MALE-FEMALE PRODUCTIVITY DIFFERENTIALS: THE ROLE OF ABILITY AND INCENTIVES

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Abstract

We consider the response to incentives as an explanation for productivity differentials within a firm which paid its workers piece rates. We show that the observed differential can be decomposed into two parts: one due to differences in ability (or strength) and the other due to differences in the response to incentives. We apply this decomposition to male and female workers from the British Columbia tree-planting industry. While women in our sample react more to incentives than do men, this difference is not statistically significant. The productivity differential that males enjoy at this firm arises because of differences in ability.

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1. Introduction and Motivation

Economists have shown great interest in measuring and explaining differences in labour-market performance between men and women. Traditional attention has focused on the earnings premium enjoyed by males and its relation to productivity differences; see, for example, Gunderson (1989). The empirical application of human capital models permits the decomposition of the premium into two parts: those explained by differences in economic characteristics, and a residual (Oaxaca, 1973). Results typically show a substantial proportion of the earnings premium is unexplained by differences in observed characteristics (Blau, Ferber, and Winkler, 1998). While these residuals are consistent with labour-market discrimination, they may also reflect behavioural differences between groups; see, for example Bowles, Gintis and Osborne (2001). Men and women may differ with respect to motivation and aggressiveness, attributes that can reflect labour market outcomes. Hakim (2000) provides a general discussion of these issues from a sociological perspective, concentrating on differences in male and female attitudes towards work and careers. From an economic perspective, Becker (1985) suggested that a comparative advantage in high-effort domestic tasks may lead women to supply lower levels of effort within the labour market.

The presence of unobservable behavioural differences is problematic for the statistical decomposition of earnings. Counterfactual calculations based on regression analysis break down when individuals differ with respect to unobservable characteristics that are correlated with variables of interest (Heckman, 1997). As such, empirical work has sought to determine whether these behavioural effects exist.

In general, two empirical approaches have been undertaken, both of which require special data. Labour-market earnings studies have focused on supplementing broad-based earnings data with measures of personality traits thought to be correlated with behaviour. Early examples of this approach are Wise (1975) and Duncan (1976). More recently, Long (1995) found significant differences in the effect of motivational factors on income among men and women. Similarly, Nyhus and Pons (2002) found that personality traits affect male and female earnings differently, suggesting that the male-female earnings gap will be affected by controlling for behaviour. Duncan and Dunifon (1998) control for potential reverse causality problems (such as success in the labour market affecting personality) by using personality measures recorded years before the data on earnings. They find that motivational traits, such as preferences for challenges and fear of failure, as well as behavioural measures, such as church attendance and participation in social clubs, significantly affect standard earnings functions.

A second, and perhaps more direct approach, is to test whether men and women react differently to the incentives inherent within various compensation systems observed in the labour market. This approach is closely related to studies that measure the impact of compensation systems on worker productivity; see, for example, Bull, Schotter and Weigelt (1987), Paarsch and Shearer (2000), Lazear (2000) and Shearer (forthcoming). Recent experimental evidence suggests that males and females react differently within competitive situations, see Gneezy, Neiderle and Rustichini (forthcoming. This may partly explain lower promotion rates among female employees and what is often referred to as the "glass ceiling."[1]

In this paper, we consider differences in male and female reactions to a real-world labour-market incentive system. We concentrate on piece-rate workers and compare the elasticity of worker effort with respect to changes in the piece rate. We exploit a unique data set created from the personnel records of a tree-planting firm operating in British Columbia, Canada. These data contain information on daily worker productivity under a variety of piece rates, along with worker characteristics. Our data show that male workers enjoy a large productivity differential *vis-à-vis* their female counterparts, in the order of 11%. This is in contrast to the experiments of

[1] *The Harvard Business Review,* June 2003, reports that while women make up more than half the managerial and professional labour pool, only 1% of chief executive positions in Fortune 500 companies are held by women in 2003.

Gneezy, Niederle and Rustichini (forthcoming), who found no difference in performance when subjects were paid piece rates. Since this difference is conditional on working conditions and piece rates, we ignore discrimination as a possible explanation, concentrating on inherent productivity differences between men and women.[2] In particular, we seek to measure how much of this difference is due to differences in worker reactions to the piece rate incentive system.

Our general approach is to replace missing data on effort with economic theory. It adds to the recent literature on applying structural models to firm records in order to investigate incentive issues; see, for example, Ferrall and Shearer (1999), Paarsch and Shearer (1999, 2000) Haley (forthcoming), Shearer (forthcoming) as well as Copeland and Monet (2002). The estimation of structural models to explain earnings differentials was first proposed and implemented be Bowlus and Eckstein (2002). We explicitly model worker effort choices as a function of the incentives in place within the firm and unobservable worker characteristics. Deriving optimal decision rules on the part of the worker and incorporating these rules directly into the estimation procedure allows us to identify the determinants of worker effort and productivity.

Behaviouralists identify incentive enhancing preferences to be those that increase a worker's equilibrium effort level as a function of his pay; see Bowles, Gintis and Osborne (2001). Here, we focus on differences in parameters that alter the worker's cost of effort. Our model admits two ways for this to obtain: differences in a worker's ability and differences in a worker's reaction to piece rates. In our model, differences in ability affect the level of effort, but not the percentage change in effort with respect to the piece rate (or elasticity). We show that differences in observed productivity, for a given piece rate, can be decomposed into that part due to differences in ability and that part due to differences in the reaction to incentives. We use our model to test if females react differently to the piece rate than do males.

[2] Interviews with firm managers revealed that workers were randomly allocated to working conditions and piece rates.

The identification of the parameters affecting effort depends on the way these parameters affect the distribution of observed productivity. Our model identifies the differences in reaction separately from ability through their effect on the variance of productivity. Individuals who react a great deal to incentives take advantage of favourable economic conditions to increase productivity: ability affects average productivity while reaction affects average and the variance.

Our framework allows us to rank workers in terms of their response to incentives. Our results suggest that individuals do differ with respect to their reactions to incentives: effort elasticities are heterogeneous. However, while the women in our sample react more to incentives than do the men, this difference is not statistically significant. The observed productivity differentials within our sample are due solely to differences in ability or strength.

The remainder of the paper is organized as follows: In section 2 we provide institutional details of the tree-planting industry in British Columbia, while in section 3, we present our data. In section 4 we develop the model of worker effort decisions and present our productivity decomposition. In section 5 we present our results, while in section 6 we summarize and conclude.

2. Institutional Details

While timber is a renewable resource, active reforestation can increase the speed at which forests regenerate and also allows one to control for species composition, something that is difficult to do in the case of natural regeneration. Reforestation is central to a steady supply of timber to the North American market. In British Columbia, extensive reforestation is undertaken by both the Ministry of Forests and the major timber-harvesting firms who hold Tree Farm Licenses.[3]

[3] In British Columbia, nearly 90 percent of all timber is on government-owned (Crown) land. Basically, the Crown, through the Ministry of Forests, sells the right to harvest the timber on this land in two different ways. The most common way is through administratively-set prices to thirty-four firms who hold Tree Farm Licenses. The Tree Farm Licenses have been negotiated over the last three-quarter century, and require that the licensee adopt specific

The mechanics of this reforestation are straightforward. Prior to the harvest of any tract of coniferous timber, random samples of cones are taken from the trees on the tract, and seedlings are grown from the seeds contained in these cones. This ensures that the seedlings to be replanted are compatible with the local micro climates and soil as well as representative of the historical species composition.

Tree planting is a simple, yet physically exhausting, task. It involves digging a hole with a special shovel, placing a seedling in this hole, and then covering its roots with soil, ensuring that the tree is upright and that the roots are fully covered. The amount of effort required to perform the task depends on the terrain on which the planting is done. In general, the terrain can vary a great deal from site to site. In some cases, after a tract has been harvested, the land is prepared for planting by burning whatever slash timber remains and by "screefing" the forest floor. Screefing involves removing the natural build-up of organic matter on the forest floor so that the soil is exposed. Screefing makes planting easier because seedlings must be planted directly in the soil. Sites that are relatively flat or that have been prepared are much easier to plant than sites that are very steep or have not been prepared. The typical minimum density of seedlings is about 1,800 stems per hectare, or an inter-tree spacing of about 2.4 metres, although this can vary substantially.[4] An average planter can plant between 700 and 900 trees per day, about half a hectare, depending on conditions. An average harvested tract is around 250 hectares.

Typically, tree-planting firms are chosen to plant seedlings on harvested tracts through a process of competitive bidding. Depending on the land-tenure arrangement, either a timber-harvesting firm or the Ministry of Forests will call for sealed-bid tenders concerning the cost per tree planted, with the lowest bidder's being selected to perform the work. The price received by the firm per tree planted is called "the

harvesting as well as reforestation plans. About 90 percent of all Crown timber is harvested by firms holding Tree Farm Licenses. The second, and less common way, to sell timber is at public auction through the Small Business Forest Enterprise Program. In this case, the Ministry of Forests assumes the responsibility of reforestation.

[4] One hectare is an area 100 metres square, or 10,000 square metres. Thus, one hectare is approximately 2.4711 acres.

bid price." Bidding on contracts takes place in the late autumn of the year preceding the planting season, which runs from early spring through to late summer. Before the bidding takes place, the principals of the tree-planting firms typically view the land to be planted and estimate the cost at which they can complete the contract. This estimated cost depends on the expected number of trees that a planter will be able to plant in a day which, in turn, depends on the general conditions of the area to be planted.

Planters are predominantly paid using piece-rate contracts, although fixed-wage contracts are sometimes used instead. Under piece-rate contracts, planters are paid in proportion to their output. Generally, no explicit base wage or production standard exists, although firms are governed by minimum-wage laws. Output is typically measured as the number of trees planted per day, although some area-based schemes are used as well. An area-based scheme is one under which planters are paid in proportion to the area of land they plant in a given day, assuming a particular stem density.

Our data were collected from a medium-sized, tree-planting firm that employed a total of 155 planters throughout the 1994 tree-planting season. This firm paid its planters exclusively piece rates; daily earnings for a planter were determined by the product of the piece rate and the number of trees the planter planted on that day. Sites to be planted were divided into plots. For each plot, the firm decided on a piece rate. This rate took into account the expected number of trees that a planter could plant in a day and the expected wage the firm wanted to pay. Thus, the piece rate should be negatively correlated with good planting conditions. All planters planting on the same plot received the same piece rate; no matching of planters to planting conditions occurred, so even though planters may be heterogeneous, the piece rate received was independent of planter type. Planters were assigned to plots as they disembarked from the ground transportation that took them to the planting site. Thus, to a first approximation, planters were randomly assigned to plots.

3. Data

Our data set contains information on the piece rate received by each planter, the planter's daily productivity, as well as the planter's age and gender. We consider only those observations for which the planter received the same piece rate for the whole day of planting. This eliminates the problem of aggregating trees planted under different piece rates. The summary statistics for the planting data, which contains 3960 planting days on 89 different planters, are given in Table 1.[5] The data are from a five month period during the spring and summer of the 1994 planting season. Workers planted 786 trees per day on average and earned, on average, $184 per day. Our data containg information on 31 different contracts, defined by the piece rate paid. The average piece rate was 25 cents per tree.

Table 1
Summary Statistics

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Number of Trees	3960	786.48	307.39	120	2260
Piece Rate	3960	0.25	0.06	0.13	0.48
Daily Earnings	3960	183.97	57.38	48.00	530.00

Of the 89 workers in the sample, 66 (or 74%) are male. In Table 2 we summarize the productivity and earnings of male and female workers, separately.

[5] Note that we have purged outliers from the original data by deleting all observations for which earnings were less than the minimum wage. We also restrict the sample to individuals whom we observe for at least 20 planting days. See Paarsch and Shearer (1999) for details.

Table 2
Summary Statistics: Male versus Female

		Trees		Earnings	
	Observations	Mean	Standard Deviation	Average	Standard Deviation
Male Planters	3080	802.70	314.22	189.25	58.50
Female Planters	880	729.73	274.94	164.13	48.43

Females planters plant fewer trees (approximately 10%) and earn less (approximately 15%) than their male counterparts. Productivity is affected by effort as well as planting conditions. To compare productivity, holding conditions constant, we condition on the terrain in which the employee was planting. Since the firm determines the piece rate as a function of planting conditions, the piece rate summarizes all relevant information regarding those conditions. Therefore, we condition on the piece rate that the worker received. Rather than specify a functional form in this regression, we include dummy variables indicating each piece rate; *i.e.*, we consider the regression of daily productivity (in logarithmic form) on planting conditions and a dummy variable indicating gender:

$$\log Y_{i,j} = \beta_0 + \beta_1 DM_i + \sum_{j=2}^{N_j} \beta_{2j} DB_j + \beta_3 AGE_i + \beta_4 AGESQ_i + \epsilon_{ij}. \tag{3.1}$$

The results are presented in Table 3 (excluding the coefficients on the terrain-specific dummy variables).

Table 3
Productivity Regression Parameter Estimates
Sample Size = 3960

Parameter	(Coef.)	(Std. Error)	(P-Value)
β_0	6.954	.033	0.000
β_1	0.113	.013	0.000
β_3	0.017	.002	0.000
β_4	$-1.7e-4$	$3.5e-5$	0.000

The results from Table 3 suggests that men are approximately 11% more productive than females at planting trees when planting conditions (the piece rate) and age are held constant.

In subsequent sections we shall investigate the causes of this productivity difference, concentrating on two possible explanations. First, male workers are more productive than female workers due to an advantage in ability (or strength); *i.e.*, their cost of effort is lower. Second, male workers are more sensitive to incentive pay; *i.e.*, their elasticity of effort with respect to the piece rate is higher than that for females.

4. Model

We model worker productivity decisions as a function of the piece rate the cost of effort. We extend the model of Paarsch and Shearer (1999) to allow for heterogeneity in response to incentives. Let the utility function of worker i be given as

$$U(W, E) = W - C_i(E),$$

where W represents earnings and $C_i(E)$ represents the planter's cost of effort. The earnings function is given by

$$W = rY$$

with Y being planter output. The cost of effort function is parameterized as

$$C_i(E) = \frac{\kappa_i \gamma_i}{\gamma_i + 1} E^{\frac{\gamma_i}{(\gamma_i+1)}} \quad \gamma > 0, \ \kappa > 0.$$

This functional form allows heterogeneity in two directions. First, κ_i captures differences in ability (or strength). A low value of κ_i increases output at all piece rates. Second, γ_i measures the elasticity of worker effort with respect to the piece rate.

Daily output follows

$$Y = ES$$

where S is a random productivity shock drawn from the distribution $F_S(s)$. The shock represents planting conditions which are beyond the planter's control, such as the slope of the terrain, hardness of the ground, and the amount of ground cover. The logarithm of the productivity shock is assumed to follow a normal distribution with mean μ and variance σ^2; the probability density function of S takes the form

$$f_S(s) = \frac{1}{s\sigma_S} \phi\left(\frac{\log s - \mu_S}{\sigma_S}\right)$$

where ϕ represents the standard normal probability density function.

We assume that s, a realization of S, is observed by planters before they choose their effort levels, but after they accept a contract. Note that the firm does not observe s; it only observes the parameters of the distribution of S: μ and σ^2. Thus, while a planter can observe average planting conditions before he begins to plant, the exact nature of the terrain to be planted is only revealed once planting begins.

The timing of events in our model is as follows:

1. for a particular contract to be planted, Nature chooses the pair (μ, σ^2), the parameters of the distribution of S;
2. the firm observes (μ, σ^2), and then chooses a piece rate r;
3. the planter observes (μ, σ^2, r), and accepts or rejects the contract;
4. if the planter accepts the contract, then he is randomly assigned to plant a particular plot of the contract;
5. for each plot, Nature chooses s, a particular value of S;
6. the planter observes s, and chooses an effort level e producing output y;
7. the firm observes y, and pays earnings ry.

To solve the model, we work backwards. First, we solve for the planter's optimal effort level conditional on a given piece rate and productivity shock. Then we solve for the firm's choice of the piece rate, taking the reaction of the planter as given. Note that in order to induce the planter to accept the contract, the contract must satisfy the planter's labour-supply constraint.

Conditional on s, a particular realization of S, planters choose effort to maximize their utility. The optimal level of effort e is

$$e = \left(\frac{rs}{\kappa_i}\right)^{\gamma_i}$$

giving output

$$y = \left(\frac{r}{\kappa_i}\right)^{\gamma_i} s^{\gamma_i+1}. \tag{4.1}$$

Taking logarithms of both sides of (4.1) yields

$$\log y = \gamma_i \log r - \gamma_i \log \kappa_i + (\gamma_i + 1) \log s,$$

or, in terms of random variables,

$$\log Y_{ij} = \gamma \log r_j - \gamma_i \log \kappa_i + (\gamma_i + 1) \log S_{ij} \tag{4.2}$$

where

$$(\gamma_i + 1) \log S_{ij} \sim N\big[(\gamma_i + 1)\mu_j, (\gamma_i + 1)^2 \sigma_j^2\big].$$

Note that the parameter γ_i gives a direct measure of the elasticity of planter i's effort with respect to the piece rate. Taking expectations of (4.2) gives

$$\mathcal{E}[\log Y_{ij}] = \gamma_i \log r_j - \gamma_i \log \kappa_i + (\gamma_i + 1)\mu_j \tag{4.3}$$

Lemma 1:
Differences in the logarithm of observed productivity can be decomposed into part due to differences in ability κ_i and part due to differences in response to incentives γ_i.

Proof: See Appendix

To convert (4.2) into an equation with a mean-zero error term, we add and subtract $(\gamma_i + 1)\mu$, which yields

$$\log Y = \gamma_i \log r - \gamma_i \log \kappa_i + (\gamma_i + 1)\mu + V \tag{4.4}$$

where V now equals $(\gamma_i + 1)\big(\log S - \mu\big)$, which is distributed normally with mean zero and variance $(\gamma_i + 1)^2 \sigma_j^2$.

As noted in Paarsch and Shearer (1999), the direct estimation of (4.4) is problematic because μ is unobserved and μ and r are correlated. To solve for this classic endogeneity problem we model the firm's decision rule in setting the piece rate as a function of μ. In the presence of heterogeneous workers we assume that the expected utility constraint is binding for a given individual, denoted h. Thus,

$$\frac{r^{\gamma_h + 1}}{k_h^{\gamma_h}(\gamma_h + 1)} \mathcal{E}\big(S^{\gamma_h + 1}\big) = \bar{u}. \tag{4.5}$$

Substituting into (4.4) gives

$$\log Y_{i,j} = \frac{\gamma_i + 1}{\gamma_h + 1} \log \bar{u} + \frac{\gamma_i + 1}{\gamma_h + 1} \log(\gamma_h + 1) - \log r_j + \gamma_h \frac{\gamma_i + 1}{\gamma_h + 1} \log k_h - \gamma_i \log \kappa_i - (\gamma_h + 1)(\gamma_i + 1)\frac{\sigma_j^2}{2} + V_{i,j} \tag{4.6}$$

where

$$V_{i,j} \sim N\big(0, (\gamma_i + 1)^2 \sigma^2\big). \tag{4.7}$$

Equation (4.6) generalizes equation (9) of Paarsch and Shearer (1999), admitting heterogeneous responses to piece rates. In particular, when γ_i equals γ_h which equals γ (4.6) collapses to equation (9) of Paarsch and Shearer (1999) allowing a test of the hypothesis of homogeneous treatment effects. Note that while heterogeneity in the cost of effort, κ, only affects the mean in the logarithm of productivity, heterogeneity in response, γ, affects both the mean and the variance of productivity. This asymmetry in effects on the distribution of productivity provides the key to identification.

Note too that (4.6) represents a nonlinear version of the heterogeneous treatment effect model familiar in the labour econometrics literature; see, for example, Heckman, Lalonde and Smith (1999) or Angrist and Kreuger (1999). Recent discussion of the estimation of such models has concentrated on the random coefficient model. Treating parameters as random variables permits concentration on the identification of their distribution rather than individual values. This is particularly advantageous in short panels. However, daily productivity can provide panels of sufficient length to estimate a fixed-coefficient model, treating each γ_i as a parameter to be estimated. This allows for the treatment of heterogeneity in a nonparametric manner.

4.1. Identification

To consider identification, we reparameterize (4.6) as

$$\log Y_{i,j} + \log r_j = a_0 + \sum_{i=2}^{N_i} a_{1i} D_i - 0.5 \sum_{i=1}^{N_i} \sum_{j=1}^{N_j} \psi_i \tilde{\sigma}_j^2 D_i D_j + V_{ij} \tag{4.8}$$

where

$$\begin{aligned}
\psi_i &= \frac{\gamma_i + 1}{\gamma_h + 1} \\
a_0 &= \psi_1 \left[\log \bar{u} + \log(\gamma_h + 1) + \gamma_h \log \kappa_h\right] - \gamma_1 \log \kappa_1 \\
a_{1i} &= (\psi_i - \psi_1) \left[\log \bar{u}_{+} \log(\gamma_h + 1) + \gamma_h \log \kappa_h\right] + \gamma_1 \log \kappa_1 - \gamma_i \log \kappa_i\,. \\
\tilde{\sigma}_j^2 &= (\gamma_h + 1)\sigma_j^2 \\
V_{ij} &\sim N(0, \psi_i^2 \tilde{\sigma}_j^2)
\end{aligned} \tag{4.9}$$

Theorem 1:
The model identifies

$$a_0, \quad a_{1i}, \quad \psi_i, \quad \tilde{\sigma}_j^2. \tag{4.10}$$

Proof: See Appendix

The model permits identification of the ranking rather than the level of individual effort elasticities. To see this note that γ_i is monotonically related to ψ_i through

$$\gamma_i = (\gamma_h + 1)\psi_i - 1. \tag{4.11}$$

Identifying the level of individual elasticities requires that individual h be present in the sample, and that a measure of alternative utility be available. This is summarized in the following Corollary.

Corollary 1:

Let individual h *(for whom the expected utility constraint is binding) be in the sample. Then, conditional on a measure of* $\bar{u}$*, the structural model identifies:*

$$\gamma_h, \gamma_i, \sigma_j^2 \tag{4.12}$$

Proof: See Appendix

Note that a test of individual h being in the sample is equivalent to testing that $\psi_i = 1$ for some i. Furthermore, note that the hypothesis of homogeneous treatment effects is equivalent to testing that $\psi_i = 1$ for all i. Despite the fact that γ_h is the value of γ for the indifferent individual, it is not necessarily the maximum value of γ in the firm since individual heterogeneity extends over two parameters in this model γ and κ. As such a test for $\psi_i = 1$ has a two-sided alternative.

5. Estimation Results

We estimate the model in three ways. First, we use a two-step estimation technique to identify the relationship between the ψ_i parameters and gender. In the first step, we estimate the the ψ_i terms as individual-specific parameters in (4.8). We then regress the estimated coefficients on individual characteristics, including gender. The second technique specifies $\psi_i = f(X_i, \delta)$ as non-stochastic function of observable characteristics. This allows us to identify the relationship between ψ_i and gender directly in (4.8). The third technique is to allow for unobservable heterogeneity: $\psi_i = f(X_i, \delta, \epsilon_i)$.

5.1. Two-Step Estimation

The results from estimating model (4.8), treating the ψ_is as individual-specific parameters, are presented in Table 4. To minimize space, we report only the average, maximum and minimum values of the estimated individual-specific parameters.

Table 4
First Stage Parameter Estimates
Sample Size = 3960

Individual-Specific Parameters				
Parameter		(Coef.)	(Std. Error)	(P-Value)
a_0		4.972	0.034	0.000
Maximum $a_i = a_{28}$		0.675	0.045	0.000
Minimum $a_i = a_{83}$		-0.496	0.049	0.000
Average a_i	0.245			
Std Dev a_i	0.224			

Individual Elasticity Parameters				
Parameter		(Coef.)	(Std. Error)	(P-Value)
Maximum $\psi_i = \psi_{26}$		0.754	0.154	0.000
Minimum $\psi_i = \psi_{52}$		0.169	0.039	0.000
Average ψ_i	0.398			
Std Dev ψ_i	0.107			

Variance Parameters				
Parameter		(Coef.)	(Std. Error)	(P-Value)
Maximum $\sigma_j = \sigma_{29}$		1.088	0.239	0.000
Minimum $\sigma_j = \sigma_{24}$		0.057	0.053	0.274
Average σ_j	0.591			
Std Dev σ_j	0.214			

Likelihood Function:	19.935

The value of the likelihood function equals to 19.935. The values of ψ_i are all less than one, with the maximum value equal to 0.754. This suggests that the indifferent individual responds the most to incentives. A test of the homogeneous treatment effects model $H_o : \psi_i = 1$ for all i is conducted by a likelihood ratio test comparing the maximized likelihood functions for the constrained and unconstrained models. The restricted likelihood value is -209.02; see Paarsch and Shearer (1999) Table 4(b). There are 209 parameters in the unrestricted model and 120 in the restricted giving a likelihood ratio statistic equal to 457.92 with 120 degrees of freedom: the pvalue is equal to zero. Thus, we conclude that workers do differ with respect to their effort elasticities; some workers respond more to incentives than others.

To consider the relative performance of male and female planters, we focus on the estimated ψ parameters which are graphed in Figure 1. The values of ψ for male and female planters are graphed in Figure 2. There is little evident from the graphs suggesting a difference between values for males and females. To investigate further the relative response of male and female workers, we regressed the individual values of $\hat{\psi}_i$ on worker characteristics, including age and gender. Specifically, we estimate the following regression:

$$\hat{\psi}_i = \delta_0 + \delta_1 Dmale + \delta_2 Age + \delta_3 Age^2 + \epsilon_i. \tag{5.1}$$

The results from this regression, along with the average bootstrapped estimate, the bootstrapped standard errors and the bootstrapped ninety-five percent confidence intervals are given in Table 5.[6]

[6] The bootstrapping procedure was conducted as follows. Errors were drawn from the parametric distribution of the structural model in (4.8). Along with the estimated coefficients, these errors were used to generate repeated samples of $\log y$. For each generated sample, the coefficients of the (4.8) were estimated and the resulting $\hat{\psi}_i$ vector was regressed on individual characteristics as in (5.1).

Table 5
Second Stage Parameter Estimates
Sample Size = 3960

Parameter	Estimated Coefficient	Bootstrapped Coefficient	Standard Error	Confidence Interval
constant	0.203	0.201	0.122	$(-0.0006, 0.407)$
dmale	-0.009	-0.010	0.013	$(-0.031, 0.010)$
age	0.009	0.009	0.006	$(-0.0009, 0.019)$
agesq	$-8.1e-5$	-8.27e-5	$7.7e-5$	$(-0.0002, 4.1e-5)$
R^2: 0.026				

The estimated ψs for male workers are slightly lower that those for females, however the difference is not statistically significant. Note as well that the R^2 for this regression is 0.026; observable characteristics explain only 2.6% of the variation in individual response to incentives.

5.2. Observed Heterogeneity

In this section, we estimate the model, incorporating $\psi_i = f(X\delta)$ directly into equation (4.8). To guarantee $\psi_i > 0$ we parameterize

$$f(x\delta) = exp\{\delta_0 + \delta_1 Dmale + \delta_2 Age + \delta_3 Age^2\}. \tag{5.2}$$

The estimated parameters are given in Table 6.

Table 6
Observed Heterogeneity Parameter Estimates
Sample Size = 3960

Individual-Specific Parameters

Parameter		(Coef.)	(Std. Error)	(P-Value)
a_0		4.969	0.036	0.000
Maximum $a_i = a_{28}$		5.646	0.052	0.000
Minimum $a_i = a_{83}$		4.472	0.061	0.000
Average a_i	0.245			
Std Dev a_i	0.224			

Elasticity Heterogeneity Parameters

Parameter	(Coef.)	(Std. Error)	(P-Value)
δ_0	-1.150	0.288	0.000
δ_1	-0.036	0.026	0.159
δ_2	0.023	0.014	0.095
δ_3	$-2.7e-4$	$2.0e-4$	0.174

Variance Parameters

Parameter		(Coef.)	(Std. Error)	(P-Value)
Maximum $\sigma_j = \sigma_{29}$		0.947	0.244	0.000
Minimum $\sigma_j = \sigma_{24}$		0.037	0.020	0.031
Average σ_j	0.504			
Std Dev σ_j	0.181			

Likelihood Function:	-200.148

The results are consistent with those of the two-step estimation procedure. In particular, while females react slightly more to incentives than males do ($\hat{\delta}_1 < 0$) the difference is not statistically significant.[7]

[7] Note that, while the individual heterogeneous elasticity coefficients (the δs) are not individually significant, the null hypothesis of constant elasticities is rejected. Estimating the model with homogeneous individuals gives a likelihood value of -209.02 while estimating the model with heterogeneous individuals gives a likelihood value of -200.21. A likelihood ratio statistic has a p-value of 0.001.

6. Discussion and Conclusion

Workers differ with respect to productive characteristics – both observable and unobservable. Controlling for these differences is of fundamental importance to interpreting the cause of observed differentials in economic outcomes as well as potential policies to overcome those differentials. We have used an economic model to decompose observed productivity differentials into component parts: ability (strength) and response to incentives. Our results suggest that individuals do respond differently to incentives, however observable characteristics explain very little of the differential responses. Moreover, we find no evidence that men and women react differently to piece rate incentives. The observed difference in productivity is explained by differences in ability.

Many jobs in the labour market do not require the physical strength of tree planting. Our results suggest that in the absence of differences in strength, males and females would have similar productivity levels in the tree-planting industry. This is consistent with the results of Gneezy et al. (forthcoming) who found no difference between male and female performance when completing intellectual tasks under piece rates.

Interestingly, these results are inconsistent with some sociological authors who have argued that male and female reactions to incentives will differ due to differences in their home life. In particular, Shimmin (1962) argued that young female workers in England during the 1950s and 60s often had their earnings expropriated by their families in return for a fixed allowance. These social conventions, which did not apply to men, dampened female responses to incentive payments; see Millward (1968) for some evidence of these effects. Our results undoubtedly reflect the changing circumstances under which females participate in the labour market today.

7. Appendix

Proof of Lemma 1:

Let

$$\mathcal{E}[\log Y_{Mj}] = \gamma_M \log r_j - \gamma_M \log \kappa_M + (\gamma_M + 1)\mu_j \tag{7.1}$$

represent average productivity of male workers and

$$\mathcal{E}[\log Y_{Fj}] = \gamma_F \log r_j - \gamma_F \log \kappa_F + (\gamma_F + 1)\mu_j \tag{7.2}$$

represent average productivity of female workers. Then

$$\mathcal{E}[\log Y_{Mj}] - \mathcal{E}[\log Y_{Fj}] = (\log r_j + \mu_j)(\gamma_M - \gamma_F) + \gamma_F \log \kappa_F - \gamma_M \log \kappa_M. \tag{7.3}$$

Adding and subtracting $\gamma_M \log \kappa_F$

$$\mathcal{E}[\log Y_{Mj}] - \mathcal{E}[\log Y_{Fj}] = (\log r_j + \mu_j - \log \kappa_F)(\gamma_M - \gamma_F) + \gamma_M(\log \kappa_F - \log \kappa_M). \tag{7.4}$$

The difference in average productivity between male and female workers can be decomposed into two parts: differences in the response to piece rates $(\gamma_M - \gamma_F)$; and differences in ability or strength $(\log \kappa_F - \log \kappa_M)$.[8]

[8] When γ and κ are random variables the decomposition holds under the condition that $Cov(\gamma, \log \kappa)$ is independent of gender. In particular,

$$\mathcal{E}[\log Y_M] = \log r \mathcal{E}\gamma_h + (\mathcal{E}\gamma_h + 1)\mu + \mathcal{E}(\gamma_h \log \kappa_h).$$

Using the fact that $\mathcal{E}(\gamma_h \log \kappa_h) = Cov(\gamma, \log \kappa) + \mathcal{E}(\gamma)\mathcal{E}(\log \kappa)$ gives

$$\begin{aligned}\mathcal{E}(\log Y_{Mj}) - \mathcal{E}(\log Y_{Fj}) =& \big(\log r_j + \mu_j - \mathcal{E}(\log \kappa_F)\big)\big(\mathcal{E}(\gamma_M) - \mathcal{E}(\gamma_F)\big) + \\ & \mathcal{E}(\gamma_M)\big(\mathcal{E}(\log \kappa_F) - \mathcal{E}(\log \kappa_M)\big).\end{aligned}$$

Proof of Theorem 1:

The parameters collected in the vector $\mathbf{a}$ are composites of structural parameters that are not separately identified except under special circumstances; see the Corollary below. The terms ψ_i and σ_j are identified through the restriction that they determine both the block-specific effects and the variance terms. While each individual adds a parameter ψ_i and each plot adds a parameter $\tilde{\sigma}_j$, observing individuals over multiple plots and multiple individuals on the same plot provides sufficient moment conditions to identify these parameters.

Proof of Corollary 1:

Without loss of generality let individual h be denoted by individual $i = 1$. Then $\psi_1 = 1$ and the constant term $a_0 = \log \bar{u} + \log(\gamma_h + 1)$ identifies γ_h, conditional on a measure of $\bar{u}$. This reflects the identification strategy followed by Paarsch and Shearer (1999).

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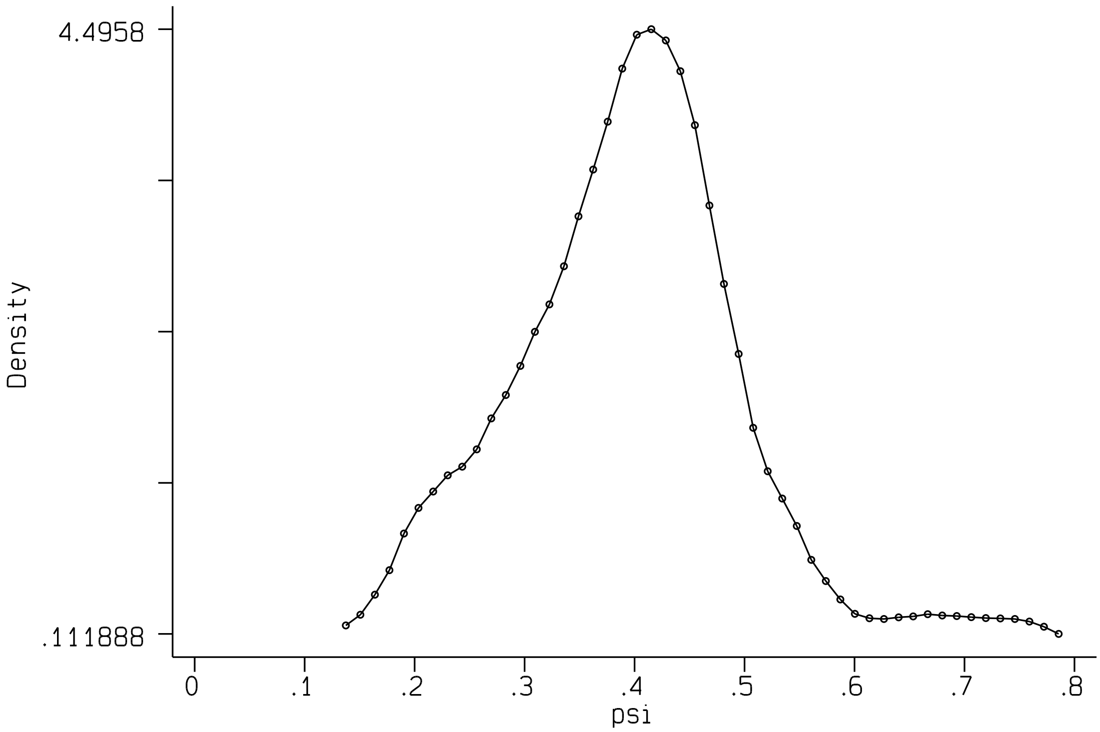
Figure 1: Kernel-Smoothed Density of Psi



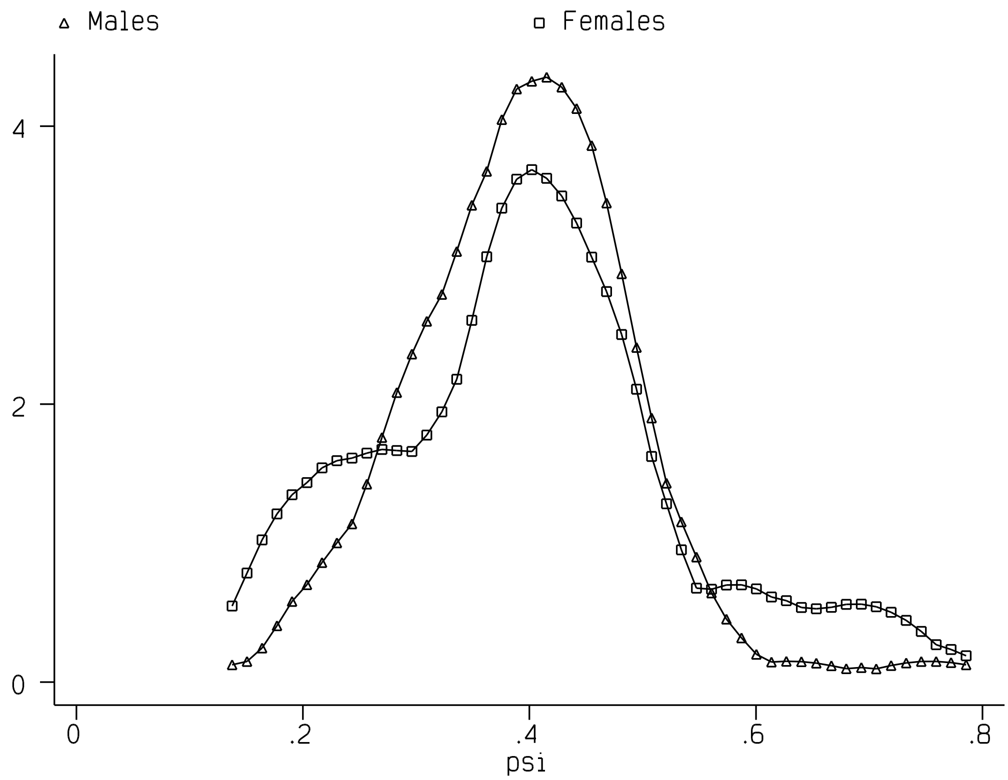


Figure 2: Kernel-Smoothed Density of Psi