PIECE RATES, FIXED WAGES AND INCENTIVES: EVIDENCE FROM A FIELD EXPERIMENT*

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Abstract

Data from a field experiment are used to estimate the gain in productivity that is realized when workers are paid piece rates rather than fixed wages – the incentive effect. The experiment, which was conducted within a tree-planting firm, recorded the daily productivity of workers who were randomly assigned to plant trees under either piece rates or fixed wages. The experiment was conducted on a subset of planting conditions (the steepness and hardness of the terrain) encountered within the firm. A theoretical model of worker and firm behaviour under piece rates and fixed wages provides the basis for the empirical work. The model derives decision rules over worker effort and the contract structure as a function of planting conditions. The reduced form of the model collapses to a simple linear equation that is estimated using ANOVA methods. The results suggest an incentive effect of 20 percent on the planting conditions encountered within the experiment. Since planting conditions potentially affect incentives, structural econometric methods are used to generalize the experimental results to out-of-sample conditions. The structural model imposes nonlinear restrictions on the ANOVA model and identifies the fundamental parameters that govern how worker effort changes as planting conditions change. Efficiency gains are realized in the estimation of the structural model by supplementing the experimental sample with non-experimental data on the same workers planting under piece rates within the same same firm. The structural model identifies a lower bound on the incentive effect that is independent of planting conditions and that is estimated to be 17 percent.

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1. Introduction

Measuring how workers react to incentives has important implications for determining the relevance of economic theories (*e.g.* Hart and Holmstrom, 1987) as well as the personnel policies that are based on those theories (Milgrom and Roberts, 1992; Lazear, 1998). Recent empirical work in this area has concentrated on using firm-level data to measure the productivity effects of different compensation systems; *i.e.* incentive effects. Examples include Ichniowski, Shaw, and Prennushi (1997), Lazear (1997) and Paarsch and Shearer (1998a, 1998b). Of particular concern in the measurement of incentive effects is the possible endogeneity of the compensation system. Since observed compensation systems represent choices made by the firm, if factors which are unobservable to the econometrician affect both the firm's choice and worker productivity, then simple comparisons of worker performance under different compensation systems will fail to identify the incentive effect (Ehrenberg, 1990; Prendergast, 1999).

Perhaps the most direct way to solve this endogeneity problem is to gather experimental evidence. An experimental setting permits the compensation system to be varied exogenously allowing direct measurement of the incentive effect. This eliminates the need for strong functional form assumptions (Paarsch and Shearer, 1998a, 1998b) or assuming certain variables as instruments (Boning, Ichniowski, and Shaw, 1998) to identify the incentive effect in the data. Experimental evidence has so far concentrated on the analysis of students completing tasks on a computer under different reward systems (see, for example, Nalbantian and Schotter, 1997). While these experiments generally confirm the existence of incentive effects, generalizing their results into personnel policy may be problematic. In particular, the size of the incentive effect in the labour market depends on unknown structural parameters. Unless laboratory experiments replicate the labour market, the reactions observed within the laboratory setting will not necessarily be representative of the reactions of workers within real firms (Wolpin, 1995). An alternative is to use the firm as a laboratory within which to conduct experiments on personnel policy. These field experiments combine the benefits of experimental economics with labour-market generated data.

This paper uses data from a field experiment to measure the gain in productivity that is realized when workers are paid piece rates rather than fixed wages. The experiment took place within a tree-planting firm operating in the province of British Columbia, Canada. The tree-planting industry is well suited to performing small scale experiments on the effects of different human-resource practices since individual daily productivity is easily observable. The firm in which the experiment was conducted usually pays its workers in proportion to the number of trees planted per day (*i.e.* a piece rate). To complete the experiment, nine male planters were randomly selected from this firm. These planters were then randomly allocated to plant under fixed wages and piece rates. Nothing else was changed in the personnel policy of the firm; the monitoring of the workers was held constant and the participating workers had no knowledge that an experiment was taking place. Each worker involved in the experiment was observed planting under both piece rates and fixed wages. In total the experiment provided 120 observations on daily productivity (60 under each compensation system).

These experimental data are used to measure the percentage difference in average productivity when workers are paid piece rates rather than fixed wages. The empirical work is based on a simple theoretical model of worker and firm behaviour under piece rates and fixed wages. The model incorporates asymmetric information over effort and specific planting conditions for a given worker, yet assumes the firm has complete knowledge of the distribution of planting conditions. The model is appealing in that its unrestricted-reduced form collapses to an ANOVA model which identifies the incentive effect on the experimental data. Results from estimating the ANOVA model suggest the incentive effect is approximately 20%.

An important issue related to experimental evidence is the generalizability of the results. In particular, the inability to randomize over all of the factors that affect experimental outcomes can limit the information provided from experimental studies (Heckman and Smith, 1995). This issue comes to light within the present context since planting conditions (particularly the difficulty of the terrain) affect worker productivity (Paarsch and Shearer, 1998b) and therefore potentially affect the incentive effect. Structural econometric methods, combined with the experimental data, are used to identify out-of-sample incentive effects. Structural methods identify behavioural parameters that determine the workers' reaction to changing conditions and compensation systems. Previous applications of structural econometric methods within the compensation literature data have considered measuring the cost of moral hazard within the firm (Ferrall and Shearer, 1998 and Margiotta and Miller, forthcoming), measuring productivity profiles (Shearer, 1996), as well as measuring the incentive effect (Paarsch and Shearer, 1998a, 1998b). The application of structural methods to experimental data is discussed in Keane and Wolpin, 1997.

The structural model imposes non-linear restrictions on the experimental ANOVA model. Identification of the incentive effect is demonstrated under three scenarios. First, estimation of the structural model on the experimental data identifies the incentive effect within the experimental sample. Second, supplementing the experimental data with nonexperimental data and estimating the structural model on the enlarged data set identifies the incentive effect on the nonexperimental data. This holds even though the nonexperimental data contains observations on piece-rate planting only. The additional data also adds important information to the estimation of the structural model which is non-linear and includes individual-specific effects. Finally, the parameter estimates from the structural model identify a lower bound to the incentive effect which is independent of planting conditions. The lower bound is attained when the incentive effect is evaluated under a degenerate distribution of planting conditions. This result follows from the fact that worker effort is fixed under fixed wages but generally adjusts to conditions under piece rates (since conditions affect the marginal return to effort). At zero variance the shock is constant and no adjustment takes place. When the variance is positive, however, the piece-rate worker can take advantage of large positive shocks and increase average productivity relative to that under fixed wages.

An important extension to the structural model is achieved by relaxing the assumption of perfect information to the firm over the distribution of planting conditions. Doing so allows the firm to make mistakes when judging planting conditions. These perception errors lead to a random-effects empirical specification that significantly improves the fit of the structural model.

The parameters of the model are estimated using maximum-likelihood techniques. Calculations based on the structural estimates applied to the experimental data lead to an incentive effect of 20.8%, closely matching the unrestricted ANOVA estimates. Furthermore, the lower bound to the incentive effect on non-experimental data is calculated to be 17%.

It is noteworthy that these results are similar to results obtained in Paarsch and Shearer (1998a) which used nonexperimental, firm-level data originating from the same industry. Paarsch and Shearer calculate an incentive effect of 21% using structural econometric methods to control for a tree-planting firm's endogenous choice between piece rates and fixed wages. The results are also similar to those obtained in Lazear (1997). Lazear argued that the change in compensation system from fixed wages to piece rates in a car windshield-installing firm formed a natural experiment. His results, based on regression methods, calculated a percentage increase in productivity of 20% associated with the switch to piece rates.

There are seven additional sections to the paper. The next section discusses the institutional details of the tree-planting industry and the firm in which the experiment took place. Section 3 outlines the design of the experiment. In Section 4 the experimental data are presented. Section 5 develops the theoretical model of productivity determination under piece rates and fixed wages, which serves as a basis for the empirical work of the paper. Identification and estimation are discussed in Section 6. The results are presented in Section 7 and Section 8 concludes.

2. Institutional Details

The tree-planting industry of British Columbia is responsible for the reforestation of recently logged tracts of land. Contracts to reforest a tract of land are typically awarded to tree-planting firms through a competitive auction whereby firms will bid on the price-per-tree that they are to receive for planting. These auctions typically take place in the autumn and are conducted by either the Ministry of Forests or the major logging firms. Planting ensues the following spring.

Tree-planting firms are typically quite small, employing less than 100 planters. These planters work under the supervision of firm managers and monitors (usually in the ratio of 10 workers to one monitor). Planters are equipped with a shovel and a sack of seedlings which fit around the planter's hip. Each day they are assigned to plant trees in an area of land. To plant a tree, the planter digs a hole in the ground, places the seedling in the ground and fills the hole in.

Planting is simple yet physically exhausting work. The productivity of the planters is determined by their effort level as well as the conditions of the terrain on which they are planting. For example, if the ground is hard and rocky or covered in underbrush, it takes more time and effort to plant a given number of trees, reducing daily worker productivity. In general, planting conditions vary a great deal. Some sites have been prepared for planting, meaning that the underbrush and slash timber has been removed (often by burning the site). Other sites are unprepared and are therefore more difficult to plant.

The firm in which the experiment took place employs approximately 90 planters per year. These planters are divided into workgroups under the supervision of one of the firm's managers (who is an owner of the firm). These workgroups are assigned to plant contracts throughout British Columbia during the planting season from February to July. The workgroup on which the experiment was performed included approximately 30 workers.

The firm typically pays its workers piece rates. Under these contracts workers are paid strictly in proportion to their individual output – no base wage is received.

Planting sites are divided into blocks which are areas of homogeneous terrain. The manager in charge of the contract sets the piece rate for each block on the basis of planting conditions on that block. Typically, higher piece rates correspond to tougher planting conditions. This is because the piece rate must satisfy the worker's labour-supply constraint. Since workers are paid in proportion to their productivity and since effort is costly, workers prefer to plant in easier ground where they can plant more trees for a given effort level. To induce planters to plant on more difficult terrain the piece rate must be increased (see Paarsch and Shearer, 1998b, for further details). While not a regular occurrence, some contracts are paid on a fixed wage basis. This occurs, for example, when planting conditions change a great deal between the time at which the contract is bid and the time at which it is planted. For example, the ministry of forests will sometimes unexpectedly prepare sites that have already been awarded. The firm may not have knowledge of the changed conditions until they arrive at the site to begin planting. When this occurs, rather than renegotiate the price per tree at which the contract is to be planted (which may be impossible due to time constraints), the firm will simply plant the contract under a fixed price and pay their planters fixed wages. In these cases fixed wages are determined by the planter's average wage under previous piece rate contracts.

3. Experimental Design

The goal of the experiment was to measure the change in worker effort as the compensation system changed from piece rates to fixed wages. Since worker productivity depends on worker effort as well as planting conditions, measuring the incentive effect required changing the compensation system while holding planting conditions constant. Randomization over blocks on which to conduct the experiment proved to be impossible since the firm did not know in advance which blocks would be planted in a given year. Contracts that were planted for the ministry of forests could involve multiple years of planting. Often, the blocks that were planted in any given year were not decided upon until just before the planting was done.

Two concerns dominated the design of the experiment and the selection of blocks. The first concern was to keep the work environment as normal as possible: workers were kept ignorant of the experiment taking place. This required explaining the change in the compensation system in a manner that would seem realistic to the workers. Workers were told that certain blocks were unpriced. None of the workers involved in the experiment questioned this explanation. The second concern was the precise measurement of the incentive effect. With this in mind the blocks that were selected were large enough to allow the repeated observation of each worker planting under each compensation system.

The experiment was therefore conducted under a randomized-block design with three blocks of land. Each block was internally homogeneous in terms of planting conditions (in that the piece rate paid to workers was constant within the block) yet differed from the other two. Each block of land was randomly divided into two parts: one to be planted under piece rates and the other to be planted under fixed wages.

A group of nine male planters was randomly selected from the firm to take part in the experiment. The sample was restricted to male planters in order to reduce the variation in observed productivity. Before beginning a particular block, planters were randomly assigned to piece rates or fixed wages. Each planter then planted an equal number of days under each compensation system on that particular block of land. Attrition (one planter unexpectedly returned to school) and differing block sizes yielded different numbers of workers planting on the different blocks; subsequently not every worker is observed on each block of land. However, any worker who is observed on a given block of land is observed under both piece rates and fixed wages on that block. Furthermore, each worker who plants on a given plot of land is observed for the same number of days (at least two) under piece rates and fixed wages.

4. Experimental Data

Table 1 presents the summary statistics for the experimental sample. The sample consists of 120 planting days, of which 60 took place under piece rates and 60 took place under fixed wages. The average daily productivity of these workers was 1146.67 trees and the standard deviation was 278.54. Workers were more productive under piece rates than fixed wages – the difference in average productivity being 219 trees. This represents an increase in average productivity of approximately 21 percent when workers were paid piece rates. Workers also earned more under piece rates. To see if the increase in earnings outweighed the increase in prodcutivity, the final column of Table 1 presents data on unit costs – daily earnings divided by daily productivity. These show that piece rates provided lower unit costs than fixed wages, the decrease being in the order of 12 percent.

Table 2 considers average productivity across the blocks used in the experiment. These blocks (denoted A, B, and C) had piece rates of \$0.17, \$0.18, and \$0.20. The average productivity under piece rates and fixed wages for each plot is given in columns 6 and 7. Notice that average productivity is higher under piece rates on each plot, although the percentage difference varies. These facts suggest that block-specific effects are an important determinant of worker productivity and incentives, reflecting differences in planting conditions.

Average productivity per plot is given in column 4. Notice the actual average productivity is not negatively related to the piece rate as would be expected from the manner in which the firm sets piece rates. Recall, the firm sets the piece rate in inverse relation to the difficulty of the planting conditions that the manager observes. However, average productivity is higher when the piece rate is \$0.18 than when it is \$0.17. The is due to the fact that the firm sometimes errs in their judgement of planting conditions during the bidding process resulting in a piece rate that is slightly too high or too low for a given plot of land.

Table 3 presents average productivity by individual planter and pay system. Column 3 shows the average productivity per planter ranges from 992.5 trees to 1330 trees per day, suggesting that individual heterogeneity is present in the sample. Columns 4 and 5 give the average productivity for each planter under piece rates and fixed wages. Again average productivity for each planter is higher under piece rates.[1]

These data also suggest that the incentive effect varies across individuals in a systematic manner. The differences in average productivity under piece rates and fixed wages are given in column 6 of Table 3. Figure 1 graphs these differences in relation to the average productivity under piece rates (the usual compensation system). The graph clearly shows that high productivity workers are those that are most affected by the compensation system.

5. Theoretical Model

This section develops a model of worker productivity under piece rates and fixed wages, incorporating the firm's choice of a piece rate. The model presents a synthesis of models developed previously in Paarsch and Shearer (1998a) and (1998b) while extending those models to allow for individual-specific heterogeneity under fixed wages. Daily productivity is determined by

$$Y = ES$$

where E represents the worker's effort level, and S is a productivity shock representing planting conditions beyond the worker's control (such as the hardness of the ground). It is assumed that S follows a lognormal distribution with parameters μ and σ^2; *i.e.*, $\ln S \sim N(\mu, \sigma^2)$. Workers have the utility function defined over daily wages, w, and effort, E,

$$U_i(w, E) = w - C_i(E)$$

where $C_i(E)$ represents worker i's monetary cost of effort and is parameterized as

$$C_i(E) = \frac{\kappa_i}{\eta} E^{\eta}, \quad \eta > 1, \kappa_i > 0$$

where κ_i captures individual heterogeneity, and η determines the curvature of the cost function. Alternative utility is given by $\bar{u}$.

[1] Averaging hides some variability in the data. In particular, analyzing individual productivity by plot and compensation system reveals that in three cases a planter planted fewer trees under piece rates than fixed wages on the same plot.

5.1. Piece Rates

Under piece rates, in accordance with the observed contract, $w = rY$ where r represents the piece rate. The timing of the model is as follows. For each plot of land to be planted:

1. Nature chooses (μ, σ^2);
2. the firm observes (μ, σ^2) and then selects a piece rate r;
3. the worker observes (μ, σ^2) and r and either accepts or rejects the contract;
4. conditional on accepting the contract the worker observes a particular value of S and chooses an effort level, producing Y;
5. the firm observes Y and pays wages.

Let e_i denote the optimal level of effort chosen by worker i. Conditional on s, a realization of S,

$$e_i = \left[\frac{rs}{\kappa_i}\right]^{\gamma} \tag{5.1}$$

where $\gamma = 1/(\eta - 1)$.

In order for workers to accept the contract it must satisfy their expected utility constraint. Given the contract has only one instrument and workers are heterogeneous, some workers will earn rents. It is assumed that the piece rate is chosen to satisfy the alternative utility constraint of the lowest-ability worker in the firm; that is, the worker with ability level κ_h where

$$\kappa_h = \max\{\kappa_1, \kappa_2, \ldots, \kappa_n\}.$$

As such, r solves agent h's expected utility constraint

$$\frac{r^{\gamma+1}}{\kappa_h^{\gamma}(\gamma+1)}\mathcal{E}\left(S^{(\gamma+1)}\right) = \bar{u} \tag{5.2}$$

where $\mathcal{E}$ denotes the expectation operator.

Output for individual i under piece rates, conditional on s, is

$$y_i^{pr} = \left(\frac{r}{\kappa_i}\right)^{\gamma} s^{\gamma+1},$$

or in terms of random variables

$$Y_i^{pr} = \left(\frac{r}{\kappa_i}\right)^{\gamma} S^{\gamma+1}. \tag{5.3}$$

Taking logarithms of (5.2) and substituting into (5.3) gives daily productivity for individual i on contract j as

$$\ln Y_{ij}^{pr} = \ln(\gamma+1) + \ln \bar{u} - \ln r_j + \gamma(\ln \kappa_h - \ln \kappa_i) - (\gamma+1)^2 \frac{\sigma_j^2}{2} + \epsilon_{ij}^{pr} \tag{5.4}$$

where $\epsilon_{ij}^{pr} = (\gamma+1)(\ln S_{ij} - \mu_j) \sim N\big(0, (\gamma+1)^2\sigma_j^2\big)$.

5.2. Fixed Wages

Under fixed wages worker effort is independent of the piece rate. However, given the worker is planting under the same general conditions, the piece rate that he would have received is informative as to what those conditions are. It is assumed that there is a lower bound to effort, denoted $\bar{e}_i$, that is enforceable within the firm. To allow effort to vary across workers in an empirically tractable manner, define

$$\bar{e}_i = \frac{\bar{\lambda}}{\kappa_i}.$$

Thus workers with lower costs of effort supply higher effort under fixed wages as well as piece rates.

Worker productivity under fixed wages is therefore

$$Y_{ij}^{fw} = \frac{\bar{\lambda}}{\kappa_i} S_{ij}. \tag{5.5}$$

Taking logarithms gives

$$\ln Y_{ij}^{fw} = \ln \bar{\lambda} - \ln \kappa_i + \mu_j + \epsilon_{ij}^{fw}$$

where $\epsilon_{ij}^{fw} = \ln(S_{ij} - \mu_j) \sim N\big(0, \sigma_j^2\big)$. Substituting in from (5.2) and rearranging gives

$$\begin{aligned} \ln Y_{ij}^{fw} = & \ln \bar{\lambda} - \frac{\ln \kappa_i}{(\gamma+1)} + \frac{\gamma}{(\gamma+1)}(\ln \kappa_h - \ln \kappa_i) + \frac{\ln \bar{u}}{(\gamma+1)} + \frac{\ln(\gamma+1)}{(\gamma+1)} \\ & - \ln r_j - (\gamma+1)\frac{\sigma_j^2}{2} + \epsilon_{ij}^{fw}. \end{aligned} \tag{5.6}$$

6. Estimation and Identification

The theoretical model leads to two empirical equations defined by (5.4) and (5.6). Since both equations have mean-zero error terms it follows

$$\mathcal{E}[\ln Y + \ln r | pr, I = i, J = j] = \ln \bar{u} + \ln(\gamma + 1) + \gamma(\ln \kappa_h - \ln \kappa_i) - (\gamma + 1)^2 \frac{\sigma_j^2}{2}$$

$$\mathcal{E}[\ln Y + \ln r | fw, I = i, J = j] = \Big(\ln \bar{u} + \ln(\gamma + 1) + \gamma(\ln \kappa_h - \ln \kappa_i) - (\gamma + 1)^2 \frac{\sigma_j^2}{2}\Big)\left(\frac{1}{\gamma + 1}\right) + \ln \bar{\lambda} - \frac{\ln \kappa_i}{(\gamma + 1)}. \tag{6.1}$$

Without loss of generality, let $I = 1$ denote the first individual in the experimental sample and let $J = 1$ denote the first plot on which experimental planting took place. Then using (5.4), (5.6) and (6.1), the empirical model can be written

$$\begin{aligned}\ln Y + \ln r = & \ln \bar{u} + \ln(\gamma + 1) + \gamma(\ln \kappa_h - \ln \kappa_1) - \Big(\ln \bar{u} + \ln(\gamma + 1) \\ & + \gamma(\ln \kappa_h - \ln \kappa_1) - \frac{(\gamma + 1)}{\gamma} \ln \bar{\lambda} + \frac{\ln \kappa_1}{\gamma}\Big) \frac{\gamma}{(1 + \gamma)} DFW \\ & + \sum_{i=2}^{9} \gamma(\ln \kappa_1 - \ln \kappa_i) DNAME_i \\ & - \sum_{j=1}^{3} \frac{(\gamma + 1)^2}{2} \sigma_j^2 DBLK_j + \\ & \sum_{i=2}^{9} \frac{\gamma^2 - 1}{\gamma + 1} (\ln \kappa_i - \ln \kappa_1) DNAME_i \times DFW \\ & + \sum_{j=1}^{3} \frac{\gamma(\gamma + 1)}{2} \sigma_j^2 DBLK_j \times DFW + \epsilon_{ij}\end{aligned} \tag{6.2}$$

where ϵ_{ij} is a mean-zero, heteroscedastic error term with

$$Var(\epsilon_{ij}) = \begin{cases} (\gamma + 1)^2 \sigma_j^2 & \text{if } DFW = 0, \\ \sigma_j^2 & \text{otherwise} \end{cases} \tag{6.3}$$

and

$$DFW = \begin{cases} 1 & \text{if payment is by fixed wages} \\ 0 & \text{otherwise} \end{cases}$$

$$DNAME_i = \begin{cases} 1 & \text{if planting is done by individual } i \\ 0 & \text{otherwise} \end{cases}$$

$$DBLK_j = \begin{cases} 1 & \text{if planting is done on block } j \\ 0 & \text{otherwise.} \end{cases}$$

The model (6.2) will be referred to as the restricted model in that its coefficients are functions of the structural parameters of the theoretical model developed in Section 5. These functions are derived from the imposition of (5.2) which links the observed piece rate, r_j, to unobserved planting conditions (μ_j, σ_j^2).

In unrestricted form the empirical model can be written

$$\begin{aligned} \ln Y + \ln r = &\alpha_0 + \alpha_1 DFW + \sum_{i=2}^{9} \alpha_{2i} DNAME_i + \sum_{j=2}^{3} \alpha_{3j} DBLK_j + \\ &\sum_{i=2}^{9} \alpha_{4i} DNAME_i \times DFW + \sum_{j=2}^{3} \alpha_{5j} DBLK_j \times DFW + \epsilon_{ij} \end{aligned} \tag{6.4}$$

where

$$\begin{aligned} \alpha_0 &= \ln \bar{u} + \ln(\gamma + 1) + \gamma(\ln \kappa_h - \ln \kappa_1) - (\gamma + 1)^2 \frac{\sigma_1^2}{2} \\ \alpha_1 &= -\Bigg(\ln \bar{u} + \ln(\gamma + 1) + \gamma(\ln \kappa_h - \ln \kappa_1) - \frac{(\gamma + 1)}{\gamma} \ln \bar{\lambda} + \\ &\quad \frac{\ln \kappa_1}{\gamma} - (\gamma + 1)^2 \frac{\sigma_1^2}{2} \Bigg) \frac{\gamma}{\gamma + 1} \\ \alpha_{2i} &= \gamma(\ln \kappa_1 - \ln \kappa_i) \\ \alpha_{3j} &= \frac{(\gamma + 1)^2}{2} (\sigma_1^2 - \sigma_j^2) \\ \alpha_{4i} &= \frac{\gamma^2 - 1}{\gamma + 1} (\ln \kappa_i - \ln \kappa_1) \\ \alpha_{5j} &= \frac{\gamma(\gamma + 1)}{2} (\sigma_j^2 - \sigma_1^2) \end{aligned}$$

and ϵ_{ij} is a heteroscedastic error term whose variance depends on the block being planted and the compensation system; *i.e.*, let

$$V(\epsilon_{ij}) = \exp\big(\delta_0 + \delta_1 DFW + \sum_{j=2}^{3} \delta_{2j} DBLK_j + \sum_{j=2}^{3} \delta_{3j} DBLK_j \times DFW\big). \quad (6.5)$$

This model is unrestricted because the behavioural restriction implied by condition (5.2) is not imposed. Note that one block-specific dummy variable must be dropped from the unrestricted model since there is no restriction equating its coefficient to the variance of the error term. Consequently the constant term and the fixed-wage dummy absorb the variance term on the first block and the block-specific dummies estimate the differences in variances across blocks.

6.1. The Incentive Effect

The incentive effect for individual i on plot j is defined as the percentage difference in expected productivity under the two compensation systems

$$h_{ij} = \frac{\mathcal{E}[Y|pr, I=i, J=j] - \mathcal{E}[Y|fw, I=i, J=j]}{\mathcal{E}[Y|fw, I=i, J=j]}. \quad (6.6)$$

The average incentive effect is then the weighted average of the incentive effects over individuals and plots:

$$H = \frac{1}{N} \sum_{i=1}^{9} \sum_{j=1}^{3} n_{ij} h_{ij} \quad (6.7)$$

where n_{ij} represents the number of observations on individual i planting on plot j.

Estimation of the incentive effect on the experimental data can proceed either from the unrestricted or the restricted model.

6.1.1. The Unrestricted Incentive Effect

The experimental data permits calculation of (6.6) by comparing average productivity under piece-rate and fixed-wage planting. Substituting from (6.4) into (6.6) gives

$$\mathcal{E}[Y|pr, I=i, J=j] = \frac{1}{r_j} exp\big(\alpha_0 + \alpha_{2i} + \alpha_{3j}\big) \times exp\big(.5(\delta_0 + \delta_{2j})\big)$$
$$\mathcal{E}[Y|fw, I=i, J=j] = \frac{1}{r_j} exp\big(\alpha_0 + \alpha_1 + \alpha_{2i} + \alpha_{4i} + \alpha_{3j} + \alpha 5j\big) \times \quad (6.8)$$
$$exp\big(.5(\delta_0 + \delta_1 + \delta_{2j} + \delta_{3j})\big)$$

The advantage of using unrestricted estimation is that the sample equivalents of these expectations are easily calculated using simple ANOVA methods – the incentive effect is identified without strong functional form or other identifying restrictions (Burtless, 1995).[2] Yet, as demonstrated in Theorem 1 below, this estimator is limited to the experimental sample, and only generalizes to conditions beyond those observed in the experiment under strong assumptions.

Definition 1 *Let:*

(i) $\mathcal{J}$ *denote the set of all possible planting conditions;*

(ii) $\mathcal{J}^e \subset \mathcal{J}$ *denote the set of conditions observed in the experimental sample;*

Theorem 1: Generalizability *The unrestricted incentive effect generalizes to planting conditions beyond the experimental sample if*

$$\alpha_{5j} = \delta_{3j} = 0 \quad \forall j \in \mathcal{J}. \quad (6.9)$$

Proof: *The proof follows immediately from the fact that (6.6) is constant across blocks if this condition holds.* ■

Furthermore, in the absence of these restrictions the unrestricted ANOVA model provides no way of extrapolating results out of the experimental sample. The incentive effect on a given plot, j', depends on the interaction terms $\alpha_{3j'}$ and $\alpha_{5j'}$. Yet, estimating these terms within a nonrestricted context requires data on planting under

[2] Note, however, that, due to heteroscedasticity, the variance does not cancel from the incentive effect; see Halvorsen and Palmquist, 1980.

both compensation systems for block j'. That is, the experiment must be performed on every plot for which an incentive effect is to be calculated. This reflects the "black box" criticism of experiments; see Heckman and Smith, 1995.

6.1.2. The Restricted Incentive Effect

Generalizing the incentive effect beyond the experimental sample requires identifying the behavioural parameters on which the worker and firm choices and resulting (observed) outcomes are based. In particular, restricting the block-specific effects to be functions of behavioural parameters which are estimated on the experimental data permits generalization. These functions are derived from (5.2) which provides a mapping between the unobservable planting conditions on a particular plot, (μ_j, σ_j), and the observable piece rate r_j. Given (5.3), (5.5) and (5.2), expectations can be conditioned on a number of parameters. However, as a precursor to subsequent empirical work, the results of this section condition on piece rates.

Lemma 1: *Conditional on a piece rate, r_j, equilibrium expected productivity under piece rates is independent of planting conditions μ_j and σ_j^2 and is given by*

$$\mathcal{E}[Y|pr, r_j, i] = \bar{u}(\gamma+1)\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\frac{1}{r_j}. \qquad (6.10)$$

Proof: The proof of Lemma 1 follows directly from substituting (5.2) into the expectation of (5.3). ∎

Since the piece rate is chosen to satisfy the worker's expected utility constraint, it contains all the relevant information concerning conditions when the worker is paid piece rates.

Lemma 2: *Conditional on a piece rate, r_j, equilibrium expected productivity under fixed wages depends on planting conditions and is given by*

$$\mathcal{E}[Y|fw, r_j, i, \sigma_j] = \left[\bar{u}(\gamma+1)\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\right]^{(1/(\gamma+1))}\frac{1}{r_j}\frac{\bar{\lambda}}{\kappa_i^{1/(\gamma+1)}}\exp-(\gamma\sigma_j^2/2). \qquad (6.11)$$

Proof: The proof of Lemma 2 follows directly from substituting (5.2) into the expectation of (5.5). ∎

Recall that the piece rate provides information as to planting conditions through (5.2). Thus, even though worker productivity under fixed wages is independent of the piece rate, the piece rate the worker would have received had the payment system been piece rates is still informative as to the planting conditions[3]. However, unlike the case for piece-rate planting, the piece rate does not contain all of the relevant information concerning expected productivity when workers are paid fixed wages. While planting conditions are the same under piece rates and fixed wages (for a given piece rate), the effort decision is different. In particular, under fixed wages worker effort is fixed and independent of conditions. Under piece rates, however, the value of the shock, S, determines the worker's marginal return to effort and therefore affects his effort level. As the distribution of shocks changes, the piece rate adjusts, not only to conditions, but also to changes in effort. This lack of symmetry between piece rates and fixed wages is reflected in the presence of the term $\exp(-\gamma\sigma_j^2)$ in (6.11), which captures the differences in worker reactions to changes in conditions, σ^2, under piece rates and fixed wages.

This situation is reflected in Figure 1. The diagonal line PP' shows combinations of μ and σ^2 that give rise to the same piece rate for a given level of utility. From (5.2) the slope of PP' is $-(\gamma+1)/2$. Furthermore, from Lemma 1, these same combinations of μ and σ^2 give rise to constant expected productivity under piece rates. However, from Lemma 2, the tradeoff between σ^2 and μ that keeps expected productivity under fixed wages constant is $-1/2$, the slope of FF'. Thus, conditional on r_j, the value of σ^2 affects $\mathcal{E}[Y|FW, r_j, i]$ and movements along PP' change the incentive effect. Intuitively, PP' is steeper than FF' since movements along FF' indicate changes

[3] Note, as well, $\bar{u}$ affects $\mathcal{E}[Y|fw, r_j, i, \sigma_j]$ only through the relationship between r_j and μ_j. That is, a higher value of $\bar{u}$ implies that a given value of r_j is associated with a larger value of μ_j (better planting conditions), leading to higher expected productivity under fixed wages.

in conditions only, while movements along PP' indicate changes in conditions and effort.

Given Lemma 1 and Lemma 2, the restricted equilibrium incentive effect is written

$$\left[\bar{u}(\gamma+1)\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\right]^{(\gamma/(\gamma+1))}\frac{\kappa_i^{1/(\gamma+1)}}{\bar{\lambda}}\exp\{\gamma\sigma_j^2/2\}-1 \tag{6.12}$$

The structural form makes clear the dependence of the incentive effect on both utility function parameters $(\kappa_i, \gamma, \bar{u}, \bar{\lambda})$ and planting conditions σ_j^2. It also makes clear the behavioural assumptions that justify imposing generalizability; namely, that planting conditions do not change and/or that workers do not react to such changes. These conditions are formalized in Theorem 2.

Theorem 2: *The equilibrium incentive effect is constant across blocks if either:*

(i) planting conditions do not change (i.e., σ_j^2 is constant across blocks);

(ii) worker effort does not react to changes in conditions (i.e., $\gamma = 0$).

Proof: The proof follows immediately from Lemma 1, Lemma 2 and (6.12). ∎

If planting conditions do not change or the worker does not react to changes in conditions then the incentive effect will be constant and the unrestricted incentive effect will provide a consistent estimate of the incentive effect under any conditions. Note as well that if σ^2 is constant or $\gamma = 0$ then $\alpha_{5j} = \delta_{3j} = 0$ as derived in Theorem 1.

Corollary 2.1: *The equilibrium incentive effect is increasing in the variance σ_j^2.*

Proof: The proof follows directly from differentiating (6.12) with respect to σ_j^2. ∎

In terms of Figure 1, movements along PP' towards P' decrease expected productivity under fixed wages – the decrease in μ required to keep r_j (and $\mathcal{E}[Y|PR]$) constant when planting under piece rates is larger than the decrease required to keep $\mathcal{E}[Y|FW]$ constant when planting under fixed wages.

Corollary 2.2: *The equilibrium incentive effect is independent of the piece rate and μ_j.*

Proof: The proof follows directly from (6.12). ∎

This is due to the fact that changes in μ and r cancel to keep expected utility constant, leaving only σ^2 as the determinant of the incentive effect. The importance of Corollary 2.2 lies in the fact that σ^2 is the only aspect of planting conditions that is required in order to measure the incentive effect. Identifying σ^2, the other structural parameters, as well as the incentive effect (both within and beyond the experimental sample) is the subject of the next section.

6.2. Identification in the Restricted Model

This section discusses the identification of the incentive effect under three scenarios: first, using only the experimental data; second, supplementing the experimental data with nonexperimental data on workers planting under piece rates; and finally, out-of-sample prediction.

Definition 2:

(i) Let $\mathcal{J}^{\tilde{e}} \subset \mathcal{J}$ denote the set of nonexperimental plots on which piece rate planting is observed.

(ii) Let $\mathcal{I}^{e}$ denote the set of individuals who partook in the experiment.

(iii) Let $\mathcal{I}^{\tilde{e}}$ denote the set of individuals who work in the firm but did not partake in the experiment.

Lemma 3: *γ is overidentified in the structural model (6.2).*

Proof: The proof follows from the fact that multiple solutions to γ exist in terms of the parameters of (6.4). In particular,

$$\gamma = \frac{\alpha_{2i} + \alpha_{4i}}{\alpha_{2i}}$$

$$\gamma = \frac{-\alpha_{5j}}{(\alpha_{3j} + \alpha_{5j})}$$

$$\gamma = \sqrt{\frac{Var\big(\epsilon_{ij}|DFW = 0\big)}{Var\big(\epsilon_{ij}|DFW = 1\big)}} - 1. \blacksquare$$

Since there are three blocks of land and nine individuals in the experiment, these amount to 14 overidentifying restrictions.

6.2.1. Identification with Experimental Data

Theorem 3: *Estimating (6.2) on experimental plots identifies*

(i) γ
(ii) $\sigma_j^2 \quad \{j \in \mathcal{J}^e\}$
(iii) $\ln \kappa_i - \ln \kappa_1 \quad \{i \in \mathcal{I}^e\}$
(iv) $\ln \bar{u} + \gamma(\ln \kappa_h - \ln \kappa_1)$
(v) $\ln \bar{\lambda} - \ln(\kappa_1)/(\gamma + 1)$

Proof: The identification of γ follows from Lemma 3. Once these restrictions are imposed in (6.2) the variance terms identify σ_j^2, and coefficients on the individual-specific dummies then identify $(\ln \kappa_i - \ln \kappa_1)$. The constant term identifies $\ln \bar{u} + \gamma(\ln \kappa_h - \ln \kappa_1)$ and the fixed-wage coefficient identifies $\ln \bar{\lambda} - \ln(\kappa_1)/(\gamma + 1)$. ∎

Corollary 3.1: *Estimation of (6.2) on experimental data identifies (6.12) for $j \in \mathcal{J}^e$ and $i \in \mathcal{I}^e$.*

Proof: *The incentive effect depends on γ, σ_j^2 and the composite expressions*

$$\left\{ \bar{u}(\gamma + 1) \left(\frac{\kappa_h}{\kappa_i} \right)^{\gamma}, \ \frac{\bar{\lambda}}{\kappa_i^{1/(\gamma+1)}} \right\}$$

which are identified by

$$\exp\{\ln \bar{u} + \gamma(\ln \kappa_h - \ln \kappa_1)\} \exp\{\ln(\gamma + 1)\} \exp\{-\gamma(\ln \kappa_i - \ln \kappa_1)\}$$

and

$$\exp\{\ln \bar{\lambda} - \ln \kappa_1/(\gamma + 1)\} \exp\{-(\ln \kappa_i - \ln \kappa_1)/(\gamma + 1)\}. \ \blacksquare$$

Complete identification of the structural model requires a normalization restriction on one of the μ_js, and a value for alternative utility, $\bar{u}$.[4] Since these assumptions are not required to identify the incentive effect this identification strategy is not followed here.

Theorem 3 and its associated Corollary 3.1 show that the structural model can be applied to experimental data to identify the restricted incentive effect (6.12). However, the benefit of structural estimation comes from its ability to calculate the incentive effect out of sample. From (6.12) the incentive effect for a nonexperimental plot $j \in J^{\tilde{e}}$ depends on σ_j^2. The next section considers how nonexperimental data on piece-rate planting can be used to identify incentive effects outside of the experimental sample.

6.2.2. Identification with Experimental and Nonexperimental Data

Theorem 4: *Supplementing the experimental sample with nonexperimental data on piece-rate planting will identify the (6.12) on any plot $j \in \mathcal{J}^{\tilde{e}}$ and for any individual $i \in \mathcal{I}^{\tilde{e}}$.*

Proof: Note (6.12) depends on σ_j^2 for $j \in \mathcal{J}^{\tilde{e}}$ as well as

$$\ln \kappa_i - \ln \kappa_h \text{ and } \frac{\bar{\lambda}}{\kappa_i^{1/(\gamma+1)}} \quad \text{for } i \in \mathcal{I}^{\tilde{e}}. \tag{6.13}$$

From (5.4) nonexperimental piece-rate data will identify σ_j^2 for $j \in J^{\tilde{e}}$ and $\ln \kappa_i - \ln \kappa_1$ for $i \in \mathcal{I}^{\tilde{e}}$, since the individuals who participate in the experiment are also observed in the nonexperimental data. ▪

Nonexperimental data on piece rate planting can identify the variance on nonexperimental plots as well as the individual-specific effects for individuals who did not partake in the experiment.

[4] To see this, note that given knowledge of σ_j^2, γ, and r_j, substituting into (5.2) recovers $(\gamma+1)\mu_j - \ln \bar{u} + \gamma \ln \kappa_h$. Normalizing one value of $\mu_j = 0$ identifies $\ln \bar{u} + \gamma \ln \kappa_h$; see Paarsch and Shearer (1998b) for details.

The inclusion of nonexperimental data also increases the number of observations on individuals who partook in the experiment, thus increasing the efficiency of the estimated individual-specific effects.

6.2.3. Out of Sample Prediction

This section considers the calculation of the incentive effect on *any* plot, whether or not productivity data is available. Since the incentive effect depends on the piece rate and planting conditions, predicting out of sample requires recovering the conditions that are associated with any given piece rate. Two possible strategies exist. First, one could use the structural parameter estimates to recover the planting conditions associated with any given piece rate and then calculate (6.12) based on those conditions. Yet, from (5.2), there are multiple combinations of μ and σ^2 that can generate a given piece rate. While in principal one could fix μ and recover the value of σ^2 as the piece rate changes, in practice this approach is limited by the parameter space. In particular, there may not exist a positive value of σ^2 generating certain piece rates for a given value of μ.

Another possibility is to bound the incentive effect for each piece rate. This line of reasoning is developed in the following theorem.

Theorem 5: *The incentive effect for individual i planting under any piece rate, r_j, has a lower bound given by (6.12) evaluated at $\sigma_j^2 = 0$.*

Proof: The proof follows directly from Corollaries 2.1 and 2.2. ∎

Intuitively, when $\sigma^2 = 0$ no effort adjustment takes place for a given piece rate since the shock is constant. However, for $\sigma^2 > 0$ workers adjust their effort level, taking advantage of large shocks, and increase average productivity relative to fixed wages.

7. Empirical Results

7.1. Unrestricted Results

The results from estimating the unrestricted ANOVA model (6.4) using maximum likelihood methods are presented in Table 4.

Evaluating (6.8) at the parameter estimates from Table 4 gives $H = 0.199$, a 20 percent increase in daily productivity when piece rates are paid rather than fixed wages. The bootstrapped 95 percent confidence interval is [0.148, 0.250]. Since the interval does not contain zero the incentive effect is statistically significant.

7.2. Restricted Results: Experimental Data

Results from estimating (6.2) using maximum-likelihood methods on the experimental data are presented in Table 6. The associated incentive effect is calculated to be 26 percent. Given that my goal is to use the structural model to make out-of-sample predictions for the incentive effect, it is troubling that the estimated, within-sample incentive effect does not match the unrestricted incentive effect on the experimental data. This is due to the fact that the structural model (5.4) imposes the restriction that average productivity is decreasing in the piece rate. Yet, as has been previously noted, this is violated in the experimental sample. Recall that in Table 2 the average productivity when the piece rate is \$0.18 is higher than when the piece rate is \$0.17.

7.3. Perception Errors

Additional flexibility is introduced into the structural model by allowing for the possibility that the firm makes mistakes when evaluating planting conditions. In particular it is assumed that for each block of land, j, the firm observes $\tilde{\mu}_j$, an unbiased estimate of actual conditions μ_j. Thus,

$$\mu_j = \tilde{\mu}_j + \nu_j \tag{7.1}$$

where $\nu_j \sim N(0, \sigma_v^2)$ and $\mathcal{E}[\tilde{\mu}_j \nu_j] = 0$. Note if $\nu_j > 0$ then actual planting conditions are better than perceived conditions.

Incorporating these errors into the model implies that observations on the same block are correlated through measurement error. Namely, given that decisions over the piece rate and labour supply depend on $\tilde{\mu}$, equation (5.4) is now written

$$\ln Y_{ij}^{pr} = \ln(\gamma+1) + \ln\bar{u} - \ln r_j + \gamma(\ln\kappa_h - \ln\kappa_i) - (\gamma+1)^2\frac{(\sigma_j^2+\sigma_v^2)}{2} + \epsilon_{ij}^{p} \quad (7.2)$$

where

$$\epsilon_{ij}^{p} = (\gamma+1)(\ln S_{ij} - \mu_j + \nu_j) = \epsilon_{ij}^{pr} + (\gamma+1)\nu_j \quad (7.3)$$

and ϵ_{ij}^{pr} is as in (5.4).

Similarly, equation (5.6) is now written

$$\begin{aligned}\ln Y_{ij}^{fw} = &\ln\bar{\lambda} - \frac{\ln\kappa_i}{(\gamma+1)} + \frac{\gamma}{(\gamma+1)}(\ln\kappa_h - \ln\kappa_i) + \frac{\ln\bar{u}}{(\gamma+1)} + \frac{\ln(\gamma+1)}{(\gamma+1)} \\ &- \ln r - (\gamma+1)\frac{(\sigma_j^2+\sigma_v^2)}{2} + \epsilon_{ij}^{f}.\end{aligned} \quad (7.4)$$

where

$$\epsilon_{ij}^{f} = (\ln S_{ij} - \mu_j + \nu_j) = \epsilon_{ij}^{fw} + \nu_j \quad (7.5)$$

and ϵ_{ij}^{fw} is as in (5.6).

The error structure is given by

$$
\begin{aligned}
\mathcal{E}[\epsilon_{ij}^{p}] &= 0 \\
\mathcal{E}\left[(\epsilon_{ij}^{p})^2\right] &= (\gamma+1)^2(\sigma_j^2+\sigma_v^2) \\
\mathcal{E}\left[\epsilon_{ij}^{p}\epsilon_{ij'}^{p}\right] &= 0 \\
\mathcal{E}\left[\epsilon_{ij}^{p}\epsilon_{i'j}^{p}\right] &= (\gamma+1)^2\sigma_v^2 \\
\\
\mathcal{E}[\epsilon_{ij}^{f}] &= 0 \\
\mathcal{E}\left[(\epsilon_{ij}^{f})^2\right] &= (\sigma_j^2+\sigma_v^2) \\
\mathcal{E}\left[\epsilon_{ij}^{f}\epsilon_{ij'}^{f}\right] &= 0 \\
\mathcal{E}\left[\epsilon_{ij}^{f}\epsilon_{i'j}^{f}\right] &= \sigma_v^2 \\
\\
\mathcal{E}\left[\epsilon_{ij}^{p}\epsilon_{ij'}^{f}\right] &= 0 \\
\mathcal{E}\left[\epsilon_{ij}^{p}\epsilon_{i'j}^{f}\right] &= (\gamma+1)\sigma_v^2.
\end{aligned}
\tag{7.6}
$$

The results from estimating this model by maximum likelihood methods are presented in Table 7. A likelihood-ratio test for the absence of measurement error ($\sigma_v = 0$) is easily rejected by comparing the log-likelihood values in Table 6 (74.83) and Table 7 (94.13). Furthermore, the average incentive effect on the three plots is estimated to be 20.8 percent which accords closely to the estimate from the unrestricted model.

7.4. Incorporating Nonexperimental Data

The non-experimental data contains observations on piece-rate planting only and includes workers who did and did not take part in the experiment. The non-experimental data come from the same general contract as the experiment; *i.e.*, the manager is the same and the planting was done at the same time of the year. This ensures that labour market conditions, which might affect effort under fixed wages, are held constant throughout the sample. In an effort to eliminate outliers from the sample, only observations for which the worker worked the standard 10 hours per day were included in the sample.

The enlarged sample includes 24 workers (each of whom is observed at least 10 times) planting under 9 separate piece rates. The data cover 30 different plots of land, for each of which the manager decided on a piece rate. Evidently a number of different blocks have the same piece rate, or equivalently the same $\tilde{\mu}_j$, yet will have different ν_js or errors of judgement on the part of the manager. The data are presented by plot in Table 8. A couple of facts seem to confirm the importance of measurement error in the data. First, the strictly monotonic relationship between piece rates and average productivity is again broken over certain ranges of piece rates. For example, average productivity on plot 1, where the piece rate is \$0.15, is much lower than average productivity on any of the plots for which the piece rate is \$0.16. Second, average productivity varies a great deal across plots with the same piece rate.

Table 9 reports results from estimating the model on both experimental and non-experimental data. To abreviate the table only the main parameters of interest are reported. The average incentive effect for workers involved in the experiment, calculated over all these blocks, is estimated to be 19.2 percent. The average incentive effect for any worker in the firm is estimated to be 17.8 percent, reflecting the fact that the experimental sample was drawn from male workers.

7.5. Out-of-Sample Prediction (Lower Bound)

Following Theorem 5, a lower bound to the incentive effect for any plot of land is given by evaluating (6.12) at $\sigma^2 = 0$. This is calculated to be 18.8 percent for those workers involved in the experiment and falls to 17.3 percent for any worker in the firm.

8. Discussion and Conclusion

This study adds to a growing body of research on measuring incentive effects. The use of experimental methods permits the direct identification of the incentive effect through a comparison of average productivity under different compensation systems. The results suggest an incentive effect of approximately 20 percent on the experimental data, and a lower bound to the incentive effect of 17 percent on the nonexperimental data.

The results also provide a useful benchmark for comparison to the results of Paarsch and Shearer, 1998a which measured the incentive effect using nonexperimental data for the same occupation. The similarity of results from these two studies provides an encouraging, if preliminary, consensus. This is particularly encouraging given the differences in empirical methodology employed by the two studies; Paarsch and Shearer relied solely on structural modeling to control for the endogenous changes in compensation systems while here identification is achieved through exogenous variation within a controlled experiment. While the results are also similar to those in Lazear (1997) less can be made of this comparison since the industries and technologies are very different.

This study also demonstrates the potential value of small-scale experiments within firms to evaluate the effects of alternative human resource policies. It presents an alternative experimental methodology to previous computerized experiments on compensation systems. For example, Bull, Schotter and Weigelt (1987) chose the structural parameters of the participants cost of effort function and reward function and then considered whether actual effort choices corresponded with predicted ones. Here, the observed reaction of workers to changes in the compensation system within the experiment is used to identify the structural parameters and then policy experiments are performed based on those parameter estimates.

Finally, the results also raise some important issues and suggest directions for future research. First, the incentive effect may be sensitive to the fixed wage that is paid to workers due to efficiency wage effects (Shapiro and Stiglitz, 1984; Macleod and Malcolmson, 1988). This could be investigated quite easily within an experimental framework by varying the wage that workers are paid under fixed wages and considering how this affects daily productivity. A related issue is why workers supply effort under fixed wages. Here, as in Lazear (1997) and Paarsch and Shearer (1998a), worker effort under fixed wages is taken as a constant, to be determined empirically, rather than as an equilibrium outcome. Equilibrium models of effort determination under fixed wages are dynamic in nature and rely on the future benefits of current performance in order to enforce effort. The aforementioned efficiency wage models suggest that the threat of firing workers for shirking and the associated loss of future surplus within the firm can enforce positive effort levels under fixed wages. Models of career concerns (Fama, 1980; Gibbons and Murphy, 1992) suggest that the market's evaluation of current performance will affect future earnings and will therefore enforce a positive effort level under fixed wages. Outside opportunities are important in both these models, and equilibrium effort as well as the incentive effect may be affected by changes in these opportunities. Developing an empirically tractable dynamic model of effort determination under fixed wages which incorporates the effects of outside opportunities will provide further insights into the incentive effect.

Table 1
Summary Statistics: Daily Productivity, Earnings and Unit Costs
Experimental Sample

		Trees:		Earnings:	Unit Costs:
	Observations	Mean	St.Dev.	Mean	Mean
Full Sample	120	1146.67	278.54	223.78	0.20
Piece Rate	60	1256	325.27	230.85	0.186
Fixed Wages	60	1037.33	162.38	216.70	0.214

Table 2 *Summary Statistics: Average Productivity by Plot*
Experimental Sample

Plot	Obs	Rate	Mean	St.Dev.	PR	FW
A	24	0.17	1273.33	188.14	1390.00	1156.67
B	48	0.18	1321.25	247.90	1500.83	1141.67
C	48	0.20	908.75	143.27	944.17	873.33

Table 3
Summary Statistics: Average Productivity, Earnings and Unit Costs, By Planter and Pay System
Experimental Sample

Planter	Observations	Total	PR	FW	Difference
1	16	1127.50	1275.00	980.00	295.00
2	12	1098.33	1220.00	976.67	243.33
3	12	1226.67	1430.00	1023.33	406.67
4	16	992.50	1000.00	985.00	15.00
5	12	1163.33	1266.67	1060.00	206.67
6	4	1330.00	1470.00	1190.00	280.00
7	16	1121.25	1165.00	1077.50	87.50
8	16	1157.50	1255.00	1060.00	195.00
9	16	1252.50	1420.00	1085.00	335.00

Table 4
Parameter Estimates of Unrestricted Model:
Experimental Sample
Sample Size = 120

Parameter	(Coef.)	(Std. Error)	(P-Value)
α_0	5.246	0.039	0.000
α_1	0.266	0.055	0.000
α_{22}	0.052	0.048	0.289
α_{23}	0.089	0.050	0.073
α_{24}	0.010	0.041	0.802
α_{25}	0.137	0.048	0.005
α_{26}	0.106	0.055	0.052
α_{27}	0.120	0.058	0.039
α_{28}	0.100	0.055	0.072
α_{29}	0.110	0.047	0.019
α_{32}	−0.043	0.023	0.058
α_{33}	−0.166	0.025	0.000
α_{42}	0.011	0.081	0.888
α_{43}	0.137	0.081	0.091
α_{44}	−0.194	0.057	0.001
α_{45}	0.005	0.080	0.948
α_{46}	0.004	0.070	0.951
α_{47}	−0.074	0.075	0.323
α_{48}	0.014	0.073	0.851
α_{49}	0.083	0.061	0.176
α_{52}	−0.059	0.036	0.104
α_{53}	−0.199	0.050	0.000
ξ_0	−2.760	0.187	0.000
ξ_1	0.458	0.249	0.066
ξ_{22}	−0.179	0.467	0.701
ξ_{23}	0.493	0.229	0.032
ξ_{32}	−0.723	0.590	0.220
ξ_{33}	0.149	0.319	0.639
Logarithm of the Likelihood Function:	119.097		

Table 6
Parameter Estimates : Restricted Model
Experimental Sample
Sample Size = 120

Parameter	(Coef.)	(Std. Error)	(P-Value)
a_0	5.420	0.041	0.000
a_1	−0.198	0.033	0.000
γ	1.296	0.287	0.000
$\kappa_2 - \kappa_1$	0.073	0.043	0.098
$\kappa_3 - \kappa_1$	0.127	0.031	0.000
$\kappa_4 - \kappa_1$	−0.029	0.024	0.233
$\kappa_5 - \kappa_1$	0.158	0.043	0.000
$\kappa_6 - \kappa_1$	0.087	0.041	0.037
$\kappa_7 - \kappa_1$	0.106	0.026	0.000
$\kappa_8 - \kappa_1$	0.099	0.041	0.019
$\kappa_9 - \kappa_1$	0.121	0.044	0.007
σ_1	0.065	0.009	0.000
σ_2	0.047	0.009	0.000
σ_3	0.168	0.023	0.000
Logarithm of the Likelihood Function:	74.83		

Table 7
Parameter Estimates : Restricted Model (Perception Errors)
Experimental Sample
Sample Size = 120

Parameter	(Coef.)	(Std. Error)	(P-Value)
a_0	5.364	0.090	0.000
a_1	−0.167	0.051	0.001
γ	1.17	0.199	0.000
$\kappa_2 - \kappa_1$	0.041	0.038	0.273
$\kappa_3 - \kappa_1$	0.102	0.038	0.009
$\kappa_4 - \kappa_1$	−0.035	0.031	0.267
$\kappa_5 - \kappa_1$	0.119	0.038	0.002
$\kappa_6 - \kappa_1$	0.097	0.042	0.023
$\kappa_7 - \kappa_1$	0.086	0.039	0.031
$\kappa_8 - \kappa_1$	0.084	0.039	0.032
$\kappa_9 - \kappa_1$	0.114	0.034	0.001
σ_1	0.062	0.008	0.000
σ_2	0.050	0.010	0.000
σ_3	0.100	0.011	0.000
σ_v	0.066	0.028	0.010
Logarithm of the Likelihood Function:	94.13		

Table 8
Summary Statistics: By Plot
Experimental and Nonexperimental Samples
Sample Size 463

Block	Observations	Piece Rate	Mean	St.Dev.
1	10	0.15	906	199.98
2	5	0.16	1644	326.01
3	12	0.16	1693.33	600.44
4	4	0.16	1300	172.82
5	2	0.17	990	42.43
6	8	0.17	1032.50	272.54
7	2	0.17	1630	183.85
8	10	0.17	582	184.62
9	24	0.17	1273.33	188.14
10	10	0.18	1248	231.17
11	34	0.18	785.29	286.86
12	25	0.18	1403.20	279.27
13	23	0.18	1232.17	174.02
14	1	0.20	500	0.00
15	9	0.20	1571.11	263.27
16	35	0.20	994.29	287.28
17	7	0.20	1014.29	44.29
18	3	0.20	1193.33	46.19
19	8	0.20	757.50	120.68
20	28	0.20	928.57	267.85
21	13	0.20	1067.69	151.56
22	48	0.20	908.75	143.26
23	16	0.22	1185	238.05
24	6	0.22	1013.33	366.75
25	12	0.22	860	67.15
26	38	0.23	825.26	263.60
27	22	0.24	1070.91	492.21
28	22	0.24	917.27	207.14
29	24	0.28	1100	230.46
30	2	0.28	880	0.00

Table 9
Parameter Estimates : Restricted Model (Perception Errors)
Experimental and Nonexperimental Sample
Sample Size = 463

Parameter	(Coef.)	(Std. Error)	(P-Value)
a_0	5.468	0.053	0.000
a_1	−0.171	0.032	0.000
γ	1.349	0.184	0.000
σ_1 (.15)	0.094	0.016	0.000
σ_2 (.16)	0.065	0.019	0.000
σ_3 (.17)	0.116	0.021	0.000
σ_4 (.18)	0.099	0.013	0.000
σ_5 (.20)	0.063	0.007	0.000
σ_6 (.22)	0.080	0.007	0.000
σ_7 (.23)	0.034	0.006	0.000
σ_8 (.24)	0.063	0.009	0.000
σ_9 (.25)	0.127	0.017	0.000
σ_v	0.055	0.011	0.000
Logarithm of the Likelihood Function:	158.38		

References

Boning, B., C. Ichniowski, and K. Shaw, 1998. "Incentive Pay for Production Workers: An Empirical Analysis." Typescript, Carnegie Mellon University

Burtless, G., 1995. "The Case for Randomized Field Trails in Economic and Policy Research." *Journal of Economic Perspectives*, 9(2): 63–84.

Bull, C., A. Schotter and K. Weigelt, 1987. "Tournaments and Piece Rates: An Experimental Study." *Journal of Political Economy*, 95(1): 1–33.

Ehrenberg, R. 1990. *Do Compensation Policies Matter?. Industrial & Labor Relations Review*, 43(3).

Fama, E. 1980. "Agency Problems and the Theory of the Firm." *Journal of Political Economy*, 88(2): 288–307.

Ferrall, C. and B. Shearer, 1999. "Incentives and Transaction Costs within the Firm: Estimating an Agency Model Using Payroll Records." *Review of Economic Studies*, 66(2): 309–338.

Gibbons, R. and K. J. Murphy, 1992. "Optimal Incentive Contracts in the Presence of career Concerns: Theory and Evidence." *Journal of Political Economy*, 100(3): 468–505.

Halvorsen, R. and R. Palmquist, 1980. "The Interpretation of Dummy Variables in Semilogarithmic Equations," *American Economic Review*, 70(3): 474-475.

Hart, O. and B. Holmstrom. 1987. "The Theory of Contracts." In *Advances in Economic Theory Fifth World Congress*, ed. by T. Bewley. Cambridge, United Kingdom: Cambridge University Press.

Heckman, J. and J. Smith, 1995. "Assessing the Case for Social Experiments." *Journal of Economic Perspectives*, 9(2): 85–110.

Holmström, B. and P. Milgrom, 1990. "Multitask Principal-Agent Analyses: Incentive Contracts, Asset Ownership, and Job Design." *Journal of Law, Economics, & Organization*, 7(sp): 24–52.

Ichniowski, C., K. Shaw and G. Prennushi, 1997. "The Effects of Human Resource Management Practices on Productivity: A Study of Steel Finishing Lines." *American Economic Review*, 87(3): 291–313.

Keane, M. and K. Wolpin, 1997. "Introduction to the *JBES* Special Issue on Structural Estimation in Applied Microeconomics." *Journal of Business and Economic Statistics*, 15(2): 111–114.

Lazear, E. 1998. *Personnel Economics for Managers.* New York: John Wiley & Sons.

Macleod, W. and J. Malcomson. 1989. "Implicit Contracts, Incentive Compatibility, and Involuntary Unemployment." *Econometrica*, 57(2): 447–480.

Milgrom, P. and J. Roberts. 1992. *Economics, Organization and Management.* Englewood Cliffs, New Jersey: Prentice Hall.

Nalbantian, H. and A. Schotter. 1997. "Productivity Under Group Incentives: An Experimental Study." *American Economic Review,* 87(3): 314–341.

Paarsch, H. and B. Shearer. 1998a. "Piece Rates, Fixed Wages, and Incentive Effects: Statistical Evidence from Payroll Records." *International Economic Review* Forthcoming.

Paarsch, H. and B. Shearer. 1998b. "The Response of Worker Effort to Piece Rates: Evidence fro the British Columbia Tree-Planting Industry." *Journal of Human Resources* Forthcoming.

Prendergast, C. 1999. "The Provision of Incentives in Firms." *Journal of Economic Literature,* XXXVII, March: 7–63.

Shapiro, C. and J. Stiglitz. 1984. "Equilibrium Unemployment as a Worker Discipline Device." *American Economic Review*, 74(3): 433–444.

Shearer, B. 1994. "Piece Rates, Principal-Agent Models, and Productivity Profiles: Parametric and Semi-Parametric Evidence from Payroll Records." *Journal of Human Resources,* 31(2): 275–303.

Wolpin, K. 1995. *Empirical Methods for the Study of Labor Force Dynamics.* Harwood Academic Publishers.

Figure 1: Difference in Average Trees Planted: By Individual Planter

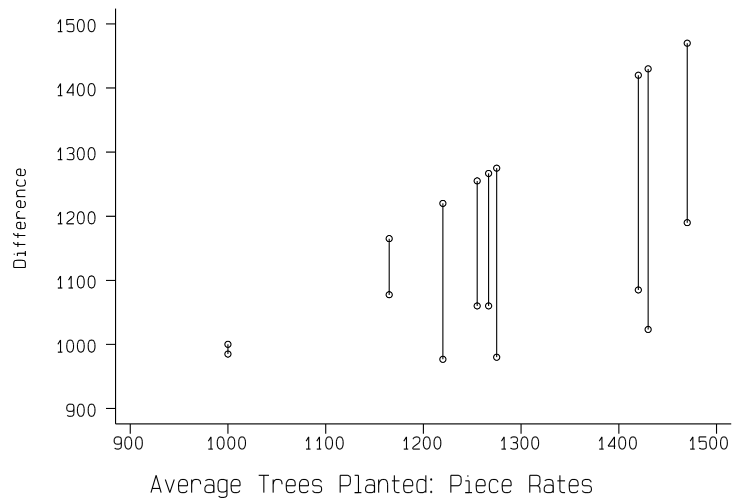

Figure 2: Expected Productivity Isoquants