

The Response of Worker Effort to Piece Rates: Evidence from the British Columbia Tree-Planting Industry

Author(s): Harry J. Paarsch and Bruce S. Shearer

Source: *The Journal of Human Resources*, Vol. 34, No. 4 (Autumn, 1999), pp. 643-667

Published by: University of Wisconsin Press

Stable URL: <http://www.jstor.org/stable/146411>

Accessed: 06-04-2018 10:34 UTC

JSTOR is a not-for-profit service that helps scholars, researchers, and students discover, use, and build upon a wide range of content in a trusted digital archive. We use information technology and tools to increase productivity and facilitate new forms of scholarship. For more information about JSTOR, please contact support@jstor.org.

Your use of the JSTOR archive indicates your acceptance of the Terms & Conditions of Use, available at <http://about.jstor.org/terms>



JSTOR

University of Wisconsin Press is collaborating with JSTOR to digitize, preserve and extend access to *The Journal of Human Resources*

The Response of Worker Effort to Piece Rates

Evidence from the British Columbia Tree-Planting Industry

Harry J. Paarsch
Bruce S. Shearer

ABSTRACT

We measure the elasticity of worker effort with respect to changes in the piece rate using panel data collected from the payroll records of a British Columbia tree-planting firm. Our data contain information on daily worker productivity and the piece rate received over a five-month period. Using a structural model to control for the endogeneity of the piece rate, we estimate this elasticity to be approximately 2.14. We also calculate a nonstructural lower bound to this elasticity equal to 0.77. Structural estimation also allows us to perform policy experiments and to compare firm profits under alternative compensation systems. Our results suggest that profits would increase by at least 17 percent were the firm to implement the optimal static contract as predicted by principal-agent theory. This increase in profits would be due to capturing worker rents after the revelation of private information over ability. Yet, only a negligible proportion of these rents could be captured while inducing workers to reveal ability truthfully, suggesting that dynamic considerations were important in determining the firm's actual choice of contract.

I. Introduction and Motivation

The role of economic incentives in determining behavior is of major interest to economists. Within the domain of labor economics, much theoretical attention has been focused on the optimal form of contracts between the firm and its

Harry J. Paarsch is a professor of economics at the University of Iowa; Bruce Shearer is a professor of economics at the Université Laval, Québec, Canada and is a member of CREFA and CIRANO. The authors acknowledge research support from SSHRC, CIRANO, and FCAR (Shearer). Useful comments and helpful suggestions were provided by participants at the American Compensation Association Academic Research Conference in Islamorada, Fla., by seminar participants at the University of Iowa, Université Laval, and Université de Québec à Montréal, and by Jean Farès, Christopher J. Flinn, David A. Green, Lawrence Katz, Joel L. Horowitz, John H. Pencavel, and an anonymous referee. Data used in this article can be obtained from the authors beginning June 2000 through May 2003 [Submitted August 1997; accepted November 1998]

workers (see, for example, Hart and Holmström 1987; Holmström and Milgrom 1990; and Baker 1992). The ability of labor contracts to affect worker productivity can also be applied to the analysis of personnel policies within the firm (as in Milgrom and Roberts 1992 and Lazear 1998). Some economists (for example, Blinder 1990) have further argued that the increase in worker productivity in response to the widespread adoption of performance-based pay would result in macroeconomic benefits.¹ For normative policy prescriptions to be valuable, however, they must be based on empirical analyses of the benefits accruing to changes in compensation systems. Empirically analyzing compensation policies and evaluating these benefits require measuring incentive effects; that is, how workers react to changes in their economic incentives.

In the past, empirical work concerning incentive models has typically involved cross-sectional or longitudinal comparisons of wages among workers who do and do not receive incentive pay (see, for example, Pencavel 1977; Seiler 1984; Parent 1997; and Booth and Frank 1997). The strength of this approach is that it is based on a wide sample of observations from different sectors of the economy and therefore provides “general” results. Yet, whereas the results of these studies are usually consistent with incentive models (thus supporting the existence of incentive effects), problems exist with their interpretation. In particular, workers who do not receive explicit incentive pay may be provided with incentives through other mechanisms, such as the promise of future promotions (as in Lazear and Rosen 1981 or Goldin 1986) or termination contracts (as in Shapiro and Stiglitz 1984 or Macleod and Malcolmson 1989). This inability to document and to understand fully the personnel policies implemented by different firms in a cross section of data makes it difficult to identify incentive effects using these methods.

An alternative approach is to concentrate on industry- or firm-level data. Such an approach combines elements of the traditional case-study methodology, once popular in the industrial organization literature (see, for example, Wallace 1937), with econometric estimation. Examples of this approach can be found in the recent work of Ferrall and Shearer (forthcoming), Shearer (1996), Lazear (1996), Paarsch and Shearer (forthcoming), and Treble (1996). Within this approach, the detailed study of the personnel policies of the firm or firms in question yields knowledge of the incentive system determining worker behavior. Measuring worker reaction to variation in the compensation system then permits identification of incentive effects. Furthermore, access to firm archives often yields direct measures of worker productivity, so the presence or absence of incentive effects does not have to be inferred indirectly through a comparison of wages.

One potential problem with both approaches is that the changes in the compensation system may not be exogenous (Ehrenberg 1990; Brown 1990). To wit, the firm may select a compensation system based on elements which are unobservable to the econometrician, but which affect worker productivity. This suggests that regression methods, which use the observed covariation between worker productivity and the

1. At least one country has taken these notions seriously. Booth and Frank (1997) report that the government of the United Kingdom has introduced tax policy aimed at inducing firms to implement incentive pay.

payment system to identify the incentive effect, may fail to provide a consistent estimate of this effect.

In this paper, we measure incentive effects with particular emphasis on piece-rate workers, those workers whose pay is proportional to their output. We use daily data on individual productivity and piece rates to measure how workers react to changes in their compensation system. Knowledge of the elasticity of effort with respect to changes in the piece rate has important implications for firms that are paying or considering paying their workers piece rates. As Stiglitz (1975) has shown, the optimal piece rate which a firm should set is an increasing function of this elasticity. Intuitively, the higher is the elasticity of effort the more beneficial it is for the firm to set a high piece rate. Although this elasticity may depend on the technology employed in a particular industry or firm, the case-study approach can still be useful as long as the characteristics of the firm are taken into account for policy proposals.

Our data were collected from the payroll records of a tree-planting firm in the province of British Columbia, Canada. This firm paid its planters piece rates exclusively, and planters received no base wage. The tree-planting industry has many advantages as a laboratory within which to estimate labor-market incentive models. Planter output is easily observable on a daily basis and compensation systems vary within firms. Moreover, the compensation systems are relatively simple, permitting straightforward analyses of incentives. For example, in the firm that we study, no team production existed and planters were not unionized. Because our data are panel in nature, we observe the daily productivity of each planter as well as the piece rate received by that planter over a period of approximately five months.

There are also practical reasons for studying the British Columbia tree-planting industry. British Columbia produces around 25 percent of the softwood lumber in North America.² The success this province has in managing its timber affects the supply of timber to North America as well as to many other parts of the globe. In addition, the scope of reforestation in British Columbia is huge. At its peak, between 1981 and 1985, almost two billion seedlings were planted. This pace has slowed somewhat but still remains important. Today, about 200 million seedlings are planted per year. An average seedling costs about \$0.50 to plant. Thus, a 10 percent improvement can yield savings of about \$10 million per year. Small improvements in personnel policy can result in large savings because of the enormous scale involved.

Using our data, we highlight the endogeneity problems inherent in the empirical analysis of compensation systems. In particular, employing regression methods, which use the observed covariance between piece rates and productivity to identify the incentive effect, we consistently estimate the elasticity of effort with respect to changes in the piece rate to be negative. Though this result seems nonsensical from the point of view of incentive theory, it obtains because piece rates are determined endogenously by the firm in response to the relative difficulty of planting in different areas. In particular, the firm chooses the observed piece rate to satisfy the labor-supply constraint of the planter, the amount the firm must at least pay the planter

2. When statistics are reported for Canada, they are reported as "East of the Rockies" and British Columbia. British Columbia is also broken up into three regions—the coast, the southern interior, and the northern interior—each of which produces more timber than any province of Canada or state of the United States.

to induce him to accept the contract, implying that piece rates are negatively correlated with average planting conditions. Because these planting conditions are unobservable to the econometrician, they enter the error term of the regression model. Thus the piece rate is, in fact, a statistically endogenous variable, and the estimate of the elasticity of effort with respect to the piece rate is inconsistent.

Obtaining a consistent estimate of the effort elasticity requires controlling for the unobservable planting conditions during estimation. We accomplish this by modeling explicitly the firm's choice of the piece rate as a function of planting conditions and planter behavior as a function of the piece rate. In our model, we incorporate asymmetric information between the firm and the planter over planter effort and planting conditions. We also allow for individual-specific heterogeneity across planters. We estimate the elasticity of effort with respect to the piece rate to be 2.14, which implies that an increase in the piece rate of one cent from the sample mean of 25 cents would increase average daily output by 67 trees, holding planting conditions constant.

Our structural estimates are sensitive to identifying assumptions, particularly with respect to measures of a planter's alternative utility. Therefore, in addition to our structural estimates, we provide a lower bound on the elasticity of effort. This lower bound is calculated to be 0.77, suggesting that an increase in the piece rate of one cent from the sample mean of 25 cents would increase average daily output by at least 24 trees, holding planting conditions constant.

Estimating the model structurally has benefits beyond controlling for the endogeneity of covariates. In particular, using estimates of the structural parameters, we can investigate how the observed contract departs from the optimal contract as predicted by theoretical incentive models. In particular, given risk-neutral planters, the optimal contract involves the planters paying the firm a fixed fee to plant trees and then receiving a piece rate equal to the price of output. The inclusion of the base fee gives the firm two instruments in the contract: one to provide incentives (the piece rate) and the other to extract rents from the planter (the base fee). In contrast, the observed contract contains only one instrument and therefore allows planters to earn rents. If the firm could charge the planters an up-front fee to plant trees, then our results suggest that firm profits would increase, on average, by at least \$31.77 per planter per day, an increase on the order of 17.25 percent. We argue that dynamic considerations are important determinants of the firm's choice of contract. In particular, by committing not to extract rents in a given period, the firm induces high-ability planters to reveal their type and produce higher output.

Our structural estimates can further be used to calculate the proportion of rent that the firm could capture while inducing workers to reveal their abilities. We estimate this proportion to be negligible, suggesting that the observed piece-rate contract was an effective means of inducing worker effort within a firm composed of heterogeneous workers.

In the next section, we describe the tree-planting industry in British Columbia as well as the compensation system with which we are concerned. In Section III we describe the sample data and present some regression results which illustrate our point concerning endogeneity. In Section IV we develop and estimate a simple theoretical model of planter-effort choice for a given piece rate, and then the choice of piece rate chosen by the firm in response to planter behavior. We use the estimated

parameters from the structural model of Section IV to investigate alternative contracts in Section V, and we conclude in Section VI.

II. Tree Planting in British Columbia

Timber is a renewable resource, but 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 that hold Tree Farm Licenses.³

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 in these cones. This ensures that the seedlings to be replanted are compatible with the local microclimates and soil as well as representative of the historical species composition.

Tree planting is a simple but 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. 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 buildup 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 intertree 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 being selected to perform the work. The price received by the firm per tree planted is called "the

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 34 firms that hold Tree Farm Licenses. These licenses have been negotiated over the last 75 years and require that the licensee adopt specific 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 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 have been 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 have been 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.

III. Sample Data and Regression Results

Our data set contains information on the piece rate received by each planter as well as that planter’s daily productivity. We considered only those planters who received the same piece rate for the whole day of planting. This eliminated the problem of aggregating trees planted under different piece rates. The summary statistics for the entire data set, which contains 4,578 observations on 155 planters planting for 31 different contracts over a five-month period in the spring and summer of 1994, are presented in Table 1. A contract was identified by a unique value for the piece rate on a particular tract. The average piece rate received by planters was about 25 cents per tree and planters planted, on average, about 764 trees per day. The average wage was about \$178 per day.

Table 1 also suggests that outliers exist in the data. For example, the recorded minimum number of trees planted in one day was 30 and the recorded minimum daily wage was \$9.30. There are two possible causes of outliers in our sample.⁵ First,

5. The existence of outliers also suggests that measurement error may be present in these data. We do not incorporate this possibility into our estimation strategy since our structural model, developed in Section IV, does not identify the elasticity of effort in the presence of measurement error; see footnote 9 below.

Table 1
Summary Statistics: Full Sample

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Number of trees	4,578	764.26	319.30	30	2260
Piece rate	4,578	0.25	0.06	0.13	0.48
Daily earnings	4,578	178.32	62.09	9.30	530.00

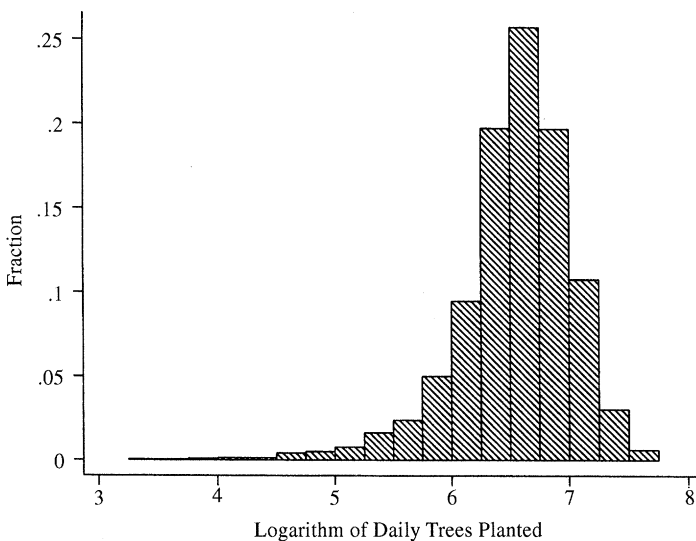


Figure 1
Histogram of the Logarithm of Daily Trees Planted, Full Sample; Sample Size = 4,578

some planters may work less than the usual eight hours per day. This may be the result of injury, sickness, or the planter's being asked to perform ancillary tasks such as collecting or sorting trees. Second, some planters may be of very low ability. By law, the firm is required to pay planters at least the minimum wage for an eight-hour day, or \$48.00 per day in 1994; planters who are incapable of consistently earning this amount through the piece-rate system are fired. In Figure 1, we present a histogram of the logarithm of trees planted daily. The presence of outliers is clearly evident from the long left-hand tail.

Our strategy for dealing with outliers is to eliminate them from the sample (see Donald and Maddala, 1993); that is, we seek an equilibrium sample of planters possessing satisfactory ability who work at least eight hours per day. Yet, identifying

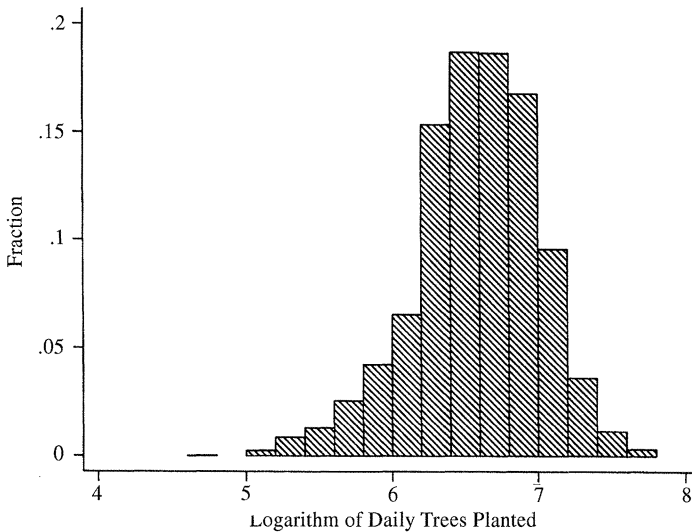


Figure 2

Histogram of the Logarithm of Daily Trees Planted, Sample Attaining Minimum-Wage Daily Earnings; Sample Size = 3,960

outliers simply on the basis of low productivity may be problematic since low productivity may reflect difficult planting conditions rather than low ability or few hours worked. Since the piece rate is adjusted by the firm to compensate for planting conditions, we identified outliers on the basis of total daily earnings. In particular, we eliminated from our sample those observations for which the planter earned less than \$48.00 per day, the minimum daily earnings permitted by government minimum-wage law for an eight-hour workday in 1994. We then further restricted the sample to planters who could consistently produce at this level. In particular, we restricted the sample to planters whom we observed at least 20 times.⁶ A histogram of the logarithm of trees planted daily for this restricted sample is presented in Figure 2, and the summary statistics for this sample are presented in Table 2. Note that the average number of trees planted daily increases slightly when compared to Table 1, as do average daily earnings.

We first considered regression methods as a way of measuring the elasticity of effort. We estimated the following log-log regression model:

$$(1) \log Y_{i,t} = \beta_{0,i} + \beta_1 \log r_t + U_{i,t}$$

where $Y_{i,t}$ is the daily productivity of planter i on contract t , $\beta_{0,i}$ is a (possibly individual-specific) constant term, r_t is the piece rate received by the planter on contract t ,

6. In Section IV B, we estimate a nonlinear model with individual-specific effects. Restricting the sample to individuals who appear at least 20 times has the added benefit of reducing problems of parameter inconsistency in this setting.

Table 2
Summary Statistics: Daily Earnings above Minimum-Wage Daily Earnings

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Number of trees	3,960	786.48	307.39	120	2,260
Piece rate	3,960	0.25	0.06	0.13	0.48
Daily earnings	3,960	183.97	57.38	48.00	530.00

Table 3
Simple Regression Results

Independent Variable	(a)	(b)
Constant	5.363 (0.031)	5.049 (0.047)
Logarithm of piece rate	-0.858 (0.021)	-0.893 (0.019)
Maximum individual-specific effect		0.700 (0.055)
Minimum individual-specific effect		-0.496 (0.071)
R^2	0.292	0.556

Notes: Dependent variable: logarithm of daily production.
 Sample size = 3,960.

and U_{it} is a zero-mean error term which in traditional analyses is assumed to have zero covariance with r_t .

We estimated Equation 1 in two different ways. First, we included as explanatory variables only a constant and the piece rate. These results are presented in Column a of Table 3. Note that the estimate of β_1 is negative, equal to -0.858 , and has a p -value which is virtually zero. Second, we included individual-specific intercepts to control for heterogeneity across individuals. These results are presented in Column b of Table 3. Again, the estimate of β_1 is negative, but now equal to -0.893 , and has a p -value which is also virtually zero.

To provide visual confirmation of our regression results, we present in Figure 3 a scatterplot of the logarithm of the number of trees planted daily versus the logarithm of the piece rate, along with the estimated regression line. Note the strikingly negative relationship.

The negative coefficient estimate on the logarithm of the piece rate paid to planters is troubling from the perspective of incentive theory. Taken literally, it suggests that when the piece rate is high, planters work less intensively than when the piece rate

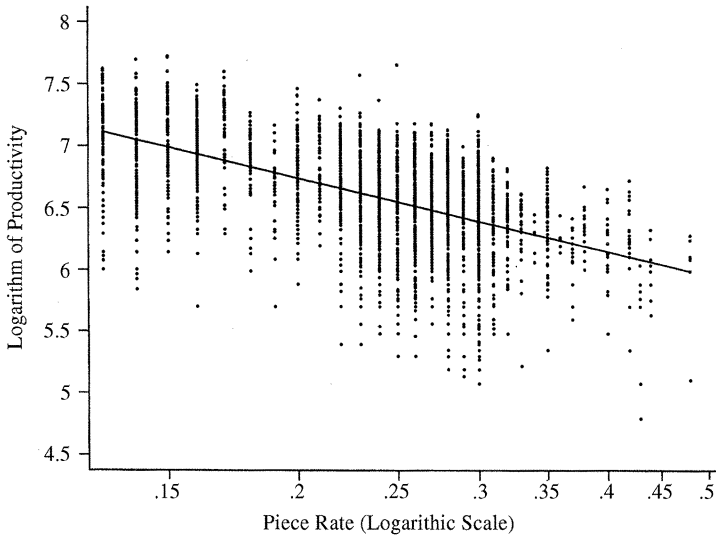


Figure 3

Scatterplot of Daily Trees Planted and Piece Rates, Sample Attaining Minimum-Wage Daily Earnings; Sample Size = 3,960

is low; this seems counterintuitive. An alternative explanation is that the piece rate is endogenous to the statistical model. In particular, if piece rates are correlated with unobservable variables which also affect planter productivity, then the observed piece rate will be correlated with the error term U_{it} in Equation 1. This correlation will result in biased estimates of the elasticity of effort with respect to piece rates because one of the maintained assumptions of least-squares estimation has been violated.

Discussions with firm principals revealed that piece rates are chosen by the firm after average planting conditions have been observed. The actual piece rate is chosen to ensure that the planter's labor-supply constraint, the amount the firm must pay the planter to induce him to accept the contract, is satisfied. A planter's productivity is a function of how hard he works and the conditions under which he is planting: it is easier to plant trees on flat terrain which is covered in loose soil than on steep rocky hillsides. For planting conditions that are favorable to productivity, planter output will be higher for any given level of effort. Since planters are paid in proportion to the number of trees they plant and since effort is costly, these planters prefer planting in favorable conditions—they can plant lots of trees for little effort. Therefore, to induce planters to plant under unfavorable conditions the firm must increase the piece rate.

The effect of this process on regression models is illustrated graphically in Figure 4. In the bottom panel, we represent the inverse relationship between the piece rate r and average planting conditions μ caused by the labor-supply constraint. In the upper panel of Figure 4, we illustrate the relationship between productivity Y and

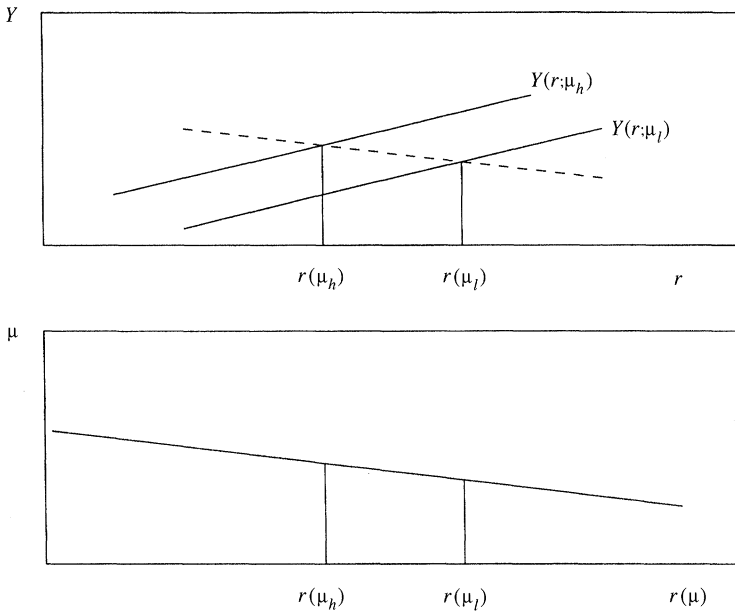


Figure 4
Example of Low- and High-Productivity Plots and the Piece Rate

the piece rate for two different levels (low μ_l and high μ_h) of planting conditions μ . The slope of the line $Y(r; \mu)$, the [productivity, piece-rate] locus, represents the incentive effect that we seek to estimate. The fact that high piece rates $r(\mu_l)$ are associated with poor planting conditions μ_l implies that productivity is lower for any value of r , shifting down the [productivity, piece-rate] locus. Since average planting conditions are unobservable to the econometrician, we have no way of controlling for the fact that the locus has shifted down and a simple regression of productivity on the piece rate connects the points on two separate loci producing the dotted line with a negative slope.

To obtain a consistent estimate of β_1 requires controlling for planting conditions. In general, three possible ways exist to do this. First, one could collect data on the planting conditions which affect the firm's choice of a piece rate. Note, however, that one would have to have *all* the information that the firm has when the firm makes its choice. If the econometrician observed only a subset of the planting conditions, then biased estimates of the incentive effect would still obtain because the set of conditions that were unobserved could still be correlated with both a planter's output and the piece rate. Gaining access to such data has proven impossible. A second possibility would be to use an instrumental variable; that is, a variable correlated with the piece rate but uncorrelated with the planting conditions. Though such a variable is easy to define, finding such a variable is generally more problematic in practice. One possibility might be to use the identity of the firm manager responsible for setting the piece rate on a given contract. In setting piece rates, different

managers may exhibit idiosyncratic behavior that is independent of planting conditions. However, such idiosyncracies are likely to be significant only over a long period of time. Given that we only have data from one planting season, during which each manager would have been responsible for at most one or two contracts, we chose not to pursue this strategy. A final approach, the one which we follow, is to model explicitly the firm's decision rule over r as a function of planting conditions and to incorporate this decision rule directly into the estimation procedure.

IV. Deriving and Estimating a Structural Model

We model unobserved planting conditions as productivity shocks that affect the output which obtains for a given level of effort on the part of the planter. We assume that productivity shocks S are draws from a particular random variable having cumulative distribution function $F(s)$ which depends on parameters μ and σ^2 . The firm decides on the piece rate r by considering the parameters μ and σ^2 . A contract is defined by the pair (μ, σ^2) and a unique value of r . We model the firm's choice of r as satisfying the planter's labor-supply constraint, conditional on average planting conditions. Thus, the firm chooses r to induce the planter to participate in planting. Note that changes in average planting conditions lead to changes in r .

We develop a simple model of planter-effort determination under piece rates with a risk-neutral planter.⁷ We assume for planters the following utility function defined over earnings W and effort E :

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

where the earnings function is given by

$$W = rY$$

with Y being planter output and the function $C(E)$ denoting the planter's cost of effort, which is parameterized as

$$C(E) = \frac{\kappa}{\eta} E^\eta \quad \eta > 1, \kappa > 0.$$

Output is assumed to be determined by the following function:

$$Y = ES$$

where S is a random productivity shock drawn from the distribution $F(s)$ having parameters μ and σ^2 and represents planting conditions beyond the planter's control, such as the slope of the terrain, hardness of the ground, and the amount of ground cover. 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, though a planter can observe average planting conditions before he begins to plant, he only learns the exact nature of the terrain to be planted once planting begins.

7. Interviews with planters suggest that variation in daily earnings is a relatively minor concern.

The logarithm of the productivity shock is assumed to follow a normal distribution with mean μ and variance σ^2 , so 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.

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 to induce the planter to accept the contract, the contract must satisfy the planter's labor-supply constraint.

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

$$e = \left(\frac{rs}{\kappa}\right)^{(1/\eta-1)}.$$

To simplify resulting expressions, let γ denote $[1/(\eta - 1)]$. Note that the second-order condition of the planter's problem is satisfied as long as γ exceeds zero, η exceeds one. Making the appropriate substitutions, we write the expressions for optimal effort and output on the part of the planter in response to a particular piece rate r as

$$e = \left(\frac{rs}{\kappa}\right)^\gamma$$

so

$$y = \left(\frac{r}{\kappa}\right)^\gamma s^{\gamma+1}.$$

Taking logarithms of both sides of the second equation above yields

$$\log y = \gamma \log r - \gamma \log \kappa + (\gamma + 1) \log s$$

or, in terms of random variables,

$$(2) \log Y = \gamma \log r - \gamma \log \kappa + (\gamma + 1) \log S$$

where

$$(\gamma + 1) \log S \sim N[(\gamma + 1)\mu, (\gamma + 1)^2\sigma^2].$$

Note that the parameter γ gives a direct measure of the elasticity of planter effort with respect to the piece rate.

Note too that Equation 2 has the same form as the regression model Equation 1 estimated above. From Equation 2, it is also clear why regression methods fail to provide a consistent estimate of the incentive effect. To convert Equation 2 into an equation with a mean-zero error term, we add and subtract $(\gamma + 1)\mu$, which yields

$$(3) \log Y = \gamma \log r - \gamma \log \kappa + (\gamma + 1)\mu + V$$

where V now equals $(\gamma + 1)(\log S - \mu)$, which is distributed normally with mean zero and variance $(\gamma + 1)^2\sigma^2$. Comparing Equation 3 to Equation 1, one notes immediately that U_{it} , the error term in Equation 1, equals $(\gamma + 1)\mu + V_{it}$, but from Figure 4 we know that the covariance between μ and r does not equal zero.⁸ Thus, one of the assumptions maintained in least-squares estimation (namely, the weak exogeneity of the covariates) has been violated.

We assume that planters have an alternative utility given by \bar{u} , so the labor-supply constraint is

$$\varepsilon[W - C(e)] = \bar{u}$$

where ε is the expectation operator taken with respect to the random variable S . Substituting optimal effort into the labour-supply constraint yields

$$\frac{r^{\gamma+1}}{(\gamma + 1)\kappa^\gamma} \varepsilon(S^{\gamma+1}) = \bar{u}.$$

Using the properties of the log-normal distribution, we obtain

$$(4) (\gamma + 1)\mu = \log \bar{u} + \log(\gamma + 1) + \gamma \log \kappa - (\gamma + 1) \log r - (\gamma + 1)^2 \frac{\sigma^2}{2}.$$

Substituting Equation 4 into Equation 3 yields an equation for the daily productivity of individual i on contract t

$$(5) \log Y_{it} = \log(\gamma + 1) + \log \bar{u} - \log r_t - (\gamma + 1)^2 \frac{\sigma_t^2}{2} + V_{it}.$$

Incorporating the planter's expected-utility constraint eliminates the endogeneity problem because V represents only unexpected deviations from average conditions.

8. Note that though μ and σ^2 are fixed for a given contract, they vary across contracts, causing the correlation between μ and r .

Therefore, it is a mean-zero error term that is uncorrelated with r . Estimation based on Equation 5 can provide consistent estimates of γ .⁹

It may be informative to consider our estimation approach within the context the analysis-of-variance (ANOVA) framework often used to evaluate experimental data. Consider the logarithm of the independent variable $\log Y_{ijk}$, which measures the logarithm of output by planter i planting on plot j for piece rate k . Ignoring higher-order effects, the logarithm of output can be decomposed into individual-specific effects (α_i) , plot-specific effects (δ_j) , piece-rate specific effects (ζ_k) , and a random error U_{ijk} in the following way using a three-way ANOVA:

$$\log Y_{ijk} = \lambda + \alpha_i + \delta_j + \zeta_k + U_{ijk}$$

We cannot use these methods to identify δ_j and ζ_k separately because there is no independent variation between plots and the piece rate in our data; conditions on any plot uniquely determine the piece rate. Furthermore, because the planting conditions on a given plot are negatively correlated with the piece rate, the estimated piece-rate effect is inconsistent. By modeling behavior, we are able to rectify this problem, but at the cost of making the estimation problem nonlinear.

A. Parameter Identification and Estimates

Our data set contains observations on 89 planters planting under 31 different contracts. Each contract t is specified by a pair (μ_t, σ_t) , which in turn determines the piece rate r_t through Equation 4. Therefore, the structural model consists of the parameter vector $(\gamma, \kappa, \mu_1, \sigma_1, \dots, \mu_{31}, \sigma_{31})^T$.

Estimating Equation 5 requires a measure of alternative utility \bar{u} . We used the daily British Columbia welfare payments to a single individual with no dependents in 1994. This measure captures what an individual would receive were zero effort supplied. In 1994, daily welfare payments were \$27.05 per day. In principle, \bar{u} defines an indifference curve in (W, E) space and can therefore be measured at an infinity of different points. For each wage earned in the labor market, however, there is a corresponding positive and unknown labor-market level of effort that gives the planter utility level equal to \bar{u} . We know the level of effort for only one point on the indifference curve: at zero labor-market effort. The planter's utility at this point is equal to his wage, which is the welfare payment he receives for not working.

Defining

$$Y_{it}^* \equiv \log Y_{it} + \log r_t - \log \bar{u},$$

we can then rewrite Equation 5 as

$$Y_{it}^* = \log(\gamma + 1) - (\gamma + 1) \frac{\sigma_t^2}{2} + V_{it}.$$

9. Equation 5 makes it clear why this model does not permit the identification of γ in the presence of measurement error. In particular, by introducing measurement error into daily productivity, the variance of the error term in Equation 5 would no longer be equal to $(\gamma + 1)^2 \sigma_t^2$, the coefficient on the contract-specific dummy variable. Therefore, one of these contract-specific dummy variables would have to be dropped and the intercept term, instead of measuring $(\gamma + 1)$, would measure $(\gamma + 1) - [(\gamma + 1)^2 \sigma_t^2/2]$ where t' is the contract for which the dummy variable is suppressed.

Table 4

Parameter Estimates of Structural Models: with and without Individual-Specific Heterogeneity

Parameter	(a)	(b)
γ	5.876 (0.038)	2.135 (0.183)
Maximum σ	0.081	0.141
Minimum σ	0.014	0.006
Average σ	0.047	0.078
Maximum individual-specific effect		1.168
Minimum individual-specific effect		0.199
Average individual-specific effect		0.737
Logarithm of the likelihood function	-1,257.790	-209.020

Note: Sample size = 3,960.

Estimating the above specification by the method of maximum likelihood is similar to estimating a linear regression with the added complication that the contract-specific variance of the productivity shock σ_t^2 enters the conditional-mean function. The elasticity of effort with respect to the piece rate is identified by the constant term.

Note that κ and the $\{\mu_t\}_{t=1}^{31}$ enter Equation 5 and Equation 4 additively. Thus, once Equation 5 is estimated, we can recover an estimate of $[(\gamma + 1)\mu_t - \gamma \log \kappa]$ by substituting back into Equation 4. However, separately identifying κ and the $\{\mu_t\}_{t=1}^{31}$ would require an additional identifying normalization, such as μ_1 's equaling zero.

Results obtained by estimating Equation 5 are given in Column a of Table 4. Our estimate of γ is 5.88, suggesting a very large elasticity of effort with respect to the piece rate. Of the 31 contract-specific variances, we only report the maximum and minimum as well as the average of the 31 values.

B. Introducing Individual-Specific Heterogeneity

Estimates of γ based on Equation 5 neglect the fact that planters may be heterogeneous with respect to their ability. To capture individual-specific heterogeneity, we admit planters who have different costs of effort. We then assume that the firm chooses the piece rate to ensure that the least-able (highest-cost) planter in the firm is indifferent between working and not working. Within this framework, all other planters earn rents.

Denoting the cost of effort for planter i by κ_i and the cost of effort for the least-able planter by k_n , which is the max $\{\kappa_1, \kappa_2, \dots, \kappa_n\}$, piece rates are then determined by

$$(6) \quad \frac{r^{\gamma+1}}{k_n^{\gamma+1}} \mathbb{E}(S^{\gamma+1}) = \bar{u}$$

while the output for individual i is determined by

$$(7) \quad Y_i = \left(\frac{r}{\kappa_i}\right)^\gamma S^{(\gamma+1)}.$$

Taking logarithms of both sides of Equation 7 yields

$$(8) \quad \log Y_i = \gamma \log r - \gamma \log \kappa_i + (\gamma + 1)\mu + V.$$

where V equals $(\gamma + 1)(\log S - \mu)$, which is normally distributed with mean zero and variance $(\gamma + 1)^2\sigma^2$. Taking logarithms of Equation 6 and substituting for the term $(\gamma + 1)\mu$ in Equation 8 yields

$$(9) \quad \log Y_{i,t} = \log(\gamma + 1) + \log \bar{\mu} - \log r_t \\ + \gamma(\log k_h - \log \kappa_i) - (\gamma + 1)\frac{\sigma_i^2}{2} + V_{i,t}.$$

Comparing Equation 9 to Equation 5 suggests that ignoring individual-specific heterogeneity will lead to an overestimation of γ because planters with low κ s will produce more output, on average, than those planters with high κ s. In essence, by allowing planters to be heterogeneous, the term that was estimated as $\log(\gamma + 1)$ in Equation 5 is now estimated as

$$\log(\gamma + 1) + \gamma(\log k_h - \log \kappa_i).$$

To estimate Equation 9, we simply add to Equation 5 individual-specific dummy variables for each planter in the sample, except the planter corresponding to k_h , for whom the term $(\log k_h - \log \kappa_i)$ equals zero. We take the planter corresponding to k_h to be the planter with the lowest average productivity in the firm. Results from estimating Equation 9 are presented in Column b of Table 4. After controlling for individual-specific effects, the estimate of γ falls to 2.14. That the individual-specific effects are jointly significant is evident from a comparison of the maximized values of the logarithm of the likelihood functions, $-1,257.79$ for the restricted model and -209.02 for the unrestricted model.

These results suggest that, holding planting conditions fixed, a 1 percent increase in the piece rate will increase productivity by 2.14 percent. In terms of measured output, an increase of the piece rate by \$0.01 from the sample mean of 25 cents will increase output by 67 trees if the conditions are held constant.

C. Prediction

To evaluate the performance of the structural model, we consider its ability to predict observed productivity for the different contracts. In Figures 5 and 6, we present the average observed productivity per contract, denoted by the circles, and the 95-percent and 99-percent confidence intervals for the average predicted productivity, which are derived from the structural parameter estimates of the model. In total, seven of the 31 95-percent confidence intervals and nine of the 31 99-percent confidence intervals encompass the observed average productivity. Given the large sample size, the structural parameters are estimated very precisely, leading to very narrow confidence intervals. Nevertheless, Figures 5 and 6 are informative about the perfor-

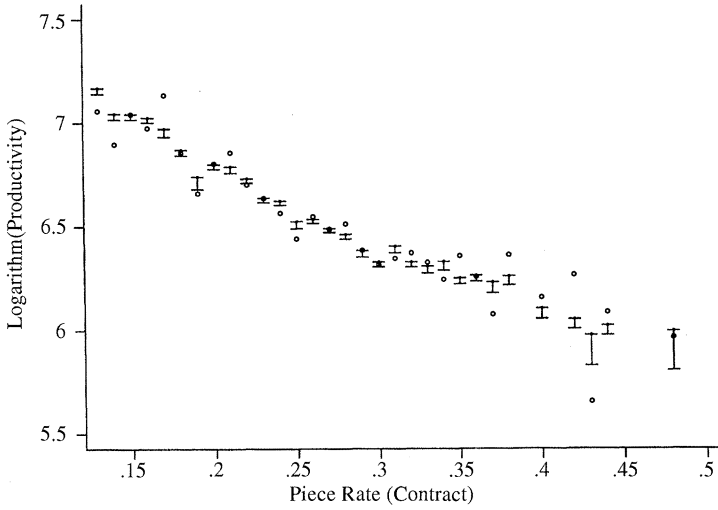


Figure 5
Ninety-Five Percent Confidence Intervals for Predicted Productivity

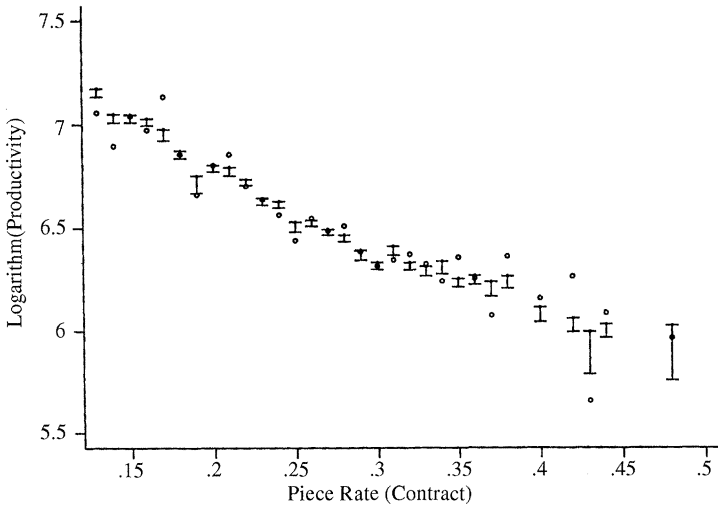


Figure 6
Ninety-Nine Percent Confidence Intervals for Predicted Productivity

mance of the model. In particular, the model has trouble fitting contracts with very high and very low piece rates.

D. Sensitivity Analysis

It is clear from Equation 9 that identification of the model depends crucially on measuring \bar{u} . Furthermore, given the effort elasticity γ is identified through the constant term in Equation 9, estimates of γ are likely to be sensitive to the value chosen for \bar{u} .

An alternative estimation strategy is to bound the value of γ . Working at the minimum wage W_m implies a positive, unknown (to the econometrician) level of effort, e_m . Thus,

$$\bar{u} = W_m - C(e_m).$$

Letting

$$\psi = \log[\bar{u} + C(e_m)] - \log(\bar{u}) > 0$$

we can then write

$$\log(W_m) = \log(\bar{u}) + \psi.$$

Substituting into Equation 9 gives

$$(10) \quad \log Y_{i,t} = \log(\tilde{\gamma} + 1) + \log(W_m) - \log r_t + \gamma(\log k_i - \log \kappa_i) - (\gamma + 1)^2 \frac{\sigma_i^2}{2} + V_{i,t}.$$

The estimated constant term in Equation 10

$$\log(\tilde{\gamma} + 1) = \log(\gamma + 1) - \psi < \log(\gamma + 1)$$

provides a lower bound. Estimates of this Equation 10 are given in Table 5. Note that the calculated lower bound to γ is 0.77. This suggests that an increase in the piece rate by \$0.01 from the sample mean of 25 cents would increase output by at least 24 trees.

V. Alternative Contracts and Rents

The contract used by the firm we have studied is restrictive in that this firm only has one instrument (the piece rate) to accomplish two tasks: the provision of incentives and the division of rents. With heterogeneous planters, some of the planters will earn rents. The expected utility of planter i is

$$\varepsilon(U) = \frac{r^{\gamma+1}}{\kappa_i^{\gamma}(\gamma + 1)} \varepsilon(S^{\gamma+1}).$$

Table 5
Parameter Estimates of Structural Model: Lower Bound with Individual-Specific Heterogeneity

Parameter	
γ	0.767 (0.103)
Maximum σ	0.250
Minimum σ	0.011
Average σ	0.139
Maximum individual-specific effect	1.168
Minimum individual-specific effect	0.199
Average individual-specific effect	0.737
Logarithm of the likelihood function	-209.020

Note: Sample size = 3,960.

Substituting for r from Equation 6 yields

$$\varepsilon(U) = \bar{u} \left(\frac{k_h}{\kappa_i} \right)^\gamma$$

Therefore, the rent earned by planter i is

$$(11) \quad \left[\left(\frac{k_h}{\kappa_i} \right)^\gamma - 1 \right] \times \bar{u}.$$

Note that this rent depends only on the individual-specific effect in Equation 9 and the measure of \bar{u} , and is therefore independent of the estimate of γ .

An alternative contract, which nests the observed contract, pays earnings of the form

$$W = B + rY$$

where B is a base “wage” (or fee) that is independent of planter productivity. The advantage of introducing a base wage is that the firm can extract rents from the planter while still providing incentives. In particular, the optimal contract solves the following problem:

$$\max_{r,B} (P - r)Y - B \text{ subject to } \varepsilon(U) = \bar{u}.$$

The solution to this problem is well known: with risk-neutral planters, the piece rate is set equal to the price of output and the base wage is adjusted to ensure the planter earns his alternative utility \bar{u} .

It is impossible to calculate the difference in profits between the fully optimal contract and the observed contract because the base wage under the optimal contract would vary across individuals and would depend on each individual’s cost of effort;

Table 6
Estimates of Expected Worker Rents, Per Day

Worker	1	2	3	4	5	6	7	8	9	10
Rent	5.96	7.20	8.15	8.23	10.39	12.02	12.36	13.57	13.85	15.48
Fee	0.81	0.85	0.87	0.87	0.96	1.01	1.01	1.04	1.04	1.09
Worker	11	12	13	14	15	16	17	18	19	20
Rent	16.40	16.79	17.01	17.14	17.37	17.95	18.06	19.92	19.96	20.89
Fee	1.10	1.11	1.11	1.11	1.11	1.11	1.11	1.17	1.17	1.18
Worker	21	22	23	24	25	26	27	28	29	30
Rent	21.61	22.58	23.64	23.89	25.64	25.84	26.02	26.09	26.86	27.07
Fee	1.19	1.20	1.22	1.22	1.26	1.26	1.26	1.26	1.27	1.27
Worker	31	32	33	34	35	36	37	38	39	40
Rent	27.16	27.49	27.56	27.69	27.94	28.41	28.81	29.34	29.67	29.68
Fee	1.27	1.27	1.27	1.27	1.28	1.28	1.28	1.28	1.29	1.29
Worker	41	42	43	44	45	46	47	48	49	50
Rent	30.37	30.53	30.61	31.26	31.56	31.95	32.43	32.51	32.65	32.67
Fee	1.29	1.29	1.29	1.30	1.30	1.30	1.30	1.30	1.30	1.30
Worker	51	52	53	54	55	56	57	58	59	60
Rent	32.70	32.75	32.80	33.28	33.45	33.75	34.70	35.96	36.16	36.77
Fee	1.30	1.30	1.30	1.31	1.31	1.31	1.32	1.34	1.34	1.34
Worker	61	62	63	64	65	66	67	68	69	70
Rent	37.25	37.45	37.61	38.43	38.90	39.15	39.37	40.45	40.83	40.98
Fee	1.34	1.35	1.35	1.35	1.36	1.36	1.36	1.37	1.37	1.37
Worker	71	72	73	74	75	76	77	78	79	80
Rent	41.01	42.25	42.49	43.07	43.58	43.92	44.85	45.10	46.01	46.13
Fee	1.37	1.39	1.39	1.39	1.39	1.40	1.40	1.41	1.41	1.41
Worker	81	82	83	84	85	86	87	88		
Rent	46.16	46.42	46.86	47.39	47.96	48.73	49.41	59.91		
Fee	1.41	1.41	1.42	1.42	1.42	1.43	1.43	2.39		

these are not identified in our model. We do, however, identify each individual's cost of effort relative to k_i , so we can estimate the rent accruing to each individual in our sample. This allows us to estimate a lower bound to the increase in profits that would accrue from the optimal compensation system. Our estimate is a lower bound because we hold the piece rate fixed.

To estimate the rents that accrued to each planter, we use the estimates of the structural model in Equation 9. The estimated rents are presented in Table 6. We estimate that the planters are earning, on average, a rent of \$30.71 per day. Thus, introducing a base wage could increase average firm daily profits by at least \$30.71 per planter.

Firm profits under the observed system are given by $(P - r)Y$. Interviews with the firm manager revealed that the bid price per tree received by the firm is typically twice the piece rate paid to the planters. This suggests that average firm profits are given by rY , which equals \$178, implying that the optimal contract would increase profits by at least $[100 \times (30.71/178)]$ or 17.25 percent. Yet, this contract is only optimal within a static context. In particular, the base wage paid to each worker depends on that worker's cost of effort (ability), k_i . If the firm were subsequently to use information on ability to extract rents from the workers, then workers would not reveal their types, and high-ability workers would produce at the same levels as low-ability workers; that is, the firm is faced with a ratchet-effect type problem

(Lazear 1986; Gibbons 1987; Kanemoto and Macleod 1992). To induce high-ability workers to reveal their type and plant lots of trees, the firm must commit to not exploiting information on worker type once it is revealed.

There exists a level of rent that the firm can extract while inducing the workers to reveal their types. By the revelation principle, the firm can charge the worker a base fee that will equate the worker's expected utility to the level of utility the worker would receive from misrepresenting his type.

Theorem 1. Without loss of generality, let workers be ordered on the basis of their respective cost of effort so that

$$k_h = \kappa_1 \geq \kappa_2 \geq \dots \geq \kappa_n.$$

An upper bound to the base fee that the firm can charge worker $i > 1$ is given by

$$B_i = \left(\frac{k_h}{\kappa_i}\right)^\gamma \bar{u} - R_{i-1}(i - 1) - \left(\frac{k_h}{\kappa_{i-1}}\right)^\gamma \bar{u} \gamma \left(1 - \frac{\kappa_i}{\kappa_{i-1}}\right)$$

where $R_i(j)$ denotes the utility an individual of type i receives from pretending to be of type j and

$$R_i(i) = R_{i-1}(i - 1) + \gamma \bar{u} \left(\frac{k_h}{\kappa_{i-1}}\right)^\gamma \left(1 - \frac{\kappa_i}{\kappa_{i-1}}\right)$$

$$R_1(1) = \bar{u}.$$

The proof of this theorem is presented in the Appendix. Theorem 1 allows us to construct a series of base wages from the relative effort cost parameters identified in Equation 9. These values are presented in the rows labelled "Fee" in Table 6. They suggest that the firm could capture only a very small part of the informational rent that workers are presently earning without violating the incentive-compatibility constraints. This suggests that the observed piece-rate contract was an effective means of inducing effort within a firm composed of heterogeneous workers.

VI. Discussion and Conclusions

In this paper, we have investigated the sensitivity of worker performance to changes in the compensation system with particular emphasis on changes in the piece rate. Using data from the payroll records of a British Columbia tree-planting firm, we have highlighted the econometric problems inherent in evaluating changes in firm compensation policy when compensation systems are endogenous. Modeling the decision rules of the worker explicitly with regard to effort, and the firm, with regard to the parameters of the compensation system, controls for this endogeneity. We estimate the elasticity of effort with respect to the piece rate to be 2.14.

This result adds to a small but growing body of direct evidence supporting the existence of incentive effects. Lazear's (1996) study of auto-glass-worker productivity under fixed wages and piece rates measured a 20 percent increase in productivity associated with the switch from fixed wages to piece rates. Meanwhile, Paarsch and

Shearer (forthcoming) estimated the gain in productivity associated with paying tree planters piece rates rather than fixed wages to be 21 percent. Furthermore, both these papers emphasize the misleading results that can be obtained through a straight comparison of productivity under different payment systems. Lazear's research highlighted the importance of worker selection effects induced by the change in the compensation system, while the research of Paarsch and Shearer emphasized the importance of the endogenous choice of the compensation system on the part of the firm.

Structural analysis has benefits beyond being able to control for endogenous regressors. In particular, we are able to investigate the relative merits of alternative compensation systems. Our results suggest that dynamic considerations are important in determining the form of the observed contract. Although workers earn rents under this contract, these rents are due to differences in worker ability. By committing not to exploit information on ability once it is revealed, the firm induces high-ability workers to reveal their type and increase their productivity.

Appendix

Proof of Theorem 1

The proof follows Gibbons (1986). To satisfy the incentive compatibility (truth-telling) constraint, the contract must satisfy

$$R_i(i) \geq R_i(j),$$

Let individuals be ranked according to their cost of effort so that

$$k_h = \kappa_1 \geq \kappa_2 \geq \dots \geq \kappa_n.$$

Denote as B_i , the base fee that an individual declaring himself to be of type i pays to the firm. Since the individual with the highest cost of effort earns zero rent, it follows that $R_1 = R_h = \bar{u}$ and $B_1 = 0$. For $i > 1$,

$$R_i(i) = \left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \bar{u} - B_i$$

$$R_i(i-1) = \left(\frac{k_h}{\kappa_{i-1}}\right)^\gamma \bar{u}(\gamma + 1) \left(1 - \frac{\gamma}{\gamma + 1} \frac{\kappa_i}{\kappa_{i-1}}\right) - B_{i-1}.$$

Therefore truth-telling implies

$$(A1) \quad R_i(i) - R_{i-1}(i-1) \geq \left(\frac{k_h}{\kappa_{i-1}}\right)^\gamma \gamma \bar{u} \left(1 - \frac{\kappa_i}{\kappa_{i-1}}\right).$$

Setting

$$B_i = \left(\frac{k_h}{\kappa_i}\right)^\gamma \bar{u} - R_{i-1}(i-1) - \left(\frac{k_h}{\kappa_{i-1}}\right)^\gamma \gamma \bar{u} \left(1 - \frac{k_h}{\kappa_{i-1}}\right)$$

ensures that Equation A1 holds with equality, and therefore B_i represents an upper bound to the base wage that the firm can charge the worker.

References

- Baker, G. 1992. "Incentive Contracts and Performance Measurement." *Journal of Political Economy*, 100(3):598–614.
- Blinder, A. 1990. *Paying for Productivity: A Look at the Evidence*. Washington D.C.: The Brookings Institution.
- Booth, A., and J. Frank. 1997. "Performance Related Pay." Typescript, ESRC Research Centre on Micro-social Change, University of Essex, UK.
- Brown, C. 1990. "Firms' Choice of Method of Pay." *Industrial and Labor Relations Review*, 43(3):165s–182s.
- Donald, S., and G. S. Maddala. 1993. "Identifying Outliers and Influential Observations in Econometric Models." In *Handbook of Statistics 11: Econometrics*, eds. G. S. Maddala, C. R. Rao, and H. D. Vinod. New York: North Holland.
- Ehrenberg, R. 1990. "Do Compensation Policies Matter?" *Industrial and Labor Relations Review*, 43(3):
- Ferrall, C., and B. Shearer. Forthcoming. "Incentives and Transaction Costs within the Firm: Estimating an Agency Model Using Payroll Records." *Review of Economic Studies*.
- Gibbons, R. 1987. "Piece-Rate Incentive Schemes." *Journal of Labor Economics*, 5(4): 413–29.
- Goldin, C. 1986. "Monitoring Costs and Occupational Segregation by Sex: A Historical Analysis." *Journal of Labor Economics* 4(1):1–27.
- Hart, O., and B. Holmström. 1987. "The Theory of Contracts." In *Advances in Economic Theory Fifth World Congress*, ed. T. Bewley. Cambridge, UK: Cambridge University Press.
- 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.
- Kanemoto, Y., and W. Macleod. 1992. "The Ratchet Effect and the Market for Second-hand Workers." *Journal of Labor Economics*, 10(1):85–98.
- Lazear, E. 1986. "Salaries and Piece Rates," *Journal of Business*, 59(3):405–31.
- . 1996. "Performance Pay and Productivity." Working Paper 5672, National Bureau of Economics Research, Cambridge, Mass.
- . 1998. *Personnel Economics for Managers*. New York: John Wiley & Sons.
- Lazear, E., and S. Rosen. 1981. "Rank-Order Tournaments as Optimum Labor Contracts." *Journal of Political Economy* 89(5):841–64.
- Macleod, W., and J. Malcomson. 1989. "Implicit Contracts, Incentive Compatibility, and Involuntary Unemployment." *Econometrica* 57(2):447–80.
- Milgrom, P., and J. Roberts. 1992. *Economics, Organization, and Management*. Englewood Cliffs, N.J.: Prentice Hall.
- Paarsch, H., and B. Shearer. Forthcoming. "Piece Rates, Fixed Wages, and Incentive Effects: Statistical Evidence from Payroll Records." *International Economic Review*.
- Parent, D. 1997. "Method of Pay and Earnings: A Longitudinal Analysis." CIRANO, Working Paper 97s-14, Université de Montréal, Montréal, Canada.
- Pencavel, J. 1977. "Work Effort, On-the-Job Screening, and Alternative Methods of Remuneration." In *Research in Labor Economics* Vol. 1, ed. R. Ehrenberg. Greenwich, Conn.: JAI Press.
- Seiler, E. 1984. "Piece Rate vs. Time Rate: The Effect of Incentives on Earnings." *Review of Economics and Statistics* 66(3):363–76.

- Shapiro, C., and J. Stiglitz. 1984. "Equilibrium Unemployment as a Worker Discipline Device." *American Economic Review* 74(3):433–44.
- Shearer, B. 1996. "Piece Rates, Principal-Agent Models, and Productivity Profiles." *Journal of Human Resources* 31(2):275–303.
- Stiglitz, J. 1975. "Incentives, Risk, and Information: Notes Towards a Theory of Hierarchy." *Bell Journal of Economics* 6(2):552–79.
- Treble, J. 1996. "Intertemporal Substitution of Effort: Some Empirical Evidence." Typescript, Department of Economics, University of Wales, Bangor, Wales.
- Wallace, D. 1937. *Market Control in the Aluminum Industry*. Cambridge, Mass.: Harvard University Press.