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CENTER DISCUSSION PAPER NO. 549

METHODS FOR ESTIMATING VALUE OF TIME
WITH AN APPLICATION TO THE PHILIPPINES

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Note: Center Discussion Papers are preliminary materials circulated to stimulate discussion and critical comments. References in publications to Discussion Papers should be cleared with the authors to protect the tentative character of these papers.

In writing this paper, I benefitted immensely from comments by T. Paul Schultz and John Strauss. The ideas and exposition also were improved by suggestions from seminar participants at Yale University. I wrote an earlier version while I was a National Institutes of Health postdoctoral fellow at the Economic Growth Center, Yale University.

Abstract

A theoretical and empirical innovation of the household production model is the appearance of wages in demand functions. However, creating reasonable econometric instruments for wages is difficult under any circumstances and is particularly troublesome when using data from developing countries, where the prevalence of nonmarket production means that few observations on wages are usually available. In this paper, alternative strategies for creating value-of-time instruments are discussed in detail and, using cross-sectional data from the Philippines, competing methods are implemented and compared. The major finding is that the theory and procedure of correcting for selection bias can substantially improve wage instruments.

INTRODUCTION

Demand equations derived from the household production model--which focuses on productive activities in the home, human capital, the opportunity cost of time, and prices as determinants of household resource allocation decisions--have been used increasingly to explain household behavior in developing countries. The model's emphasis on time allocation and the price of time, a quantity and a price that are absent from standard consumer demand models, is a theoretical innovation that has improved our understanding of many family-level decisions that have a distinct economic content, including those pertaining to fertility, health, nutrition, labor supply, education, migration, and agricultural production. However, that innovation is also the source of an empirical burden: the need to create reasonable measures of time prices.

Unlike the price of homogeneous commodities, the price of time is intimately linked to individual human characteristics and is therefore difficult to measure as a purely exogenous variable. Using individual wage rates to measure the value of time, which would capture the heterogeneous nature of labor, is made difficult by the fact that wages are generally observed only for people who work in market jobs. In developing countries, where there are high levels of self employment, wide use of unpaid family labor in income-producing activities, and substantial reliance on home production for consumption needs, wages are rarely observed. Many strategies have been followed to estimate wages in the face of this problem, including reliance on community wage rates, simple and complex regressions to create wage instruments, estimates of both wage offers and reservation wages, and begging the question altogether by dropping value-of-time variables.

One of the advantages of regression methods is that they facilitate

detection and correction of selection bias, which is potentially a serious problem in samples for which few wage observations are available. There is little regard in the literature, however, for statistical problems that are inherent in the selection-correction procedure and almost no knowledge of the effect of selection bias on wage predictions and the performance of wage instruments in demand equations.

This paper discusses alternative methods for estimating the value of time for married women in a developing country context, bringing together different strands of the literature that help to structure the exercise. A model is outlined in the next section that demonstrates why wage estimates are necessary and how theory helps to specify the solution to the wage-estimating problem. Then the literature is examined to point out how empirical solutions differ. Finally, wage and earnings estimates are presented for a sample of Philippine women, and conclusions are drawn about competing wage estimation approaches.

MODEL

The form of a typical but simplified household production model and its implications are illustrated below. Suppose a household maximizes the following concave utility function:

$$U = U(C, L_i) \tag{1}$$

C = a vector of home-produced commodities, such as nutrition, health, child quality, or number of children

L_i = leisure of the i th household member ($i=1, \dots, n$)
 $C, L_i \geq 0$

Each commodity is produced in the home using purchases of market goods and household members' time, with positive but decreasing marginal productivity of

inputs:

$$C = f(X, TH_i; E) \quad (2)$$

X = a vector of market-purchased goods used to produce each element in C , per unit of C

TH_i = home time of the i th household member used to produce each C , per unit of C

E = fixed components of household technology such as skills or home capital goods

Leisure is modeled as a decreasing function of the two alternatives:

$$L_i = h(TM_i, TH_i; T) \quad (3)$$

TM_i = market work of the i th family member

T_i = total time available

$h' < 0$

The household is limited in its goods purchases by pecuniary and time constraints that define the standard linear full-income constraint:

$$(p'X + \sum w_i TH_i)C + \sum w_i L_i \leq Y + \sum w_i (TM_i + TH_i) \quad (4)$$

p = price vector of market inputs

Y = nonlabor household income

w_i = market wage rate of i th family member

The household's problem is therefore to maximize the Lagrangean:

$$\ell = U[f(X, TH; E), h(TM, TH; T)] + \lambda[Y + \sum w_i (TH + TM) - (p'X + \sum w_i TH)C - wL] \quad (5)$$

in which, for notational simplicity, the subscripts have been dropped. The

maximization problem yields the following first-order conditions:

$$\frac{\partial \ell}{\partial X} = \frac{\partial U}{\partial f} \frac{\partial f}{\partial X} - \lambda pC \leq 0, \quad X \geq 0, \quad \text{and} \quad X \left[\frac{\partial \ell}{\partial X} \right] = 0 \quad (6)$$

$$\frac{\partial \ell}{\partial TM} = \frac{\partial U}{\partial h} \frac{\partial h}{\partial TM} + \lambda w \leq 0, \quad TM \geq 0, \quad \text{and} \quad TM \left[\frac{\partial \ell}{\partial TM} \right] = 0 \quad (7)$$

$$\frac{\partial \ell}{\partial TH} = \frac{\partial U}{\partial f} \frac{\partial f}{\partial TH} + \frac{\partial U}{\partial h} \frac{\partial h}{\partial TH} + \lambda w - \lambda wC \leq 0, \quad TH \geq 0, \quad \text{and} \quad TH \left[\frac{\partial \ell}{\partial TH} \right] = 0 \quad (8)$$

$$\frac{\partial \ell}{\partial \lambda} = Y + \sum w_i (TH + TM) - (p'X + \sum w_i TH)C - wL \leq 0, \quad \lambda \geq 0, \quad \text{and} \quad \lambda \left[\frac{\partial \ell}{\partial \lambda} \right] = 0 \quad (9)$$

Because the utility function is assumed to be concave in its arguments, the second-order conditions for a maximum are satisfied, and optimal values of the

endogenous variables can be expressed as implicit functions of the exogenous variables. The following reduced-form demand equations for goods, time, and commodities can be written:

$$\bar{X} = \bar{X}(p, w, Y; E) \quad (10)$$

$$\overline{TM}_i = \overline{TM}_i(p, w, Y; E) \quad (11)$$

$$\overline{TH}_i = \overline{TH}_i(p, w, Y; E) \quad (12)$$

$$\bar{C} = \bar{C}(p, w, Y; E) \quad (13)$$

In this exposition, knowledge of T, TM, and TH at the optimum for each family member fixes the residual demand for leisure (L). Equations (10) through (13) imply that values of the endogenous variables are jointly determined by prices, wages, nonlabor income, and household technology.

In empirical work, any one of these reduced-form equations can be estimated independently, with unbiased coefficients. However, any such undertaking requires exogenous values for prices (p) and wages (w). Community prices and wages are natural choices because they are arguably determined in the market at a level that is beyond the influence of household decisions. However, if analysts desire wage estimates that more explicitly take into account individual characteristics, a set of problems is created that can be illustrated using the first-order conditions.

One or more family members are likely to work at home and not in the market, so there will be many situations in which a corner solution is chosen for equation (7) but an interior solution is chosen for equation (8), giving rise to the following inequality:

$$\frac{\frac{\partial U}{\partial h} \frac{\partial h}{\partial TM}}{w} \leq \frac{\frac{\partial U}{\partial f} \frac{\partial f}{\partial TH} + \frac{\partial U}{\partial h} \frac{\partial h}{\partial TH}}{w(1 - C)} \quad (14)$$

At the most obvious level, equation (14) indicates that the decision to stay out of the labor market is not a random event. For the person who works

at home but not in the market, the value to the household of the last hour devoted to home work is greater than the value of devoting that hour to market work. If equation (14) is slightly modified so that the "price" of work is W_o , the wage offer, and the "price" of work at home is W_r , the reservation wage, we have the following:

$$\frac{\frac{\partial U}{\partial h} \frac{\partial h}{\partial TM}}{W_o} \leq \frac{\frac{\partial U}{\partial f} \frac{\partial f}{\partial TH} + \frac{\partial U}{\partial h} \frac{\partial h}{\partial TH}}{W_r(1-C)} \quad (14a)$$

For given utility and production functions, there is some combination of a wage offer and a reservation wage at which the two sides of the equation are equal and the household is just indifferent to this member's moving from $TM=0$ to working in the market. For that person and anyone who works in the market, $W_r = W_o = w$. For an individual who does not work in the market, equation (14a) implies that $W_r > W_o$.

The value of w necessary to equalize the two sides depends on both the utility and production functions. The marginal valuation of hours devoted to market work depends only on the labor-leisure choice (the utility function), while the marginal valuation of nonmarket work depends on both the labor-leisure choice and marginal productivity in nonmarket activities. Variables that affect productivity at home, such as land and business holdings, do not affect productivity in the market.²

To extend this line of reasoning to wages, the implication is that market wage offers, which are determined by characteristics that affect market productivity, are not affected by a number of variables that do, however,

² This approach assumes, of course, that productivity in the market and productivity in the home are not both affected by the same variables. The efficiency wage literature is concerned directly with this issue. See Bliss and Stern (1978) for the conditions under which such an assumption would hold.

affect reservation wages through the marginal productivity of nonmarket work. This distinction can be pursued in empirical work to create restrictions which allow identification of the coefficients in the wage offer and reservation wage equations.

STRATEGIES FOR ESTIMATING THE OPPORTUNITY COST OF TIME

Researchers cannot avoid predicting wages, even if most of the sample reports wages. Errors in measurement, unobserved on-the-job training effects, and faulty observations on hours can all be transmitted to the wage variable, requiring some sort of instrumental variable estimation technique if wages are to be used as independent variables in other regressions (Schultz, 1980).

Consequently, a decision must be made about creating proxies for w . Following is a list of alternative strategies with citations for studies using each technique:

- (1) Use a community wage rate obtained from another survey, create a community wage by averaging reported wages from the sample being used, or ask a community leader to estimate a market wage rate (Khandker, 1985).
- (2) Drop those observations for which the wage is missing (Grossman, 1972).
- (3) Instead of using a wage variable, use highly correlated variables (age, race, ethnicity, education) as substitutes for wages in a reduced form demand equation (Akin et al., 1985).
- (4) Estimate a wage function for people who report wages, then use the estimated coefficients to create a wage instrument for the entire sample (Smith, 1981; McCabe and Rosenzweig, 1976).
- (5) Realizing that observations on wages are not randomly missing, use the procedure in (4) after correcting for possible sample selection bias (Anderson, 1982).

The first alternative (a community wage rate) has some desirable

features. It is exogenous to the household and, relative to a predicted wage, collinearity between the wage variable and other household- or individual-level regressors is probably reduced. For historical series, community or national wage averages trace general movements in wage rates (Schultz, 1985).

The principal drawback of the community wage strategy is that it discards information about the effects on wages of individuals' human capital investments, such as training and education. A common argument in favor of community wages is that the only alternative to work at home for rural women is work as agricultural laborers, so a community-level agricultural wage adequately captures the opportunity cost to them of working at home. However, a number of studies (Rosenzweig, 1984; Anderson and Leiserson, 1980) have demonstrated that labor markets in rural areas of low-income countries are well developed and that the return to human capital investments can be quite high. It is unlikely under any circumstances that highly educated women face the same wage offers as uneducated women or that they are equally productive outside the market.

The second approach (dropping observations with missing wages) is difficult to defend. If only a few observations are eliminated and wage data are randomly missing, the loss of information only reduces the efficiency of parameter estimates. If observations are discarded nonrandomly, which would be the expectation given the theory outlined above, the sample is transformed from a censored sample into a truncated sample.

The third option (using proxies) at least retains the whole sample, but it is difficult to imagine a proxy for wages that should not itself appear in demand equations. The fourth approach (OLS without a selection correction)

has been used in the past to avoid problems caused by the other procedures. However, the literature on selection bias has established that if those who work in the market are systematically different from nonworkers in terms of unmeasured characteristics that affect wages (such as innate ability or desire to participate in the market), this procedure generates inconsistent parameter estimates for the wage equation.

Through the utility maximization process discussed earlier, households or individuals formulate a reservation wage (W_r), which is the wage at which they are indifferent between supplying hours to the market or staying at home. Similarly, people face a demand signal, or wage offer (W_o), from the market. The supply and demand functions are shown below as linear equations (Heckman, 1974, 1976, 1979; Schultz, 1980):

$$W_o = \alpha_0 + \alpha_1 H + \alpha_2' Z + \varepsilon_1 \quad (15)$$

$$W_r = \beta_0 + \beta_1 H + \beta_2' X + \varepsilon_2 \quad (16)$$

H \equiv hours of market work,
 Z, X \equiv overlapping vectors of explanatory variables, and
 $\varepsilon_1, \varepsilon_2$ \equiv jointly normal errors with zero mean and covariance matrix:

$$\begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}$$

If $\alpha_1=0$ and hours adjust to equate W_o and W_r , the probability of working is given by $F(Q)$, where F is the normal distribution function and Q is shown below.³

³ The assumption that $\alpha_1=0$ simply means that the household or individual faces a perfectly elastic demand curve for labor hours--the usual assumption that any number of hours can be supplied at the market wage. The following definitions apply to equation (17):

$$\varepsilon = (\varepsilon_2 - \varepsilon_1) / \sigma_\varepsilon$$

$$Q = \frac{\alpha_0 + \alpha_2'Z - \beta_0 - \beta_2'X}{\sigma_\varepsilon} \quad (17)$$

The population means of the two dependent variables are given by the following equations:

$$E(W_o | \varepsilon \leq Q) = \alpha_0 + \alpha_2'Z - \sigma_{1\varepsilon} \left[\frac{f(Q)}{F(Q)} \right] + V_1 \quad (18)$$

$$E(W_r | \varepsilon > Q) = \beta_0 + \beta_1H + \beta_2'X + \sigma_{2\varepsilon} \left[\frac{f(Q)}{1-F(Q)} \right] + V_2 \quad (19)$$

V_1 and V_2 are residuals with $E(V_i)=0$. The $f(Q)/F(Q)$ and $f(Q)/1-F(Q)$ terms correct the residuals for truncation, and their coefficients measure the covariance between the errors in the participation equation and the respective wage equation. Using the fourth (simple least squares) procedure to create wage estimates fails to incorporate the selection term in equation (18), wrongly forcing $\sigma_{1\varepsilon}=0$ and thus biasing the remaining coefficients.

Using the fifth (selection-correcting) procedure to estimate wages has many desirable characteristics. It allows wage offers to be affected by human capital variables, retains the whole sample, creates unbiased parameter estimates in the wage function, allows estimation of reservation wages, and avoids combining wage effects into other regressors. Equation (18) can be estimated by maximum likelihood; alternatively, Heckman and others have developed two-step procedures that are widely used.⁴

$$\sigma_\varepsilon^2 = \text{Var}(\varepsilon_2 - \varepsilon_1) = \sigma_1^2 + \sigma_2^2 - 2\sigma_{12}$$

$$\sigma_{2\varepsilon} = \text{Cov}(\varepsilon_2, \varepsilon) = (\sigma_2^2 - \sigma_{12})/\sigma_\varepsilon$$

$$\sigma_{1\varepsilon} = \text{Cov}(\varepsilon_1, \varepsilon) = (\sigma_{12} - \sigma_1^2)/\sigma_\varepsilon$$

⁴ The two-step probit (based on the normal error distribution) has been adapted to a logit-based model (Weibull distribution) by Hay (1980) and Lee (1983), and to the linear probability model (uniform distribution) by Olsen (1980a). In another paper, Olsen (1980b) offers a statistically inconsistent least squares approximation to the Heckman maximum likelihood method. In

Equations (18) and (19) provide unbiased estimates of the population means of W_o and W_r , but these means are conditional on working and not working, respectively. How can a researcher predict a single opportunity cost of time for everyone? One obvious strategy is to predict a market wage for workers from equation (18) and a reservation wage for nonworkers from equation (19), conditional on prior knowledge about whether they work in the market. A second and more common approach is to predict a market wage for everyone from equation (18), but that procedure creates a wage estimate for nonworkers conditional on their working in the market, which is counterfactual.

A third strategy is to predict an unconditional wage offer for the whole sample, which is an average weighted by the probability of working in the market:

$$E(W_o) = [E(W_o | \varepsilon \leq Q)]F(Q) + [E(W_o | \varepsilon > Q)][1-F(Q)], \text{ or} \quad (20)$$

$$E(W_o) = \alpha_0 F(Q) + \alpha_2' Z[F(Q)] - \sigma_{1\varepsilon} f(Q). \quad (21)$$

Equation (21) is based on the fact that the observed wage offer is zero for nonworkers; hence, its expectation is zero (Maddala, 1983).

STATISTICAL COMPLICATIONS ASSOCIATED WITH SELECTION BIAS CORRECTIONS

Substantial research has been devoted to detecting selectivity bias and to technical aspects of the various correction procedures. A gap exists, however, between theorists, who have been concerned with consistency and efficiency of parameter estimates, and users of the selection model, who have

still another paper, Olsen (1982) demonstrates a maximum likelihood estimator that allows for skewed convolutions of the normal distribution. For applications of the probit procedure see Maddala (1983). For an example of the logit procedure see Blau (1981); for the Olsen linear probability procedure see Pitt and Rosenzweig (1985); and for the Olsen nonnormal estimator see Anderson (1982).

been primarily interested in prediction. Two shortcomings of the literature are a lack of regard for econometric problems caused by the selection correction method and little knowledge of its impact on wage predictions. For researchers interested in simply creating a wage instrument, it is an open question whether correcting for selectivity bias has a strong enough effect on wage predictions to make the associated statistical costs worthwhile. The remainder of this section is devoted to discussing statistical problems that may be introduced by the selection correction.

Validity of Selection Rules

In any sample, values of the dependent variable may be missing due to nonreporting by individuals who participate in the labor market. There is a strong temptation to suspect that other selection rules cause nonreporting and to compensate for them in order to fill in the missing values. Unless there is a theoretical reason to expect nonreporting to be systematically determined, however, the OLS residuals should not be truncated. The potential for identification problems and multicollinearity resulting from multiple selection criteria (discussed below) dictate that trivial selection rules be avoided.⁵

Nonnormality of Errors

It is so common in research to assume that random variables are drawn

⁵ One study (Behrman et al., 1980) estimates wages for a sample of Nicaraguan women, 46 percent of whom participate in the labor force. About 8 percent of the workers do not report wages. The authors posit a sequential decision-making process in which the women first decide whether to work, then decide whether to report earnings. However, no theoretical reasoning justifies why failure to report earnings is other than a random event, so it is difficult to justify the choice of variables that explain reporting. None of the coefficients for variables chosen to explain nonreporting is significantly different from zero, and selection on reporting is not statistically significant in the wage equations.

from normal populations that few analysts are likely to be troubled by the assumption that the errors in equations (15) and (16) have a bivariate normal distribution. However, detection of selection bias actually depends on a truly normal error distribution appearing to be nonnormal because of truncation. If the errors appear to be nonnormal because they actually come from a nonnormal distribution, selection bias may be inferred when it is not the problem (Olsen, 1982).

The recent literature has explored the sensitivity of the selection correction to nonnormality. Goldberger (1983), through a simulation exercise, shows that the Tobit model is sensitive to departures from normality to a degree that is positively related to the amount of truncation. Olsen (1982) tests for selectivity bias in wage estimates for teenagers under the alternative assumptions of normal and nonnormal errors. He finds that the underlying distribution is probably nonnormal but that selection is statistically significant--and the estimated coefficients similar--under either assumption about the errors.

Anderson (1982) describes similar results for wage estimates for a sample of Guatemalan men. She compares wage instruments estimated three different ways--least squares, selection correction assuming normally distributed errors, and selection correction under the assumption of nonnormal errors. The estimated wage elasticities in a fertility demand equation are nearly identical for wage instruments created using either least squares or selection-corrected coefficients, but correcting for nonnormal errors increases the elasticity nearly four-fold. Anderson concludes that selection bias is less important for her sample than are nonnormal errors. The Olsen and Anderson studies suggest that nonnormal errors may not strongly affect the

detection of selection bias or estimated coefficients, but Anderson's findings show that the effects may not be entirely neutral when the point is to create wage instruments in demand equations.

Identification

This is a simultaneous equations model, yet little attention is usually paid to identification. If the parameters of the offered wage equation (18) are estimated using the working subsample, the selection effect can be identified if the matrix $[Z \quad \hat{f}(Q)/\hat{F}(Q)]$ is full rank. This result is guaranteed if the participation equation is estimated by probit or logit because even if Z and the determinants of \hat{Q} are identical, $\hat{f}(Q)/\hat{F}(Q)$ is a nonlinear function of \hat{Q} and will not be perfectly collinear with Z . Researchers often rely on the nonlinearities implicit in the estimation method to identify the wage coefficients.⁶ If the full model represented by equations (18) and (19) is estimated, recovering the coefficients of the reservation wage equation requires that at least one variable in Z be excluded from X . Alternatively, $\sigma_{12}=0$ can be assumed. Any approach contains an element of arbitrariness.

Multicollinearity

Because $[\hat{f}(Q)/\hat{F}(Q)]$ is a nonlinear function of variables that appear in both Z and X , if nonlinear terms are incorrectly excluded from Z (such as the square of experience), their nonlinear effects may be picked up by the selection term in the wage equation (Olsen 1980a). The coefficient on the selection term might therefore be incorrectly judged to be statistically

⁶ In the linear probability model, however, identification requires that at least one regressor appearing in the participation equation be excluded from the wage offer equation (Olsen, 1980a). If there is more than one selection criterion and the criteria are sequential, identification requires additional exclusionary restrictions (Behrman et al., 1980).

significant when it is actually picking up the effects of excluded nonlinear terms. Moreover, as the presence of nonlinear and interaction terms in Z increases, the potential for multicollinearity between those regressors and the selection correction term rises Olsen (1980a). Multiple selection criteria exacerbate this problem; the same variables are likely to enter the different selection rules and the wage equation.

Two-Stage versus Full Maximum Likelihood

Although the popular two-step probit/OLS selection correction procedure produces consistent estimates of the coefficients of the wage equation, the efficiency gains in using the full information maximum likelihood alternative can be substantial, and other problems (such as incorrect t-statistics) are avoided (Wales and Woodland 1980). Does efficiency matter? The answer from Monte Carlo experiments seems to be resoundingly positive. Under conditions most likely to prevail in empirical work--considerable overlap among exogenous variables in the selection criterion and those in the wage equation--the precision of the two-step estimator declines sharply. The maximum likelihood estimator, in contrast, is insensitive to this type of correlation if there is selection bias. In addition, its precision increases as the covariance between ϵ_1 and ϵ_2 in equations 15 and 16 goes up, which is what we are trying to measure (Nelson 1984). The more serious is the selectivity problem, the more important efficiency becomes, so the two-step estimator is least desirable under exactly the conditions that prompt its use.

This review suggests that while the problems caused by not correcting for selectivity when it actually exists are well understood, the complications resulting from the correction itself may also be serious. The performance of different estimating procedures in creating wage instruments is consequently

an important consideration.

ESTIMATION

The goal of the empirical work is to implement and evaluate the various wage estimation methods using a single set of data. The data come from the first panel of the Bicol Multipurpose Survey, which includes 1,903 households and their 12,000 residents in the Bicol region of the Philippines (Popkin and Roco, 1979). The sample is reduced for this work to 1,688 households (89 percent of the total) for which both husband and wife were present in 1978.

There are three elements of the economic environment that cause problems for creating value-of-time estimates. One element is diversity of human capital formation and employment opportunities. In the Bicol sample, 78 percent of the married women had a primary education or less, 10 percent had done some high school work, and 12 percent had completed high school (half of whom--6 percent--had gone on to college). This dichotomy between a mass of women with little schooling and a small number of highly educated women is reflected in the working subsample's occupations. About 78 percent were employed in low-skilled jobs (petty trading, handicraft-making, and farm labor) for which wage offers might be adequately approximated by a community-level agricultural wage, while 8 percent worked as school teachers or in administrative and clerical positions. A community or agricultural wage would not capture offered wages for these "outliers" with substantial schooling and modern sector jobs, nor would it capture differences in productivity at home that are due to variation in human capital.

A second element is diversity of economic activities. In industrialized economies, employment patterns can be specified in terms of particular jobs or

professions. In the Bicol region, as in other rural economies, there is generally little specialization. Three-fifths of the sample households were agricultural in 1977, but almost all households, whether farm or not, raised livestock and poultry. Approximately 32 percent were engaged in two or more separate economic activities (such as farming and trading), not counting wage jobs.

The large variety of economic activities causes problems for both the researcher and the women. The researcher must sift out of this complex information a summary measure of their opportunity cost of time. The women, who may be engaged in several different economic activities over a year's time--as paid laborers, unpaid family workers, and unpaid but income-seeking entrepreneurs--must give reasonable answers to a field worker who asks whether they have an occupation, how much they earn, and how many hours they work.

The third environmental element is the large proportion of the sample (42 percent) who considered themselves to be primarily housewives. Those women were engaged in productive work that was not traded and therefore not valued in the market; consequently, no information is reported on their value of time or hours of work. In fact, if those who did not work and those who worked but did not report earnings are combined, earnings and wage observations are missing for 70 percent of the women.

Creating a Community Wage Variable

Although the Bicol survey does not contain community-level wage data, it does contain three different variables that can be used to create agricultural wage averages:

- (1) What farmers paid per day for hired workers,
- (2) What farmers estimated as the replacement cost per day for each family member who worked on the farm, and

(3) Daily wage rates for people who worked as farm laborers.

Averages are calculated across crops for each farmer, then these numbers are averaged across farmers within communities,⁷ development zones, or provinces. Table 1 contains community wage averages for this sample.⁸

Table 1 about here

Within each category of worker (men, women, and children), community averages vary substantially by calculation method. Although in farm work we might expect men to be paid the most, women somewhat less, and children least, this ordering is not maintained across all calculations. There is, however, close agreement between the average wage farmers reported paying hired workers for cultivation (the top group of numbers in the table) and average estimated replacement cost for family workers (the third group of numbers). The standard deviations for these two calculations are also similar and relatively small. For these reasons and because of relatively large sample sizes, "estimated replacement cost for family workers" is the most likely choice for a community wage variable. Even so, 11 percent of the barangays have missing values for women, and for the other 89 percent of the communities, wage estimates are based on an average of only about six women each. The average daily wage for women in this sample is estimated to be 5.1 pesos per day by this measure.

⁷ The survey contains 100 communities, 20 development zones, and 3 provinces. Each community contains about 20 sample households.

⁸ Additional difficulties become obvious when these calculations are undertaken. Farmers pay different wages for different crops, they pay differentially for cultivating relative to harvesting, and they use different payment methods. Rice cultivators are generally paid by the day while harvester/threshers are paid a share of the harvest.

Specifying the Wage Function

Equations (15) and (16) require specification of the determinants of the wage offer, Z , and the reservation wage, X . Table 2 contains a list of the variables chosen for analysis.

Table 2 about here

Wage offer. The wage offer is a Mincer-type equation, where the estimated coefficients measure the realized rate of return to human capital investments in schooling and experience. The standard proxy for experience, age minus education minus 6, is used because it is an exogenous measure of potential work experience. The linear and quadratic terms allow for a positive but diminishing return to additional years of experience. Education enters in the standard linear form as a proxy for human capital investments in schooling (it is also, of course, an element in the experience calculation).

Variables are also included in the wage offer equation to control for available opportunities. City residence measures availability of market work in the modern wage sector, which is concentrated in cities, and should have a positive effect on wage offers. Travel time from house to town center controls for differences in infrastructure development.

Reservation wage. City residence is excluded from the reservation wage equation partially to help identify the coefficients but also because differing labor market conditions in urban and rural areas do not affect reservation wages or home productivity. Transport time to the municipal center is included because additional time required for traveling to carry out home duties (such as marketing) should raise reservation wages (and lower participation).

"Husband's wage" should also appear as a regressor because if the wife is a secondary worker, her husband's wage will raise her reservation wage. There are so few observations on men's wages for the same reasons that there are few observations on women's wages that the determinants of the husband's offered wage--experience and education--are included directly. Husband's experience and education should have positive effects on reservation wages and negative effects on participation.

Similarly, nonlabor income--including rents, winnings from gambling, pensions, interest, and gifts--should raise the reservation wage and reduce the probability of participating. Agricultural land and business ownership measure land and capital assets that raise productivity in nonmarket activities and reduce the probability of participating in the labor market. Asset holdings, such as the house, lot, and vehicles, are included as a proxy for accumulated or endowed wealth and should negatively affect participation.

One important exclusion from the reservation wage equation is number of children. Child-bearing and work decisions are closely related, and the number of children at home is undoubtedly connected with the reservation wage. However, child-bearing and labor market decisions simultaneously affect each other, and it is rarely possible to include exogenous variables that identify fertility from women's work decisions in a cross section. Because one important use of wage instruments is to estimate the response of fertility to wages, wages must be estimated on the basis of variables that are exogenous to both work and fertility decisions.

Labor market participation. The decision rule governing participation in the labor market is the difference between the explanatory variables in the offered and reservation wage equations (equation 17). Differentiating workers

from nonworkers is, however, a treacherous task. Women were asked their occupations, their earnings if they worked, the number of hours worked in a week, and the number of weeks worked during 1977. Of 1686 women,⁹ 978 reported that they were "...engaged in [some] type of occupational work in 1977" and named an occupation. When asked if they were paid for their work, 515 out of 978 replied "yes" and reported earnings and hours. For the 463 who worked but did not get paid, there are no reported earnings, hence no wage estimate. The possible responses are organized schematically in figure 1.

Figure 1 about here

The main issue is what to do about the 463 women who claimed to work but did not get paid. One possible strategy is to follow the Behrman et al. (1980) assumption that earnings responses are not randomly missing for working women; instead, women decide whether to participate, then those who participate decide whether to report earnings. An alternative is to more carefully define market workers. If a woman worked but received no earnings, the work was almost certainly carried out as an unpaid family laborer. It would be irrational to work without pay otherwise, so the only women who should be counted as having market jobs are those who said they worked and received remuneration. In the terminology of the rural labor supply literature, the underlying concern is with an off-farm labor supply function.

Wage Estimates

Table 3 reports results for the wage offer equation estimated three ways: full information maximum likelihood for the selection model, the two-step

⁹ The sample of 1688 women has been reduced to 1686 because of missing values for variables used in the analysis.

(probit/OLS) selection procedure, and OLS without a selection correction. The two selection-corrected estimates depend on the participation equation, which is also reported and will be discussed first.

The coefficient signs in the participation equation are generally as expected. Experience (the number of years since leaving school) has a positive but decreasing effect on participation. Woman's education raises the probability of working in the market, but husband's education (and, *pari passu*, his wage) reduces it. Although the household's nonlabor income, assets, and agricultural land holdings have the expected negative signs, they are not statistically significant. Owning a business, however, significantly reduces participation. Living in a city raises the probability of working, but distance to a town has no discernable effect.

Table 3 about here

For the MLE wage equation, experience has a positive but decreasing effect on wages that disappears for the average person in the sample at about 50 years of age. Education has a strong positive effect on wages, with an 18 percent return to a additional schooling. City residence increases wages, but transport time has a slight positive effect as well: living in a city raises the average wage, but greater isolation also has a positive effect. The covariance across errors in the wage and participation equations ($\sigma_{1\epsilon}$) is highly significant, indicating that selection bias is important for this sample.

Alternative Estimation Strategies: Effects on the Coefficients. A first test of the different estimation methods is to compare coefficients across the three wage equations reported in table 3. The main difference is that the

selection bias procedures (MLE and two-step) identify a stronger role for the independent variables than does the simple OLS equation. The absolute magnitude of the coefficients increases substantially in the consistent two-step estimate relative to the uncorrected OLS estimates; they do the same again under the efficient MLE procedure. Relative to the uncorrected OLS coefficients, for example, the slope for education increases by nearly 30 percent under MLE; for city residence, the coefficient increases by about 67 percent. The MLE estimate shows a positive and slowly declining effect of experience on wages that goes to zero at 43 years. For the two-step approach, experience has a positive effect on wages through 63 years (outside the potential range of experience for most people); but the OLS estimate detects no effect of experience on wages.

The coefficient on the inverse of Mills' ratio (from equation 10: $\sigma_{1\varepsilon}$) is 59 percent larger in the MLE estimate as compared to the two-step estimate, and it is far more precisely estimated. In the OLS estimate, the selection coefficient is of course constrained to zero. The gain in efficiency from the MLE method is important for this sample, which is consistent with Nelson's (1984) Monte Carlo experiment. The coefficients are biased toward zero in the simple OLS procedure; moreover, although selection bias is strong, it is not well detected by the two-stage method.

Interpreting the Effects of Selection. The coefficients in the MLE version suggest that if women were randomly picked out of the population and given more schooling, their offered wages would rise about a third faster than the already substantial effect estimated using a sample containing only those women who already work. Similarly, experience has a much stronger (although decreasing) effect on wage offers once selectivity bias is corrected. Women

with more education and experience are more likely to select themselves into the labor force; filtering out the participation effect isolates the true effect of schooling and experience on market wage offers for randomly chosen women.

Even though the effects of education and experience are enhanced by the selection correction, a premium is also paid for unobserved characteristics of women who are more likely to engage in market work. The sign on the selection coefficient¹⁰ indicates that for given education, experience, and residence, the mean of the offered wage is raised as the probability of participating in market work increases. This finding is consistent with the notion that women who choose to engage in market work are relatively more productive there than at home.

Table 4 about here

In table 4, the effect of the selection correction on predicted wages is made clearer. The first column of numbers shows the average of predicted wages based on the MLE wage offer estimates, but without the selection term. These numbers indicate that on the basis of experience, education, and residence only, women in the working sample would be offered, on average, .18 pesos per hour; nonparticipants would receive average offers of .12 pesos. When participation is added, the predicted wage offer goes up to 1.02 pesos and .84 pesos, respectively. For the average participant, the probability of participating alone accounts for 82 percent of the wage offer.

¹⁰ Note that in estimating the wage offer equation (18), we are estimating $-\sigma_{1\varepsilon}$ as the coefficient on the selection-correction term. If the estimated sign on this term is negative, as it is in table 3, the total effect of the selection term is positive.

Table 4 also demonstrates how the high premium paid to participation amplifies the error of estimating wage offers for nonparticipants as if they were participants. The final column, the "shadow value of time" is constructed using the wage offer for participants $[E(W_o | \varepsilon \leq Q)]$ and the reservation wage for nonparticipants $[E(W_r | \varepsilon > Q)]$.¹¹

Figure 2 about here

Figure 2 shows the distribution of the log wage, both actual and predicted, for the working subsample. The distribution of actual wage offers is relatively flat and wide. The actual distribution is not necessarily the true distribution of wage offers because there are so many possible problems with the variable, as discussed earlier. The OLS and MLE predictions have almost identical distributions, tightly grouped around the mean except for a skewed upper tail. Judging only from this illustration, it appears that for workers, correcting for selection bias has little impact on the distribution of wage predictions.

It is interesting to note that the mean of the log hourly agricultural wage (derived from a complex series of calculations based on data provided by the husband) is strikingly similar to the mean of the regression-based estimates (based on information from the wife about her own hours and earnings). As expected, however, the agricultural wage has a much tighter distribution that fails especially to capture variations at the upper end of the distribution.

¹¹ An alternative would be to construct a wage offer for nonparticipants given that they do not participate: $E(W_o | \varepsilon > Q)$.

Figure 3 about here

Figure 3 illustrates the distribution of the log of the OLS, MLE (selection-corrected), and community wage offers for the entire sample, along with the log of the "shadow" value of time. Although the similarity of the OLS, MLE, and community wage distributions is maintained for the whole sample, the predicted shadow value of time has a distribution that differs significantly from the others.

Effects of Wage Instruments on Inferences in a Demand Estimate

Table 5 contains a simple Tobit estimate of the demand for modern prenatal care by Bicolano women in 1977. The equations contain the price of prenatal visits at the closest public clinic or hospital, transport time from the woman's barangay to the same facility, the value of household assets, mother's age, urban/rural residence, mother's education, and mother's value of time. The estimated equations differ only in construction of the wage variable. The first contains no instrument for the value of time. The others contain, respectively, the community wage, OLS wage prediction, MLE wage offer, and MLE shadow value of time. A discussion of the demand model and related policy issues can be found in Akin et al. (1985); we are only interested in the effects of using different wage instruments.¹²

¹² Although identification of the wage instrument in the prenatal care equation may be arbitrary, it is clearly identified by both the nonlinear estimation procedure used to create it and by exclusionary restrictions in the prenatal demand model.

Table 5 about here

Generally speaking, adding a value-of-time instrument to the regression containing no wage has little effect on most of the coefficients, a fortuitous event in view of the assumed orthogonality of the regressors. The price of a visit and transport time both tend to reduce the number of prenatal visits. Assets and living in a city tend to increase the number of visits. Age has little perceptible effect.

The community (or agricultural) and MLE wage instruments have negative signs but are statistically insignificant. The OLS instrument is statistically significant and has a strongly negative effect on demand. Despite the similar distributions of the MLE and OLS instruments, the two methods must create substantially different wage estimates for specific women in order to have such dissimilar impacts in this regression. The final column contains the shadow wage, which is assumed to be the correct measure of the value of time. The coefficient is negative and statistically significant at the 89 percent level.

That the wage instruments are consistently negative in their effect on demand suggests that time cost is a deterrent to women when they consider whether to seek prenatal care. The positive impacts of education and urban residence on prenatal care demand tend to be underestimated in the absence of a wage instrument, which suggests that the nonwage contribution of those variables is biased downward by not accounting for the value of time.

If a value-of-time instrument were to be selected without the help of theory; that is, solely on the basis of large t-statistics, the desired sign, and large quantitative impact, the OLS instrument would be chosen in this

case. However, the correct way to measure value of time is using the shadow wage; the OLS prediction is riddled with theoretical and statistical problems that make choosing it an incorrect strategy. The OLS instrument overestimates by large magnitudes the absolute effects of both the wage and education variables. Although the community wage instrument represents a reasonable estimation strategy, the lack of variation in that variable across individuals reduces its ability to explain behavior.

CONCLUSION

There are many potential statistical problems associated with using a selection-corrected wage instrument, apart from the fact that the procedure is more complicated than possible alternatives. For the Philippine sample analyzed in this paper, however, correcting for selection bias has a number of desirable effects:

1. It provides a method to estimate wages that captures the heterogeneous nature of both home and market workers. The community wage performs poorly, as would be expected, in capturing differences across individuals in productivity.
2. Correlation across the errors in the wage offer and participation equations is strong; consequently, compensating for selection bias makes a large difference in the coefficients of the wage-estimating equation. The added efficiency of the MLE procedure improves the detection of selection bias over the two-stage procedure. Although the distribution of the resulting wage instrument does not differ substantially from the OLS instrument, its impact in the prenatal demand equation is quite different.
3. The selection-correction procedure permits calculation of reservation wages for those who do not work, which is desirable on theoretical grounds. Using reservation wages in combination with wage offers to construct a shadow value of time for women not working in the market makes a considerable difference in both the distribution of the wage instrument and its performance in estimates of the prenatal care demand equation.

One advantage of combining the household production framework with Heckman's statistical procedure is that theory helps to define restrictions that allow identification of coefficients in both the reservation and offered wage equations. This procedure helps to make sense out of missing values that might otherwise be the cause for multiple sample selection corrections. The resulting wage offer and reservation wage specifications provide a simple framework in which considerations that have a distinct development economics flavor (such as productivity outside the market) logically enter the reservation wage equation but do not also enter the wage offer equation.

The approach used in this paper is dependent on the assumption that families that work agricultural parcels or own businesses have opportunities for productive work outside the labor market that are not readily available to other households. Decisions to farm or to run a business are partially determined by offered wages; however, the relatively large fixed physical and human capital assets necessary for farming or running a business are probably safely taken as predetermined over the one-year period covered in the Bicol survey.

Although the central purpose of this paper has been to examine different methods of measuring the value of time for a sample in which only a small percentage report wages, it is worthwhile to note the high return to education estimated for the women. The rate of return to additional schooling is about 18 percent in the selection-corrected estimates of offered wages. In the reservation wage equation, the rate of return is about 5 percent. Increased schooling for women has--at least for this sample--the capability of raising their productivity both in the market and at home. This is evidence that additional investment in human capital can raise "full" incomes--the ability

to produce commodities either by buying inputs from the market or by producing them at home--even if employment opportunities in the modern sector are slow to materialize.

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Table 1. Community Agricultural Daily Wage Averages, Bicol Region, Philippines, 1978.

Method of Calculation	Men	Women	Children
Actually paid by farmer, all crops--cultivation only			
Mean (pesos per day)	5.8	5.0	4.4
Standard deviation	1.5	1.2	1.2
Number of people	777	496	129
Percent of communities	91	81	44
Actually paid by farmer, all crops--cultivation and harvesting			
Mean (pesos per day)	7.7	7.9	7.7
Standard deviation	2.1	3.1	4.4
Number of people	847	602	237
Percent of communities	92	87	65
Estimated replacement cost for family workers			
Mean (pesos per day)	6.3	5.2	4.9
Standard deviation	1.3	2.3	1.7
Number of people	1439	566	410
Percent of communities	94	89	74
Actually received by farm workers			
Mean (pesos per day)	8.2	5.7	6.6
Standard deviation	3.4	2.9	5.9
Number of people	396	42	66
Percent of communities	78	25	31

Source: Bicol Multipurpose Survey, 1978.

Note: Children are those less than 15 years old at the time of the survey; they are not included in the other columns. "Number of people" is the number contributing data to the calculation. "Percent of communities" refers to the proportion of all communities for which a community wage could be calculated. Not all communities had workers in all categories.

Table 2. Determinants of Wage Offers and Reservation Wages

Wage Offer	Reservation Wage	
	Overlapping	Identifying
Experience	Experience	Husband's experience
Experience squared	Experience squared	Husband's experience squared
Education	Education	Husband's education
City residence		Nonlabor income
Travel time to town center	Travel time to town center	Household assets
		Land area owned
		Whether family owns a business

Table 3. Labor Market Participation and Wage Estimates for Married Women, Bicol Region, Philippines, 1978.

Column Definition:	Mean (Standard Deviation)	Participate, report wage	Log wage	Log wage	Log wage	Reservation wage
Estimation method:		MLE ¹	MLE ¹	Two- Step	OLS	Calculated from MLE
Mean of dependent variable		.297	-.231	-.231	-.231	
Intercept		-.740 (3.5)	-4.243 (9.4)	-2.698 (4.6)	-1.682 (5.6)	-2.705
Experience (years)	29.0 (14.5)	.035 (2.2)	.037 (1.9)	.021 (1.3)	.012 (0.7)	-.035
Experience squared	1051.7 (980.7)	-.0005 (2.1)	-.0004 (1.4)	-.0002 (.6)	-.00001 (0.05)	.0005
Education (years)	6.5 (3.7)	.061 (4.3)	.180 (7.9)	.155 (8.7)	.139 (8.7)	.052
Husband's experience (years)	32.3 (15.0)	-.025 (1.6)				.052
Husband's experience squared	1269.3 (1098.2)	.0003 (1.5)				-.0006
Husband's education (years)	6.8 (3.8)	-.028 (2.4)				.056
Net nonlabor income/100	7.8 (39.6)	-.0004 (.3)				.0008
Household assets	6088.4 (16923)	-.000003 (1.0)				.000006
Land area owned (hectares)	.96 (2.3)	-.018 (1.2)				.037
Family owns business or trade	.38 (.49)	-.270 (5.0)				.562
Lives in city barangay	.15 (.36)	.271 (2.9)	.564 (2.8)	.329 (2.1)	.192 (1.3)	
Time to town center (min.)	51.4 (69.8)	-.0002 (.4)	.002 (1.6)	.002 (2.1)	.002 (2.2)	.002
Standard Error (σ_1)			1.860 (20.9)	1.348	1.229 (31.6)	.881 (σ_2)
Covariance (σ_{1E})			-1.685 (14.2)	-.684 (2.0)		.394 (σ_{2E})
Chi-square (Likelihood ratio test)		83.4		105.7	94.8	
F statistic				17.9	20.6	
R-square				.17	.16	
Sample size	1686	1686	1686	500	500	

Notes: The numbers in parentheses are t-statistics for the coefficient directly above except in the first column, where they are standard deviations.

¹These two columns come from a single maximum likelihood estimation for the full model.

Table 4. Average Predicted Wage Offers and Reservation Wages for Workers and Nonworkers

Type of Worker	Mean Wage Offer Without Selection Term	Mean Wage Offer With Selection Term	Mean OLS Wage Offer	Mean Shadow Value of Time
Participants in the labor market	.18	1.02	.95	1.02
Nonparticipants	.12	.84	.76	.45

Note: These numbers are estimated pesos per hour, not logs.

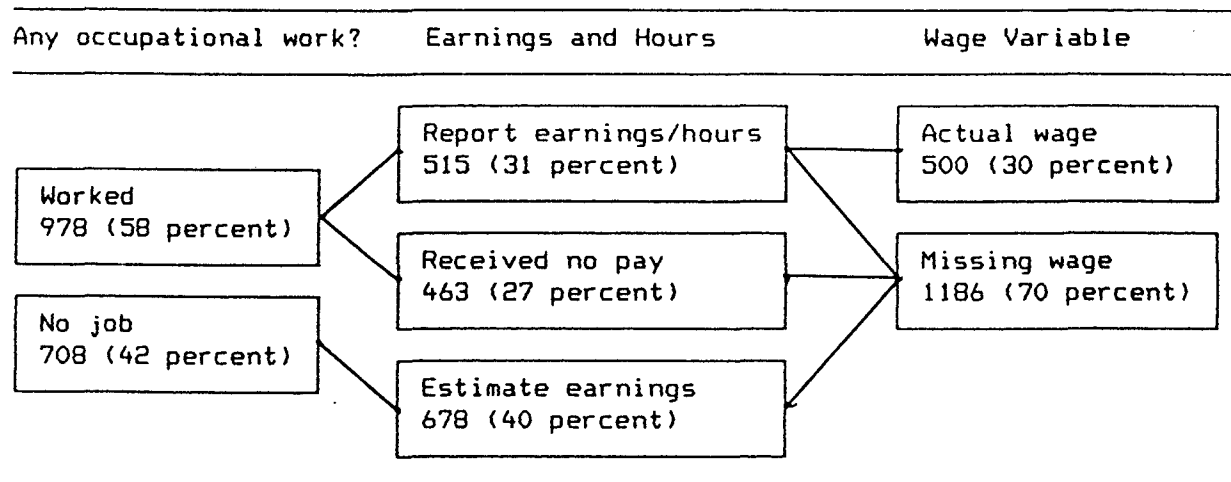
The estimates in the second column are based on equation 18, where everyone is treated as if they worked [$E(W_0 | \varepsilon \leq Q)$], which is the way wage offers are typically estimated but is counterfactual for women who are not working. We cannot say on the basis of this table that nonparticipants should be working because their mean expected wage offer (.84) is greater than their mean predicted reservation wage (.45). Such a comparison would require estimating $E(W_0 | \varepsilon > Q)$ for them.

Table 5. Tobit Estimates for Number of Modern Prenatal Visits by Married, Pregnant Women--Using Different Instruments for Value of Time. Bicol Region, Philippines, 1977.

Independent Variables	No wage	Community wage	OLS wage	MLE wage offer	MLE Shadow Value
Intercept	-3.6 (2.4)	-2.8 (1.5)	-5.4 (3.1)	-4.0 (2.5)	-4.1 (2.7)
Public clinic price	-.36 (1.7)	-0.4 (1.6)	-.28 (1.2)	-.33 (1.5)	-.32 (1.4)
Transport time to public	-.02 (2.8)	-.02 (2.9)	-.02 (1.9)	-.02 (2.5)	-.02 (2.6)
Value of household assets	.00 (2.3)	.00 (2.3)	.00 (2.7)	.00 (2.3)	.00 (2.8)
Mother's age	.03 (.74)	0.03 (.73)	.07 (1.6)	.04 (.93)	.04 (1.0)
Live in city or town	1.45 (2.3)	1.38 (2.1)	1.66 (2.6)	1.54 (2.4)	1.55 (2.4)
Mother's education	.38 (4.2)	.38 (4.2)	.78 (3.5)	.46 (3.2)	.48 (4.4)
Agricultural wage		-1.2 (.66)			
OLS wage			-3.3 (2.0)		
MLE wage offer				-.78 (.74)	
Shadow value of time					-1.2 (1.6)
Sigma	5.06 (20.9)	5.05 (20.9)	5.02 (20.9)	5.03 (20.9)	5.04 (20.9)
Sample size	507	507	507	507	507
Likelihood ratio test (Chi-square 7 = 20.3)	66.8	67.2	70.76	67.4	69.4

Note: Asymptotic t-statistics in parentheses.

Figure 1. Labor Market Participation and Earnings Responses, Bicol Multipurpose Survey, 1978.



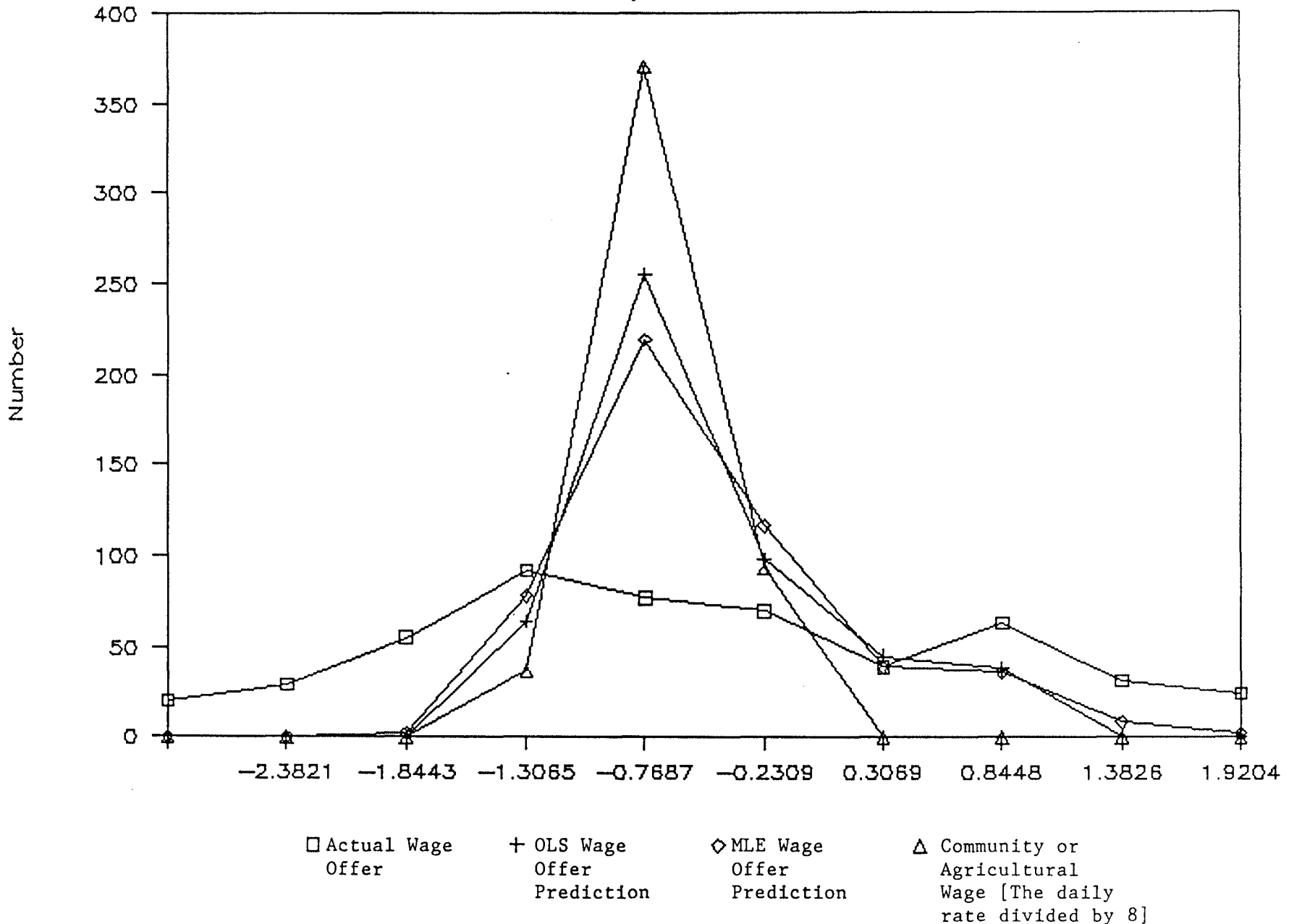
Note: Wages are calculated by dividing annual earnings by annual hours.

There are 500 nonmissing observations on wages rather than 515 because 15 women who reported earnings did not report hours.

Figure 2

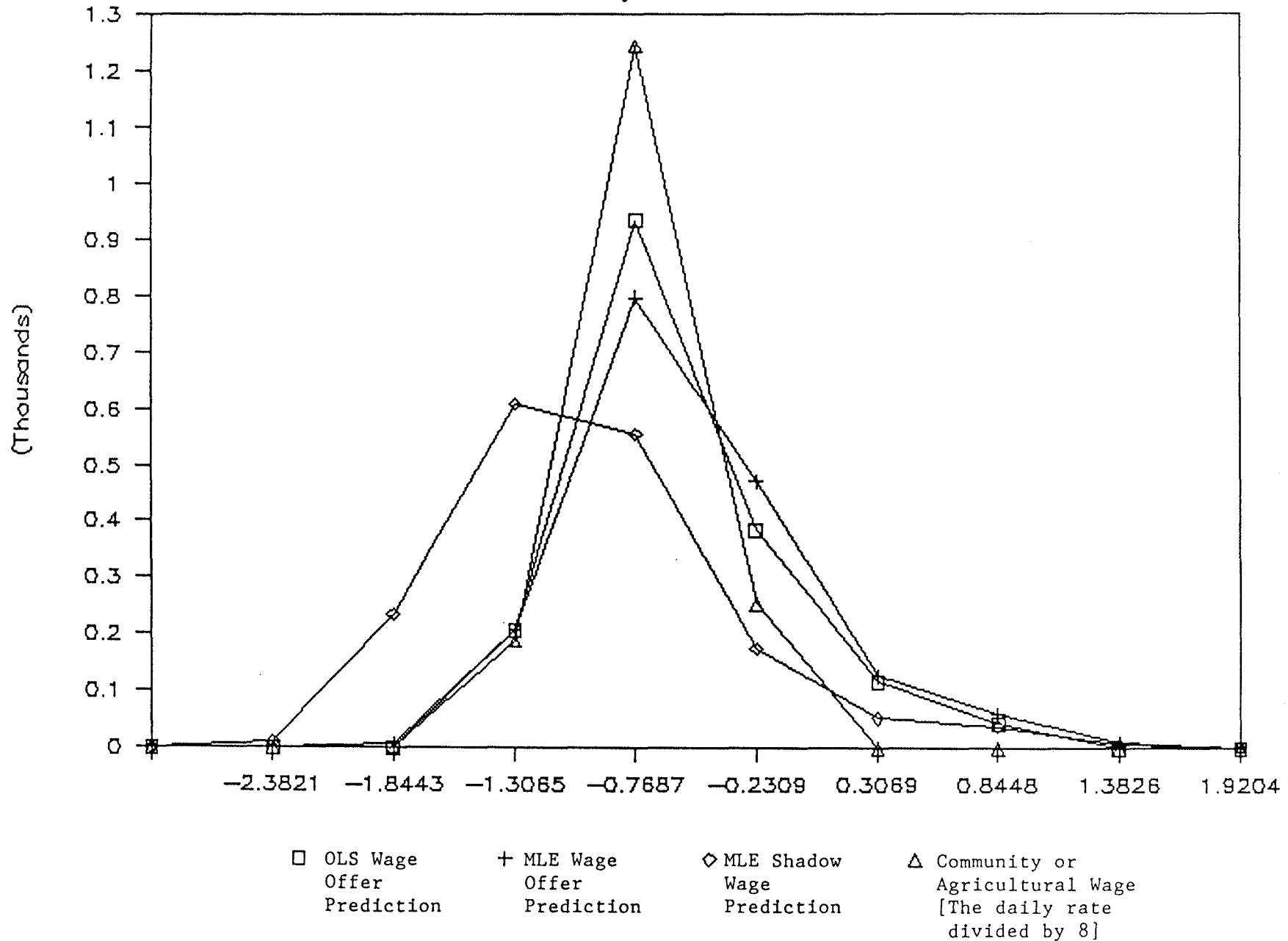
Distribution of Wage Offers for Workers

Log Values



Note: The numbers on the X-axis are the lower boundary of the relevant range, so the points on the graph lie above the left boundary rather than the midpoint.

Figure 3
 Value of Time Distribution, Full Sample
 Log Values



Note: The points on the graph lie above the lower boundary of the relevant range.