. All moments were estimated in nominal terms and then adjusted for the price level.

15 Data on educational attainment is available for 1952, 1957, 1959, 1962, and 1964-1970 on a consistent basis for males 18 years of age and older. Moments of the distribution for missing years were estimated by interpolation, which should be reasonable since the distributions only change slowly.

16 This procedure was not feasible for adjusting the skewness of incomes. Unfortunately, our measure of educational skewness (defined as two times
mean minus median divided by the standard deviation) was almost always negative so that we could not take logarithms. In those cases, some alternative regression methods were attempted, although this point becomes minor in that skewness was later dropped from the analysis.

17 Somewhat more formally, if \( \frac{\mu_{w}}{h_{2}} = \frac{\mu_{w}}{h_{1}} \) and

1. \( \ln \mu_{w} = \ln h + \ln \mu_{w} \), then assuming that human capital is composed of two components, age \((G)\) and schooling \((S)\) as follows:

2. \( h = \gamma G^\alpha S^\beta \), \( \gamma \), \( \alpha \), \( \beta \) parameters. Taking expected values (assuming \( G \) is a constant),

3. \( \mu_{h} = E(h) = E(\gamma G^\alpha S^\beta) = \gamma G^\alpha E(S^\beta) \) taking logarithms,

4. \( \ln \mu_{h} = \ln \gamma G^\alpha + \ln [E(S^\beta)] \)
   \[ = \ln \gamma G^\alpha + \beta \ln [E(S)] \]
   \[ = a + \beta \ln [M] \]

and substituting (iv) into (i), we get

5. \( \ln \mu_{w} = a + \beta \ln [M] + \epsilon \)

where \( \epsilon = \ln w_{2} \).

18 To be precise, the 1959 and 1969 values were set at the Census of Population "relatives" and a trend line was computed by interpolation. The "non-trending" index values were then multiplied by this trend line in order to obtain values for the intermediate years. One complication was that only 5 income intervals were provided in the 1970 census data, whereas 11 intervals were published in 1960. In order to compute trends, we aggregated the 1960 data into 5 (comparable) income intervals so as to minimize any estimation bias due to this effect.
Although the non-trended series was used, some of the series (farmers, in particular) exhibited a trending pattern. As a result, time and time squared were included in the autocorrelation regressions.

Three observations were deleted because there were zero farmers/farm laborers, and we could not divide by zero in constructing the dependent variable.

The critical value at the .005 level of confidence is $\chi^2(6) = 18.6$. The test statistic obtained by restricting $\delta_{1i} = 0$ for all $i$ was 19.5. The test statistic obtained by restricting $\delta_{2i} = 0$ for all $i$ was 27.9.
REFERENCES


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## TABLE A-1
Summary Statistics

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<th>Variance</th>
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### TABLE A-2

**Correlation Coefficients**

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Note: The table above represents the correlation coefficients between various variables. Each cell indicates the correlation coefficient between the row variable and the column variable. The values range from -1 to 1, with 1 indicating a perfect positive correlation, -1 indicating a perfect negative correlation, and 0 indicating no correlation.
### TABLE A-3

**CORRELATION COEFFICIENTS**

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FIGURE 1
INCOME MEANS

Professionals/Managers
Craftsmen
Clerical Sales
Operatives Laborers
Services
Farmers and Farm laborers
FIGURE 2
INCOME VARIANCE

Professionals
- Managers

Farmers
Farm Laborers

Clerical
Sales

Craftsmen

Operatives
-Laborers

- Services-