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Household Production, Time Allocation, and Welfare in Peru

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and
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Simulation exercises suggest that it is difficult to reduce inequalities in per capita consumption by changing wage and education policies.

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This paper — a product of the Women in Development Division, Population and Human Resources Department — is part of a larger effort in PRE to determine if and how women's productivity (and thus family welfare) are improved when women are given more access to education, extension, training, credit, health care, and other public resources. Copies are available free from the World Bank, 1818 H Street NW, Washington, DC 20433. Please contact Maria Abundo, room S9-125, extension 36820 (46 pages with figures and tables).

Dagsvik and Aaberge use data from the Peruvian Living Standard Survey (PLSS) to analyze (1) inequality in the distribution of income, (2) men and women's participation in the labor market and variations in their work hours, and (3) the relationship between variations in the labor supply and income inequality.

Their purpose: to study the effect of changes in education and wage rates on production, consumption, and allocation of time. For example, how many men and women would participate in wage work if education were increased? How would policy changes affect the mean level and degree of inequality in the distribution of economic welfare?

They conclude:

Entrepreneurial income is the most important source of income in rural and other urban areas. Male wage earnings contribute almost 40 percent of the household's consumption, which seems to reflect their share of total household hours of work. Women's earnings contribute about 17 percent of consumption.

But consumption and welfare are considerably less equally distributed than hours of work.

Proportional wage changes have only a small effect on behavior. Remarkably, wage increases also have little effect on the unequal distribution of per capita consumption. Even when wage rates are increased by the same amount the indirect effect is small — but the increase does moderately reduce the inequality in distribution of per capita consumption.

Dagsvik and Aaberge use a decomposing method to analyze income inequality. They use a structural neoclassical model to analyze household production, consumption, welfare, and allocation of time. They use per capita (or per adult equivalent) household income or consumption as an indicator of welfare.

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HOUSEHOLD PRODUCTION, TIME ALLOCATION, AND WELFARE IN PERU

1. Introduction

This paper uses the Peruvian Living Standard Survey (PLSS) data to analyze (a) inequality in the distribution of income, (b) labor market participation of men and women and the variations in hours of work, and (c) the relationship between variations in labor supply and income inequality. We use a decomposing method to analyze income inequality. Furthermore, we utilize a structural neo-classical model to analyze household production, consumption, time allocation and welfare. The purpose is to study the effect on production, consumption, and time allocation of changes in education and wage rates. For example, how many men and women would participate in wage work if education were increased? And how would policy changes affect the mean level and the degree of inequality in the distribution of economic welfare?

Most of the available information on economic inequality in developing countries refers to the distribution of income among earners. Although this information constitutes an important element for understanding the labor market and the related distribution of income, it is less helpful in the analysis of inequality as a welfare issue. A more relevant indicator of welfare is per capita (or per adult equivalent) household income or consumption. This paper uses this indicator in an analysis of economic inequality. Our methodological approach is based on a summary measure of inequality which is closely related to the Gini coefficient. The essential difference is that our proposed measure of inequality gives more weight than the Gini coefficient to transfers related to the very poor.

Based on the estimates of an econometric model of production, consumption and time allocation, we have examined the impact of changes in wage rates and education on economic inequality. In particular we demonstrate how female labor and education affect economic inequality among households.

The structural econometric model we develop and estimate is convenient for simulating certain types of policy experiments. It is of particular interest to apply empirically founded behavioral models to assess the labor supply response and the corresponding impact on economic welfare from various policy measures. Specifically, given similar economic conditions in Peru as of 1985, our study suggests what we may be able to achieve, and how, for example, different measures would affect economic inequality.

The theoretical model is based on the neoclassical model for consumption and time allocation. Provided the data are not corrupted by measurement error, this framework is useful since:

- No one can spend more than his or her income. (In other words the budget constraint plays a role.)
- There is also a time constraint of 24 hours a day.

- It is reasonable to assume that people are not indifferent with respect to different levels of leisure and consumption. Thus we introduce the notion of preferences and represent them by utility indexes.

In standard models of labor supply the decision-maker is assumed to maximize utility with respect to leisure and consumption (subject to the budget constraint). One objection to this framework, however, is that individuals and households in developing countries can hardly be viewed as having full freedom of choice. On the contrary their job and production opportunities are often severely constrained. An individual's opportunities are influenced by education and experience, by the structure of the economy, and by government and sector-specific policies. Thus it is crucial that a realistic economic model of household behavior accommodate variations in opportunities across households.

The econometric model used in this study differs somewhat from the standard models in that the underlying decision variable is latent and is denoted position. By position we mean a particular combination of market and nonmarket activities, such as agricultural production combined with work in a wage-earning job. A position is characterized by specific attributes, like type and level of output and input factors, hours of work, wage rates, and so on. These attributes are assumed fixed, given the position. The choice problem is viewed as one in which the household selects the best "package" of attributes from a set. This choice set is known to the household but is unobservable to econometricians.

The set of household-specific feasible positions is represented in the model by a distribution function called the <u>opportunity distribution</u> (density). The opportunity density represents an aggregate measure of choice opportunities and it is defined as the fraction of positions with specified levels of attributes that are feasible to the household. For example, if the attributes are job-specific hours, wages, and profits in own-farm production, the opportunity density measures the amount of positions with a specific level of wages, hours, and profits that is feasible. Due to unobserved heterogeneity in opportunities across households, it is natural to interpret the opportunity density as a <u>probability density</u>. Specifically, it is the probability that a particular position-specific combination of attributes is feasible to a (randomly selected) household.[1/]

The econometric model is simultaneous in consumption, hours of work, wage rates, and profit conditional on family size and schooling. By conditional we mean that we have specified a conditional density for chosen hours of work, consumption, wage rates, and output given the chosen family size and schooling. Thus the model is consistent with the notion of simultaneous choice in all the attributes including schooling and family size.

[1/] This approach was developed and applied by Dagsvik (1988) and Dagsvik and Strøm (1989), and it is related to the models developed by McFadden (1973) and Ben-Akiva and others (1985).

While the introduction of the opportunity distribution in addition to the specification of a household utility function is appealing, it raises problems of functional form and the identification of parameters of the opportunity density and utility function. Even if these parameters cannot be fully identified without strong assumptions, the formulation has the advantage in that it suggests a natural and convenient way of taking into account unobserved heterogeneity in opportunities and introduces variables for individual qualifications as well as variables that characterize the community and the environment. At this stage the opportunity density is specified as a function of the individual's education. Specifically, the fraction of feasible wage work positions is specified as a function of years of schooling. Similarly the fraction of nonagricultural self-employment positions is specified as a function of level of schooling. This enables us to simulate the effect of increased education on the allocation of time in different sectors while keeping wage rates and preferences fixed. We can also study the effect of schooling through increased wages while keeping the opportunity density fixed.

The labor supply functions that correspond to the utility function are not linear in the parameters But our assumptions imply convenient expression for the probability distribution of (observed) consumption and labor supply. This distribution is a function of the parameters of the utility function and it is used in a maximum likelihood estimation procedure. Once the parameters of the utility function have been estimated, we can simulate individual household response.

This paper is organized in the following way. Section two presents a brief discussion on the methodology of measuring economic inequality and then applies the methodology on observed distributions [illegible] rs of work, household income, and per capita income as a measure of welfare. Section three outlines the structural econometric model. Section four reports the estimation results for the econometric model. Section five discusses the policy simulation results. The results are summarized and policy implications discussed in the concluding section of the paper.

2. Labor Market Activity, Income Formation, and Welfare

This section supplements the information on labor market activity and distribution of welfare reported in Newman (1987) and Glewwe (1987). One objective is to examine the relative differences in hours of work among employed males and females by estimating the inequality in the actual distribution of hours of work. For this purpose we employ a Gini-related measure of inequality, which also represents our basis for studying the distribution of income and welfare.

Second, we identify the contribution from wage work, agricultural self-employment, nonagricultural self-employment, and unpaid fa[illegible] work to the distribution of hours of work by employed males and females. More precisely we decompose the inequality in the actual distribution of hours of work. We use a similar approach to assess the contribution of wage earnings of males, females, and children to the level of inequality in the distribution of household consumption. In this way we obtain important information about economic structure and the functioning of the labor market. This information is, however, less help[illegible] in the analysis of economic inequality from a welfare perspective. A more relevant indicator of welfare is per capita household income, which also constitutes the basic variable in our study on welfare.

2.1. Measurement and Decomposition of Inequality

A common approach for measuring inequality in distributions of income is to employ the Gini coefficient, which satisfies the principles of scale invariance and transfers. The principle of scale invariance states that inequality should remain unaffected if each income is altered by the same proportion and it requires, therefore, the inequality measure to be independent of the scale of measurement. The principle of transfers implies that if a transfer of income takes place from a richer to a poorer person without changes in the relative positions, the level of inequality diminishes. The reader is referred to Sen (1972) for a more comprehensive discussion of the normative implications of different measures of inequality.

The Gini coefficient (G) is related to the Lorenz curve (L) in the following way

$$(2.1) \qquad G = \int_0^1 [1-2L(u)]du.$$

The Gini coefficient offers a method for ranking distributions and quantifying the differences in inequality between distributions. This strategy, however, suffers from certain inconveniences. Evidently no single measure can reflect all aspects of inequality of a distribution, it can only summarize it to a certain extent. Consequently, it is important to have alternatives to the Gini coefficient. As pointed out by Atkinson (1970), the Gini-coefficient assigns more weight to transfers in the centre of an unimodal distribution than at the tails. As an alternative to the Gini coefficient, we will employ an inequality measure - the A-coefficient - that assigns more weight to transfers at the lower tail than at the centre and the upper tail.

The A-coefficient (see Aaberge 1986) has a similar geometric interpretation and relation to the inequality curve M defined by

$$(2.2) \qquad M(u) = \frac{E[X|X \le F^{-1}(u)]}{EX}, \qquad 0 \le u \le 1,$$

as the Gini-coefficient has to the Lorenz curve. Here X has distribution function F. The A-coefficient is defined by

$$(2.3) \qquad A = \int_0^1 [1-M(u)]du.$$

If X is an income variable, then M(u) for a fixed u expresses the ratio of the mean income of the poorest 100u percent of the population to the mean income of the population. The egalitarian line of the Lorenz curve is the straight line joining the points (0,0) and (1,1). The egalitarian line of the M-curve is the horizontal line joining the points (0,1) and (1,1). Thus the universe of M- curves is bounded by a unit square, while the universe of Lorenz curves is bounded by a triangle. Therefore, there is a sharper visual distinction between two different M-curves than between the two corresponding Lorenz curves. Note that the M- curve will be equal to the diagonal line (M(u)=u) if and only if the underlying distribution is uniform (0,a) for an arbitrary chosen a. The A-coefficient then takes the value 0.5, while the maximum attainable value is 1 and the minimum attainable value is 0.

Note that M(u) = L(u)/u, which implies

$$(2.4) \qquad A = \int_0^1 \frac{1-L(u)}{u}\, du.$$

Alternative expressions for G and A are given by

$$(2.5)\qquad G = \frac{1}{EX}\int_0^{\infty}\int_0^{y}(y-x)dF(x)dF(y) = \frac{1}{EX}\int_0^{\infty} y(2F(y)-1)dF(y)$$

and

$$(2.6)\qquad A = \frac{1}{EX}\int_0^{\infty}\int_0^{y}\frac{(y-x)}{F(y)}dF(x)dF(y) = \frac{1}{EX}\int_0^{\infty} y(1+\log F(y))dF(y),$$

respectively.

Given the inequality in the distribution function F measured by A or G, the next step is to identify the sources that make substantial contributions to the inequality. Assume that the main variable X is the sum of s different factor components,

$$(2.7)\qquad X = \sum_{i=1}^{s} X_i$$

According to Aaberge (1986), A and G satisfy the following decomposition rules

$$(2.8)\qquad A = \sum_{i=1}^{s}\frac{\mu_i}{\mu}\alpha_i$$

where μ_i/μ is the ratio between the means of X_i and X, respectively, and α_i is, loosely spoken, the conditional A-inequality of factor i given the units rank order in X. Analogously,

$$(2.9)\qquad G = \sum_{i=1}^{s}\frac{\mu_i}{\mu}Y_i$$

where Y_i related to G has a similar interpretation as α_i related to A.

Notice that α_i and Y_i are measures of interaction between factor i, X_i, and the sum X. Assume for example that $\mu_i > 0$. Then, a negative value of α_i or Y_i expresses negative interaction and means that factor i has an equalizing effect on the inequality in the distribution F of X. A positive value expresses a disequalizing effect on the inequality in F. For $\mu_i < 0$, then positive values of α_i and Y_i express an equalizing effect on the inequality in F. For $\mu_i < 0$, then positive values of α_i and Y_i express an equalizing effect on the inequality in F.

2.2. Inequality in Distributions of Hours of Work for Males and Females

In this section we focus on the distribution of hours of work among employed persons. The objective is to estimate inequality in distributions of hours of work, i.e., relative differences in hours of work among employed persons. A similar study for children and households is reported in Aaberge and Dagsvik (1990).

Table 1. Employment Rates, Annual Mean Hours of Work and A-Inequality in Distributions of Hours of Work for Males and Married and Unmarried Females, by Region

	Males			Females								
				All			Married			Unmarried		
	Employment rates	Annual mean hours	A-Inequality	Employment rates	Annual mean hours	A-Inequality	Employment rates	Annual mean hours	A-Inequality	Employment rates	Annual mean hours	A-Inequality
Peru	.82	2,351	.396(.004)	.64	1,746	.521(.004)	.69	1,728	.521(.005)	.57	1,775	.521(.006)
Lima	.77	2,356	.398(.008)	.51	1,594	.569(.008)	.55	1,580	.586(.011)	.47	1,611	.547(.012)
Other urban	.76	2,286	.434(.008)	.56	1,656	.563(.007)	.62	1,613	.573(.009)	.49	1,717	.546(.011)
Rural	.91	2,388	.370(.006)	.79	1,858	.467(.005)	.81	1,344	.455(.066)	.75	1,912	.483(.008)

Note: Numbers in parenthesis are standard deviations.

Table 1 examines regional employment and regional distributions of hours of work for employed males and females aged 15-70[2/]. The participation rates for males and females are considerably higher in rural than in urban areas. Rates for married females are higher than those for unmarried females, perhaps due to an income effect. Females in rural areas work considerably longer than females in urban areas. Males also work longer in rural areas, but the difference is less significant.

The figures in table 1 may cover large individual differences in hours of work. We now employ the A-coefficient as a measure of the relative differences in hours of work (see section 2.1); corresponding results based on the Gini coefficient are given in Appendix 1. The estimates of the A-coefficient are displayed in table 1.

The inequality estimates show large individual variations in hours of work, particularly among females. Except for rural women, the inequality in the distribution of hours of work is significantly higher than if the individual hours of work were generated randomly, i.e. from a uniform (0,a) distribution for an arbitrary a. There are not, however, significant discrepancies in inequality between the distribution of hours of work for married and unmarried females. Inequality is lowest in the rural area for both males and females.

[2/] Individuals are classified as employed if they worked one hour or more during the seven days or 12 months prior to the survey. The definition and measurement of annual hours of work are reported in Appendix 2.

The observed distribution of hours of work is the result of a process where the individuals make decisions on hours of work in each sector simultaneously. The sectors are defined as (1) wage work, (2) nonagricultural self-employment, (3) agricultural self-employment, and (4) unpaid family work. By decomposing the overall inequality in the distribution of hours of work with respect to these sectors, we obtain information about the contribution of each sector to the overall inequality. (It is understood that the behavioral labor market adjustments are given).

By applying the decomposition method for the A-coefficient, we obtain the results in table 2. For females the first and third column (second and fourth for males) give the relative contribution from each sector to overall inequality and to total hours of work, respectively. The fifth and sixth column give the interaction coefficients. The positive interaction coefficients demonstrate that each sector has a disequalizing influence on the distribution of hours of work in each region. Note that the sectoral contribution to overall inequality for females is equal to the products of the figures in columns three and five divided by 100. Consequently, the sum of the first four sectoral inequality contributions for females in table 2 is equal to the overall inequality (0.521) in the distribution of hours of work for females in Peru.

Table 2. Decomposition of the A-inequality in Distributions of Hours of Work for Females and Males, With Respect to (1) Wage Work, (2) Nonagricultural Self-Employment, (3) Agricultural Self-Employment and (4) Unpaid Family Work, by Region

Region (level of inequality for females and males)	Employment sector	Sectoral fraction of overall inequality (percent)		Sectoral fraction of total hours of work (percent)		Interaction coefficient	
		Female	Male	Female	Male	Female	Male
	1	21.9	39.9	22.0	42.9	0.518	0.368
Peru	2	28.5	27.2	24.1	20.3	0.618	0.531
(0.521)	3	7.5	17.7	7.8	16.1	0.501	0.435
(0.396)	4	42.1	15.2	46.1	20.7	0.476	0.292
	1	53.2	58.3	52.8	66.6	0.573	0.348
Lima	2+3	37.8	40.4	33.0	29.8	0.653	0.539
(0.569)	4	9.0	1.3	14.2	3.6	0.360	0.144
(0.398)							
	1	25.4	44.7	26.1	50.4	0.547	0.385
Other urban	2+3	53.8	50.7	45.8	39.4	0.661	0.558
(0.563)	4	20.8	4.6	28.1	10.2	0.417	0.195
(0.434)							
	1	8.6	26.8	7.5	24.4	0.536	0.403
Rural	2	13.1	8.3	11.2	6.8	0.543	0.451
(0.467)	3	13.2	35.2	13.6	31.9	0.455	0.409
(0.370)	4	65.1	29.7	67.7	36.9	0.449	0.298

Note: Fraction of overall inequality =

$$\frac{\text{Fraction of total hours of work) x (Interaction coefficient)}}{\text{Overall inequality}}$$

Example:

Wage sector's fraction of overall inequality for females in Peru

$$= \frac{22.0 \times 0.518}{0.521} = 21.9$$

According to table 2, wage work plays a predominant role for males and females in Lima and for males in other urban areas. In rural areas males and females work mainly in the agricultural sector, but the wage work accounts for almost 25 percent of the total hours of work for rural men.

The large interaction coefficients in table 2 suggest that females with long total hours work more hours in each sector than females with short total hours of work. To a certain extent this conclusion is also valid for males. For males, however, there is a weak interaction between the hours worked as an unpaid family worker and total hours of work. This means that males with short total hours of work do nearly as much unpaid family work as males with long total hours of work. Note that the self-employment sectors have the largest interaction coefficients, which implies that these sectors make the largest contributions to the observed differences in hours of work among males and females.

2.3. Inequality in distribution of household consumption

This section deals with measurements of economic inequality. Such studies depend on the definition of income, the unit of observation, the period of time over which the chosen income variable is measured, and a summary measure of inequality.

We define the basic income variable as consumption defined as: [3/]

consumption $= \Sigma$ wage earnings

$+ \ \Sigma$ net entrepreneurial income

$+ \ \Sigma$ other income.

In this definition savings are included in consumption. Note that consumption of home-grown food and other in-kind income is given a monetary value so that net entrepreneurial income include consumption of these items. The basic unit of observation is the household and the reference period is one year. The "Σ" in the definition of consumption means sum over all persons who lived in the household during the year in question.

As a supplement to the information on individual variations in hours of work given in section 2.2 we give estimates of the A-coefficient for the regional distributions of hours of work among households:

Peru	Lima	Other urban areas	Rural areas
0.487	0.497	0.492	0.458
(0.004)	(0.009)	(0.008)	(0.006)

(Standard deviations in parenthesis)

The figures for Lima and other urban areas are approximately equal to the inequality in a uniform (0,a) distribution. When we plot the respective underlying inequality curves, however, we find that households in the lower and upper tails of the observed distribution have longer hours of work than in the uniform (0,a) distribution. As for the distribution of hours of work among individuals (see table 1) the inequality in the corresponding distribution among households is lowest in rural areas.

In spite of large inequality in the household distribution of hours of work, we cannot automatically ascertain the immediate implication for the inequality in the corresponding distribution of household consumption. The distribution of consumption is the result of preferred hours and offered wages and prices, and will therefore depend

[3/] See appendix 2 for details.

on the wage rate, the returns to self-employment activities, the hours of wage work and self-employment, and nonlabor income as well as the interdependence among these variables. For example, if households with high returns to self-employment activities work longer hours than households with low returns to their self-employment activities, and if in addition there exists a positive relationship between wage rates and the household's hours of work in the wage sector, then we must expect more inequality in consumption than in the distribution of hours of work.

Table 3 shows mean and median household consumption and inequality in the distribution of consumption among households. Note that these estimates are based on fewer observations than the estimates used in tables 1 and 2 because we have excluded households with observed negative net entrepreneurial income. The large figures of the A-coefficient in table 3 reveal extreme income inequality. The mean consumption of the richest 5 percent of the households is 128 times the mean consumption of the poorest 50 percent of the households, and 1,355 times the mean consumption of the poorest 10 percent.

Table 3. Mean and Median Distribution of Household Consumption (in intis), and A-Inequality Among Households, by Region

	Peru	Lima	Other urban areas	Rural areas
Number of observations	4,622	1,287	1,316	2,019
Mean	42,500 (10,066)	40,120 (2,250)	71,104 (32,912)	25,373 (8,273)
Median	11,433	22,344	15,660	4,423
A-inequality	0.864 (0.033)	0.680 (0.016)	0.892 (0.049)	0.895 (0.034)

Note: In intis (Peruvian Currency) at June 1985 prices. Standard deviations in parenthesis.

Table 4. Mean Consumption for Households Living in Peru by Deciles Decomposed with respect to Females, Males and Childrens Wage Earnings and with respect to the Households Net Entrepreneurial Income and Other Income

Decile	Mean household consumption	Decile specific mean wage earnings for Females (15-70)	Males (15-70)	Children (7-14)	Decile specific mean net entrepreneurial income for households	Decile specific mean of other income for households
1	397	13	40	2	324	18
2	1,700	80	222	15	1,296	87
3	3,443	192	793	27	2,268	163
4	6,077	387	1,954	42	3,270	394
5	9,478	884	3,634	29	4,203	718
6	13,643	1,367	6,086	63	5,244	883
7	19,082	1,741	8,220	35	7,630	1,456
8	27,073	4,665	10,902	214	10,723	1,924
9	41,140	4,718	15,592	53	16,970	3,807
10	302,982	20,460	31,874	326	242,670	7,651
All	42,500	3,315	7,948	85	29,461	1,691

Note: Intis at June 1985 prices.

The results in Table 3 show that the inequality in the distribution of consumption is considerably higher in rural areas than in Lima, even though hours of work were more equally distributed in rural areas. To obtain information on why inequality varies across distributions, we will examine the impact of different income sources on overall inequality. By decomposing the inequality in the actual distribution of consumption by males, females, and children's wage earnings, and by households' net entrepreneurial income, we may see why the consumption distributions differs across regions. By applying the decomposition method for the A-coefficient, we obtain the results in table 5. The interpretation is analogous to the interpretation of table 2. To give an impression of the variations behind the coefficients for Peru in table 5, table 4 displays mean household consumption by deciles, corresponding mean earnings for males, females, and children, mean entrepreneurial household income and mean other income for each decile. Since the decile-specific mean wage earnings for females increases with increasing deciles, the corresponding interaction coefficient takes a large positive value, which is in accordance with the estimate (0.842) in table 5. But if the decile-specific means are equal, then the corresponding interaction coefficient would become zero or approximately zero.

Table 5. Decomposition of the A-inequality in the Distribution of Consumption by Males, Females, and Children's Wage Income, and by Net Entrepreneurial Household Income Plus Other Income, by Region.

Region (Level of inequality)	Income (consumption) factor	Fraction of overall inequality (percent)	Fraction of consumption (percent)	Interaction coefficient
PERU (0.864)	Females (15-70) wage earnings	7.6	7.8	0.842
	Males (15-70) wage earnings	16.0	18.7	0.742
	Childrens (7-14) wage earnings	0.1	0.2	0.635
	Households net entrepreneurial income	72.7	69.3	0.906
	Other income	3.6	4.0	0.767
LIMA (0.680)	Females (15-70) wage earnings	18.5	17.0	0.741
	Males (15-70) wage earnings	35.9	39.5	0.618
	Childrens (7-14) wage earnings	0	0.1	-0.076
	Households net entrepreneurial income	38.2	34.9	0.744
	Other income	7.4	8.5	0.596
OTHER URBAN (0.892)	Females (15-70) wage earnings	5.1	5.6	0.805
	Males (15-70) wage earnings	8.1	11.5	0.629
	Childrens (7-14) wage earnings	0.1	0.1	0.741
	Households net entrepreneurial income	84.8	80.2	0.943
	Other income	1.9	2.6	0.665
RURAL (0.895)	Females (15-70) wage earnings	2.2	2.4	0.829
	Males (15-70) wage earnings	9.7	10.9	0.795
	Childrens (7-14) wage earnings	0.3	0.4	0.774
	Households net entrepreneurial income	85.7	84.1	0.911
	Other income	2.1	2.2	0.866

Male wage earnings in Lima provide almost 40 percent of household consumption which is attained at the expense of about 43 percent of the households total hours of work in wage employment by male members of the household. For females, the corresponding figure is about 17 percent, which reflects 17 percent of the households hours of work. However, despite the fact that this particular structure in the distribution of hours of work among households is maintained in the distribution of consumption among households, consumption is considerably more unequal than hours of work. The explanation is that the interaction coefficients referring to the consumption distribution for Lima, given in table 5, are considerably larger than the corresponding interaction coefficients related to the distribution of hours of work reported in Aaberge and Dagsvik (1990). This result is due to skew distributed wage rates and a positive correlation between wage rates and hours of work. By applying a particular non-linear decomposition method (not reported here) we also found that the wage rates contributed more strongly to inequality in the distribution of household consumption than hours of work in the wage sector. These effects are stronger for females than for males.

Note that the interaction coefficient for children's wage earnings in Lima is weakly negative, which means that children's wage earnings have a modest equalizing effect on the distribution of consumption among households. This effect is in contrast with the effect of children's wage work on the inequality of the corresponding distribution of hours of work and is mainly due to nonworking children of rich households with low or medium total hours of work. In both cases the children's contribution to overall inequality is of minor importance, as shown in the first column of table 5.

In contrast to the results for Lima, wage earnings in other urban areas yield a modest contribution to total household consumption, compared to the contribution of the household's hours in wage work to the households total hours of work. The fractions are, respectively, 17 and 40 percent. For the same reason as for Lima the interaction coefficients related to the distribution of consumption are considerably larger than the corresponding interaction coefficients for the distribution of hours of work. Similar results hold for the rural areas, although the distribution of household consumption seems to a greater extent to reflect the distribution of household hours of work.

2.4. Inequality in Distributions of Per-Capita Household Consumption

The information in section 2.3 about the economic structure of the labor market must be interpreted cautiously when analyzing welfare because of the variations in household composition and size. To allow for the fact that some households have several persons while others have just one, we need an alternative to household consumption as an indicator of welfare. Clearly, an index of welfare using the information on household size and composition is required. In the PLSS data an equivalence scale accounts for this heterogeneity. Specifically, the costs of children are specified in terms of fractions of one adult. The weights are 0.2 for a child under 7 years old, 0.3 for a child aged 7 to 12, 0.5 for a child 13 to 17, and 1 for a person over 17. The sum of these weights for each household is used as the scale. Consumption per capita is defined as household consumption relative to the equivalence scale and it is used as an indicator of household welfare. Note that these weights are consistent with the weights estimated for Sri Lanka and Indonesia by Deaton and Mullbauer (1986) and have been applied by Glewwe (1987) in analyzing the distribution of welfare in Peru in 1985-86. Glewwe's analysis is based on expenditure data rather than on income data.

The lack of sufficient data makes it impossible to distinguish consumption levels among members of the household. Therefore we have to assume that the welfare level of an individual is equal to the per capita consumption of the household. It is particularly interesting to examine the relationship between the distribution of per capita household consumption among households and the distribution of per capita household consumption among persons.

Table 6 shows average welfare levels for Lima, other urban areas, and rural areas. The figures show considerable differences in welfare between adults and children, and between urban and rural areas. The large differences between corresponding medians and means indicate extremely skewed distributions, which are confirmed by the estimates of the A-coefficient in table 7.

Table 7 shows only insignificant differences in inequality across per capita household consumption among households and persons. This is in line with the results reported by Berry (1988). More surprising is the finding that the inequality in per-capita household consumption differs little from inequality in the corresponding distribution of total household consumption (compare tables 3 and 7). This result is due to an extremely unequal distribution of consumption (income) in Peru in 1985-86. Glewwe (1987) reports that this was also the case in 1966, when the Gini-coefficient for per capita income inequality among persons was 0.666. We estimate the Gini-coefficient of the distribution of per capita household consumption among persons in 1985-86 to be 0.789 (see Appendix 1, table G3).

Table 6. Mean and Median Per Capita Consumption Among Persons by Sex, Age, and Region

Population	Peru		Lima		Other urban areas		Rural areas	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
All	11,692	3,332	10,668	5,983	19,139	4,190	7,454	1,404
	(24,126)		(6,541)		(6,952)		(10,633)	
Females	13,282	3,508	10,406	6,036	25,154	4,143	6,654	1,332
	(7,376)		(2,256)		(2,185)		(2,935)	
Males	12,207	3,820	11,529	6,418	20,013	4,423	7,097	1,516
	(7,004)		(2,090)		(2,054)		(2,860)	
Children[a]	10,118	2,965	10,118	5,404	13,630	3,945	8,150	1,380
	(9,746)		(2,195)		(2,713)		(4,838)	

Note: Intis figures at June 1985 prices. Number of observations in parenthesis.

[a] Less than 15 years old.

Table 7. A-inequality in Distributions of Per Capita Consumption Among Households and Persons, by Region

	Peru	Lima	Other urban areas	Rural
Households	.857 (.029)	.676 (.017)	.881 (.048)	.895 (.032)
Persons	.856 (.014)	.662 (.008)	.883 (.021)	.888 (.016)

Note: Standard deviations in parenthesis.

3. The Econometric Framework of a Structural Neoclassical Model

3.1. Theoretical Model

This section focuses on the essential features of our framework and its relationship to the traditional approach in the empirical analyses of labor supply (see Killingsworth 1983). For the sake of simplicity we take the case of one individual. The traditional approach starts by postulating a direct (or indirect) utility function in leisure (nonmarket activities) and consumption from which the labor supply function is derived by maximizing utility subject to the budget constraint. (Alternatively, the labor supply function is postulated directly so that it is consistent with a well-defined utility function). In this approach it is assumed that the individual is free to adjust his or her hours of work. The notion of rationing with respect to job offers or hours of work is rarely taken into account. Another feature of most empirical models is the assumption of linear labor supply curves. Linear supply functions imply a particular and quite restrictive form of the utility function that seems unjustified a priori. For example it implies that the "backward bending case" is excluded a priori.

The alternative empirical approach we use here is consistent with neoclassical theory but it departs from the econometric specifications used by others. We assume that the essential choice variable is "job" or "position" and that hours of work and wage rates are determined once the position is given. By position we understand a particular combination of market and nonmarket activities. For example, one position may be defined as specific farmwork tasks combined with a particular wage work job. Thus hours of work and wage rates are attributes that characterize the positions. Let (H_j, W_j) be the hour-wage combination of position. Here j is an indexation of the position. For nonmarket positions, $W_j=0$. The choice set is assumed known to the individual but is unobserved by the econometrician. Only the hours of work and wage rates are observed. That is, the hour-wage combination associated with the chosen position is observed.

To make the exposition as simple as possible, we assume that the set of feasible positions, B, (choice set) is finite (relative to the individual). The individual's maximization problem can be described as follows. The budget constraints are given by

(3.1) $h = H_j$

(3.2) $C = H_j W_j + I$

(3.3) $j \in B$

where I is nonlabor income. Equation (3.1) states that for a given position j, hours of work are given. The third equation states that B is the set of feasible positions. Equation (3.2) is the standard economic budget constraint.

Let

$$U(h,C,j) = v(h,C) + e_j$$

be the individual's utility of hours of work, h, consumption, C, and position, j. We assume that this utility can be decomposed in a structural term, v(h,C), (common to observationally identical individuals) and a random term, e_j, that reflects individual preferences for positions with the same level of hours and consumption. Thus e_j takes into account heterogeneity in tastes across individuals with respect to positions as well as the unobserved attributes of the positions.

The random term e_j is assumed independent of the choice set of feasible positions. Thus our approach is in fact a type of disequilibrium model in which the choice opportunities are considered fixed. The individual's problem is to find the position $j \in B$ that maximizes

$$v(H_j, H_j W_j + I) + e_j.$$

Now let B(h,w) be the set of positions for which $H_j = h$, $W_j = w$, $j \in B$ and let n(h,w) be the number of positions in B(h,w).

Formally, the probability that the optimal position has hour-wage combination (h,w) is expressed as

$$\phi(h,w) = P\{ \max_{j \in B(h,w)} (v(H_j, H_j W_j + I) + e_j) = \max_{j \in B}(v(H_j, H_j W_j + I) + e_j) \}.$$

Moreover, if we assume that the random preference terms e_j are independent, extreme value distributed across positions, we get immediately from the formal theory of discrete choice as developed by McFadden (1973) (see Maddala, 1983) that

$$(3.4) \qquad \phi(h,w) = \frac{n(h,w)\exp(v(h,hw+I))}{\sum_{x,y} n(x,y)\exp(v(x,xy+I))}.$$

Let

$$g(h,w) = \frac{n(h,w)}{\sum_{x,y} n(x,y)}$$

be the fraction of positions with hours and wages equal to (h,w) that are feasible. By inserting in (3.4) we get

$$(3.5) \qquad \phi(h,w) = \frac{g(h,w)\exp(v(h,hw+I))}{\sum_{x,y} g(x,y)\exp(v(x,xy+I))}.$$

This model is analogous to the one developed by Ben-Akiva et al. (1985). The function ϕ expresses the labor supply density. Its observable counterpart is the fraction of individuals who work h hours at wage rate w. Instead of the usual specifications where the labor supply density is expressed as a function of the parameters of the labor supply function we realize from (3.5) that in our model the density is expressed as a function of the structural part of the utility function.

Moreover, this model allows the notion of rationing. Specifically, (3.5) expresses the aggregate labor supply as a simple function of the mean utility, v, and the opportunity density, g(h,w).

Let us consider a particular extension to the case where the individual has the choice of participating in two sectors -- wage work and informal self-employment. In this case the set of feasible positions consists of combinations of market activities and type of production. Thus a specific position defines the type of wage work, type of production, and so on. To a position j there correspond attributes

$$(\tilde{H}_j, H^*_j, W_j, T_j)$$

where $\tilde{H}_j$ and H^*_j are hours of work in wage work and self-employment, W_j is the wage rate, T_j is a variable characterizing technology (unobservable) associated with position j.

Now the budget constraints take the form

$$(3.6) \qquad C = \tilde{H}_j W_j + Y_j + I$$

$$(3.7) \qquad Y_j = F (H^*_j) T_j$$

where $F(H^*_j) T_j$ is a profit function conditional on hours and Y_j is the profit. (For analytical convenience we assume the structure to be of the multiplicative form.)

The essential postulate that ensures identification is that the opportunity density with respect to offered hours is assumed to be uniform. We assume no constraints on hours of work (given that work in the respective sectors is available). The offered distribution of wages across positions (conditional on education) is assumed to be log normal with mean dependent on experience and level of schooling (splines). The opportunity density of the profit (conditional on hours) is assumed log normal with mean that is log linear with an interaction term in hours. Unlike Jacoby (1988) our approach accounts for possible simultaneous equation bias, and does not distinguish between output from agricultural and nonagricultural self-employment. In the actual empirical application below a continuous analogue to the discrete model above has been estimated. For details we refer to Dagsvik and Aaberge (1989).

3.2. Model specification

The preferences are represented in the model by a Box-Cox type utility function that is additively separable in consumption and in each of the individual's leisure. The leisure terms are parameterized as a function of age and for females we have added the number of children below six years of age in interaction with hours of work in the wage sector. Thus the systematic term, v, of the utility function is assumed to have the form:

$$(3.8)\quad v(\underset{\sim}{h}, \underset{\sim}{\tilde{h}}_F, C, f) = \alpha_2 \frac{\left(\left(1+\frac{C}{1000}\right)^{\alpha_1}-1\right)}{\alpha_1}$$

$$+ \sum_j (\alpha_4 + \alpha_5 \log A_{jM} + \alpha_6(\log A_{jM})^2) \frac{(L_{jM}^{\alpha_3}-1)}{\alpha_3}$$

$$+ \sum_j (\alpha_8 + \alpha_9 \log A_{jF} + \alpha_{10}(\log A_{jF})^2) \frac{(L_{jF}^{\alpha_7}-1)}{\alpha_7}$$

$$+ \alpha_{11} \sum_j \tilde{h}_{jF} f_j + \alpha_{12} \sum_j D_{jM}$$

where L_{jr} is defined by

$$L_{jr} = 1 - \frac{h_{jr}}{8760}, \quad r = F,M,$$

C = per capita household consumption,

f_j = number of children less than six years,

A_{jr} = age of household member j, gender r = F,M,

h_{jr} = total annual hours of work for household member j, gender r

$\tilde{h}_{jF}$ = annual hours of wage work, female j,

and

$$D_{jM} = \begin{cases} 1 & \text{if male j has hours of work in (2475, 2525)} \\ 0 & \text{otherwise.} \end{cases}$$

Except for the term $\alpha_{11} \sum_{j} h_{jF} f_j$, utility is assumed additively separable in consumption and leisure. Note that apart from the peak at full-time (2475,2525) the utility of consumption is concave and increasing when $\alpha_1 < 1$, $\alpha_3 < 1$, $\alpha_7 < 1$,

$$\alpha_4 + \alpha_5 \log A_{jM} + \alpha_6 (\log A_{jM})^2 > 0$$

and

$$\alpha_8 + \alpha_9 \log A_{jF} + \alpha_{10} (\log A_{jF})^2 > 0.$$

The dummy variable, D_{jM}, allows males to have a particular preference for total hours of work in the interval (2575, 2525). The motivation for introducing this dummy is that the data shows a marked concentration of hours in this interval both for males that are engaged in wage work as well as in farm and nonfarm self-employment. This can only cccur

(1) if males have a particular preference for full-time work,

(2) if there are constraints on hours (there are more full-time work positions relative to other positions),

(3) if the data are corrupted by measurement errors.

The estimated model is consistent with all these explanations but we are not able to identify which is the true one.

The conditional profit function for the rural area given inputs is specified as

$$(3.9)\quad \log Y = \beta_0 + \beta_1\log(1+h_M) + \beta_2\log(1+h_F) + \beta_3\log(1+h_c) + \beta_4\log(1+h_M)\log(1+h_F) + \beta_5\log(1+TOTWET) + \beta_6\log(1+TOTDRIED) + \beta_7 MAXED + T$$

where

Y = profit of household from self-employment (both farm and nonfarm)

h^*_M = total male hours of work in self-employment

h^*_F = total female hours of work in self-employment

h^*_c = total child hours of work in self-employment

TOTWET = total area of watered land

TOTDRIED = total area of dry land

MAXED = length of schooling of most educated member of the household

T = random error term - normally distributed.

T is supposed to account for unobserved choice variables that affect the production technology. The distribution of the technology attribute, T, is assumed to be normal N(0,t), and it is assumed to be independent of other input factors. Note that the land variables appear only in agricultural production, not in nonfarm production.

The conditional profit function for Lima is specified as

$$(3.10)\quad \log Y = \beta_0 + \beta_1\log(1+h^*_M) + \beta_2\log(1+h^*_F) + \beta_3\log(1+h^*_M)\log(1+h^*_F) + \beta_4\, MAXED + T.$$

Let g_y be the fraction of all self-employment positions that are feasible for the household. Let g_r be the fraction of feasible positions for an individual of sex r, r=F,M, that are nonfarm self-employment positions. Let g^{**}_r and $\tilde{g}_r$ be defined analogously as the corresponding opportunity probabilities for farm self-employment and wage work, respectively.

We have parameterized g_y as

$$(3.11)\quad 1 - g_y = \frac{\beta}{a+\beta(1-a)},$$

where

$$\beta = \prod_{r=F,M} [(1-g^*_r)(1-g^{**}_r)]^{m_r}$$

and m_F, m_M are the numbers of females and males in the household and $1 \geq a \geq 0$ is a parameter. The case a=1 corresponds to the case in which all self-employment opportunity sets are independent across household members. The particular parametrization (3.11) has been chosen for computational convenience. Finally, we have introduced g_s which is the fraction of feasible self-employment positions that yields positive profit during a period (one year). The rationale behind g_s is that in addition to a limited set of feasible self-employment positions is the fact that a successful business does not necessarily yield positive profit through every period. In fact the data demonstrates that profit is negative for some households during the period of the data collection. We may interpret alternatively as the (average) fraction of the year the business is likely to operate with positive profit. A rigorous treatment of the choice of self-employment activity would of course require a model for decision under uncertainty.

The offered wage densities are assumed log normal where the means depend on experience, SPLYRSC1, SPLYRSC2, SPLYRSC3 where experience is defined as age minus length of schooling minus 6 and

$$(\text{SPLYRSC1, SPLYRSC2, SPLYRSC3}) = \begin{cases} (x,0,0) & \text{if } x \leq 5 \\ (5,x\text{-}5,0) & \text{if } 5 < x \leq 10 \\ (5,5,x\text{-}10) & \text{if } x > 10 . \end{cases}$$

4. Summary statistics and parameter estimates

The summary statistics of the variables generated from the household survey data are presented in Table 8 for Lima and rural areas. There are differences in observed household behavior in production and consumption, and in individual and household attributes. For example, consumption (income) per capita is much higher in Lima than in rural areas. Women in Lima spend more hours in wage work than women in rural areas; women in rural areas spend more hours in self-employment. However rural households record higher profits from self-employment than do households in Lima. This is not surprising given that nonfarm production is dominant in Lima while agricultural production is the leading activity in the self-employment category. Interestingly, female wage workers earn more in rural areas than male wage workers. For more details see section 2 and Aaberge and Dagsvik (1990).

The parameters of the opportunity density and of the utility function are estimated simultaneously by a modified maximum likelihood procedure. The estimates of the utility function are presented in Table 9, while the estimates of the opportunity density are given in Table 12. The estimates of the wage and profit functions are shown in Tables 10 and 11 respectively. We have also estimated the wage equations and the profit function by ordinary least squares. This procedure may lead to biased estimates since it does not account for the fact that households do not maximize profit but the utility of consumption and leisure. Consequently, the conditional expectation of the error term in the profit function given the hours is in general a function of these hours because they enter the utility function through consumption and leisure. The results are reported here only for Lima and rural areas.

Table 8. Household and Individual Sample Statistics

Variables	Lima, Mean (Standard deviation)		Rural Areas, Mean (Standard deviation)	
Household Statistics				
Number of households 898				
Consumption per capita (intis)	6,900	(150)	2578	(86)
Female hours of work in wage work (yearly)	832	(44)	101	(13)
Female hours of work in self-employment (yearly)	638	(44)	2232	(49)
Male hours of work in wage work (yearly)	2,171	(61)	594	(29)
Male hours of work in self-employment (yearly)	907	(50)	2724	(51)
Childrens hours of work in self-employment (yearly)	53	(10)	4	(0.1)
Total gross revenue from self-employment (intis)	10,700	(600)	9056	(385)
Total profit from self-employment (intis)	6,300	(400)	7183	(311)
Number of children below 7	0.84	(0.03)	1.34	(0.03)
Number of children below 14	1.08	(0.04)	1.39	(0.03)
Number of females 15-70	1.79	(0.04)	1.52	(0.02)
Number of people above 70	0.09	(0.01)	0.08	(0.01)
Equivalence scale	4	(0.10)	3.7	(0.04)
Individual Statistics				
Number of females 15-70, 1,611				
Number of males 15-70, 1,539				
Participation rates in				
wage work for females	0.32	(0.01)	0.07	(0.01)
self-employment for females	0.35	(0.01)	0.85	(0.01)
wage work for males	0.63	(0.01)	0.34	(0.01)
self-employment for males	0.35	(0.01)	0.89	(0.01)
Hours of work in				
wage work for females (yearly)	463	(21)	67	(7)
self-employment for females (yearly)	356	(20)	1477	(25)
wage work for males (yearly)	1,267	(32)	387	(17)
self-employment for males (yearly)	529	(27)	1777	(25)
Wage rate, females (intis per day)	5.25	(0.40)	7.38	(2.45)
Wage rate, males (intis per day)	6.41	(0.20)	2.98	(0.30)

Table 9. Parameter Estimates for the Utility Function

Variables	Coefficients	Lima Estimates (t-values)	Rural Areas Estimates (t-values)
Consumption	α_1	-0.776 (7.9)	-12.941 (4.0)
	α_2	4.832 (7.3)	35.891 (2.0)
Leisure, males	α_3	-3.605 (9.5)	-7.680 (14.9)
	α_4	43.258 (5.4)	3.189 (3.3)
	α_5	-23.194 (5.3)	-1.704 (3.3)
	α_6	3.134 (4.1)	0.231 (3.3)
Leisure, females	α_7	-1.454 (5.7)	-5.380 (12.6)
	α_8	86.655 (5.5)	5.057 (2.8)
	α_9	-46.354 (5.3)	-2.475 (2.5)
	α_{10}	6.369 (3.2)	0.320 (2.3)
$10^{-3} \Sigma \bar{h}_{jF} f_j$	α_{11}	-0.149 (2.3)	-0.152 (2.2)
ΣD_{jM}	α_{12}	2.234 (18.8)	2.231 (19.7)

Note: t-values in parenthesis.

Table 10. Wage Equations for Lima. Simultaneous ML Estimation Procedure Versus Ordinary Least Squares

	LIMA				RURAL AREAS			
	Males		Females		Males		Females	
	OLS	Simultaneous ML	OLS	Simultaneous ML	OLS	Simultaneous ML	OLS	Simultaneous ML
Intercept	0.049	-0.105	-0.596	-0.674	0.352	0.395	0.473	0.451
	(0.4)	(0.8)	(3.5)	(3.8)	(6.2)	(5.4)	(4.0)	(3.2)
SPLYRSC1+ SPLYRSC2	0.092	0.100	0.126	0.125	0.040	0.034	-	-
	(8.4)	(8.2)	(8.2)	(7.9)	(3.5)	(2.3)		
SPLYRSC3	0.117	0.136	0.126	0.150	0.284	0.306	0.303	0.540
	(10.1)	(9.9)	(6.2)	(6.5)	(6.1)	(4.8)	(3.0)	(3.4)
Experience	0.050	0.038	0.056	0.050				
	([illegible] 3)	(5.7)	(5.7)	(5.0)				
$(\text{Experience})^2/100$	-0.060	-0.039	-0.073	-0.063				
	(5.3)	(3.1)	(3.5)	(3.1)				
Standard error	0.659	0.660	0.780	0.753	0.888	0.933	1.856	1.316
		(40.4)		(32.9)		(34.4)		(17.7)
R^2	0.27		0.25		0.09		0.06	

Note: t-values in parenthesis.

Table 11. Parameter Estimates of the Conditional Profit Function

	LIMA				RURAL AREAS			
Variable	OLS		Simultaneous ML estimate		OLS		Simultaneous ML estimate	
Intercept	2.681	(5.9)	3.078	(7.1)	4.246	(7.1)	2.181	(2.5)
Male labor	0.756	(13.3)	0.572	(10.5)	0.329	(4.3)	0.543	(4.9)
Female labor	0.756	(11.0)	0.487	(8.7)	0.222	(2.7)	0.393	(3.4)
Interaction, female-male labor	-0.085	(9.8)	-0.061	(7.6)	-0.031	(3.0)	-0.053	(3.5)
Child labor					-0.0004	(0.4)	-0.010	(0.7)
Watered land					0.419	(7.5)	0.443	(5.2)
Dry land					0.264	(7.6)	0.249	(4.8)
Maxed	0.047	(2.4)	0.072	(4.0)	0.578	(9.7)	0.734	(7.3)
Standard error	1.356		1.257	(31.9)	1.303		1.445	(31.3)
R^2	0.33				0.18			

Note: t-values in parenthesis.

Table 12. Estimates of the Opportunity Probabilities

SECTOR	Opportunity Probability Function	LIMA	RURAL AREAS
Agricultural self-employment males	$\log \frac{g^{**}_{1M}}{1-g^{**}_{1M}}$	-2.804	1.932 (19.3)(24.0)
Nonagricultural self-employment males	$\log \frac{g^{*}_{1M}}{1-g^{*}_{1M}}$	-0.197 (2.5)	-1.501 + 0.027S (13.0) (1.5)
Wage work, males	$\log \frac{\tilde{g}_{1M}}{1-\tilde{g}_{1M}}$	-0.488 + 0.103S (2.6) (5.4)	-0.545 + 0.042S (5.5) (1.9)
Agricultural self-employment, females	$\log \frac{g^{**}_{1F}}{1-g^{**}_{1F}}$	-1.198 (12.5)	1.656 (24.0)
Nonagricultural self-employment females	$\log \frac{g^{*}_{1F}}{1-g^{*}_{1F}}$	0.007 (0.1)	-0.516 (9.4)
Wage work, females	$\log \frac{\tilde{g}_{1F}}{1-\tilde{g}_{1F}}$	-1.236 + 0.152S (7.0) (8.1)	-2.656 + 0.162S (15.2) (4.7)
Household profit from self-employment	a	-0.577 (8.0)	
Positive profit from self-employment	$\log \frac{g_s}{1-g_s}$	1.884 (12.2)	

S = Length of schooling.

Note: t-values in parenthesis.

The estimates of Table 9 imply that the systematic term (3.8) of the utility function is strictly concave and increasing in consumption and leisure. The estimates also show that the utility of leisure is U-shaped as a function of age with a minimum at 40.6 years for males and 37.4 for females in Lima. In rural areas the corresponding ages are 40.3 and 47.8. Moreover, the impact of small children seems to be the same in Lima as in rural areas.

The functional form (3.8) implies that the corresponding labor supply functions are highly non-linear and cannot be expressed in closed form. As a consequence the parameters of Table 9 do not have a simple interpretation in terms of elasticities. Table 10 shows that education and experience are very important determinants for the wage rate in the wage work sector of Lima. It also shows that the selectivity bias is negligible for Lima but for rural areas OLS seems to underestimate the effect of education for females. The bias is however not significantly different from zero. Due to few observations experience has been excluded from the wage equations for the rural areas. In addition SPLYRSC1 and SPLYRSC2 have been excluded for females in rural areas for the same reason. The justification for imposing the same coefficient of SPLYRSC1 as of SPLYRDSC2 is that preliminary estimation runs produced estimates that were quite close. For the rural areas the model is estimated conditional on farms with positive profit from self-employment. The reason for this is that there are few observations with zero or negative profit for households with self-employment activity. More important, preliminary estimation results suggest that the type of farms with reported zero or negative self-employment are essentially different from the rest of the sample.

Although the difference between the OLS and the ML estimates in Table 11 is not statistically significant the results seem to indicate that in the rural areas OLS seems to underestimate the impact of male and female labor, and the education variable MAXED (the length of schooling of the highest educated member of the family). In Lima OLS seems to underestimate the impact of male and female labor and overestimate the impact of MAXED. Recall that the OLS estimates may be biased (i.e., simultaneous equation bias) while the ML estimates are obtained by a procedure that take into account that the input factors are endogenous.

The profit-function estimates also imply that the Cobb-Douglas structure is rejected since there is a strong negative interaction between male and female hours of work. In contrast to the result for the rural areas MAXED seems to be of little importance for the level of the profit in Lima. Thus the return to education in self-employment is much higher in rural areas (0.7) than in Lima (0.1). The estimates of the opportunity probabilities in Table 12 show that length of schooling has a substantial effect on the opportunities for wage work, particularly for females in Lima and in rural areas. Recall that the parameter a accounts for possible dependence in self-employment opportunities across family members where a = 1 corresponds to independence. Since a is estimated to be 0.577, independence is ruled out. The last line of Table 12 implies that g_s is estimated to be 0.87. Thus, on average, the self-employment businesses in Lima will produce positive profit a fraction of 0.87 per year (given that labor input take place).

5. Policy Simulation Results for Lima

Using the econometric framework above we can perform complex simulation experiments that take into account the household budget constraint, differences in age, schooling, and household size and composition. In addition we are able to account for unobserved heterogeneity, represented in the model by random error terms associated with the wage, conditional profit, and utility function. After the model has been estimated it is possible to perform simulations since we then "know" the parameters of the structural part of the utility, the wage, and the profit function, and the probability distributions of the related random terms.

In practical policy simulation experiments we proceed as follows. For each household the respective random terms are drawn from the corresponding probability distributions. The maximization of the utility function is a pure numerical problem given the observed household characteristics. The resulting hours that maximize utility are the female and male labor supply in each sector. This procedure is performed for each household in the sample to obtain participation rates, distribution of labor in each sector, and consumption and profits from self-employment. Note that this procedure implies exact aggregation. Unfortunately, since the model is so rich it is quite costly to perform precise simulations. We have therefore only carried out approximate simulations in which the approximation error is of moderate size. Figures 1-6 in Appendix 3 show the observed and simulated distribution of male and female hours of work and per capita consumption. These figures demonstrate that the model is capable of reproducing the survey data fairly well.

We confine the analysis to households with at least one female and one male adult, where per capita household consumption does not exceed 20,000 intis. Note that this selection was not made in Section 2.

The simulation experiments relate to the effect of changes in wages and education on labor supply, wage earnings, profit from self-employment, and distribution of economic welfare.

5.1. Wage effects

Table 13 reports the effect of wage changes on participation probabilities and on mean hours worked in each sector. The table shows that a 20 percent increase has only a small effect on labor supply. For the females, mean hours of work and participation in the wage sector increase by 5.8 and 3.2 percent respectively. The effect on mean hours and participation in self-employment is almost negligible. The cross effect on male participation rates and mean hours of work in each sector is negligible.

Recall that the sum of the participation rates across sectors may be greater than one because many individuals work in both sectors. When male wages are increased by 20 percent, their participation and mean hours of work in the wage sector increase by 1.6 and 2.7 percent, respectively. In the self-employment sector, male participation and mean hours of work fall by 1.2 and 2 percent respectively, while female participation and mean hours of work fall by 2 and 2.4 percent. The drop in female labor supply reflects the income effect that stems from the increase in male wages. When both male and female wages increase by 20 percent, the impact is similar but weaker.

The largest effect is obtained when the female wages go up by 20 percent of the mean wage. Then participation and mean hours in wage work rise 3.8 and 8 percent, respectively. Table 13 shows that mean hours in the wage sector increase by 4 percent. The drop in participation and mean hours recorded in self-employment sector, however, is small. So is also the change in male labor supply.

Table 13. Changes in Participation Rates, Annual Hours of Work, Earnings, and Consumption as a Result of Wage Increments (Percentage Changes From Base Case)

Percentage increase	Sector specific participation: Wage work F	M	Selfemployment F	M	Sector specific annual hours of work (unconditional)*): Wage work F	M	Wage earnings (unconditional) (intis): Selfemployment F	M	Wage earnings (intis) F	M	Consumption (intis) F	M
Base case	0.32	0.62	0.34	0.35	414	1165	414	492	2300	8100	17900	27800
20 percent increase in female wages	3.2	-0.6	-0.9	-1.2	5.8	-0.7	-0.5	-0.4	30.0	-1.2	6.3	5.0
20 percent increase in males wages	-1.9	1.6	-2.0	-1.2	-2.2	2.7	-2.4	-2.0	-4.6	22.3	17.1	11.9
20 percent increase in both females and males wages	0.6	0.6	-1.8	-1.4	1.9	1.9	-1.5	-2.4	19.8	20.5	21.2	11.5
Female wage rates increased by 20 percent of the mean wage	3.8	-1.4	-0.9	0	8.0	-1.4	-1.5	0	25.0	-0.8	5.0	4.7
Male wage rates increased by 20 percent of the mean wage	-2.9	2.1	-0.9	-2.3	-3.6	3.8	-0.5	-3.5	-4.5	17.6	14.0	7.0
Female and male wage rates increased by 20 percent of the mean wage	1.6	1.0	-2.3	-2.9	3.4	2.0	-2.7	-4.3	19.7	15.1	16.2	8.6

*) Recall that conditional hours in the respective sectors can be obtained by dividing the unconditional hours by the corresponding participation rates.

Table 14. Changes in Mean Level and Inequality in the Distribution of Per Capita Household Consumption as a Result of Wage Increments (percentage change)

	Mean level	A-coefficient	Gini-coefficient
Base case	7,600 (in intis)	0.566	0.438
20 percent increase in female wages	5.3	2.1	3.2
20 percent increase in male wages	11.9	0.6	0.7
20 percent increase in both female and male wages	11.6	-1.3	-1.6
Female wage rates increased by 20 percent of the mean wage	4.9	0	0.7
Male wage rates increased by 20 percent of the mean wage	6.4	-3.0	-3.4
Male and female wage rates increased by 20 percent of the mean wage	8.6	-3.0	-3.4

When males wages increase by 20 percent of the mean level, their participation and hours of work in the wage sector increase by 2.1 and 3.8 percent respectively. In the self-employment sector, their participation and mean hours decrease 2.3 and 3.5 percent. The corresponding income effect implies that female participation and mean hours in the wage sector decrease 2.9 and 3.6 percent respectively, while there is almost no change in female participation and mean hours in the self-employment sector.

Table 14 demonstrates that wage changes have a modest effect on inequality in the distribution of per capita consumption among households. A 20 percent increase has very little distributional impact, reducing inequality by 3 percent (A-coefficient). This reduction corresponds to introducing a proportional tax of 3 percent and then increasing each household's per capita consumption by an equal share of the total tax revenue. In other words the transfer to each household is equal to 3 percent of the mean consumption per capita (before taxes). A similar increase in female wages increases the mean level of the household's per capita consumption by 4.9 percent, while the level of inequality is not influenced. This result corresponds to increasing each household's per capita consumption by 4.9 percent. Note that the relative changes in inequality are larger when inequality is measured by the Gini coefficient than by the A coefficient, particularly when female wages are increased by 20 percent. This means that the central part of the distribution of per capita consumption is more strongly influenced by wage changes than the lower part of the distribution.

Note that we only report aggregate effects here. We have also done wage change simulations for a two-person family for the particular case in which all the random terms are equal to zero and without any choice constraints. The results are not reported here. (See Dagsvik and Aaberge, 1989). These simulations demonstrate that the elasticities of hours are highly dependent on the level of the wage rates. The reason the corresponding aggregate effects are much smaller may be due to the large heterogeneity in wage rates and the fact that in many families one or several persons are "stuck" in corner solutions, that is, they participate at most in one sector. Such families are therefore less responsive to wage changes than families where all members work in both sectors. In addition, restrictions on opportunities prompt a large number of corner solutions.

5.2. Education effects

Table 15 shows the impact of education through the opportunity probabilities. Here the wage rates and the education variable (MAXED) in the conditional profit function are kept unchanged. Thus we study the pure "opportunity" effect. Contrary to the wage simulations above, e obtain a large effect from increased education. If female education is increased by one year, female participation in the wage sector increases by 9.2 percent. The change in the participation rate in self-employment, however, is within the simulation error margin. If male education is increased by one year, participation in wage work increases by 3.4 percent, and remains unchanged for the self-employed. If the minimum education for females is increased to nine years, female participation in the wage sector increases by 19 percent. When males' level of schooling is increased analogously, male participation in the wage sector increases by 3.9 percent. The cross effects appear to be negligible.

Table 15. Effects of Education on Sector-Specific Participation Rates When Wages Are Fixed (percentage change)

	Sector-specific participation rates			
	Wage work		Self employment	
	F	M	F	M
Base case	0.32	0.62	0.34	0.35
One year of additional schooling for females	9.2	-1.4	0	0
One year of additional schooling for males	-1.3	3.4	0	-0.6
One year of additional schooling for both males and females	7.6	2.4	0	-0.9
Nine years of schooling as a lower limit for females	19.0	-1.0	0	-0.3
Nine years of schooling as a lower limit for males	-1.3	3.9	0	-0.9
Nine years of schooling as a lower limit for both males and females	18.0	3.5	0	-1.2

Table 16 reports the impact of increased education on labor supply. Here only MAXED is kept unchanged. In other words the increase in schooling affects both wages and the choice set of work positions. The first line demonstrates that the wage effect seems to be small compared to the impact through the opportunity probabilities. In Table 15 we found that the corresponding female participation rate increased 18 percent, or only 3.5 percentage points less than we obtained by increasing minimum schooling to nine years without keeping the wage rate fixed. The subsequent effect on mean hours of work in the wage sector is a 25.6 percent increase for females and a 2.7 percent decrease for males. The corresponding increase in the conditional mean hours given participation in the wage work sector for females is 3.3 percent. The other income and cross effects on hours are small. The mean wage earnings for females increases dramatically to 42.6 percent.

If the minimum level of schooling for males is increased to nine years the impact on labor supply is much less. In this case participation in wage work rises 5.6 percent for males and falls 3.5 percent for females. Mean hours of wage work increase 6.7 percent for males and decline 4.4 percent for females. Other income and cross effects on labor supply are small. Wages increase by 14.8 percent for males and fall by 5 percent for females. But the total effect on household income is larger than it was when the minimum education for females was raised to nine years.

When both males and females have at least nine years of education, female participation and mean hours in wage work increase by almost the same amount as in the "marginal" case reported in the first line of Table 16. Male participation and mean hours in wage work increase by 3.7 and 3 percent respectively, which is much less than the response in the "marginal" case (second line).

We have also carried out simulations in which MAXED is increased. The results (not reported here) show a very small impact on profits.

Table 16. Changes in Participation Rates, Annual Hours of Work, Earnings and Consumption as a Result of Additional Schooling and Subsequent Increase in Wage Rates. (percentage changes from base case)

Percentage increase	Sector specific participation				Sector specific annual hours of work (unconditional)*)		Wage earnings (unconditional) (intis)		Wage earnings (intis)		Consumption (intis)	
	Wage work		Self-employment		Wage work		Self-employment					
	F	M	F	M	F	M	F	M	F	M	F	M
Base case	0.32	0.62	0.34	0.35	414	1,165	414	492	2,300	8,100	17,900	27,800
Nine years of schooling as lower limit for females	21.5	-1.8	1.2	-0.6	25.6	-2.7	-1.5	0	42.6	-2.0	8.4	6.5
Nine years of schooling as lower limit for males	-3.5	5.6	0	-1.7	-4.4	6.7	0	-3.5	-5.0	14.8	11.2	7.6
Nine years of schooling as lower limit for both males and females	19.0	3.7	0.9	-1.4	20.5	3.0	-1.2	-2.4	33.9	11.1	17.3	11.2

Table 17. Effect of Education on Mean Level and Inequality in the Distribution of Per Capita Consumption among Households with a Subsequent Increase in Wage Rates. (percentage changes from base case)

	Mean level	A-coefficient	Gini-coefficient
Base case	7,600	0.566	0.438
Nine years of schooling as lower limit for females	5.3	0	0
Nine years of schooling as lower limit for males	6.6	-1.8	-1.8
Nine years of schooling as lower limit for both males and females	10.5	-3.0	-3.2

Earlier we concluded that the impact of wage changes on inequality in the distribution of per capita consumption is modest. Table 17 demonstrates that this is also the case when schooling is increased. In spite of a considerable increase in mean per capita consumption, the reduction of inequality in the distribution of per capita consumption is surprisingly small. Since the changes in inequality are the same whether it is measured by the Gini-coefficient or the A-coefficient, we can conclude that changes in schooling have the same impact on the lower part of the distribution of per capita consumption as on the central part of this distribution.

6. CONCLUSION

The data show that male wages play a dominant role in household consumption in Lima, while entrepreneurial income is the most important income source in rural and in other urban areas. In Lima males wage earnings contribute by almost 40 percent of the household's consumption, which seems to reflect their share of total household hours of work. For females the corresponding shares are both about 17 percent. The same relationship holds for rural areas. Despite the similarity, consumption is considerably less equally distributed than hours of work. This is also the case when we examine the distribution of welfare. As an indicator of welfare we apply household consumption relative to an equivalence scale. This indicator accounts for some of the heterogeneity in household demographic composition.

The estimated structural model departs from the assumption that the members of a household behave so as to maximize a household utility function, given available work resources and production opportunities. The corresponding econometric approach differs from the traditional labor supply models in the literature. Our particular approach has the advantage of being well-suited for taking into account latent opportunity constraints, the interdependence between each persons activities in different sectors, and the interdependence between household members. Since many households have more than two adults, this is a major challenge.

It may not be obvious that the neoclassical type model used in this analysis is appropriate for examining Peru's labor market. The analysis rests on the assumption that the data reflects the heterogeneity of preferences and opportunities to a "large" extent. For example, it may be questionable if essential background information about the heterogeneity in customs and value systems across social classes, ethnic groups, and "professions" is reflected in the data. It is also essential that the data on hours, participation and economic variables are not corrupted by measurement errors. Such errors in economic variables may occur if, for instance, household members are engaged in black-market activities, or if a substantial part of the goods and labor markets operates by trading services and goods without explicit prices. This is particularly relevant in countries where inflation is high, as in Peru. Also we assume that the average number of feasible wage positions with low (offered) hours is the same as the number of feasible wage positions with high offered hours. Under the assumption that there are no restrictions on hours of work in the self-employment sector, it is possible to test this assumption.

If we are willing to accept the neoclassical point of departure as well as the assumptions about the data and the choice environment, the estimation results reported here demonstrate that the parameters are determined with remarkable precision and have the expected signs according to economic theory. The model also reproduces the aggregate distributions of hours and consumption fairly well.

The simulation results for Lima demonstrate that proportional wage changes have only a small effect on behavior It is also remarkable that the wage increases have very little effect on the inequality in the distribution of per capita consumption. Even when wage rates are increased by the same amount the indirect effect is small. This increase does, however, moderately reduce the inequality in the distribution of per capita consumption.

These simulation exercises show that it is very difficult to reduce inequality in per capita consumption by changing wage and education policies.

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APPENDIX 1

Estimates of Inequality based on the Gini coefficient

The tables below correspond with the following tables for the A-coefficient: Table G1 corresponds to table 1, table G2 corresponds to the data on page 15, and table G3 to table 3.

Table G1. Gini-Inequality in Distribution of Hours of Work for Males and Married and Unmarried Females, by Region

Region	Males (15-70)	Females (15-70)		
		All	Married	Unmarried
Peru	.249	.362	.364	.359
Lima	.251	.404	.426	.379
Other urban	.275	.404	.415	.387
Rural	.231	.318	.312	.328

Table G2. Gini-Inequality in Distribution of Hours of Work among Households, by Region

Peru	Lima	Other urban	Rural
0.344 (0.003)	0.349 (0.007)	0.351 (0.007)	0.320 (0.005)

Note: Numbers in parenthesis are standard deviations.

Table G3. Gini-Inequality in Distribution of Per Capita Consumption among Households and Persons by Region

Consumption by	Peru	Lima	Other urban	Rural
Households	.787 (.043)	.567 (.021)	.830 (.068)	.843 (.048)
Persons	(.789) (.020)	.553 (.010)	.835 (.030)	.835 (.023)

Note: Numbers in parenthesis are standard deviations.

APPENDIX 2

Definition of main variables

The model used here follows the definitions in the Peru Living Standards Survey. We record information on the two most important jobs held by each individual in the last seven days and in the last 12 months prior to the survey. Therefore annual hours of work and wage earnings are defined by (A.1) and (A.2).

Table A1. Measures of annual hours of work and wage earnings

	Last 7 days			Last 12 months		
	Weekly hours of work	Weekly wage earnings	Number of week	Weekly hours of work	Weekly wage earnings	Number of weeks
Main job	h_1	k_1	r_1	h_2	k_2	r_2
Second job	h_3	k_3	r_3	h_4	k_4	r_4

(A.1) Annual hours of work $= \sum_{i=1}^{4} r_i h_i$

and

(A.2) Annual wage earnings $= \sum_{i=1}^{4} r_i k_i$.

To illustrate we show three possible outcomes of h_1, h_2, r_1 and r_2 in Table A2.

Table A2. Three examples of observations of main jobs in the course of 12 months

	Last 7 days		Last 12 months	
Outcome	Weekly hours of work	Number of weeks	Weekly hours of work	Number of weeks
1	40	50	0	0
2	0	0	40	50
3	40	28	30	24

Based on wage earnings and annual hours of work, wage rate is given by:

$$\text{wage rate} = \frac{\text{Annual earnings}}{\text{Annual hours of work in wage sector}}$$

Table A3 shows how profits from farm and non-farm production are measured.

Table A3. Measure of profits from farm and nonfarm production

	Farm	Nonfarm
Revenue	TOTREV	REVCONS
Expenses	EXFARM = (TOTINP + TPTLIVST)	EXPENSES = (TOTAL MTHLY EXPENSES*NO. MTHS ENTER-PRISE OPEN IN LAST YEAR)
Value added	PROFARM = TOTREV - EXPFARM	PROFITS = REVCONS - EXPENSES

Figure 1. Observed and simulated distributions of annual hours of work for females living in rural areas.

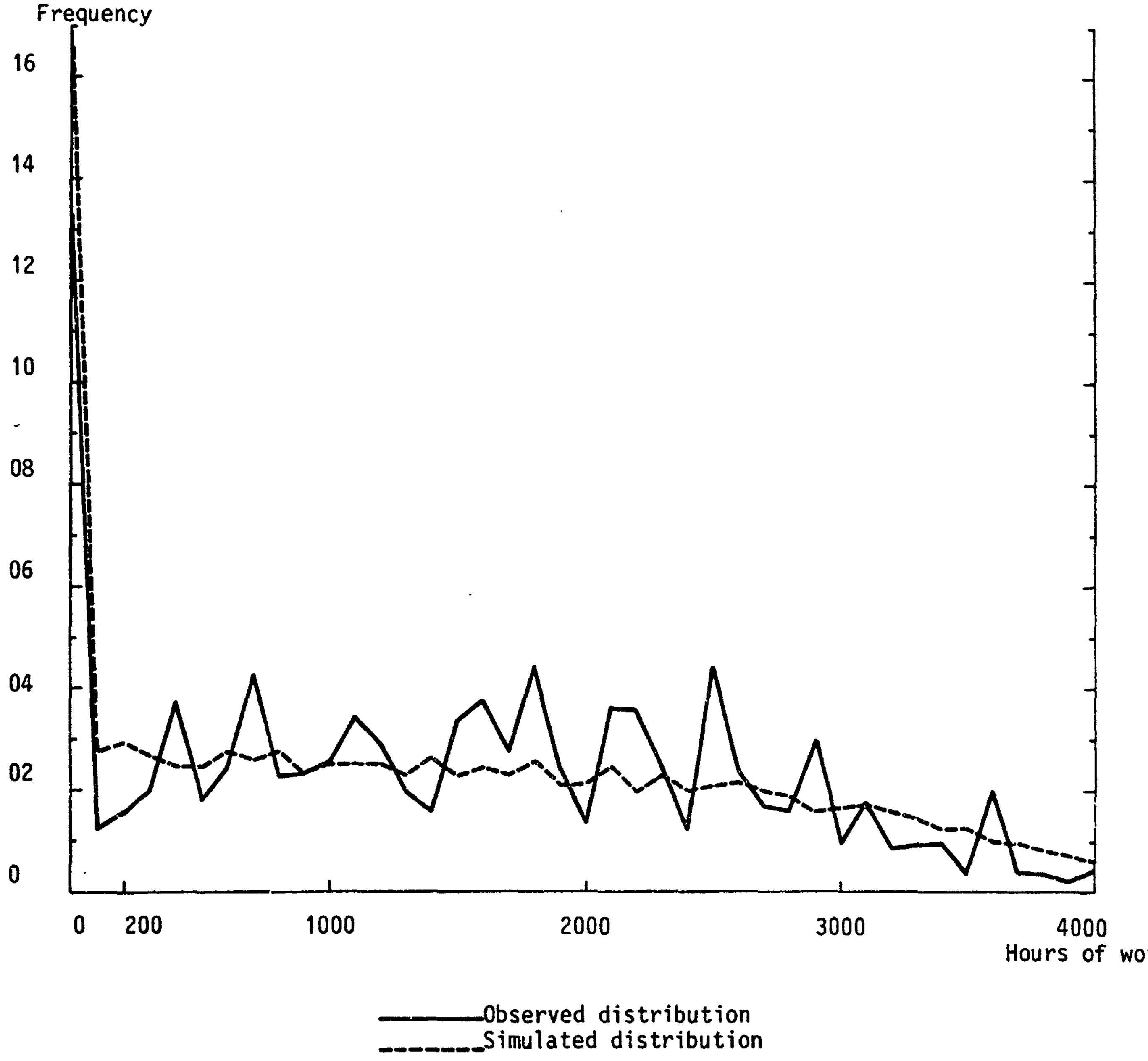


Figure 2. Observed and simulated distributions of annual hours of work for males living in rural areas.

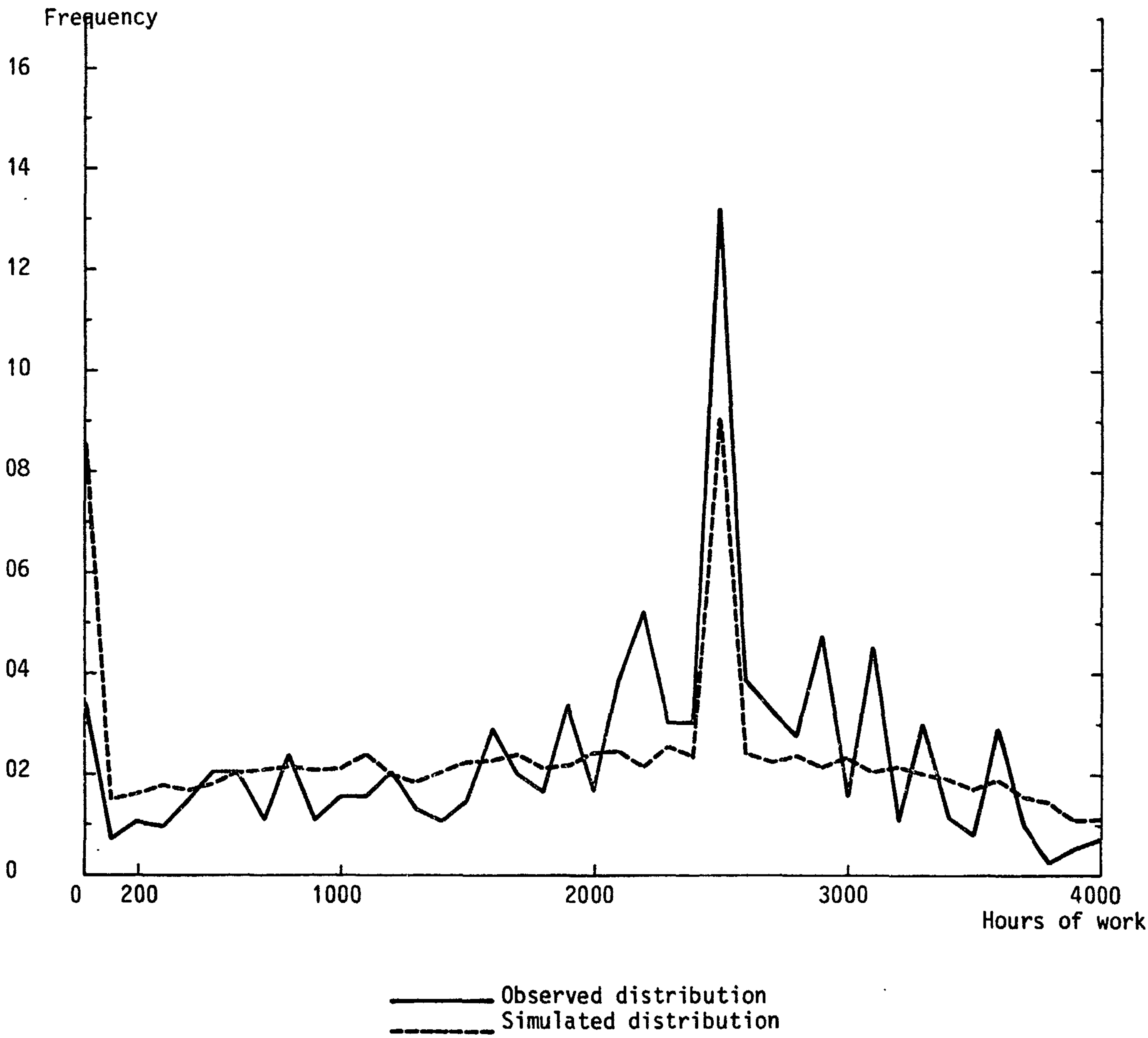


Figure 3. Observed and simulated distributions of per capita consumption among households living in rural areas.

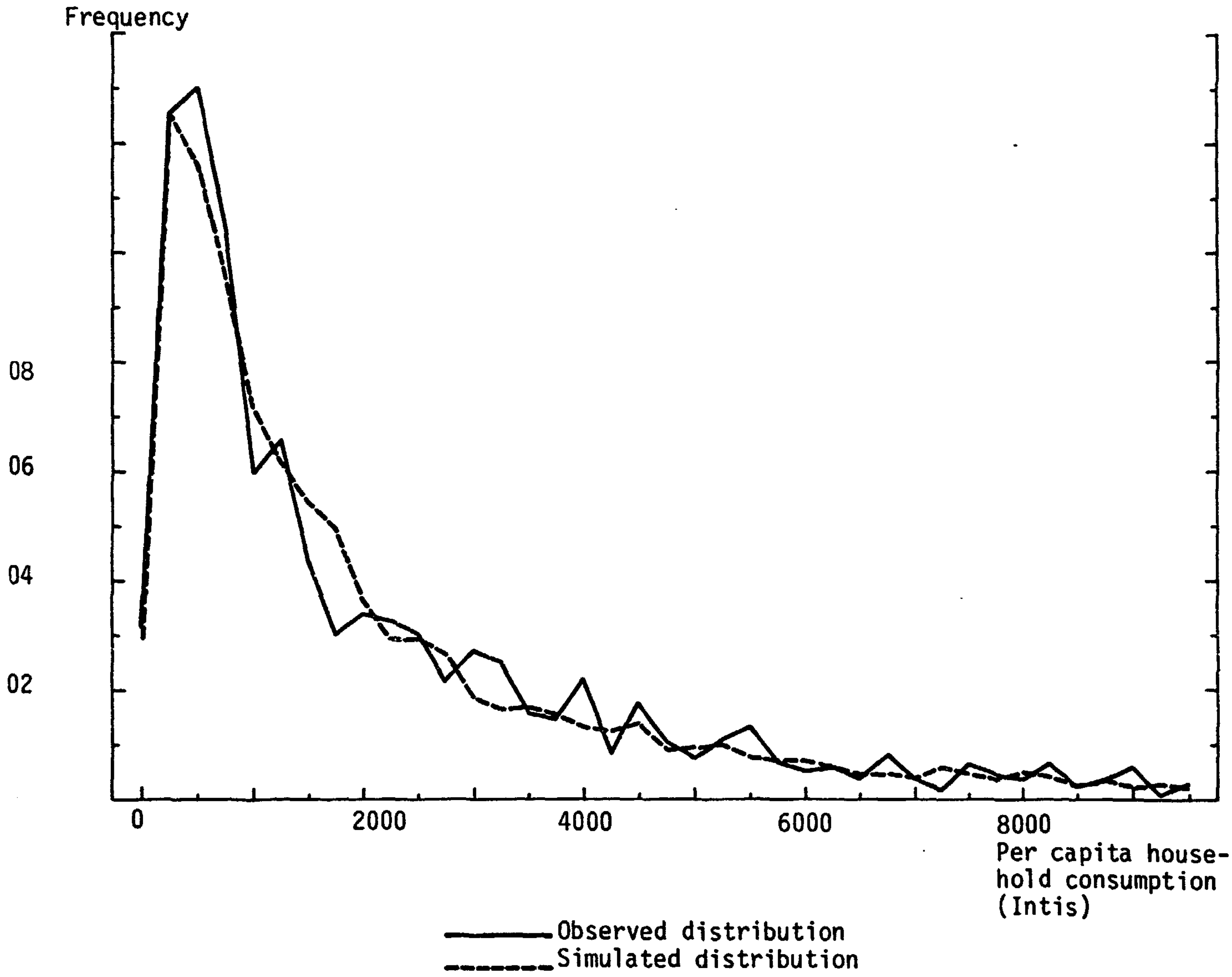


Figure 4. Observed and simulated distributions of hours of work for females living in Lima

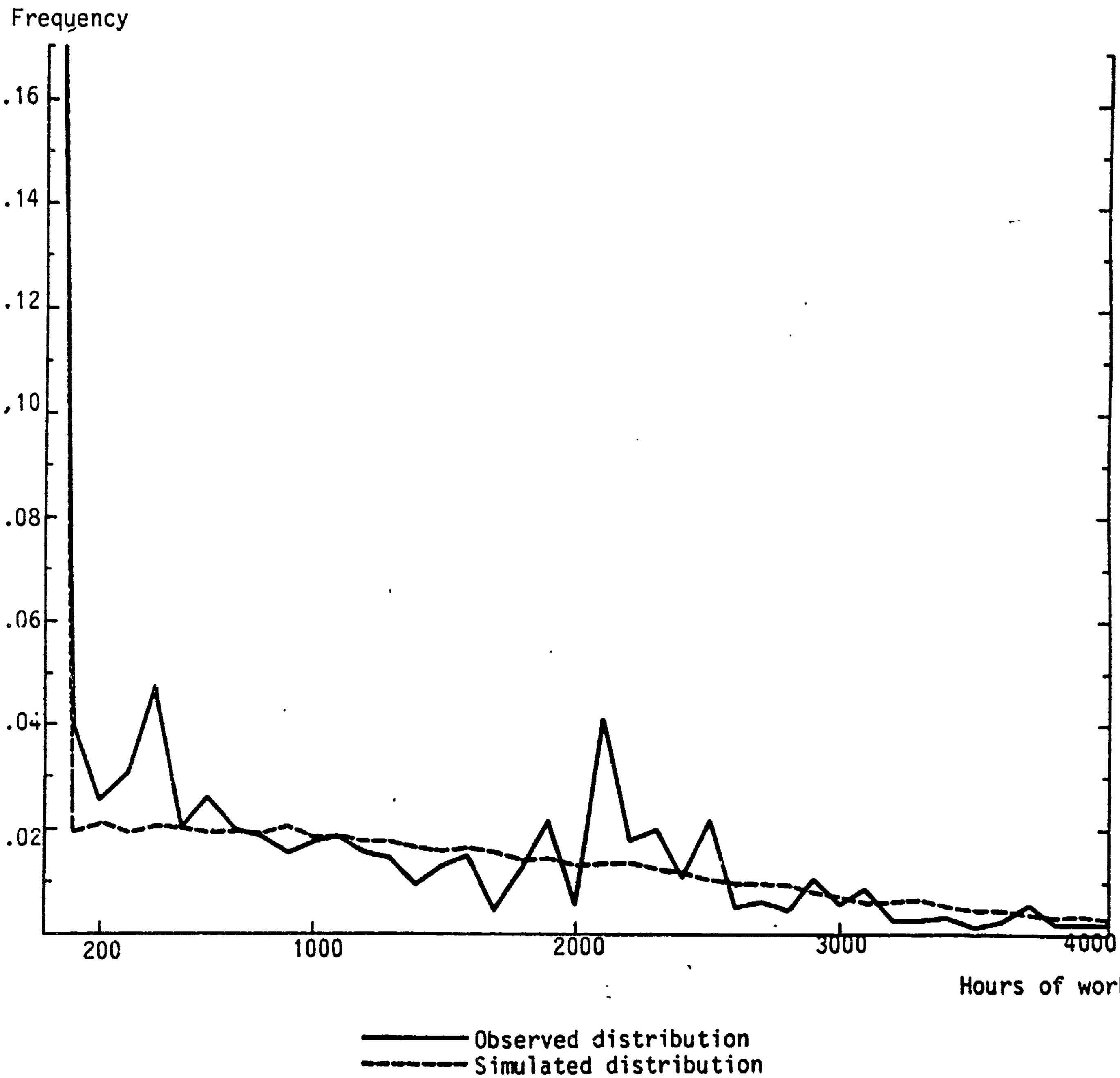


Figure 5. Observed and simulated distributions of hours of work for males living in Lima

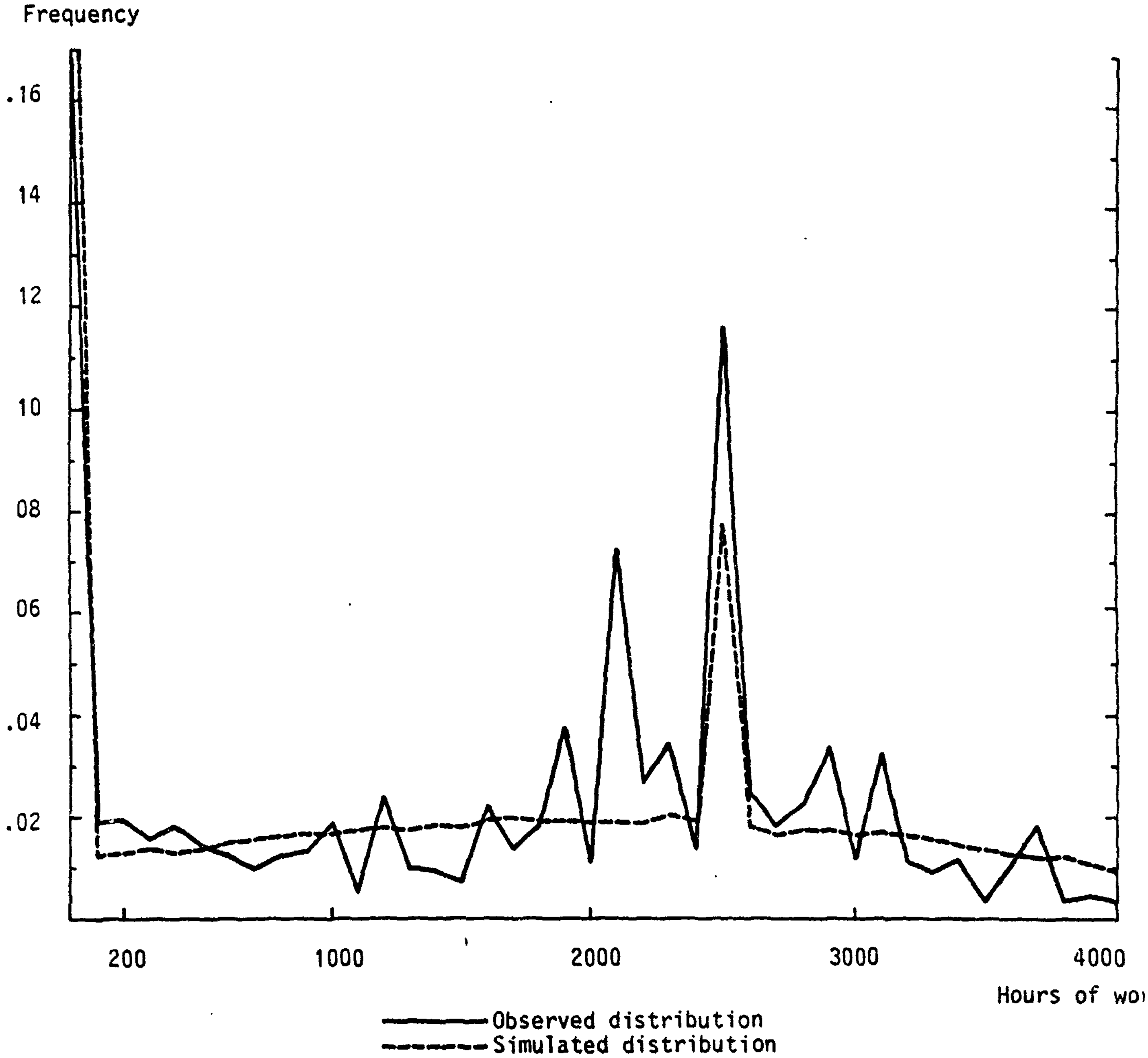
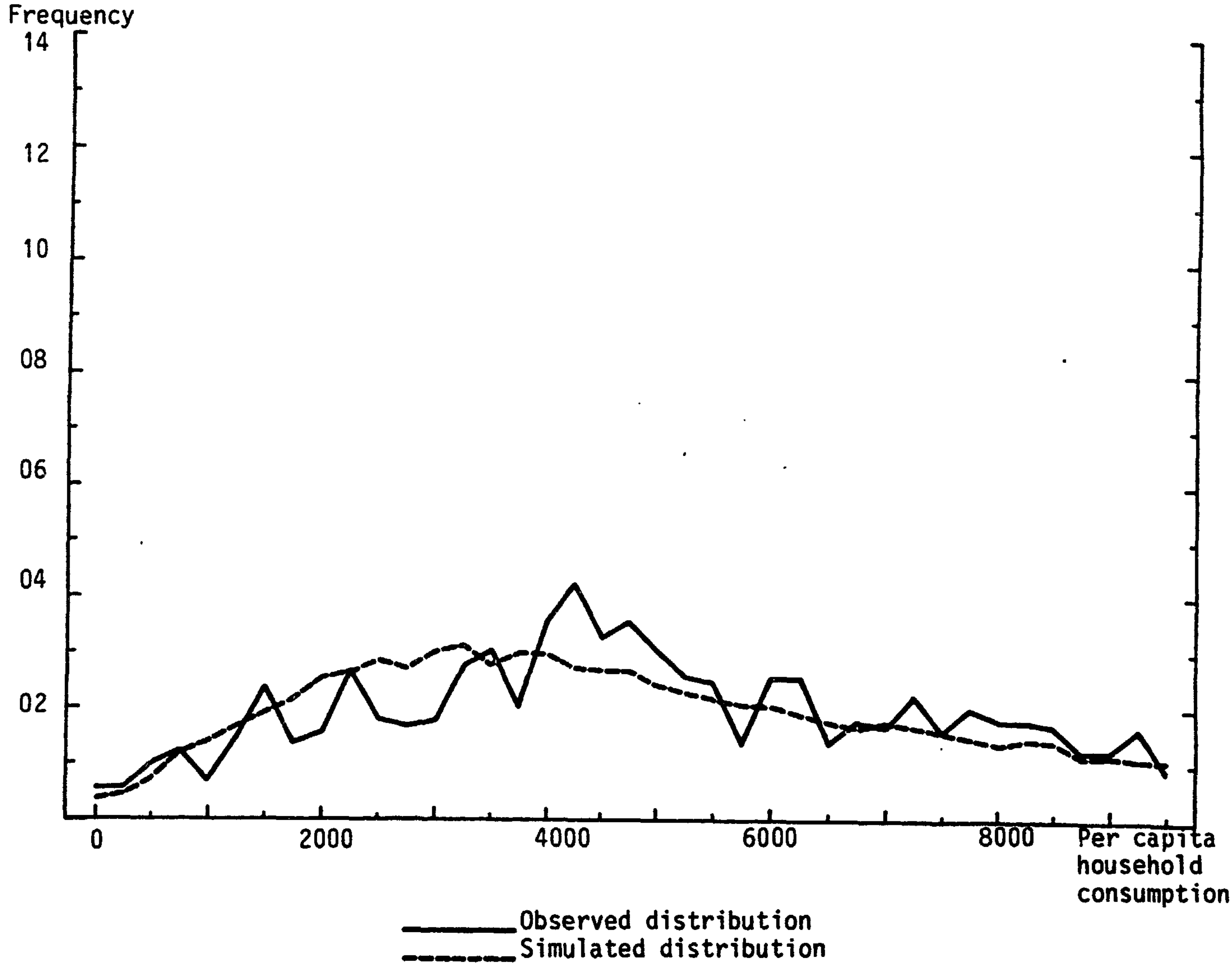


Figure 6. Observed and simulated distributions of per capita consumption among households living in Lima



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