

Comparative Advantage, Information and the Allocation of
Workers to Tasks: Evidence from an Agricultural Labor Market

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To understand the occupational distribution of workers characterized by any set of observed characteristics such as sex, height, or skin color requires attention to a variety of mechanisms that have been identified in the literature as determining who gets what jobs. Among these are the operation of comparative advantage, the influence of preferences over occupations by workers and over worker characteristics by employers, and the effects of partial employer ignorance about workers' productivities and thus the reliance on statistical averages. Given that observed worker characteristics may be correlated with both their own productivities and preferences, may be arguments in employers' preference functions, or may provide employers with partial information on worker productivity in a setting characterized by incomplete information, it is not surprising that the relative importance of these factors has not been identified.

One salient example of a strong relationship between a measurable worker characteristic and the task distribution that has generated much controversy is the well-known disproportionate allocation of women to weeding versus other agricultural activities in Asian agriculture. Table 1 presents the allocation of time to agricultural tasks based on detailed survey data from three Asian societies - the Philippines, India and Pakistan - that show how women are "overrepresented" in weeding activities compared to men. These data also suggest that the differentials in time allocation may be particularly strong when women are engaged in activities compensated using time wages, compared to when their compensation may more directly be related to their productivity (self-cultivation and piece-rate work). The reasons for this salient feature of Asian agriculture, where the technology of production is well known and the labor market is much less complex than in developed societies, still have not been settled. For example, Boserup, in her important distinction between "plow" agricultural and "shifting" cultivation, suggests that the observed division of labor in the plowing economies in Asia reflects a natural comparative advantage; another observer of this pattern, however, Kalpana Bardhan (1984), assumes that the predominance of women in certain agricultural activities reflects employer discrimination and monopsony power.

The notion that employer preferences importantly influence the occupational distribution

of workers in both developed and low-income countries has been the focus of a large literature that is mostly inconclusive. In addition, some economists have argued that it is not possible to test whether occupational allocations are in part the result of preferences by workers that covary with observed characteristics (Zellner, 1975). Tests of the roles of differential productivities in occupational allocations, in the absence of direct observations on productivity, are also known to be difficult. As pointed out in Heckman and Sedlacek (1988), the principal problem that arises in attempts to test the idea that workers are allocated according to comparative advantage is comparative advantage itself - because workers undertaking a particular task may be particularly well-suited to that task (or unsuited to the alternative), the sample of people for which one observes a wage observation in a particular task is not a random sample of the population as a whole and thus the estimated wage equation by task is subject to selectivity bias.

The solution proposed in Heckman and Sedlacek (HS) to identify the operation of comparative advantage and obtain consistent estimates of occupation-or task-specific wage equations makes use of statistical methods that correct for selectivity bias. The advantage of this approach is that, as long as the distributional and other assumptions required by the approach are met, it provides consistent estimates of the parameters on measured variables in the wage and task allocation equations. A comparison of these equations thus makes it possible to assess directly whether individuals with attributes that make them more likely to do a particular task are also likely to be better remunerated in that task and to test for the possibility that worker preferences also influence the allocation across tasks. Moreover, the selectivity correction model provides additional evidence on the issue of comparative advantage by indicating whether unmeasured aspects of productivity influence the allocation decision.

There are two difficulties with the selection-correction modelling approach. First, it requires the imposition of a significant amount of structure on the data. While flexible distributional assumptions can be used, as in HS, this approach increases the computational burden and data requirements of the process. Moreover, the fact that consistent estimation of the wage equation requires use of information from the allocation equation implies that any misspecification in the latter will also contaminate the estimates of the former.

Second, the approach does not permit an assessment of the role of imperfect information in the allocation of workers to tasks. Although the parameters of the wage and allocation equations under imperfect information will be estimated consistently using the selection model, the approach does not provide insight into the question of whether or not employers have complete information on worker productivity. Thus, for example, it is not possible to distinguish between a world in which most women perform a particular task because they have comparative advantage in it from one in which many women have comparative advantage in other tasks but are allocated to a particular task because women *on average* have comparative advantage in that task and employers cannot differentiate women with comparative advantage in different tasks (and similarly for men); i.e., statistical discrimination.

In this paper, we show that with data from a labor market in which (1) productivity estimates for workers are explicitly available and (2) the same worker is observed earning wages in different activities, tests can be performed of the roles of comparative advantage, information problems and preferences in determining the allocation of workers across tasks with minimal imposition of structure not implied by economic theory. The data we use to carry out the tests, from the Bukidnon area of the Philippines, is also characterized by a marked division of agricultural tasks by sex (Table 1), and provides information on individual worker's abilities based on their piece-rate wages.¹ We thus apply the methods to explaining in particular why women weed and men harvest.

In section 1, we set out the theoretical and statistical framework that establishes tests for the existence of comparative advantage and the role of preferences under perfect information in determining the sorting of workers among tasks based on task-specific piece-rate wage data.

Section 2 expands the framework to incorporate imperfect information and to establish tests of

¹In Foster and Rosenzweig (1993) we exploited these data by using observations on both time wages and piece-rate wages for the same workers regardless of task to draw inferences about the roles of information and preferences solely in wage determination. In that analysis, only one type of skill was assumed so that comparative advantage was not present. Thus, individual workers were assumed to have identical productivity across tasks. Observations on workers who work in multiple tasks and under different payment regimes are used here to test these assumptions (which are rejected) and to identify the roles of task-specific skills, employer information and preferences in task allocations.

the role of employer perceptions in task allocation when time wages are paid. The estimation method is briefly described in section 3, which is followed in section 4 by a description of the data and a discussion of sample selectivity and the determinants of payment regimes. The test results based on methods which impose no distributional assumptions are presented in section 5, which also includes a discussion of estimates from the standard probit selection model applied to the same data. The estimates indicate that in the labor market that we study, which is not atypical of most rural labor markets of Asia, a one-factor productivity model adequately describes the data, that more productive workers have a comparative advantage in harvesting relative to weeding and that productivity differences sort workers across these tasks according to the theory of comparative advantage. The tests also indicate that the greater presence of female workers in weeding activities compared to men is not due to women preferring such activities compared to men; in the piece-rate sector differential productivities and comparative advantage appear to explain the division of labor by sex. We also find, however, that more than half of the variance in the true productivity of workers is not known by employers and this ignorance is manifested in the task allocations by sex in the time-wage market. In that sector, in which employers appear to select workers for tasks, employers do not prefer men over women in harvesting among workers perceived to have the same productivity, but the disproportionate presence of women in weeding among workers compensated by time wages in part arises from statistical discrimination. Employer expectations about worker productivity, given worker-observed characteristics, are, however, unbiased. Finally, the normal-distribution version of the selection model provides results that are broadly but not entirely consistent with the findings that exploit direct information on the productivity of workers who engage in multiple tasks.

I. Perfect Information Labor Markets

a. Theory

We begin the analysis by examining a labor market environment in which there is perfect information about worker productivity available to both employers and researchers. We show the circumstances under which it is possible, with information on actual worker productivity,

to differentiate among and to test for the existence of three determinants of the allocation of workers among tasks: (1) differences in the productivity of workers at different tasks (comparative advantage); (2) preferences of individuals for different types of work, and (3) preferences of employers for different types of workers.

The role of comparative advantage in task allocation under perfect information is captured by the Roy model (1951), which has been recently formalized by Heckman and Sedlachek (1985). The basic features of the model are that each worker i has endowments μ_{ji} , one for each possible task j , reflecting the productivity in each of the tasks. In the absence of preferences of workers and employers for particular tasks or types of workers, respectively, the allocation of workers to tasks will be the result of each worker choosing the occupation in which that worker is most highly rewarded given the task prices. Task prices reflect the relative value of the two activities given the demand for the two types of work on the part of employers as well as the availability of workers by type. Specifically, if w_{jit} is the log wage that would be received by worker i at time t working at task j and π_{jt} is the log of the j^{th} task price (i.e., the price per unit of output in task j) received by worker i at time t then we may write

$$w_{jit} = \pi_{jt} + \mu_{ji} \tag{1}$$

and the worker will choose task j whenever $w_{jit} > w_{kit}$ for all $k \neq j$.

While the above model incorporates the possibility that worker heterogeneity is characterized by multiple productivity factors, a significant simplification arises if one factor is sufficient--that is if $\mu_{ji} = \lambda_j \mu_i$ where the λ_j and μ_i are task and individual-specific effects, respectively, and λ_1 is normalized to one so that $\mu_i = \mu_{i1}$. This simplification assumes that workers who are more productive² in one task are also more productive in the other task but the percentage by which

²Although μ_i is by construction equal to the *log* of productivity (as measured by output per unit time in task 1), we will in general refer to it simply as "productivity" except when it is important to distinguish between actual productivity and its log.

one worker is more productive than another is different in the two tasks.³ Under these conditions the wage equation (1) may be written

$$w_{jit} = \pi_{jt} + \lambda_j \mu_i \quad (2)$$

Equilibrium in this context with two tasks can be illustrated by a simple figure that plots the log wage in each task as a function of μ_i (see figure 1). If both tasks are performed in the economy the task prices will adjust (thus shifting the intercepts of the lines in figure 1) to equate supply and demand in the two tasks. In equilibrium, for $\lambda_2 > 1$, there is some M such that the less productive workers (those with $\mu_i < M$) will receive a higher wage in task 1 and thus will choose that activity while more productive workers (those with $\mu_i > M$) will choose task 2.

If the labor markets operate as a spot market⁴ in which workers choose different tasks in each period, exogenous changes in the demand for the two tasks will result in changes in the task prices (thus shifting the intercepts of the two lines) that equilibrate demand and supply for the two tasks. Figure 1 illustrates the case where there is an increase in the demand for task 1, which results in a shift in the allocation of workers toward that sector and an increase in the average productivity of workers in that sector. Workers with intermediate levels of productivity (in this case those with $M < \mu_i < M'$) will select different tasks at different points in time, and thus the share of time allocated by an individual to task 1 and the probability of working at task 1 at all will be decreasing in μ_i . If a_i denotes the share of time spent by individual i in task 1 over a given interval then we may write, in linear form, the task allocation equation corresponding to (2), as⁵

$$a_i = \theta_0 + \theta_\mu \mu_i \quad (3)$$

³If worker A earns 10 percent more than worker B in task 2 (i.e., if $\mu_{2A} = \mu_{2B} + .1$) then A should earn $\lambda_1 \times 10$ percent more in task 1.

⁴This assumption is made primarily for purposes of illustration; however, as discussed below, it provides a reasonably approximation to agricultural labor markets in many developing countries including the area of the Philippines that is studied in this paper.

⁵In a two factor world, of course, $a_i = a(\mu_{1i}, \mu_{2i})$. We focus on the one-factor model for ease of presentation; moreover, as shown below, a one-factor model adequately capture the structure of wages in the rural area of the Philippines that is the focus of our empirical analysis.

where θ_0 and θ_μ are constants. Note that observed characteristics, x_i , do not appear in either (2) or (3), as productivity, known by employers and employees, is the sole determinant of worker and employer choice.⁶

Incorporation of worker preferences into the model is straightforward. If worker utility at time t depends on the wage received and the task performed then the share of time spent in the different activities will depend on tastes for different tasks. The basic structure of the model changes, however, depending on how tastes are distributed among workers. In the simplest case where there is no heterogeneity in tastes (e.g., everyone prefers task 1 to task 2), relative task prices will adjust to reflect the relative desirability of the two tasks and the basic structure of the model will be unchanged, i.e., equations (2) and (3) are sufficient to describe the wage economy. If tastes are correlated with productivity but not with observed characteristics x_i net of productivity then if more productive workers prefer task 2, the relationship between productivity and the share of time spent in the task 1 will mimic or reinforce the comparative advantage result, while if the opposite is true it is possible that more productive workers will be observed to spend *less* time doing the task in which they have comparative advantage. This latter point is important because it implies that it may be difficult to distinguish the hypothesis that more productive workers choose task 1 because they are more productive (and thus better compensated) in that sector from the hypothesis that more productive workers simply prefer doing task 1 in the sense that they would undertake that task even if they were not more highly rewarded for doing it. As we show below, this difficulty can be addressed if there are information asymmetries.

If tastes for tasks on the part of workers are correlated, but not perfectly, with a k -vector of observed characteristics x_i , then the share of time spent in the different activities will be related to x_i net of both productivity μ_i and task prices. Thus

⁶Note that the allocation in any particular period will also depend on the task prices in that period. Equation (3) should be thought of as the result of aggregating period-specific allocation decisions which depend on task prices in the respective period. Thus in a given labor market for a specified interval the task-price effects may be captured as a constant.

$$a_i = \theta_0 + \theta_\mu \mu_i + \theta_x x_i \quad (4)$$

where θ_x is a k -dimensional parameter vector. Competition among employers will ensure, however, that wages reflect the preferences of workers only to the extent that relative prices are affected. Thus, wages and x_i do not covary, net of the productivity of workers and task prices, even if preferences for tasks covary with x_i .⁷

Employer preferences over the attributes of workers doing particular types of tasks will influence both the wages paid to workers net of task prices and the share of time spent by workers in different occupations. If there is employer *taste discrimination* with respect to a particular characteristic of workers x_i in the sense of Becker (1971) then wages will covary with x_i net of productivity and the task prices. Assuming a log-linear effect and allowing for the possibility that taste discrimination operates differentially in the two different sectors, the wage equation becomes

$$w_{jit} = \pi_{jt} + \lambda_j \mu_i + \beta_j x_i \quad (5)$$

If worker characteristics x_i are differentially rewarded in the two tasks ($\beta_1 \neq \beta_2$) then these characteristics will also influence the allocation of the workers to tasks, as in (4), even in the absence of differential worker preferences over tasks. Note that the key distinction between the effects of employer and worker preferences is thus that observed worker characteristics affect the allocation of workers as well as wages net of productivity and task prices in the former case

⁷That is equally productive men and women doing the same task will receive the same wage even if *ceteris paribus* men prefer to do one task and women the other. This implication is also used by HS. If, however, there is imperfect competition, monopsonistic employers might exploit worker preferences. In that case worker characteristics observed by employers and correlated with worker preferences will enter the wage equation.

while in the latter the x_i 's only affect task allocations.^{8 9} These results with respect to the correlation of x_i with wages and task allocations, net of worker productivity and task prices, are summarized in the first two columns of Table 2.

b. Identification of the roles of comparative advantage and preferences in the complete information setting using piece-rate wages

We have shown that by estimating the appropriate wage and allocation equations it is in principle possible to test for and measure the roles of productivity and preferences in determining the allocation of workers to tasks in an economy. The principal problem is that, even in the case of complete information among market actors, the equations include a variable that is not generally measured - actual worker productivity. Without this information, tests of the hypothesis that workers are allocated according to comparative advantage have necessarily been based on methods that impose substantial structure on the data. Moreover, because it is necessary to condition on worker productivity in order to determine whether employer or worker preferences importantly influence wages or allocations, tests for these effects have generally been inconclusive.

In this section, we show how tests of the number of unique productivity factors and of the significance of comparative advantage and of preferences in determining task allocation under perfect information can be carried out with minimal structure imposed by using data characterizing an environment, not uncommon in low-income labor markets, in which (1) workers are paid on a piece-rate basis for some part of the year, so that productivity estimates for

⁸Of course employee preferences will affect wages through their effect on the equilibrium task prices; the point is that they do not lead to differential wages by characteristics net of task, productivity, and the task price. Note that, even if it is found that employer preferences are expressed in wage rates net of task prices, this does not necessarily imply imperfect competition. It is possible that all employers share the same preferences, for example.

⁹We ignore here the possibility that employers only exercise their tastes by excluding individuals from particular tasks, in which case this distinction is of little value from an empirical perspective and of little relevance in the setting which will be the focus of our analysis, where most individuals are found to do both tasks. More problematically, using this approach it does not seem possible to distinguish a model based on worker preferences from one in which employers exercise their tastes by excluding individuals from particular tasks but are prohibited by legal or other means from paying different wages to equally productive individuals within tasks.

workers are explicitly available, and (2) the same worker is observed earning wages in different activities/occupations.

It is easily seen how piece-rate data may be used to conduct an analysis of the allocation of workers to tasks in the presence of complete information. First note that the piece-rate wage earned by a worker in a particular task on a given day is the product of the piece-rate price for that task on that day and the amount produced in that day (productivity), where the latter consists of a persistent component reflecting the amount of work done by the individual and a residual reflecting measurement error and idiosyncratic variation arising from, for example, the fact that variation in crop density will imply that the amount of crop picked by a given worker will vary from day to day. Taking logarithms yields the wage equation (1) plus an error term:

$$w_{jit} = \pi_{jt} + \mu_{ji} + e_{jit} \quad (6)$$

In order to use piece-rate data to obtain productivity estimates from equation (6), it is first necessary to obtain estimates of the piece-rate price terms. OLS cannot be used for this purpose, however, for the reasons discussed in HS. If two piece-rate observations are observed for a sub-sample of the population, however, consistent estimates of π_{jt} may be obtained (exclusive of a constant) by estimating equation (6) in first differences (within individuals). The fact that a sub-sample of individuals with two piece-rate observations is not necessarily a random sample of the population presents no particular problem for the estimation of the π_{jt} because, by assumption, all individuals face the same task price. By subtracting task-price effects from the piece rate wages one is left with consistent estimates of worker productivity $\hat{\mu}_{jit} = \mu_{ji} + e_{jit}$

If it is additionally assumed that the measurement errors are uncorrelated, the covariance of two of the estimates of $\hat{\mu}_{jit}$ for the same task, $\sigma(\hat{\mu}_{ji1}, \hat{\mu}_{ji2}) = \sigma^2(\mu_{ji})$, provides a consistent estimate of the variance of task-specific productivity in the population among those with at least two piece-rate observations in that task. Moreover, by further imposing the plausible restriction that the variance of the measurement error term is the same across all workers, a comparison of the measured variance of μ_{ji} among those workers with only one piece-rate observation to the same measure taken from the population with more than one piece-rate observation provides a

test of whether the variance in productivity within the two groups is the same because

$$\sigma^2(\hat{\mu}_{j1t}) = \sigma_2^2(\mu) + \sigma_2^2(e_{j1t}).$$

It is also possible to test whether a one-factor model adequately describes the distribution of productivity across workers. Consider a respecification of (6) in which we normalize according to one occupation or task (and suppress the task prices). Assume that the log piece-rate wage for individual i in occupation 1 at time t is given by

$$w_{1it} = \mu_i + e_{1it} \quad (7)$$

Then for any other occupation j the log piece-rate wage for the same individual is given by (8) if there is a unique productivity factor for that occupation

$$w_{jit} = \lambda_j \mu_i + \eta_{ji} + e_{jit} \quad (8)$$

where η_{ji} is the occupation-specific productivity factor for individual i and λ_j is an occupation-specific parameter.

With two piece-rate observations for each occupation inclusive of the normalized occupation it is possible to identify the variances of the normalized or common productivity factor μ_i and the task-specific productivity factors η_{ji} as well as to identify the λ_j as long as the time-varying productivity shocks e_{jit} are orthogonal. In that case, the observed sample moments, for two piece-rate wage occupations, are given by:

$$\sigma(w_{jit}, w_{1it}) = \lambda_j \sigma^2(\mu_i) \quad (9)$$

$$\sigma(w_{1i1}, w_{1i2}) = \sigma^2(\mu_i) \quad (10)$$

$$\sigma(w_{ji1}, w_{ji2}) = \lambda_j^2 \sigma^2(\mu_i) + \sigma^2(\eta_{ji}) \quad (11)$$

There are three independent equations derived from the four wage observations relating the three observed moments to the three model parameters. Thus, the variances of the common and occupation-specific productivity factors are identified and it is possible to test whether a one-

factor model is adequate, i.e, $\sigma^2(\eta_{ji})=0$. In the one-factor case, the parameter λ_j , which is also identified, characterizes the extent of comparative advantage across the two tasks.

With additional information on worker allocations in the piece-rate sector, it is also possible to test for the operation of comparative advantage and worker preferences in the allocation of workers to tasks within a sector where problems of imperfect information do not arise. In particular, the allocation equation (equation 4) parameters reflecting the operation of comparative advantage and of preferences in terms of the observed moments for the wages and task allocations are:

$$\theta_{\mu} = \frac{\sigma(a_p, w_{j1})\sigma(x_p, x_i) - \sigma(a_p, x_i)\sigma(w_{j1}, x_i)}{\sigma(w_{j1}, w_{j2})\sigma(x_p, x_i) - \sigma(w_{j1}, x_i)^2} \quad (12)$$

and

$$\theta_x = \frac{\sigma(a_p, x_i)\sigma(w_{j1}, w_{j2}) - \sigma(a_p, w_{j1})\sigma(w_{j1}, x_i)}{\sigma(x_p, x_i)\sigma(w_{j1}, w_{j2}) - \sigma(w_{j1}, x_i)^2} \quad (13)$$

where it has been assumed for notational simplicity that x_i is a scalar. As discussed, if comparative advantage plays a role in occupational allocations, then $\theta_{\mu} \neq 0$ and in the absence of worker preferences that are related to measured characteristics of workers, occupational allocations should not be influenced by any measured characteristic x_i net of actual productivity so that $\theta_x=0$. Testing for employer preferences is more difficult because both wages and allocation are influenced under this variant of the model; however, following a suggestion of HS some insight can be gained by comparing separate estimates of piece-rate prices for individuals with different characteristics.¹⁰

¹⁰Because task prices estimated in this way are only determined up to a constant, this approach will not identify employer discrimination by sex if that discrimination results in a constant sex-premium across tasks and time periods. Unfortunately the data set we use does not contain information on piece-rate prices that might otherwise be used to address this issue directly. In any case, it seems unlikely that employers would use different piece-rate prices for different individuals doing the same task in the same period even if they paid different wages when compensating these individuals on a time-rate basis.

2. Imperfect Information in the Labor Market

a. Theory

The principal additional implication for the allocation of workers across occupations in the absence of complete information on worker productivity is that employers are unable either to match perfectly workers to jobs or to attract the right workers to the right jobs by adjusting wages appropriately and thus must use observable characteristics to assign wages and determine allocations. To capture this idea in the existing framework let $\mu_i^* = E(\mu_i | x_i)$ denote the expectation of the log of productivity based on characteristics known to the time-wage employer and assume that the actual log of productivity may be written as the sum of μ_i^* and a residual u_i with distribution F_u that does not depend on x_i :¹¹

$$\mu_i = \mu_i^* + u_i \quad (14)$$

Then because competition among employers will ensure that the wage received by individual i is equal to the expected value of having him work at task j (i.e., his expected productivity given observed characteristics x_i), his log time wage w_{jit}^T , may be written

$$\begin{aligned} w_{jit}^T &= \pi_{jt}^T + \ln E(e^{\lambda_j^T \mu_i} | x_i) \\ &= \pi_{jt}^T + \lambda_j^T \mu_i^* + \ln \int e^{\lambda_j^T u} dF_u(u) \\ &= \pi_{jt}^T + \lambda_j^T \mu_i^* + \kappa_j^T \end{aligned} \quad (15)$$

where the superscript T identifies the log wages and prices as those associated with time-rate employment. Note that equation (15) differs from equation (2) by the presence of the constant κ_j^T and by the fact that μ_i^* , expected log productivity, appears in the wage equation rather than μ_i . It is worth noting that the fact that κ_j^T is a task-specific constant implies that in a comparison of two

¹¹This assumption will hold, for example, if log-productivity is a linear function of worker attributes only some of which are observable to the employer and the vector of unobservable characteristics can, in turn, be written as a linear function of the observable characteristics and an i.i.d. (across individuals) error vector. Among other things, this restriction rules out the possibility that information is more precise for individuals with greater exposure to the labor market as shown by Foster and Rosenzweig (1993) in the context of India. This assumption is necessary in order for the log time wage to be written as a linear function of μ_i^* and a task-specific constant (see equation (15)).

individuals, the one with higher *expected log productivity* will also have higher *expected productivity* and thus a higher time wage for the same task and time period.

Allocations under time wages may be characterized using a figure analogous to figure (1) by replacing μ_i on the horizontal axis with μ_i^* ; there will now be some intermediate level of *expected productivity* such that those workers with characteristics yielding an *expected productivity* above that level will receive higher wages if they work at task 2, while those with an *expected productivity* below that level will receive higher wages if they work at task 1. Thus in the absence of preferences over particular tasks by the workers and over particular types of workers by employers, the share of time allocated by an individual to task 1 will depend, analogously to the perfect information case, only on his *expected productivity* and task prices; x_i will not covary with tasks net of μ_i^* . However, again analogously to the perfect information case, when workers are heterogeneous in preferences for tasks that are correlated with *employer observable* characteristics of the worker x_i , the share of time spent in task 2 (weeding) will depend on *expected productivity* as well as x_i but wages will not covary with x_i net of μ_i^* and task prices, as in (4).

In the imperfect information environment it is possible that worker task preferences are correlated with characteristics that are *unobservable* to the employers and also correlated with *productivity* (including *productivity* itself). Thus the allocation equation under these circumstances includes not only μ_i^* and x_i but also u_i , so that:

$$a_i^T = \theta_0^T + \theta_\mu^T \mu_i^* + \theta_u^T u_i + \theta_x^T x_i \quad (16)$$

This equation allows us to distinguish the comparative advantage hypothesis from the hypothesis that more productive workers simply happen to prefer to undertake the task in which they have comparative advantage, a distinction which, as noted above, cannot be made in the perfect information case. The idea is that workers with similar levels of *expected productivity*, μ_i^* , will receive similar time wages; thus if workers with higher u_i are found to be spending more (or less) time in the sector in which they have comparative advantage, then we may infer that worker

preferences are importantly influencing the allocation of workers to tasks.¹²

Finally, insights drawn from the complete information case are also applicable in the case of employer preferences: taste discrimination by employers will imply that workers with particular observed characteristics will receive higher wages given their expected productivity, a fact that will alter the share of time that individuals spend in particular tasks. Thus, in the most general form the wage equation can be written

$$w_{jit}^T = \pi_{jt}^T + \lambda_j^T \mu_i^* + \kappa_j^T + \beta_j^T x_i \quad (17)$$

An implicit assumption of the analysis of the labor market in the imperfect information setting is that employer expectations are correct in the sense that the subjective distribution of worker productivity of the employer, conditional on the observed characteristics of the worker, is equal to the actual distribution of productivity among all workers with those characteristics. It is possible, however, that employers misperceive the relationship between x_i and productivity. Because μ_i^* is taken to be the *true* expected productivity given x_i rather than the subjective expectation of the employer, this possibility is easily captured by equations (16) and (17): for example, if employers *incorrectly* assume that males are better at task 2 than are females then, net of the true expected productivity, males are likely to receive higher wages and spend a greater share of their time in that activity. Thus it is not possible to distinguish between employers' biases in preferences and in information.

The third and fourth columns of Table 2 present a summary of the relationships between observed worker characteristics x_i and wages and task allocations given expected productivity and task prices in the imperfect information environment, based on equations (16) and (17).

Although all of the implications about the covariation of x_i with wages and task allocations under the different scenarios of preferences (or ignorance) are identical between the perfect and imperfect information settings, there is an important difference: in the former case one must have

¹²Of course, if preferences are not correlated with the unperceived component of worker productivity, it is possible that $\theta_u^T=0$ while preferences may still play a role in the distribution of workers across occupation.

available a measure of actual worker productivity while in the latter case one must identify that component of worker productivity that is known by employers. Inferences drawn from relationships (4) and (5) involving actual productivity when employers are partially ignorant of true productivity can be incorrect. It may be established, for example, that the coefficient on an x_i variable in the allocation equation (16) in terms of the moments of the observed variables and perceived productivity μ_i^* is

$$\theta_x^T = \frac{\sigma(a_i^T, x_i) \sigma^2(\mu_i^*) - \sigma(a_i^T, \mu_i^*) \sigma(x_i, \mu_i^*)}{\sigma^2(x_i) \sigma^2(\mu_i^*) - \sigma(x_i, \mu_i^*)^2} \quad (18)$$

Consider, now an alternate version of equation (16) with expected productivity replaced with true productivity, (μ_i^* replaced by μ_i), and dropping u_i for simplicity:

$$a_i^T = \tilde{\theta}_0^T + \tilde{\theta}_\mu^T \mu_i + \tilde{\theta}_x^T x_i \quad (19)$$

Now the analog to equation (18) is

$$\tilde{\theta}_x^T = \frac{\sigma(a_i^T, x_i) \sigma^2(\mu_i) - \sigma(a_i^T, \mu_i) \sigma(x_i, \mu_i)}{\sigma^2(x_i) \sigma^2(\mu_i) - \sigma(x_i, \mu_i)^2} = \frac{N_1 + \sigma(a_i^T, x_i) \sigma^2(u_i)}{N_2 + \sigma^2(x_i) \sigma^2(u_i)} \quad (20)$$

where N_1 and N_2 denote the numerator and denominator of equation (18), respectively.

In the absence of worker preferences with respect to tasks and employer taste discrimination $\theta_x=0$ and thus $N_1=0$. But under these circumstances $\tilde{\theta}_x^T$ will not be zero if both $\sigma^2(u_i)>0$ and $\sigma(a_i^T, x_i)>0$.¹³ The first of these conditions is exactly the condition that some aspects of productivity are not known by time-wage employers. The second says that x_i is correlated with a_i^T as will be the case if x_i is known by the employer and correlated with productivity. Thus, the finding that identically-productive workers with different values of x_i have different distributions of time in different tasks does not necessarily imply either that workers have preferences with respect to tasks or employers exercise taste discrimination in environments where employers are

¹³Because actual productivity is, in effect, a noisy estimate of employer-perceived productivity (equation 14), this result is simply a manifestation of measurement-error bias.

partially ignorant of worker productivities and use x_i as a productivity signal.

An analogous equation holds for wages: if true productivity is used instead of perceived productivity to estimate equation (17) worker characteristics that are known by the employer and predict productivity will appear to affect wages even when structurally $\beta_j^T=0$. This, along with the differential allocation across tasks reflect, of course, statistical discrimination (see, e.g., Aigner and Cain 1977): among workers with the same true productivity, that worker with the higher employer-perceived productivity will receive a higher wage in both tasks, receive a higher differential wage in the high-wage task (due to comparative advantage), and work more in the high-wage task as a result.

b. Estimation under incomplete information using piece-rate and time wages

As noted, in the presence of incomplete information the problem of identifying the determinants of task allocations is more complex because, even when actual productivity is known, it is also necessary to obtain an estimate of that component of actual productivity that is perceived by employers. While direct observations of expected productivity are not available, we now show that the key parameters of the allocation and wage equations (assuming a one factor model) can be estimated consistently using information for each worker on one piece-rate wage observation (w_{jit}^P),¹⁴ one time-wage observation (w_{jit}^T), and at least one worker characteristic that is correlated with productivity and can be argued on *a priori* grounds to be (i) observed by the employer and (ii) not itself subject to taste discrimination by him. That is, we assume the existence of a signaling equation that relates a worker's actual productivity to a subset of the measured characteristics y_i of the worker that are also known by the employer and to which the employer is otherwise indifferent,

$$\mu_j^* = \delta' y_i + \varepsilon_{it} \tag{21}$$

¹⁴Assuming a one factor model, it does not matter from which task the piece and time-rate wages are taken as long as there is sufficient information on both tasks to obtain a precise estimate of the parameter λ_2 . Thus, to simplify subsequent discussion it will be assumed that, unless otherwise stated, all piece-rate wages are from task 1 and all time wages from the same task (either 1 or 2).

As in the perfect information case, the sample moments may be used to construct estimates of the model parameters. In particular, using equations (7), (14), (17), and (21) and allowing for measurement error with respect to the time wage, it may be shown that, when $\beta_j^T=0$,¹⁵ the comparative advantage λ^T coefficient in the case of imperfect information is:

$$\lambda_j^T = \frac{\sigma(y_i, w_{ijt}^T)}{\sigma(y_i, w_{ijt}^P)} \quad (22)$$

where we have assumed that the component of employer-perceived productivity that is not measured ϵ_i and the measurement errors in wages are orthogonal. These same equations also imply that the variance in perceived worker productivity is

$$\sigma^2(\mu_i^*) = \frac{\sigma(w_{ijt}^P, w_{ijt}^T) \sigma(y_i, w_{ijt}^P)}{\sigma(y_i, w_{ijt}^T)} \quad (23)$$

from which, as shown in Foster and Rosenzweig (1993), with information on the variance of true productivity obtained from the covariance of two piece rate wages, as above, it is possible to identify the variance of the unobserved component of productivity, $\sigma^2(u_i)$. It is also possible to determine that component of the variance of expected productivity that is not directly observed by the econometrician, $\sigma^2(\epsilon_i)$.

The roles of both observed, and hence rewarded, and unobserved productivity in task allocations can also be identified using information on two piece-rate and one time-rate observations for workers. For example, in the special case in which θ_x^T is assumed to be zero the expressions $\theta_{p,r}^T$ and θ_u^T in terms of observed moments are simply

¹⁵Analogous but more complicated expressions that allow for $\beta_j^T \neq 0$, can also be derived. The estimates that we obtain, described below, allow for the most general model.

$$\theta_{\mu^*}^T = \frac{\sigma(w_{1it}^p, a_i^T)}{\sigma(w_{1it}^p, w_{1it}^T)} \quad (24)$$

and

$$\theta_u^T = \frac{\sigma(w_{1it}^p, a_i^T)\sigma(x_p, w_{1it}^T) - \sigma(w_{1it}^T, a_i^T)\sigma(x_p, w_{1it}^p)}{\sigma(w_{1it}^p, w_{1i2}^p)\sigma(x_p, w_{1it}^T) - \sigma(w_{1it}^p, w_{1it}^T)\sigma(x_p, w_{1it}^p)} \quad (25)$$

respectively. Even when all measured worker characteristics x are included in the allocation equation,¹⁶ exclusion of at least one characteristic from the wage equation (i.e., the assumption that there is at least one worker characteristic about which employers do not care other than as a predictor of productivity) is sufficient for identification of all of the parameters of the allocation equation.

3. Estimation Method

The estimation method that we use to implement the test of the two-factor model and to obtain the estimates of the task allocation and wage equations matches the theoretical moments of the system of equations, e.g., the right-hand-sides of equations (9) through (11), denoted by Σ , to the sample moments, e.g., the left-hand-side variables in (9) through (11), denoted by M . The objective function $Q=(m-\sigma(\phi))'\Omega(m-\sigma(\phi))$ is minimized with respect to the parameter vector ϕ ; m is the vector of elements obtained by stringing out the lower triangular elements of the matrix M , $\sigma(\phi)$ is the corresponding vector obtained from Σ which depends on the set of model parameters ϕ , and Ω is a weighting matrix. The weighting matrix is that which corresponds to the "optimal minimum distance" estimator discussed by Chamberlain (1982, 1984), also known as the optimal

¹⁶Recall that if the preferences of the worker depend on productivity, expected productivity may vary by task if the willingness of a worker to do a task in a particular period signals something additional about his productivity to the employer. In this case, expected productivity in a particular period (as measured from one time-rate wage equation) will be a noisy estimate of average expected productivity, thus biasing the coefficient on expected productivity to zero. Even if this is the case, however, this specification may be used to test for the effect of unobserved productivity on allocation to task.

weighting matrix (OWM) or arbitrary generalized least squares estimator (AGLS) estimator¹⁷ This estimator yields consistent parameter estimates and standard errors without imposing any parametric distributional assumptions.

As noted, for all of our tests we need at least two measures of productivity (piece-rate wages) for the same task for each worker to identify the relevant parameters of each equation. This is because each task-specific piece-rate wage is a noisy measure of productivity but each measure can be used, in effect, as an instrument for the other. However, more efficient estimates can be achieved by including groups of workers for whom we have only one productivity observation under the assumption that the parameters including the variances in measurement errors and in all other unobserved constructs, such as productivity μ , are the same for all workers. The generalization of the OWM method to multiple groups, with cross-group parameter constraints, is straightforward. As noted, if it assumed only that measurement error variances are the same for workers regardless of their participation in task and payment regimes, then it is possible to perform identification tests involving the assumption of equality for subsets of parameters across groups. In particular, tests, reported below, of the equality of the group-specific variances of productivity μ provide information on whether subsamples of workers chosen on the basis of payment regime (which determines whether or not productivity is measured) or task are representative of the entire population of workers.

4. The Data and Sample Selectivity

The critical information needed to identify the operation of comparative advantage and of preferences, if any, in determining the allocation of workers across occupations or tasks that does not require auxiliary assumptions is the productivity of workers. As noted, one important indicator of worker productivity is a worker's performance under a piece-rate regime.¹⁸ The data

¹⁷This estimator was used by Abowd and Card (1989) to estimate an error components model of U.S. wage rates.

¹⁸An important assumption of the tests that we have discussed is that productivity as measured in the piece-rate labor market is a relevant measure of productivity in the time-wage labor market. There are a number of potential problems with this assumption. It might be argued, for example, that productivity differentials depend on differences in effort in addition to differences in fixed characteristics like strength or skill level. Because the returns to effort are

used in this paper are well-suited to an analysis of these issues. They are from a stratified random panel of 448 farming households in Bukidnon in northern Mindanao, Philippines where, as is typical of agriculture in the Philippines, piece-rate and time-wage work coexist.¹⁹ These households were interviewed in four rounds at four month intervals in 1984-85 as part of an International Food Policy Research Institute study by Bouis and Haddad (1990). In addition to detailed information on agricultural production (principally of corn, rice and sugar cane) and basic anthropometric and demographic information for each household member that may be relevant to productivity and plausibly known by employers, the survey provides extensive information on labor market activity in the study area.

For every individual in the sample households and in each round we observe days worked off the farm and average daily wages received by crop, task and type of payment (piece-rate versus time-wage).²⁰ Information on days worked by family and hired laborers on the farm and supervisor-days by crop, task and type of payment is also available for each study household in each round. Thus each round provides averages of (t-specific) daily spot-market prices and aggregates of the binary task allocation decisions made in each daily spot market. We use the totals across all four rounds of task-specific days to construct measures of task allocations by form of payment for each worker. Individual observations on wages are based on the reported

greater when an individual is paid on a piece-rate basis than when he/she is paid time wages, one would expect greater differences in productivity in the piece-rate and the time wage sector. While this argument has merit, it should be recognized that because individuals with more favorable endowments (e.g. those with greater strength or skills) will need to provide less effort to produce the same output as those with lower endowments, these workers are likely to do more effective work in a given day than workers with less favorable endowments in both sectors. Thus while differences in the return to effort in the two sectors will affect productivity differentials, it will not affect the ranking of workers by productivity.

¹⁹Although we focus on the distinction between piece-rates and time-wage earnings, there is some heterogeneity in the form of payment within each type of work. Piece-rates includes cash payments on a unit basis as well as in-kind payments that are a share of the harvest. It should also be noted that the appropriate unit to be used in the piece-rate payment for plowing or weeding may, for example, be the plot of land.

²⁰58.7 percent of men and 31.5 percent of women aged 18-59 in the sample households were observed to work at least once in the labor market.

average wages in each round by task so that a worker with two task-specific wage “observations” under one payment regime is a worker who has worked at least one day in two different rounds at that task under the specified payment regime.

The tasks performed by all workers are divided into four categories - plowing and sowing, weeding, harvesting and other. More than 93% of wage workers, totalling 657 workers, perform both weeding and harvesting activities over the course of the four-round sample period, and weeding and harvesting account for 94% of all days spent by agricultural wage workers in agricultural activities. We thus focus on the allocation of time between these major task categories. The allocations of work time by men and women across these two tasks are similar to those reported in Table 1 with respect to all tasks - among these workers, of whom 62% are men, of the days spent either harvesting or weeding for time wages across all four rounds, men and women spend 63.2% and 93.7% of their days weeding, respectively. The corresponding figures for piece-rate days are 18.4% and 30.0%, respectively.²¹

Our strategy is to exploit the piece-rate data provided for workers who work for piece rates to test first whether a one-factor productivity model accurately characterizes the data and then, on the basis of that structure, to test the hypothesis that comparative advantage and/or worker preferences are reflected in the task allocations, under the reasonable assumption that neither information problems nor wage discrimination afflicts piece-rate payment regimes. For testing issues of asymmetric information and discrimination the tests require that we have information on time-wage workers who also receive at least one piece-rate wage, to gauge their productivity. It is important therefore to assess the selectivity of subsamples of such workers chosen on the basis of payment regimes. In particular, it should not be the case, as was evidently true in the United States in the late nineteenth and early twentieth centuries (Goldin (1986)), that women primarily work in piece-rate jobs while men work for time-wages.

²¹In order to carry out the various stages of the analysis detailed in the previous section it is necessary to use samples of workers with varying numbers of harvesting and weeding observations by form of payment. Table A in the Appendix presents a breakdown of the sample of weeding or harvesting wage workers for various combinations of payment-method and tasks.

Employment under both payment regimes, however, is the norm for both men and women in the study area over the course of the study period. This is in part due to the fact that at certain times of the year only one or the other form of payment method is offered due to differing time-sequences of agricultural tasks across employers. During other parts of the year, both piece-rate and time-wage jobs are available.²² Of adult workers in the sample households who contribute at least two observations to the labor market data (i.e., at the very least they performed the same job in two different rounds or different jobs in the same or different rounds), 70.7 percent of men and 67.7 percent of women worked both for piece-rate and time wages. Of workers with at least four wage observations during the sample period, 89 percent of women and 82 percent of men received both time and piece-rate wages. Moreover, although women are more likely to be in the labor market during the corn-harvest period and are therefore more likely to be paid piece rates (which are typically paid during corn harvest operations), net of this particular activity we cannot reject the hypothesis that men and women are equally likely to do piece work.²³ This is not surprising, given that neither men nor women are attached to particular employers. Long-term contractual arrangements serving as disciplinary mechanisms are absent and differentials in labor-force commitment, which do vary by sex in this setting, are irrelevant.²⁴ Thus, those workers who are employed under both time-wage and piece-rate regimes do not

²² This gives rise to the possibility of adverse selection, with those workers having higher levels of u , that part of productivity unobserved by employers, being more likely to participate in piece-rate tasks when offered the choice. Evidence of this tendency is provided in Foster and Rosenzweig (1993).

²³The following logistic regression was estimated using the sample of wages by task and type of payment weighted by the number of days worked:

$$\text{logit PIECE} = -.997 - .1043 \text{ MALE} + 3.390 \text{ CORNHARV}$$
where PIECE is one if the task is paid using piece-rates, MALE is one for males, and CORNHARV is one if the task was corn harvesting. The hypothesis that coefficient on MALE is not significantly different from zero is not rejected at conventional levels of significance (p -value=.474). Note that the fact that women are not "crowded" into piece-rate jobs suggests the absence of taste discrimination, although it is not inconsistent with statistical discrimination.

²⁴Although 34.1 percent of all those who work in the labor force are only observed to contribute one observation, these individuals contribute relatively few days to the labor market. Specifically, those contributing observations with both forms of payment contribute 0.5 percent of all days to the labor market.

constitute an especially select sample of rural Philippines labor market workers as a whole.

Although the evidence suggests that worker characteristics do not appear to be related to payment method, the type of agricultural activity does affect the likelihood that piece-rate or time wages are used. In particular, harvesting activities are far more likely to be paid on a piece-rate-basis (59.1% of all harvesting days are compensated by piece-rate wages) compared to weeding activities (14.6% of weeding days). As a consequence, less than a third of workers are observed to have worked at least once as both weeders and harvesters for piece-rates. Is this group of workers selective with respect to productivity? What affects payment type within task? One important factor is that the relationship between supervisory costs and the number of workers employed is quite different in the two payment regimes. For example, when few workers are employed on a time-wage basis then these workers are typically monitored by having them work alongside family members--there is no need for any individual to give up other productive activities to supervise these workers. As the number of workers increases, however, this situation changes and explicit supervision becomes necessary. By contrast, under piece rates, because of the need to monitor output (so that appropriate compensation can be paid), someone must be available to supervise even one worker. Because one supervisor is likely to be able to keep track of the output of a number of workers, the supervisory cost per worker is likely to be decreasing in the number of workers employed in the piece-rate sector. By implication supervisory costs per worker may be lower under time wages when there are relatively few workers and under piece rates when a larger number of workers are hired.

To affirm that costs of supervision are associated with payment regimes within the same task or crop, we regressed the number of supervisor-days per hired-worker-day on the number of hired labor days categorized by type of wage contract for each of the study households that employed wage workers. Because we anticipated that the choice of piece work and the number of hired workers may in part reflect differences in supervisory costs associated with employer attributes we removed employer-specific fixed effects. The fixed-effects estimates, reported in Table B in the Appendix, indicate that, for a given farm and within an activity, supervision costs per worker decrease significantly with the number of piece-rate labor days and increase

(although not significantly) with the number of time-wage labor days. There seem to be fixed costs associated with piece-rate supervision, thus making piece-rates most useful in periods when many workers are employed and, presumably, on farms that employ large numbers of hired laborers. The point estimates indicate that supervisory costs will be lower for piece rates than for time wages when the number of workers per day employed in a particular task exceeds 1.64.^{25 26}

If per-worker supervisory costs are lower when relatively large numbers of workers are employed then we should observe that large farms are more likely to employ workers on a piece-rate basis for a given task compared to small farms. In order to test this hypothesis we estimated a logistic regression, weighted by days worked, relating piece-rate use to task, crop and owned area. The resulting estimates clearly show that large farms are more likely to use piece-rates:

$$\begin{aligned}
 \text{piece} = & -1.95 - .307\text{plow} + .618\text{weed} + 3.24\text{harv} \\
 & (15.5)(2.60) \quad (6.66) \quad (30.3) \\
 & .871\text{sugar} + .122\text{rice} - .235\text{corn} + .0584\text{land} \\
 & (7.85) \quad (0.98) \quad (1.53) \quad (12.8)
 \end{aligned}
 \tag{26}$$

where "piece" represents piece-rate payments, "land" is owned land area, and the other variables control for crop and task (asymptotic t-ratios are in parentheses).

These analyses thus indicate that most wage workers are employed under both of the two basic payment methods and that, within tasks, payment form depends importantly on the characteristics (size) of the employer and does not appear to vary with the sex of workers. An important implication of this is that because the same employer is not likely to employ the same worker for both piece-rate and also for time-rate wages in the same task, the existence of information on workers' individual productivity in the economy, based on piece-rate performance,

²⁵ This figure is obtained by equating the predicted supervisor costs in time-wages and piece-work as a function of labor days in a particular round and dividing by the average number of days per round (120):

$$1.64 = 10^2 \cdot .0780 / (120 \cdot (.0203 + .0193)).$$

²⁶ Decisions about the relative advantage of piece-work versus time-work will also reflect differences in the profitability of the two types of payments net of supervisory costs; however, as long as differences in per-worker profitability net of supervisory costs are not systematically related to the number of workers employed, the conclusion that piece-work will be more advantageous for large employers will be maintained.

does not necessarily mean that the information is well-diffused among employers. The Philippines setting thus appears to be well-suited to an investigation of the roles of both comparative advantage in the piece-rate sector and information constraints and employer preferences in the determination of (time) wages.

5. Results

a. Is there only one productivity factor?

In order to carry out the tests of the determinants of the distribution of workers across the weeding and harvesting activities and the role of sex and other visible worker characteristics in task allocations, it is first necessary to test whether a two-factor or one-factor productivity model best fits the data - whether weeding and harvesting skills are distinct. To do this requires, as noted, a sample of workers with two-piece rate observations in both weeding and harvesting in order to eliminate the influence of measurement error. A problem with this test is that the estimates are obtained from a sample that may not be representative of the population as a whole. In particular, if this sub-sample is a small part of the sample of wage workers then the power of the test is likely to be reduced because those doing both tasks are likely to be especially good (or especially bad) at both.²⁷ However, if the one factor model does accurately characterize the data, then because λ_1 is a parameter rather than the moment of a selected population estimates of λ_1 based on those who do both piece-rates will be relevant to the population at large.

As was discussed, payment methods within tasks appear to be a function of land size and perhaps other technical features of agricultural production but not workers. Indeed, in the Bukidnon sample, in only five of the 29 barrios surveyed does one observe any significant proportion (more than 9%) of worker-days allocated to weeding compensated by piece-rates. Such work is not available at all in more than half of the barrios. Moreover, as expected, in the five barrios with significant piece-rate weeding work, average landholdings are 54% larger than

²⁷We find that although relatively few individuals contribute to this sub-population, the selectivity appears to be based on the availability of both piece-rate tasks in different regions rather than aspects of the workers themselves.

those in the other barrios (6.97 versus 4.54 acres), a difference that is statistically significant at the .007 level. To perform the test of the one-factor model therefore, we use the subsample of wage workers who resided in the five barrios where weeding under piece-rates is a significant option. The number of workers working for piece-rates in those barrios with at least one wage observation in both weeding and harvesting is 83, which is 81% of all wage workers who harvested or weeded in that barrio.

In testing the one-factor model, in order to minimize the selectivity of the sample we used all of the 81% of workers with at least one piece-rate observation in both activities across the four rounds. These piece-rate workers consist of three groups: (i) those workers who worked in at least two rounds in each activity across all four rounds of the data, the sub-sample minimally necessary and sufficient for identification of the model; (ii) those who worked in at least two rounds in harvesting and in only one round in weeding and (iii) those workers who worked in only one round in each activity. Under the assumption that the measurement error variances in each group are the same, we can test whether the productivity variances are identical across groups and thus the validity of treating all of these workers as if they were drawn from the same distribution.

Table 3 reports the estimates and test statistics for the one- and two-factor models estimated from the three-group sample using moment equations (9), (10), and (11) augmented to allow for task prices (round and task-specific dummies, which are not reported). The first column reports the estimates under the assumption that there is one factor. This model fits the data as indicated by the chi-square statistic, which indicates whether the set of 15 restrictions on the data implied by the model are rejected. The addition of the second factor (the relaxation of one restriction), reported in the second column, does not add significantly to the model fit. Thus the assumption that there is one skill type with respect to weeding and harvesting is not rejected. In both models we also could not reject the hypothesis that the productivity variances, measured with evident precision, are equal across the three groups. The estimate of λ_2 in the one-factor model in column one, also estimated with precision, indicates that those workers that are more productive receive a greater return in harvesting than in weeding; more productive workers

evidently have comparative advantage in harvesting.

b. The comparative advantage hypothesis and worker preferences in the piece-rate sector

The comparative advantage hypothesis and the estimates in Table 3 imply that more productive workers should allocate themselves within the piece-rate sector, where employer preferences and information are irrelevant, disproportionately to harvesting. To test this hypothesis along with the hypothesis that women prefer to weed relative to men net of productivity differences, we estimated the allocation equation (4) in the piece-rate sector using the OWM method using all workers who worked in at least one round for a piece-rate harvest wage. These workers were divided between those who worked in at least two rounds for harvest piece-rate wages and those with only one piece-rate harvest wage and the constraint was imposed that the measurement error variances are equal across groups. Given this assumption, we could not reject the hypothesis that the μ variances are also equal.

The first column of Table 4 reports the OWM estimates of the effect of increased productivity on the likelihood that a worker weeds (proportion of all piece-rate days across the four rounds spent weeding) based on the restricted model, which cannot be rejected, that workers in the groups differentiated by the number of harvest piece-rate observations have the same productivity distribution. This estimate, which is precise, indicates that more productive workers, who have a comparative advantage in harvesting (Table 3), are less likely to be observed weeding. The column-two estimates indicate, moreover, that net of productivity, women are no more likely than men to weed; there is no evidence that women prefer weeding compared to men. The model fits the data, suggesting that in the piece-rate sector comparative advantage, and not worker preferences, explains the allocation of men and women across the harvesting and weeding tasks.

c. Comparative advantage and discrimination in the time-wage sector

To test whether comparative advantage operates in the time-wage sector and to test whether there is discrimination in that sector with respect to sex, we use a sample of workers with at least two harvest piece-rate wage observations (from which we obtain an estimate of their

productivity robust to measurement error) and at least one time-wage observation combined with a sample of workers with only one piece-rate and at least one time-wage observation.²⁸ As for the test of comparative advantage in the piece-rate sector, we first estimate the allocation equation using true productivity (equation (19)). The first column of Table 5 reports the OWM estimates of the share of total days worked for time wages over the four rounds that were spent weeding as a function of actual productivity μ . These estimates confirm the comparative advantage hypothesis - more productive workers (as measured in the piece-rate sector) evidently worked fewer days in weeding tasks than less productive workers over the survey period.

In the second column of the table, we also include a sex dummy in the specification. In this case, unlike in the piece-rate sector, the coefficient is significant at the .11 level, suggesting that, among equally productive men and women, women spend more days weeding than men. This model also fits the data, indicating again that workers observed working for harvesting piece-rate wages in only one round are drawn from the same productivity distribution as workers observed at least twice in piece-rate harvesting. Because the results from the piece-rate sector did not support the hypothesis that women prefer weeding, the result that women work more days in weeding under time wages than do men net of differences in productivity is consistent with the hypotheses that there is statistical discrimination, tastes discrimination or both.

To distinguish between tastes and statistical discrimination, it is necessary, as noted, to estimate time wage and time-wage task allocation equations using perceived, not actual, productivity. Table 6 reports estimates of the model incorporating equations (8), (14), (21), (17) and (16) using the OWM method applied to workers with at least one weeding time-wage and

²⁸It is worth noting that, at least in principle, the extent of imperfect information and its implications for worker allocations could be different for the small subset of wage workers involved only in time-rate employment who are, of necessity, excluded from the analysis. If, for example, information were more precise for time-rate only workers compared to those working for both forms of payment, then the estimates presented below might somewhat understate the extent to which more productive workers are allocated to harvesting in the time-wage sector as a whole although they would accurately portray the situation among the vast majority of workers (i.e., those working for both forms of payment). The fact, as discussed below, that those time-rate workers with only one piece-rate observation do not differ significantly from those with multiple piece-rate observations suggests, however, that the extent of this difference, if present, is likely to be small.

with at least one harvest piece-rate wage observation across all four rounds, the most common category of worker. Again, two groups of workers are used - those workers with only one harvest piece-rate wage observation and at least one weeding time wage and those workers with at least two harvest piece-rate wage observations and at least one weeding time wage. The set of worker characteristics (x_i) assumed to be observable by employers consists of the worker's height, sex, age and schooling.

The model is estimated in three variants. In the first, the allocation equation (16) includes only the perceived (by employers) productivity variable μ^* . In the second, the allocation equation also includes the component of productivity that is not observed by the employer, u_i , as determined by the fact that it is not reflected in the time wages. This specification permits a test of the hypothesis that only rewards as determined by the employer, based on his available information, matter for the task allocation in the time-wage sector. As noted, this approach permits us to distinguish the hypothesis of comparative advantage from the hypothesis that worker preferences that are related to productivity, but not observable characteristics such as sex, net of productivity are responsible for the allocation of workers to tasks. Finally, in the third variant of the model a dummy for sex is included in the allocation equation, which permits a test of the hypothesis that employers discriminate against female workers by allocating them to a particular activity in greater proportions than men who have the same expected productivity, given the information available to the employer (tastes discrimination).

The first column of Table 6 reports the estimated relationships between perceived productivity and the measured characteristics of workers plausibly known by employers, and the estimates of the variances of that part of employer-perceived productivity that is not captured by the measured variables ($\sigma^2(\epsilon)$) and of that part of actual productivity not known by employers ($\sigma^2(u)$). The variance estimates indicate that the proportion of the total variance in productivity that is not known by employers is 45.9%; there is clearly an information problem in this spot-market labor market. The results also indicate that men, taller workers and older workers (the age range of workers is from 10 through 59) are more productive (and thus relatively more so in harvesting activities), while those wage workers with more schooling are less productive in these

agricultural tasks.²⁹

A natural question that arises in this context is how it can be that employers do not know worker productivity even though piece-rate payment is common. The answer has to do with two facts: (1) given the nature of agricultural production the demand and supply of hired labor is quite variable and (2) production in any particular day has a substantial stochastic component. The implication of the first fact is that there is little incentive on the part of employers to invest in the acquisition of information about a particular worker--a worker who is hired during the harvesting season for a few days may not be needed during the planting season, and may not be available in other periods because his labor is needed on his own farm. The implication of the second fact is that a worker must be observed for a substantial number of days before an accurate assessment of productivity can be made. A comparison of the data on the variance in the log of the piece-rate wage rates with the variance in the log of productivity as estimated from the piece-rate wage indicates that the stochastic component is 78% of the total variation in the piece-wage.³⁰

The second column of Table 6 reports the estimated relationship between employer-perceived productivity and the time wage in weeding (λ_2^T), which like that for true productivity in the piece-rate wage sector is less than one, suggesting that in the time-wage sector those workers perceived to be more productive are thought by employers to have a comparative advantage in harvesting. All three specifications of the task-allocation equation that include perceived productivity, reported in the last three columns of Table 6, also indicate that comparative advantage operates in task allocations in the time-wage market. The second specification (column 4) also indicates that the component of productivity not known by employers plays no role in task allocation, suggesting that any unmeasured characteristics,

²⁹This latter result does not, of course, imply that schooling reduces productivity, but is likely the result of selection within the population of adults to agricultural wage work.

³⁰Note that this noise does not present a problem for the estimation of the effects of productivity on allocation because, given our methods, we only require that there is information on the covariation between productivity and allocation across workers, not the actual productivity level of each worker.

including tastes, that are correlated with productivity do not play a role in the allocation of workers across tasks.

Finally, in the last specification, we find that employers do not, among workers with the same perceived productivity, allocate workers across tasks according to their sex. These findings along with those of Tables 4 and 5 thus suggest that the disproportionate presence of female workers in the weeding activity compared to that of men is not due to either employer bias or worker preferences; it is the result of real productivity differences and of employers' partial information on workers' true abilities and their (evidently unbiased) knowledge of overall differences in the productivities of women and men in the labor market. Ignorance but not preferences or bias plays a role along with comparative advantage in the division of labor between men and women in this Philippines wage labor market.³¹

d. Estimates based on selection-correction models

A central feature of our ability to identify the effects of comparative advantage has been the use of multiple wage observations for the same person performing different tasks and receiving different forms of payment, which avoids the problem of selectivity that arises in the context of empirical analysis of the Roy model. It is therefore of interest to determine the extent to which these results can be replicated with a more traditional approach that does not make use of this type of information. We therefore also examine estimates obtained from the same data using a standard probit-selection model of wages and occupations.³² Because the selection approach, as noted, does not straightforwardly permit identification of the effects of worker and

³¹Evidence that information asymmetries affect wage payments in a number of different ways in other rural Asian societies is presented in Foster and Rosenzweig (1993).

³²In preliminary analysis we estimated a bivariate probit model of task choice given form of payment but could not reject the hypothesis of independence across tasks (t-value of 0.66 and 1.14 piece-rate and time wages respectively); we thus present results using univariate probit selection for each sector. An alternative specification would have been the trinomial probit model used by HS; although we also consider three sectors this procedure would not be appropriate for our analysis because activity in the three sectors is not mutually exclusive: over a given interval an individual may be involved in both weeding and harvesting. A quadrinomial probit model allowing for simultaneous work in different tasks could in principle be used but would be extremely demanding in terms of computational resources.

employer preferences we focus on the issue of whether this approach yields interpretable evidence on the allocation of workers by comparative advantage.

In order to be able to interpret the results of the standard selection estimation procedure in terms of the parameters of our model we first rewrite the time wage and selection equations as function only of observables and residuals. The wage equation, obtained by substituting (21) into (17) is

$$w_{jit}^T = \pi_{ji}^T + \lambda_j^T (\delta^T y_i + \epsilon_{ij}) + e_{jit}^T \quad (27)$$

For the selectivity equation, consistent with the specification of the share equation (16), we assume that a latent variable A_{jit}^* that represents the propensity for i to undertake activity j in a given round may be written as a function of μ_i^* , u_i and x with w_{jit}^T observed if and only if $A_{jit}^T > 0$. Taking a linear approximation and substituting in (21) yields³³

$$A_{jit}^T = \phi_{jt}^T + \phi_{j\mu}^T (\delta^T y_i + \epsilon_{ij}) + \phi_{ju}^T u_i + \phi_{jx}^T x_i + e_{Ajit}^T \quad (28)$$

It is further assumed that all residuals exhibit a joint normal distribution. Identification of the regression coefficients is obtained from i) the distributional assumption and ii) the exclusion of some x variables from the wage equation. This means that with semi-parametric estimators of selection, it is necessary to assume that a subset of the measured variables available to the researcher that affect task choices either are not observed by the employer or are not considered to be relevant to productivity, net of y , by the employer.

Maximum likelihood estimation of (27) and (28) provides an estimate of the covariation of the residuals from those equations, which is $\rho^T = \phi_{j\mu}^T \lambda_j^T \sigma^2(\epsilon_{ij})$.³⁴ This corresponds to the selection term in the selectivity-corrected wage equation from two-step estimation (Heckman, 1974). Thus under time wages, allocation by comparative advantage will only be evident in terms of the

³³ A_{jit}^* is a latent variable denoting desired activity in sector j in a period t . Thus for $A_{1it} > 0$ and $A_{2it} > 0$, $a_i = \sum_t A_{1it}^* / (\sum_t A_{1it}^* + A_{2it}^*)$ and the linearized equations (16) and (28) have the same structure with the exception that that the constant in the latter is allowed to vary by time and task.

³⁴This equation follows the standard practice of assuming that equation (29) has been normalized so that the compound residual has variance one.

unobservables if $\sigma_{\mu}^2(\epsilon) \neq 0$, that is if employers know something about worker characteristics other than those observed by the researcher. If workers are paid by piece rates, however, any variation in productivity that is not explained by characteristics included in the wage equation will result in a correlation in the residuals of the wage and selection equations. That is, using notation analogous to that in equations (27) and (28), the relevant correlation for piece rates is $\rho = \phi_{\mu} \lambda \sigma^2(\epsilon_i)$, where in this case ϵ is that component of true productivity not measured by the y , as opposed to that part of employer-perceived productivity that is not measured.³⁵ Thus, our prior results indicating that workers with higher μ have a comparative advantage in harvesting (λ for weeding < 1) and thus work more as harvesters ($\phi_{\mu 2}$ (weeding) $< \phi_{\mu 1}$ (harvesting)), implies that ρ will be greater for harvesting than weeding. This will also be true for time wages; however, our finding that time-wage employers know little about worker productivity net of height, schooling, sex and age (the y we use) suggests that both estimated task-specific ρ^T 's could be close to zero.

To implement the selection model we sampled for each payment regime/ task in each round one wage observation for each worker. We used each worker's assets - farm acreage, land value, and total wealth - as well as family size, family sex composition, and the means of the adult family workers for height, schooling and age as variables (x) that influence an individual worker's task selection but not wages. We included in the wage equations worker age, height, sex, and schooling. The resulting estimates of the wage equations, available by request from the authors, are broadly consistent with the results from the previous analyses. Consistent with the evidence of employer ignorance, neither of the ρ^T 's was statistically different from zero while at least one of the ρ 's was statistically significant by conventional standards when piece rates were used. Moreover, the coefficients on the observable worker characteristics in each payment regime show that those more likely to undertake weeding in terms of observable characteristics are likely to receive lower wages and that those more likely to undertake harvesting are likely to

³⁵The corresponding wage and latent activity equations under piece rates are $w_{jit} = \pi_{ji} + \lambda_j (\delta' y_i + \epsilon_i) + e_{jit}$ and $A_{jit} = \phi_{j0} + \phi_{j\mu} (\delta' y_i + \epsilon_i) + \phi_{jx} x_i + e_{Ajit}$, respectively.

receive higher harvest wages. This result is consistent with the notion that more productive workers are likely to undertake harvesting rather than weeding.

The selectivity terms for the two tasks under piece-rate wages, however, are of the same magnitude, suggesting either that (i) the allocation equation parameters are the same across tasks so that more productive individuals are relatively likely to work in the piece-rate sector (than to not work at all or to work on-farm or for time-rate wages) but not differentially in the two tasks or (ii) there are two productivity factors, so that those who are weeding are relatively productive in weeding and those harvesting are relatively productive in that task. Neither of these interpretations is supported by our less restrictive analysis that makes use of worker movements across payment regimes and tasks and measures of productivity.

The results from a simple version of the standard selection-correction analysis thus do not appear to completely uncover the role of comparative advantage as a determinant of the allocation of workers to activities. The implementation of the selection model used (probit selection into each task), however, does not adequately address the multi-faceted occupational choice faced by workers in this population and imposes an arbitrary distributional assumption. A more complex procedure might well yield more interpretable results.³⁶

6. Conclusion

Although there is an extensive literature documenting the sometimes large differences in worker characteristics such as sex and age across occupations in many countries of the world, studies of occupational stratification have provided limited insight into the factors that explain these patterns, particularly in circumstances in which information asymmetries may be important. In this paper we have shown how piece-rate and time-wage data can be used to distinguish, without the imposition of ad hoc structure, among four possible mechanisms that may influence the sorting across occupations of workers characterized by particular measured characteristics: (1) comparative advantage (2) preferences on the part of workers (3) preferences on the part of

³⁶ Indeed, HS find that it is necessary to make a number of alterations to the standard approach in order to obtain results that adequately fit their data.

employers, and (4) statistical discrimination.

We applied these methods to data collected from a unique panel data set from a casual labor market in rural Philippines which displays a common and controversial activity stratification in which women devote a substantially greater amount of time than do men to weeding compared to other agricultural activities. The tests provided a number of striking results. First, variations in productivity with respect to weeding and harvesting can be adequately characterized by a one-factor model. That is, workers who are more productive in one sector (weeding) are also more productive in harvesting, although more productive individuals have a comparative advantage in harvesting. Second, as predicted on the basis of economic theory, we find evidence that the activity allocations in the piece-rate labor market are significantly related to productivity differentials: more productive workers are in fact more likely to work in harvesting, although seasonal variation in the relative demand for the two tasks implies that most workers will undertake both tasks over the course of the year. Because women in this labor market on average have productivity levels that give them comparative advantage in weeding, this result partially explains the allocation of women to the weeding sector in this economy. Third, we find no evidence that the allocation of workers to tasks in either the piece-rate or the time-wage sector is due to preferences on the part of workers for certain types of activities that are correlated with observed characteristics of the workers. Thus, the fact that more women are found to be weeding in this sector cannot be attributed to preferences on the part of women for this activity. Moreover, in the context of the time-wage sector we can also rule out the possibility that allocations result from preferences that are correlated with unobserved (to the employer) aspects of productivity. Fourth, we find no evidence that the allocation of workers to tasks in either sector is a result of tastes discrimination on the part of employers.

Our results also suggest, however, that there are information problems in the time-wage sector and that statistical discrimination plays an important role in the allocation of workers in that sector. Because women are *on average* less productive than are men in these tasks and therefore have comparative advantage in weeding and because employers cannot completely discern differences in individual worker productivity, given a man and a woman with equal levels

of productivity, the woman is more likely to be employed in weeding. Given that information asymmetries play no role in the allocation of workers to tasks in the piece-rate sector, this result also explains why occupational segmentation by sex is greater for time-wage employment than for piece-rate employment or on-farm work, a salient feature of Asian agriculture.

Finally, it should be noted that the finding that the allocation of workers by sex to tasks in the rural Philippines results from comparative advantage as well as informational asymmetries does not imply that preferences on the part of workers are not important in that labor market, only that worker preferences are not correlated with sex. Indeed, task prices can reflect worker preferences and preferences expressed in household allocations may play a role in determining differentials across workers in productivity. In this paper we have taken existing productivity differentials as given. Our results also do not imply that employers' preferences do not play an important role in other labor markets. Nor does the finding that a single factor adequately characterizes variation in productivity in an agricultural labor markets imply that a single-factor can adequately characterize variation in productivity in other, more complex, labor markets, although a one-factor wage model has been found to fit based on U.S. labor market data in Card and Lemieux (1993). Nonetheless, the evidence from this paper suggests that inferences about the relative importance of worker and employer preferences as determinants of the allocation of workers to tasks should not be drawn without a careful assessment of the contributions of comparative advantage and information asymmetries.

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Table 1
Percentage of Total Days in Agricultural Tasks Spent Weeding by Men and Women in Three Asian Countries

Sex	For Time Wages	On-farm	For Piece-rate Wages
<u>Bukidnon, Philippines (1984-85)</u>			
Male	36.6	N.A.	15.8
Female	77.2	N.A.	21.3
<u>Ten ICRISAT Villages, India (1975-85)</u>			
Male	3.24	3.80	N.A.
Female	33.7	27.0	N.A.
<u>Northern Pakistan (1986-89)</u>			
Male	N.A.	5.95	N.A.
Female	N.A.	16.1	N.A.

Table 2
Testable implications of an observable worker characteristic (x) on wages and task allocations under alternative models and specifications

	Perfect Information		Imperfect Information			
	Equation:		Equation:		Equation:	
	(5)	(4)	(17)	(16)	(5)	(4)
	β_i	θ_x	β_i^T	θ_x^T	β_i^T	θ_x^T
(1) comparative advantage and x correlated with μ and μ^*	0	0	0	0	>0	<0
(1) + worker preferences:						
all workers prefer task 2	0	0	0	0	>0	<0
more productive workers prefer task 2	0	0	0	0	>0	<0
type x workers prefer task 2	0	<0	0	<0	>0	<0
(1) + employer preferences:						
type x workers preferred	>0	?	>0	?	>0	?
type x workers are preferred in task 2 or employers incorrectly believe x workers more productive on average ^b	>0 ^a	<0	>0 ^a	<0	>0 ^a	<0

^aRefers to task 2 only

^bBecause employer beliefs do not influence payments if workers are paid on a piece-rate basis implications in the case of incorrect beliefs only apply in the presence of imperfect information.

Table 3
 Test of Single Versus Two-Factor Model Based on
 Piece-Rate Observations: OWM Estimates

Factor	(1)	(2)
λ_2	.611 (4.45) ^a	.449 (2..50)
$\sigma^2(\mu_1)$.0822 (3.94)	.0837 (4.01)
$\sigma^2(\eta_2)$	--	.0260 (1.38)
χ^2 (d.f.)	20.9 (15)	17.6 (14)
Number of workers	83	83
Number of observations	216	216

^aAbsolute value of asymptotic t-ratio in parentheses.

Table 4
 OWM Estimates of the Determinants of the Proportion
 of Piece-rate Days Spent Weeding: Tests of
 Comparative Advantages and Sex Preference^a

	Piece-rate Workers with at Least One Piece-rate Harvest Observation	
θ_{μ}	-.830 (2.26) ^b	-.790 (3.08)
Male (θ_x)	--	.156 (1.12)
$\sigma^2(\mu)$.0619 (3.86)	.0742 (5.25)
$\chi^2(3)$	27.6	31.8
Number of workers	103	103
Number of observations	304	304

^aSample of wage workers in barrios where piece-rate weeding activities are offered.

^bAbsolute value of asymptotic t-ratio in parentheses.

Table 5
 OWM Estimates of the Determinants of the Proportion
 of Time-wage Days Spent Weeding: Tests of
 Comparative Advantages and Statistical Discrimination
 by Sex

	Time-wage Workers with at Least One Piece-rate Harvest Observation	
$\tilde{\theta}_\mu^T$	-.471 (2.14) ^a	-.430 (1.93)
Male ($\tilde{\theta}_x^T$)	--	-.116 (1.63)
$\sigma^2(\mu)$.0863 (3.18)	.0863 (3.18)
$\chi^2(3)$	1.71	1.71
Number of workers	282	282
Number of observations	653	653

^aAbsolute value of asymptotic t-ratio in parentheses.

Table 6
 Determinants of Perceived Productivity, Time Wages in Weeding and the Proportion of
 Time-Wage Days Spent Weeding: Tests of Employer Control and Tastes
 Discrimination: OWM Estimates

Worker Characteristic	μ^*	Weeding Time- Wage	Proportion Time-wage Days Weeding		
			(1)	(2)	(3)
$\theta_{\mu^*}^T$	--	.211 (2.10)	-.610 (3.41)	-.607 (3.39)	-.649 (2.30)
θ_u^T	--	--	--	-.116 (0.29)	--
θ_x^T					
Male	.172 (2.76) ^a	--	--	--	.0193 (0.21)
Height(x100)	.455 (1.04)	--	--	--	--
Age	.0373 (1.70)	--	--	--	--
Age squared (x100)	.737 (1.81)	--	--	--	--
Schooling	-.0273 (1.99)	--	--	--	--
$\sigma^2(\epsilon)$.0283 (1.23)	--	--	--	--
$\sigma^2(u)$.0276 (2.01)	--	--	--	--

Number of workers =360, Number of observations=818.

^aAbsolute value of asymptotic t-ratio in parentheses.

Table A

Sample Criteria	Sample Size (%)	Percent Total Days	Percent of piece-rate days weeding	Percent of time-wage days weeding	Percent male
Total wage workers harvesting or weeding ^a	657 (100)	100	8.62	74.1	62.4
At least one time-wage weeding	424 (64.5)	81.5	8.15	86.8	63.9
At least one piece-rate harvest observation	454 (69.1)	74.4	5.38	78.6	63.9
+ at least one time-wage observation	291 (44.3)	65.6	5.93	78.6	69.8
+ at least one weeding time-wage observation	268 (40.8)	61.6	5.67	85.7	68.7
+at least one piece-rate weeding observation	63 (9.59)	20.1	31.1	84.2	66.7
At least two piece-rate harvest observations	217 (33.0)	53.6	5.29	82.3	72.4

^a 93.4% of all wage workers are workers who weed and/or harvest. Weeding and harvesting are 94% of all days spent by agricultural wage workers in agricultural activities.

Table B
 Fixed-Effects Estimates: Effect of Worker-Days per Round
 By Payment Method on Supervisory-Days per Worker-Day

Variable	Coefficient	t-ratios
Piece-work labor days (x10 ⁻²)	-.0203	2.73
Time-wage labor days (x10 ⁻²)	.0193	1.60
Piece work	.0780	12.2
Plowing, planting	.0337	6.27
Weeding	-.0241	3.13
Harvesting	-.0598	7.47
Sugar	.00827	0.88
Rice	-.00737	0.87
Corn	.0159	1.53
F(9,5444)	30.1	
Number of tasks	5909	
Number of households	455	

Figure 1
Allocation of Workers to Task by Productivity

