THE RESPONSE OF WORKER EFFORT TO PIECE RATES: EVIDENCE FROM A FIELD EXPERIMENT*

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Abstract

We analyse data from a field experiment designed to measure the incentive effect of a change in the piece rate. The experiment was conducted within a tree-planting firm operating in British Columbia, Canada. This firm typically pays its workers piece rates, with the rate paid being determined by planting conditions. During the experiment, for a given set of planting conditions, workers were observed planting under the regular (control) piece rate paid and a higher (treatment) rate. We use this experimental change in the piece rate to identify the elasticity of worker productivity and effort using different statistical approaches. First, we consider ANOVA methods. Regressions of daily productivity on the piece rate yield an estimate of the elasticity of output with respect to changes in the piece rate of 0.39. While the ANOVA methods have the advantage of placing minimal restrictions on the data, they are limited in their ability to predict the effects of alternative (unobserved) contracts. Therefore, we turn to structural estimation using the experimental data. Our structural estimate of the elasticity is 0.37, very close to the ANOVA estimate. We estimate that the introduction of a base wage into the contract given workers would increase firm profits between 7 and 13 percent.

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1. Introduction and Motivation

The incentive effects of contracts play a central role in the modern theory of the firm. Economic theorists have modelled the ability of contracts to align the interests of workers and firms (Hart and Holmström (1987), Holmström and Milgrom (1990), Milgrom and Roberts (1992), Baker (1992)). In the related and recently-developed field of personnel economics (Lazear (1998)) compensation systems are considered policy instruments of the firm which can be used to improve the performance of workers. Recently, data from payroll records have been used to estimate the effects of contracts on worker and firm performance. The observed variation in contracts is related to observed measures of performance in order to estimate incentive effects and to measure the importance of asymmetric information; examples include Ferrall and Shearer (1999), Paarsch and Shearer (1999, 2000), Lazear (2000), Copeland and Monet (2002), Haley (2003) as well as Bandiera, Barankay, and Rasul (2004).

One potential problem with payroll data is that the observed changes in contracts may be endogenous because the contract is a choice variable on the part of the firm (Prendergast (1999), Chiappori and Salanié (2003)). If firms select a compensation scheme based on factors unobserved by the econometrician, but which affect worker productivity, then regression methods will fail to provide a consistent estimate of the incentive effect.[1] The observed covariation between worker productivity and the payment system confounds incentives with variation in unobservables.

Experiments provide a simple, yet powerful, way in which to solve these endogeneity problems. The exogenous variation in policies permits the application of less restrictive statistical methods to measure the effects of policy changes (Burtless (1995)). At the firm level, evaluating changes in personnel policies using field experiments has a long history, dating back to the Hawthorne experiments in the 1920s and 1930 (Gillespie (1991), Jones (1992)). Field experiments combine the benefits

[1] Paarsch and Shearer (1999), Haley (2003) as well as Bandiera, Barankay, and Rasul (2004) have investigated the setting of piece rates in three separate industries: tree planting, logging timber, and fruit picking. In all cases, the piece rate is chosen as a function of expected productivity.

of real-world, firm-level data with convincing exogenous variation in policy (French (1954)).

In this paper, we analyse data from a field experiment designed to measure the incentive effect of piece-rate compensation. The experiment was conducted within a tree-planting firm operating in the province of British Columbia, Canada. The workers in this firm are typically paid piece rates; an individual's daily earnings are strictly proportional to the number of trees he or she planted during a given day. Planting is performed on large tracts of land called *blocks*. Under non-experimental conditions, the piece rate for a particular block is chosen by the firm as a function of planting conditions — the slope of the terrain to be planted, the softness of the soil, and so forth. When conditions render planting difficult, reducing the number of trees that can be planted on a given day, the firm increases the piece rate in order to satisfy a labour-supply constraint. Since planting conditions are unobserved by the econometrician, the correlation between planting conditions and piece rates induces endogeneity. In fact, a regression of observed productivity on piece rates using non-experimental data yields a negative relationship.

The experiment took place on three different blocks during the 2003 planting season. During the experiment, each homogeneous block was divided into two parts, one part to be planted at the regular piece rate (as determined by conditions) and the other to be planted at an experimental (treatment) piece rate. The treatment piece rate represented an increase of up to twenty percent over the regular piece rate. Participants in the experiment were observed under both the regular and the treatment piece rate for a given block. In total, the experiment provided 197 observations on daily productivity, 109 at regular piece rates and 88 at treatment piece rates.

We use these data to estimate the response of workers to changes in the piece rate using two different statistical approaches. First, we apply unrestricted analysis-of-variance (ANOVA) techniques. These methods allow us to decompose average productivity into block-specific effects, individual-specific effects, and the treatment effect of changing the piece rate. As such, an ANOVA provides an unrestricted estimate of the change in productivity during the experiment. Our results suggest that an increase in the piece rate was accompanied by an increase in worker output; the elasticity of worker productivity with respect to experimental changes in the piece rate is estimated to be 0.39. We consider the importance of potentially confounding factors such as weather, fatigue, and endogenous participation, but find them to be unimportant both economically and statistically.

The ANOVA estimates have no direct interpretation in terms of economic fundamentals. What is more, the ANOVA methods are limited in their ability to predict behaviour under alternative contracts, unobserved in the experiment (Wolpin, 1995). We use structural econometric methods, applied to the experimental data, to evaluate contractual performance. Using the structural model, we estimate the output elasticity to be 0.37, very close to the ANOVA estimate. Based on these results, we estimate that the introduction of a base wage into the contract would increase firm profits between 7 and 13 percent.

The paper is organized as follows: In the next section, we describe the tree-planting industry in British Columbia as well as the compensation system in the firm. In section 3, we describe our experiment's design, while in section 4 we describe the sample data and present the ANOVA results. In section 5, we consider the potential confounding effects of fatigue and weather, while in section 6 we consider experimental and structural identification of effort-elasticity parameters. In section 7, we perform policy analysis and in section 8 we conclude.

2. Tree Planting in British Columbia

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

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

Tree planting is a simple, yet physically exhausting, task. It involves digging a hole with a special shovel, placing a seedling in this hole, and then covering its roots with soil, ensuring that the tree is upright and that the roots are fully covered. The amount of effort required to perform the task depends on the terrain on which the planting is done. In general, the terrain can vary a great deal from site to site. In some cases, after a tract has been harvested, the land is prepared for planting by removing the natural build-up of organic matter on the forest floor so that the soil is exposed, also known as *screefing*. 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 1800 stems per hectare, or an inter-tree spacing of about 2.4 metres, although this can vary substantially.[2] Depending on the conditions, an average planter can plant between 700 and 1100 trees per day, about half an hectare.

Typically, tree-planting firms are chosen to plant seedlings on harvested tracts through a process of competitive bidding. Depending on the land-tenure arrangement, either a timber-harvesting firm or the Ministry of Forests will call for sealed-bid tenders concerning the cost per tree planted, with the lowest bidder's being selected to perform the work. The price received by the firm per tree planted is called the *bid price*. Bidding on contracts takes place in the late autumn of the year preceding the planting season, which runs from early spring through to late summer. Before the

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

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 seedling density.

3. Experimental Design

Our data were collected at a medium-sized, tree-planting firm. This firm pays its planters piece rates exclusively. Daily earnings for a planter are determined by the product of the piece rate and the number of trees the worker planted on a particular day; no base wage is included in the contract. Blocks to be planted are divided into *plots* to be planted by individual planters. For each block, the firm decides on a piece rate. This rate takes into account the expected number of trees that a planter can plant in a day and the expected wage the firm wants to pay. It is important to note that under non-experimental conditions the piece rate is the same for all plots in an entire block. No matching of planters to planting conditions occurs in this firm so, even though planters may be heterogeneous, the piece rate received is independent of planter characteristics.

During the experiment, each block was divided into two parts. One of these parts was then randomly chosen to be planted under the regular piece rate, the other to planted under the treatment piece rate. The treatment piece rate represented an increase of between eight and twenty percent above the regular piece rate.

Two limitations in the design of the experiment warrant discussion. First, in order to avoid any possible Hawthorne effects,[3] workers were kept ignorant of the fact that they were participating in an experiment. To accomplish this, the firm needed a reasonable explanation for why the piece rate was changing on similar planting conditions. Workers were told that conditions on the treatment blocks had changed since the original bids had been tendered and that the original bid price had been high.[4] While this was convincing to the planters, it required spatial separation of the plots to be planted under each piece rate. As such, individual plots could not be randomly assigned to regular and treatment piece rates, but rather half of the block was randomly assigned to regular and half to treatment piece rates.

The need to present the experiment within the natural workings of the firm also restricted the temporal design of the experiment. The firm commits to planters not to reduce the piece rate. Also, the firm does not pay different piece rates to workers planting in close proximity to one another, on similar ground, at the same time. Consequently, the planting under the regular piece rate was completed *before* the planting under the higher treatment piece rate.

4. Sample Data and Endogeneity Problems

Our data set contains information on the piece rate set for each block, which we shall denote by r, and the piece rate received by each planter, which we shall denote by p, as well as that planter's daily productivity, which we shall denote by Y.

In Table 1, we present summary statistics concerning all 197 observations from the experiment. A total of 21 workers were observed during the experiment, planting

[3] Workers who know they are taking part in an experiment may alter their behaviour, independent of the experimental treatment. In a series of experiments designed to investigate the effects of illumination on productivity at the Hawthorne plant of General Electric, researchers allegedly found such results. It is noteworthy, however, that in a re-examination of data from the Hawthorne plant Jones (1992) found no evidence of such effects.

[4] This happens sometimes when the block has been unexpectedly prepared (screefed) by the Ministry of Forests.

Table 1
Summary Statistics: Full Sample, 197 Observations

Variable	Mean	St.Dev.	Minimum	Maximum
Number of Trees	944.03	341.92	375	1965
Regular Piece Rate	0.21	0.02	0.18	0.23
Piece Rate Paid	0.23	0.03	0.18	0.28
Daily Earnings ($Cdn)	214.77	69.25	89.70	451.95

on three different blocks, over a three-month period in the spring and summer of 2003, 109 on control plots and 88 on treatment plots. The piece rates paid to planters during the experiment ranged from 18 to 28 cents per seedling, with an average of 23 cents. The regular (or control) piece rates ranged from 18 to 23 cents per seedling, with an average of 21 cents. On average, workers planted 944 seedlings per day and earned $215 (Canadian) per day.

To highlight the endogeneity problem in "non-experimental" data, we regressed the logarithm of trees planted each day on the logarithm of the regular piece rate paid using the 109 control-group observations. In Table 2, we present the results from estimating the following regression model:

$$\log Y_{i,j} = \alpha_{0,i} + \alpha_1 \log r_j + U_{i,j} \tag{4.1}$$

where $Y_{i,j}$ represents trees planted by individual i on plot j, r_j represents the piece rate received per tree planted on plot j, and $\alpha_{0,i}$ is a, possibly individual-specific, intercept. When individual-specific heterogeneity is ignored, the estimates in column (a) of Table 2 suggest that increasing the piece rate decreases average productivity; the estimated elasticity of productivity with respect to piece rate is -2.46 and statistically significant. Admitting individual-specific heterogeneity in the intercept — column (b) of Table 2 — results in an increased estimated elasticity, but it is still negative, -1.77, and statistically significant.

The negative coefficient estimate on the logarithm of the piece rate paid to

Table 2
Simple Regression Results
Dependent Variable: Logarithm of Daily Production
Sample Size = 109

Independent Variable	(a)	(b)
Constant	2.901	3.842
	(0.290)	(0.394)
Logarithm of Piece Rate Paid	−2.461	−1.774
	(0.186)	(0.265)
Maximum Individual Effect		0.572
		(0.137)
Minimum Individual Effect		−0.281
		(0.081)
R^2	0.620	0.863

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 is low. An alternative explanation is that the piece rate is endogenous to the statistical model. In particular, if piece rates are correlated with unobserved factors that also affect planter productivity, then the observed piece rate will be correlated with the error term $U_{i,t}$ in (4.1).[5] This correlation will result in biased estimates of the elasticity of productivity with respect to piece rates because one of the maintained assumptions of least-squares estimation has been violated.

Having experimental data avoids the endogeneity problem by providing exogenous variation in the piece rate for a given set of planting conditions. In Tables 3 and 4, we present the summary statistics for the regular (or control) and treatment data sets which contain 109 and 88 observations, respectively. The average piece rate received by planters in the control group was about 21 cents per tree, while in the treatment group it was about 26 cents per tree. On average, the control group planted

[5] The manner in which the firm chooses the piece rate as a function of planting conditions generates this correlation.

Table 3
Summary Statistics: Control Sample, 109 Observations

Variable	Mean	St.Dev.	Minimum	Maximum
Number of Trees	888.85	325.46	390	1765
Piece Rate	0.21	0.25	0.18	0.23
Daily Earnings	182.65	50.40	89.70	317.70
Maximum Daily Temperature (Celsius)	13.76	4.40	8.00	21.10
Daily Precipitation (Millimetres)	5.23	7.54	0.00	26.40
Cumulative Days Worked	0.99	0.98	0	3

Table 4
Summary Statistics: Treatment Sample, 88 Observations

Variable	Mean	St.Dev.	Minimum	Maximum
Number of Trees	1012.385	351.23	375	1965
Piece Rate Paid	0.26	0.02	0.23	0.28
Daily Earnings	254.56	68.98	105.00	451.95
Maximum Daily Temperature (Celsius)	16.11	7.08	8.40	25.60
Daily Precipitation (Millimetres)	3.09	4.31	0.00	13.40
Cumulative Days Worked	1.52	1.03	0	3

888 seedlings per day, while the treatment group planted 1012 seedlings.

To consider the statistical significance of our results further, we augmented (4.1) to incorporate experimental variation in the data. In particular, we considered the following regression:

$$\log Y_{i,j} = \beta_{0,ij} + \beta_1 \log \tilde{p}_j + U_{i,j} \tag{4.2}$$

Table 5
Treatment/Control Regression Results
Dependent Variable: Logarithm of Daily Production
Sample Size = 197

Independent Variable	
Constant	7.577
	(0.153)
Logarithm of $\tilde{p}$	0.393
	(0.089)
Maximum Individual Effect	0.527
	(0.083)
Minimum Individual Effect	−0.314
	(0.056)
Maximum Site Effect	−0.413
	(0.046)
Minimum Site Effect	−0.545
	(0.048)
R^2	0.881

where $\tilde{p}_j$ represents the piece rate paid on a particular plot, *i.e.*,

$$\tilde{p}_j = \begin{cases} p_j & \text{for treatment group observations} \\ r_j & \text{for control group observations,} \end{cases}$$

and $\beta_{0,ij}$ represents a constant term that is individual and plot specific. Note that the exogenous variation in the piece rate directly identifies the elasticity of productivity with respect to piece rates. The results from estimating (4.2) are presented in Table 5.

The estimated elasticity is positive, 0.39, and statistically significant, but smaller than previous estimates. Paarsch and Shearer (1999) estimated a lower bound to the elasticity to be over 0.77, while Haley (2003) estimated it to be 0.41.[6]

[6] The point estimate of the elasticity calculated by Paarsch and Shearer was over 2, while Haley's was 1.5. We discuss reasons for the differences in estimates in section 6. Note too that, while the estimates of Paarsch and Shearer (1999) and Haley (2003) are estimates of the effort elasticity, the comparison is still valid because their models imply equality between effort and productivity elasticities.

5. Controlling for Confounding Effects

Given the before-after nature of the experiment, it is important to account for the effects of other factors which could be changing at the same time as the experimental treatment and which could possibly affect productivity. We concentrate on two, weather and fatigue.

5.1. Role of Weather

To control for weather, we collected data on daily rainfall and maximum temperature for the days and regions in which the experiment took place. We augmented the experimental regression to include these variables, considering the following regression:

$$\log Y_{ij} = \beta_{0,ij} + \beta_1 \log \tilde{p}_j + \beta_2 Temp_{ij} + \beta_3 Precip_{ij} + U_{ij} \tag{5.1}$$

The results from (5.1) are presented in Table 6. We present three sets of results. In the first column, we give least-squares (OLS) coefficient estimates. In the second column, we present OLS standard errors and, in the third and fourth columns, we present, respectively, heteroscedastic-consistent standard errors, and robust heteroscedastic-consistent standard errors that admit for non-independent observations due to common, unobserved, daily shocks. The associated p-values are given in parentheses.

The rainfall and temperature coefficients are statistically insignificant and their inclusion has little effect on the production elasticity estimate.[7] This suggests that macro-weather shocks are not playing a major role in the experimental data.

5.2. The Role of Fatigue

Another potential confounding element that could influence the ANOVA results is worker fatigue. Since the piece rate was increased only after planting was completed at the regular rate, workers may, in general, be more tired on treatment-rate days

[7] A joint test of the hypothesis that the coefficients on rainfall and temperature are zero produces p-values of 0.56 (OLS standard errors), 0.54 (heteroscedastic-robust standard errors), and 0.12 (robust heteroscedastic standard errors with non-independent observations).

Table 6
Treatment/Control Regression Results
Dependent Variable: Logarithm of Daily Production
Sample Size = 197

Independent Variable	Coefficient Estimate	OLS Std Error	Robust Std Error (Independence)	Robust Std Error (Clustering)
Constant	7.554	0.229 (0.000)	0.275 (0.000)	0.225 (0.000)
Logarithm of $\tilde{p}$	0.398	0.100 (0.000)	0.113 (.001)	0.117 (0.003)
Maximum Individual Effect	0.525	0.083 (0.000)	0.052 (0.000)	0.046 (0.000)
Minimum Individual Effect	−0.315	0.056 (0.000)	0.058 (0.000)	0.057 (0.000)
Maximum Site Effect	−0.402	0.073 (0.000)	0.079 (0.000)	0.050 (0.000)
Minimum Site Effect	−0.547	0.083 (0.000)	0.093 (0.000)	0.064 (0.000)
Maximum Daily Temperature	0.001	0.005 (0.307)	0.005 (0.778)	0.004 (0.731)
Total Daily Precipitation	0.002	0.002 (0.760)	0.002 (0.297)	0.001 (0.068)
R^2	0.881			

than on control-rate days. We proxy fatigue by cumulative days worked since the last day of rest. From Tables 3 and 4 average cumulative days worked is higher on treatment-rate days (1.52) than on control-rate days (0.99). A Poisson regression of days worked on a dummy variable indicating treatment-rate days suggests that the difference is statistically significant; the p-value for the equality of means is 0.001.

To control for fatigue, we included previous days worked directly into the conditional mean function for productivity and use regression analysis. These results are presented in Table 7.

Table 7
Regression Results: Fatigue
Dependent Variable: Logarithm of Daily Production
Sample Size = 197

Independent Variable	Coefficient Estimate	OLS Std Error	Robust Std Error (Independence)	Robust Std Error (Clustering)
Constant	7.541	0.160 (0.000)	0.157 (0.000)	0.177 (0.000)
Logarithm of $\tilde{p}$	0.376	0.092 (0.000)	0.091 (.000)	0.108 (0.003)
Maximum Individual Effect	0.530	0.083 (0.000)	0.052 (0.000)	0.047 (0.000)
Minimum Individual Effect	−0.312	0.056 (0.000)	0.058 (0.000)	0.054 (0.000)
Maximum Site Effect	−0.409	0.049 (0.000)	0.041 (0.000)	0.034 (0.000)
Minimum Site Effect	−0.543	0.048 (0.000)	0.042 (0.000)	0.041 (0.000)
Cumulative Days Worked	0.007	0.010 (0.453)	0.011 (0.660)	0.012 (0.602)
R^2	0.881			

Previous days worked has no statistically significant effect on productivity in the sample. What is more, the estimate of the elasticity of productivity with respect to the piece rate changes very little with its inclusion.

5.3. The Role of Participation

If unobservable factors also affect fatigue levels, then optimal participation decisions may truncate the error term of observed productivity. Participation decisions can lead to two, possibly opposing, effects. First, workers who participate on treatment-rate days are likely to have lower-than-average levels of fatigue, giving rise to a standard sample-selection problem. Counteracting this, the experimental increase in the piece

Table 8
Cumulative Days Worked and Participation

	Participation		
Days Worked	0	1	Total
0	2	58	60
1	0	66	66
2	1	43	44
3	1	30	31
Total	4	197	201

rate can directly affect worker participation; the higher rents under the treatment piece rate could induce workers to show up to work at fatigue levels that would normally cause them to stay home.

In this subsection, we exploit the fact that absences were recorded during the experiment. Since these absences occurred on days for which the experiment took place, they were voluntary absences on the part of the workers. Furthermore, since everyone involved in the experiment received the same piece rate on a given day, we know what piece rate the planter forwent by his or her absence.

To investigate the importance of participation decisions in our sample, we tabulate, in Table 8, participation and cumulative days worked during the experiment.

The participation rate during the experiment was extremely high, around 98 percent; workers decided not to work on only 4 days during the experiment. What is more, there is little to suggest that fatigue caused these decisions. Two of the non-participation days occurred at the beginning of the week, before any planting had taken place. This suggests that selection is of minor importance in the experimental sample.

In Table 9, we document that participation decisions are almost identical between treatment and control groups. The participation rates are 98.2 percent and 97.8 percent, respectively, suggesting that the experimental variation in the piece rate had a negligible effect on participation.

Table 9
Participation in Treatment and Control Groups

	Participation		
	0	1	Total
Treatment	2	88	90
Control	2	109	111
Total	4	197	201

As a final indication of the importance of participation in our results, we estimated a Probit model linking participation to days worked and experimental rents. This allowed us to examine whether experimental variation in the piece rate affected participation, for a given number of days worked. In particular, we considered the following model:

$$P_{it}^{*} = \gamma_0 + \gamma_1 Days_{it} + \gamma_2(\log \widetilde{p} - \log r) + U_{it}, \tag{5.2}$$

estimated using the experimental sample. Here, γ_1 captures the effect of cumulative days worked $Days_{it}$ on participation decisions, while γ_2 captures the effect of experimental rents $(\log \tilde{p} - \log r)$. Since we observe the individual absences in this sample and since we know the piece rate that was paid on any given day, the term $(\log \tilde{p} - \log r)$ is defined for every individual in the experimental sample, even on days they did not work.

The estimation results are presented in Table 10. There is no evidence that cumulative days worked or variation in the piece rate had any affect on participation during the experiment.

Given these high participation rates, and their similarities between the control and treatment groups, we ignored endogenous participation decisions as an important factor affecting our ANOVA results.[8]

[8] We have also estimated a complete structural model incorporating participation decisions and productivity decisions based on observable and unobservable factors. The results were very similar to those presented. Given participation does not seem to be playing a significant role in the experiment, we omit these results from the paper.

Table 10
Maximum-Likelihood Estimates: Probit Model
Dependent Variable: Participation

Independent Variable	Coefficient	Std. Error	p-Value
Constant	2.102	0.354	0.000
Days Worked	−0.001	0.191	0.995
$\log \tilde{p} - \log r$	−0.440	1.870	0.814
Log. Likelihood Function	−19.600		

6. A Structural Model

Results in previous sections provide estimates of the response of worker output to experimental changes in the piece rate. Yet it may be of interest to consider the profit performance of the observed contract *vis-à-vis* alternative contracts. This presents two potential problems. First, behaviour may change as the contract changes. Effort levels are sensitive to contracts and must be predicted as the contract changes. Second, any comparison must consider contracts that are acceptable to both the firm and the workers; *i.e.*, a proposed contract must satisfy expected-utility constraints. Taking these factors into account requires estimating a structural model in which the parameters determining worker utility and productivity are identified.

In this section, we develop and estimate a simple structural model of worker and firm behaviour under the observed piece-rate contract. We exploit the experimental variation in the piece rate to identify the parameters of the model. These parameters are then used, in section 7, to consider the relative performance of the observed contract.

6.1. Productivity

We assume that daily productivity, Y, is determined by

$$Y = ES$$

where E represents the worker's effort level, S is a productivity shock representing planting conditions beyond the worker's control (such as the hardness of the ground). We assume that S follows a lognormal distribution with parameters μ and σ^2. Planters have a utility function U defined over earnings I and effort E. For a given piece rate r, earnings I equal rY or rES. We assume that the cost of effort function for planter i is of the form:

$$C(E) = \kappa_i \frac{\gamma}{(\gamma+1)} E^{\frac{(\gamma+1)}{\gamma}} \quad \kappa_i > 0\ , \gamma > 0$$

where κ_i denotes the planter-specific component of costs and γ characterizes the curvature of $C(\cdot)$. We further assume a separable utility function in I and E of the following form:

$$U(I, E) = \big[I - C(E)\big] = \left[rES - \kappa_i \frac{\gamma}{(\gamma+1)} E^{\frac{(\gamma+1)}{\gamma}}\right]. \tag{6.1}$$

Timing

For each block of land, j, to be planted, the timing of events in the model is as follows:

1. Nature chooses (μ_j, σ_j^2) for block j.
2. The firm observes (μ_j, σ_j^2) and then selects a piece rate r_j.
3. The worker observes (μ_j, σ_j^2) for block j, and is offered the contract r_j for planting on that block; the planter either accepts or rejects the contract.
4. Conditional on accepting the contract the worker is randomly assigned to plant on a particular plot of block j (*i.e.*, the planter draws a particular value of S). The planter then chooses an effort level E and produces Y.
5. The firm observes Y and pays earnings I.

6.2. Control-Group Observations

Letting e_i denote the optimal level of effort chosen by worker i, then conditional on s, a particular value of S, a worker's optimal effort if given by

$$e_i = \left(\frac{rs}{\kappa_i}\right)^{\gamma}$$

which then yields the following observed-productivity equation:

$$y_i = \frac{r^\gamma}{\kappa_i^\gamma} s^{\gamma+1}. \tag{6.2}$$

In order for a worker to accept the contract offered, it must satisfy his expected-utility constraint. Given the contract has only one instrument and workers are heterogeneous, some workers will earn rents. We assume that the piece rate is chosen to satisfy the alternative utility constraint of the lowest-ability worker in the firm. The worker with lowest ability level has the highest cost parameter κ_h; *i.e.*,

$$\kappa_h = \max(\kappa_1, \kappa_2, \ldots, \kappa_n).$$

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

$$\frac{r^{(\gamma+1)} \exp[(\gamma+1)\mu + 0.5(\gamma+1)^2\sigma^2]}{(\gamma+1)\kappa_h^\gamma} = \bar{u}. \tag{6.3}$$

Taking logarithms and substituting from (6.3) into (6.2) yields the following empirical specification in terms of random variables:

$$\log Y_{ij} = \log(\gamma+1) + \log \bar{u} - \log r_j + \gamma \log\left(\frac{\kappa_h}{\kappa_i}\right) - 0.5(\gamma+1)^2\sigma_j^2 + V_{ij} \tag{6.4}$$

where V_{ij} equals $(\gamma+1)(\log S_{ij} - \mu_j)$ is distributed normally with mean zero and variance $(\gamma+1)^2\sigma_j^2$.

6.3. Treatment-Group Observations

Under our experiment, the piece rate on block j is exogenously increased from r_j to p_j for part of the block, chosen at random and comprising the treatment plots. Worker productivity on the treatment plots is then given by the following observed-productivity equation:

$$y_{ij} = \frac{p_j^\gamma}{\kappa_i^\gamma} s^{\gamma+1}. \tag{6.5}$$

Given that conditions have not changed, r_j still satisfies (6.3), yielding the following empirical specification in terms of random variables:

$$\log Y_{ij} = \log(\gamma+1)+\log \bar{u}-\log r_j+\gamma \log\left(\frac{\kappa_h}{\kappa_i}\right)-0.5(\gamma+1)^2\sigma_j^2+\gamma\log\left(\frac{p_j}{r_j}\right)+V_{ij} \quad (6.6)$$

6.4. Identification Results

To identify the parameters of the model we combine (6.4) and (6.6) to yield

$$\log Y_{ij} = \log(\gamma+1)+\log \bar{u}-\log r_j+\gamma \log\left(\frac{\kappa_h}{\kappa_i}\right)-0.5(\gamma+1)^2\sigma_j^2+\gamma\log\left(\frac{\tilde{p}_j}{r_j}\right)+V_{ij} \quad (6.7)$$

or

$$\log Y_{ij} = a_0 + \log(\gamma+1) - \log r_j + \gamma a_{1i} - 0.5(\gamma+1)^2\sigma_j^2 + \gamma\log\left(\frac{\tilde{p}_j}{r_j}\right) + V_{ij} \quad (6.8)$$

where

$$\tilde{p}_j = \begin{cases} p_j & \text{for treatment group observations} \\ r_j & \text{for control group observations} \end{cases} \quad (6.9)$$

is the piece rate the worker actually received for planting.

Theorem 1: Identification

Part (i) *If the marginal individual h is in the experimental sample, then maximum-likelihood estimation of (6.8) on the experimental sample identifies the parameters:*

(i) γ;

(ii) $\sigma_j \quad \forall j$;

(iii) $[\log(\kappa_h) - \log(\kappa_i)]$;

(iv) $\log \bar{u}$.

Part (ii) *If the marginal individual h is not in the experimental sample, then maximum-likelihood estimation of (6.8) on the experimental sample identifies the parameters:*

(i) γ;

(ii) $\sigma_j \quad \forall j$;

(iii) $[\log(\kappa_1) - \log(\kappa_i)]$;

(iv) $\log \bar{u} + \gamma[\log(\kappa_h) - \log(\kappa_1)]$.

Proof of Theorem 1

Part (i)

> *The experimental difference between $\tilde{p}_j$ and r_j directly identifies γ. Given γ, the variance of $\log y$ on a given plot identifies σ_j^2. Given individual h is in the sample the individual specific term, a_{1i}, identifies $[\log(\kappa_h) - \log(\kappa_i)]$ and the constant term then identifies $\log \bar{u}$.*

Part (ii)

> *When individual h is not in the experimental sample, the constant term identifies $\log \bar{u} + \gamma[\log(\kappa_h) - \log(\kappa_1)]$, where κ_1 is the effort cost of the normalized individual 1. The individual-specific parameter, a_{1i}, identifies $[\log(\kappa_1) - \log(\kappa_i)]$.*

Table 11
Maximum-Likelihood Estimates: Structural Model
Dependent Variable: Logarithm of Daily Production
Sample Size = 197
Standard Errors are in parentheses.

Parameter	(a)	(b)	(c)	(d)
γ	0.330	0.443	0.336	0.366
	(0.091)	(0.167)	(0.043)	(0.108)
a_0	4.732	4.728	4.771	4.764
	(0.051)	(0.054)	(0.029)	(0.072)
σ_1	0.074	0.036	0.040	0.014
	(0.008)	(0.110)	(0.071)	(0.131)
σ_2	0.081	0.057	0.042	0.014
	(0.016)	(0.112)	(0.063)	(0.131)
σ_3	0.138	0.104	0.103	0.100
	(0.015)	(0.109)	(0.072)	(0.164)
σ_W		0.045		0.024
		(0.034)		(0.036)
σ_ν			0.059	0.058
				(0.046)
Logarithm of Likelihood Function	29.246	37.675	41.069	44.370

The marginal benefit of experimental data *vis-à-vis* non-experimental data for estimating the structural model is now clear. Experimental variation in the piece rate directly identifies the elasticity of effort.[9] In the absence of such variation, $\tilde{p}_j$ equals r_j and identifying γ requires a measure of alternative utility, $\bar{u}$ and the estimated value of γ will be sensitive to any such a measure.[10]

We estimated (6.7) using the experimental data. The results are given in Table 11, column (a). The estimate of the elasticity of effort with respect to the piece rate

[9] Note that the restrictions embodied in (6.7) permit the interpretation of γ as the elasticity of effort with respect to the piece rate. In the absence of these restrictions, the parameter on the experimental variation in the piece rate identifies the output elasticity.

[10] This is the identification strategy followed by Paarsch and Shearer (1999) and Haley (2002).

γ is 0.33 and its estimated standard error is 0.09. The value of the logarithm of the likelihood function is 29.25.[11]

The experimental estimate of γ is statistically significant, though substantially smaller than that of Paarsch and Shearer (1999) or Haley (2002). What is more, from the estimate of a_0 and γ we can recover an estimate of $\bar{u}$ under the hypothesis that the marginal individual was in the experimental sample. This gives an estimate of $\bar{u}$ of \$85.31, considerably larger than that imposed by Paarsch and Shearer (1999) or Haley (2002). Given the identification results, this suggests that the values of $\bar{u}$ used by Paarsch and Shearer as well as Haley to identify γ were too low.[12]

6.5. Correlated Weather Shocks and Perception Errors

Increased flexibility can be obtained in the structural model by introducing daily weather shocks W and perception errors. Perception errors capture the possibility that the firm may misjudge actual planting conditions on a given block. Let daily output be given by

$$Y = EWS \tag{6.10}$$

where S and W are independent random variables, with $\log S$ being distributed normally having mean μ_j and variance σ_j^2 and $\log W$ being distributed normally having mean μ_{Wj} and variance σ_W^2.[13] We assume that the value of W is observed after participation decisions are made, but before effort is chosen. To account for perception errors on a given block, we assume that at the beginning of the contract

[11] In Table 11, we provide an estimate of a_0 or $\log \bar{u} + \gamma[\log(\kappa_h) - \log(\kappa_1)]$.

[12] The result is not completely conclusive; the fact that the estimated value of $\bar{u}$ is higher than the assumed value is not, in itself, evidence of mis-specification. Recall, from Theorem 1 that, if the marginal individual is not in the sample, the estimated coefficient from the experimental sample estimates $[\log \bar{u} + \log(\kappa_h) - \log(\kappa_1)]$. We consider additional explanations for the differences in results in section 8.

[13] We subscript average weather shocks by Wj to denote the fact that the firm's expectations of weather shocks may differ across contracts because they take place at different times of the year. We do not allow these expectations to change daily since expected weather will affect the setting of the piece rate and the piece rate is constant for a given contract.

both the firm and the worker observe $\tilde{\mu}_j$, an unbiased estimate of true conditions, μ_j; *i.e.*,

$$\mu_j = \tilde{\mu}_j + \nu_j \quad \nu_j \sim N(0, \sigma_\nu^2), \quad \mathcal{E}(\nu_j | \tilde{\mu}_j) = 0. \tag{6.11}$$

Optimal effort is

$$e = \left(\frac{rws}{\kappa_i}\right)^\gamma.$$

Substituting into productivity and taking logarithms yields

$$\log Y = \gamma \log r - \gamma \log \kappa_i + (\gamma+1) \log W + (\gamma+1) \log S. \tag{6.12}$$

The piece rate is chosen to satisfy

$$\frac{r_j^{\gamma+1} \exp[(\gamma+1)\tilde{\mu}_j + 0.5(\gamma+1)^2(\sigma_j^2 + \sigma_\nu^2)] \exp[(\gamma+1)\mu_{Wj} + 0.5(\gamma+1)^2 \sigma_W^2]}{(\gamma+1)\kappa_h^\gamma} = \bar{u}. \tag{6.13}$$

Substituting (6.13) into (6.12) yields

$$\begin{aligned} \log Y_{itj} = & \log \bar{u} + \log(\gamma+1) - \log r_j + \gamma(\log \kappa_h - \log \kappa_i) - \\ & 0.5(\gamma+1)^2 \left(\sigma_j^2 + \sigma_W^2 + \sigma_\nu^2\right) + \gamma(\log \tilde{p}_j - \log r_j) + \varepsilon_{ijt} \end{aligned} \tag{6.14}$$

where

$$\varepsilon_{ijt} = (\gamma+1)\left(\log w_t - \mu_{Wj}\right) + (\gamma+1)(\log S_{ij} - \mu_j) + (\gamma+1)\nu_j.$$

The error structure is given by

$$\begin{aligned}
\mathcal{E}(\varepsilon_{ijt}) &= 0 \\
\mathcal{E}(\varepsilon_{itj}\varepsilon_{itj}) &= (\gamma+1)^2(\sigma_j^2+\sigma_W^2+\sigma_\nu^2) \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{i'j't}) &= (\gamma+1)^2\sigma_W^2 \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{i'jt'}) &= (\gamma+1)^2\sigma_\nu^2 \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{ij't'}) &= 0 \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{i'jt}) &= (\gamma+1)^2(\sigma_W^2+\sigma_\nu^2) \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{ijt'}) &= (\gamma+1)^2\sigma_\nu^2 \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{ij't}) &= (\gamma+1)^2\sigma_W^2.
\end{aligned} \tag{6.15}$$

Estimates of different versions of (6.14) are given in Table 11 — columns (b), (c), and (d). In column (b), we allow for weather shocks, but no perception errors; *i.e.*, σ_W is positive while σ_ν is zero. The estimate of γ is 0.44 and the value of the logarithm of the likelihood function increases to 37.675. In column (c), we present estimates of the model without weather shocks, but allowing for perception errors; *i.e.*, σ_W is zero while σ_ν is positive. The estimate of γ is 0.34 and the value of the logarithm of the likelihood is 41.069. Finally, in column (d), we present estimates of the model with both perception errors and weather shocks; *i.e.*, σ_W and σ_ν both positive. Here, the estimate of γ is 0.37 and the value of the logarithm of the likelihood function is equal to 44.370.[14]

In general, the individual variance parameters are not precisely estimated, although the value of the logarithm of the likelihood function increases substantially

[14] Strictly speaking, we cannot compare models with variances set to zero using the standard likelihood-ratio test as the variance parameters, when set to zero, are on the boundary of the parameter space, so standard, first-order asymptotic methods are invalid. We do so here simply to provide the reader with some feeling for how much better the models fit when perception errors and daily shocks are included.

by their inclusion. At the same time, the estimate of the effort elasticity γ is precisely estimated, ranging from 0.33 to 0.44.

6.6. Goodness of Fit

In order to evaluate the performance of the structural model, we calculated 95-percent confidence intervals for the predicted values of the logarithm of daily productivity. We concentrate on the version of the model with perception errors and random daily shocks. In Figure 1, we present these confidence intervals, along with the actual observations, by individual employee. To avoid clutter, we place observation number on the horizontal axis. The confidence interval corresponding to each observation is marked by a "C" to denote control observations and a "T" to denote treatment observations. The actual observation is symbolized by the regular piece rate for the plot on which the observation occurred. The logarithm of daily productivity is given on the vertical axis.

The model fits the data quite well, although, in strict terms, the model is rejected by the data. In all, ninety percent of the observations fall within the 95-percent confidence intervals. What is more, since the output and effort elasticities coincide in our model, we can compare the estimated output elasticity from the structural model to that from the ANOVA model. We note that these parameters are very close, 0.37 for the structural model and 0.39 for the ANOVA model; any mis-specification does not have a large effect on the estimated parameter of interest. As always, there is a trade-off in the application of structural models to data. Invariably, structural models do not fit the data as well as their unrestricted counterparts. However, structural models allow one to make behavioural interpretations of the results and to investigate alternative policies unobserved during the experiment. We develop this latter point in the next section.

7. Policy Analysis: Alternative Contracts and Costs

Estimating the structural model allows us to predict the performance of alternative contracts, not observed during the experiment. It is noteworthy that the observed contract has only one instrument, the piece rate. Given changing planting conditions, the piece rate must accomplish two tasks: providing incentives for effort and guaranteeing labour supply. A contract that includes a base wage allows the firm to separate the tasks of two instruments, the piece rate providing incentives and the base wage satisfying labour supply. In this section, we consider how the introduction of a base wage into the contract would affect firm profits.

The base-wage contract includes a base wage B and a piece rate R and takes the form

$$I = B_{ij} + RY.$$

To compare contracts, we denote

$$E(r) = \left(\frac{rsw}{\kappa_i}\right)^{\gamma}$$

the effort level under the observed piece-rate contract, and

$$E(B,R) = \left(\frac{Rsw}{\kappa_i}\right)^{\gamma}$$

the effort level under the alternative base-wage contract.

We solve for the base-wage contract that would give each worker the same utility level he or she currently earns under the observed contract. From equation (6.1), expected utility is given by

$$\mathcal{E}(U_{ij}^{r}) = \frac{r_j^{\gamma+1}\exp[(\gamma+1)\tilde{\mu}_j + 0.5(\gamma+1)^2(\sigma_j^2+\sigma_\nu^2)]}{\kappa_i^{\gamma}(\gamma+1)\exp[-(\gamma+1)\mu_{Wj} - 0.5(\gamma+1)^2\sigma_W^2]}.$$

From equation (6.13),

$$r_j^{\gamma+1}\exp[(\gamma+1)\tilde{\mu}_j+0.5(\gamma+1)^2(\sigma_j^2+\sigma_\nu^2)]\exp[(\gamma+1)\mu_{Wj}+0.5(\gamma+1)^2\sigma_W^2] = \bar{u}(\gamma+1)\kappa_h^{\gamma}.$$

Substitution yields

$$\mathcal{E}(U_{ij}^{r}) = \left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\bar{u}.$$

Under the base-wage contract, expected utility is given by

$$\begin{aligned}\mathcal{E}[U_{ij}^{(B,R)}] &= \mathcal{E}\left[B + RE(B,R)WS - \kappa_i \frac{\gamma}{\gamma+1} E(B,R)^{\frac{(\gamma+1)}{\gamma}}\right] \\ &= B + \frac{R^{(\gamma+1)} \exp[(\gamma+1)\tilde{\mu}_j + 0.5(\gamma+1)^2(\sigma_j^2 + \sigma_\nu^2)]}{\kappa_i^\gamma (\gamma+1)\exp[-(\gamma+1)\mu_{Wj} - 0.5(\gamma+1)^2\sigma_W^2]} \\ &= B + \frac{R^{(\gamma+1)}}{r^{(\gamma+1)}}\left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \bar{u}.\end{aligned}$$

Solving for the level of B that guarantees current utility yields

$$B_{ij}(R) = \left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \bar{u}\left[1 - \frac{R^{(\gamma+1)}}{r^{(\gamma+1)}}\right]. \tag{7.1}$$

Given $B(R)$ and R, we can write expected profits per worker under any base-wage contract as

$$(P-R)R^\gamma \bar{u}\left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \frac{(\gamma+1)}{r^{\gamma+1}} - \bar{u}\left(\frac{\kappa_h}{\kappa_i}\right)^\gamma\left[1 - \left(\frac{R}{r}\right)^{\gamma+1}\right]. \tag{7.2}$$

Maximizing equation (7.2)with respect to R yields the standard solution

$$\hat{R} = P,$$

from which it follows

$$\hat{B} = \left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \bar{u}\left[1 - \frac{P^{(\gamma+1)}}{r^{(\gamma+1)}}\right].$$

Expected profits per worker under the base-wage contract are

$$\pi^{(B,R)} = -\hat{B} = \left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \bar{u}\left[\frac{P^{(\gamma+1)}}{r^{(\gamma+1)}} - 1\right].$$

Under the piece-rate contract, expected profits per worker are given by

$$\pi^r = \frac{(P-r)}{r}\left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \bar{u}(\gamma+1). \tag{7.3}$$

Corollary 1.

Expected profits per worker under the observed and base-wage contracts as defined by (7.3) and (7.2) are identified from (6.8) and are given by

$$\begin{aligned} \mathcal{E}(Profit|r) &= \frac{P-r}{r}\psi_i(\gamma+1) \\ \mathcal{E}(Profit|R,B) &= \frac{(P-R)}{r^{\gamma+1}}R^{\gamma}\psi_i(\gamma+1) - \psi_i\left[1-\left(\frac{R}{r}\right)^{\gamma+1}\right] \end{aligned} \tag{7.4}$$

where

$$\begin{aligned} \psi_i &\equiv \exp(a_0)\exp(\gamma a_{1i}) = \bar{u}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}; \\ a_0 &= \log\bar{u} + \gamma[\log(\kappa_h) - \log(\kappa_1)]; \\ a_{1i} &= [\log(\kappa_1) - \log(\kappa_i)]. \end{aligned}$$

Proof of Corollary 1

The proof follows from the fact that profits are functions of observables and estimated parameters. We concentrate on the case (ii) of Theorem 1, when the marginal individual is not in the experimental sample. Let

$$\begin{aligned} a_0 &= \log\bar{u} + \gamma[\log(\kappa_h) - \log(\kappa_1)] \\ a_{1i} &= [\log(\kappa_1) - \log(\kappa_i)]. \end{aligned}$$

and define

$$\psi_i \equiv \exp(a_0)\exp(\gamma a_{1i}) = \bar{u}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}.$$

Finally, note that a_0, a_{1i}, and γ are identified from (6.8).

In Table 12, we present a summary of contractual performance on each experimental block, evaluated at the estimates from Table 11 (d); *i.e.*, allowing for daily shocks and perception errors. In the first column, we present the piece rate paid under the actual contract, while in the second column we present the optimal piece rate under the base-wage contract. In the third column, we present the average base-wage

Table 12 *Base-Wage Contract Profits*

Block	Rate Paid	Optimal Rate	Base Wage	π^r	$\pi^{(B,R)}$	Percent Increase
I	0.180	0.332	−189.15	166.84	189.15	13.4%
II	0.230	0.349	−111.03	102.22	111.03	8.6%
III	0.230	0.332	−94.17	87.62	94.17	7.5%

under the base-wage contract; in the fourth column, we present expected profits under the actual piece-rate contract, in the fifth column, we present expected profits under the base-wage contract, and in the sixth column we present the percent increase in expected profit by switching to the base-wage contract.

We estimate the percentage increase in expected profits to be between 7 and 13 percent. Since the base-wage contract is the optimal contract, this gives a measure of the contractual inefficiency within the firm.[15]

8. Discussion and Conclusions

Economists are increasingly turning to experiments to gather data concerning individual behaviour. Experiments allow for the random allocation of treatments, simplifying identification and estimation. Field experiments extend the benefits of exogenous variation in treatments to real-world data, facilitating the generalization of statistical results. Field experiments provide a simple, yet powerful, tool for analysing the effects of different personnel policies within the firm.

We have analysed data from one such field experiment, designed to measure the reaction of workers to changes in piece-rate incentives. The experimental variation in the piece rate allows for the direct measurement of reactions within an unrestricted

[15] Despite the fact that the percent increase in profits depends only on observables and γ, it is not identified at the unrestricted estimates of the ANOVA model. This occurs because the percentage increase in profits depends only on γ *in the restricted model.* It does not necessarily depend only on γ, in general. The policy analysis is only valid if undertaken at the restricted estimates.

framework. Our results suggest that workers do react to incentives. We report an output elasticity with respect to changes in the piece rate of 0.39. This accords with previous results obtained by Paarsch and Shearer (1999) and Haley (2003): piece rate payment systems do affect worker behaviour. On a broader scale, our results are also consistent with the literature investigating incentive effects. Specifically, as Paarsch and Shearer (2000), Lazear (2002), and Shearer (2004) have also found, incentives do matter.

At a more detailed level, the measured experimental reaction to incentives is lower than previous, non-experimental, estimates; see, for example, Paarsch and Shearer (1999) and Haley (2003). A number of possible explanations for this exist. First, previous models used structural econometric methods to identify the effort elasticity. As demonstrated in Theorem 1, these models required identifying assumptions concerning the value of alternative utility and the estimate of the effort elasticity is sensitive to those assumptions. Another potential contributing factor to the low experimental response is that worker effort may not be a continuous variable. In particular, upper limits to effort and productivity may exist. A structural model which assumes that worker response is continuous to incentives may over estimate the resulting incentive effect, particularly if daily worker effort is situated near the upper bound. A final consideration is that the effort elasticity may be heterogeneous. To date, researchers have estimated models with constant elasticities, or homogeneous treatment effects. Yet the varying results may reflect the fact that treatments are heterogeneous, either across planters or sites. Paarsch and Shearer (2004) have presented one attempt to consider such a model. Future investigation of these issues will increase our understanding of the efficiency of incentive systems within firms.

We have also considered the relative benefits of estimating structural and econometric models using experimental data. In general, the ability to generalize experimental results to evaluate policies unobserved within the experimental setting represents the major advantage of structural estimation. In fact, experiments are also beneficial to structural estimation methods, providing exogenous variation which reduces the sensitivity of the results to functional-form assumptions.

Our results suggest that a contract which includes a base wage, in addition to a piece rate, will increase firm profits between 7 and 13 percent. It is important to note, however, that such a contract may come with added, unmodelled, costs. In particular, whereas the piece-rate contract is only plot specific, the base-wage contract is individual and plot specific. The costs of negotiating such a contract may outweigh the benefits of its implementation; see, for example, Ferrall and Shearer (1999) for a discussion of the role implementation costs play in the determination of contracts. Note too that under the base-wage contract individuals may have an incentive to misrepresent their abilities in order to extract rents from the firm. One interpretation of our results is to provide a lower bound to the cost of implementing such a contract.

Our results also suggest a number of directions for future research. Income effects may affect effort elasticities as they do other labour-supply decisions. Indeed, to the extent that income effects are important, our results on the introduction of a base wage maybe overstated. In general, it is difficult to identify an income and a substitution effect from changes in the piece rate alone. Experimental methods are an obvious remedy, allowing researchers to vary both the piece rate and a base wage independently. Dickens (1999) has provided an example within a laboratory setting; field experiments would provide the opportunity to confirm his results within the labour market.

We also ignore dynamic elements in the contracting environment. Yet worker effort decisions may depend on fatigue levels (or effort costs) that are the result of previous effort levels. Under these circumstances, worker-effort decisions will take account of their effect on future income levels, giving rise to a dynamic model of effort choice. Dynamics may also be important in the choice of the contract. In particular, the firm may have incentive to change the contract as information about conditions or worker type is revealed. While the consequences of a lack of commitment have been identified by theorists, empirical work has yet to measure their importance. These extensions remain important areas of future research.

Figure 1

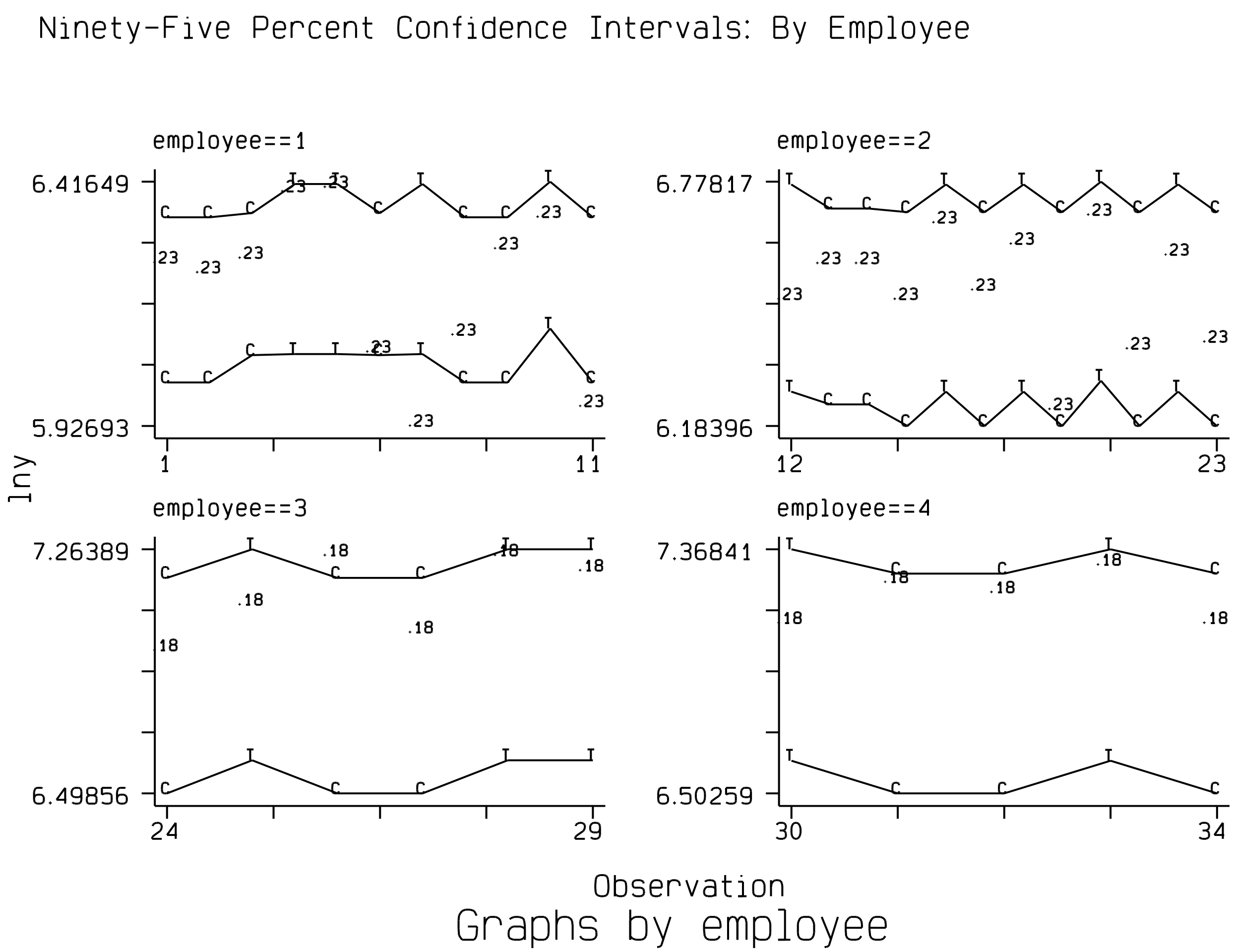

Ninety-Five Percent Confidence Intervals: By Employee
employee==1
employee==2
employee==3
employee==4
6.41649
5.92693
6.77817
6.18396
7.26389
6.49856
7.36841
6.50259
1
11
12
23
24
29
30
34
lny
Observation
Graphs by employee

Figure 1 (continued)

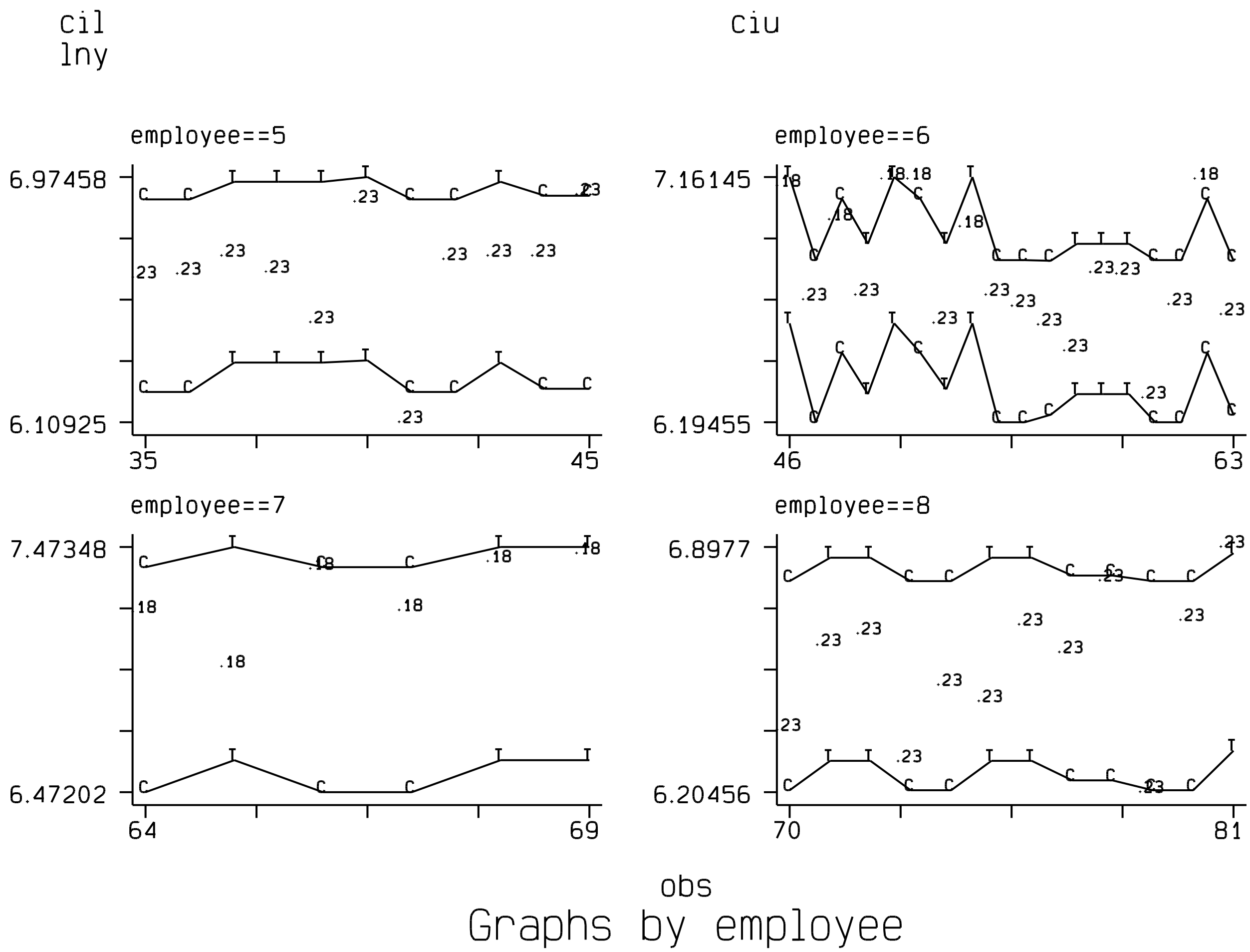


Figure 1 (continued)

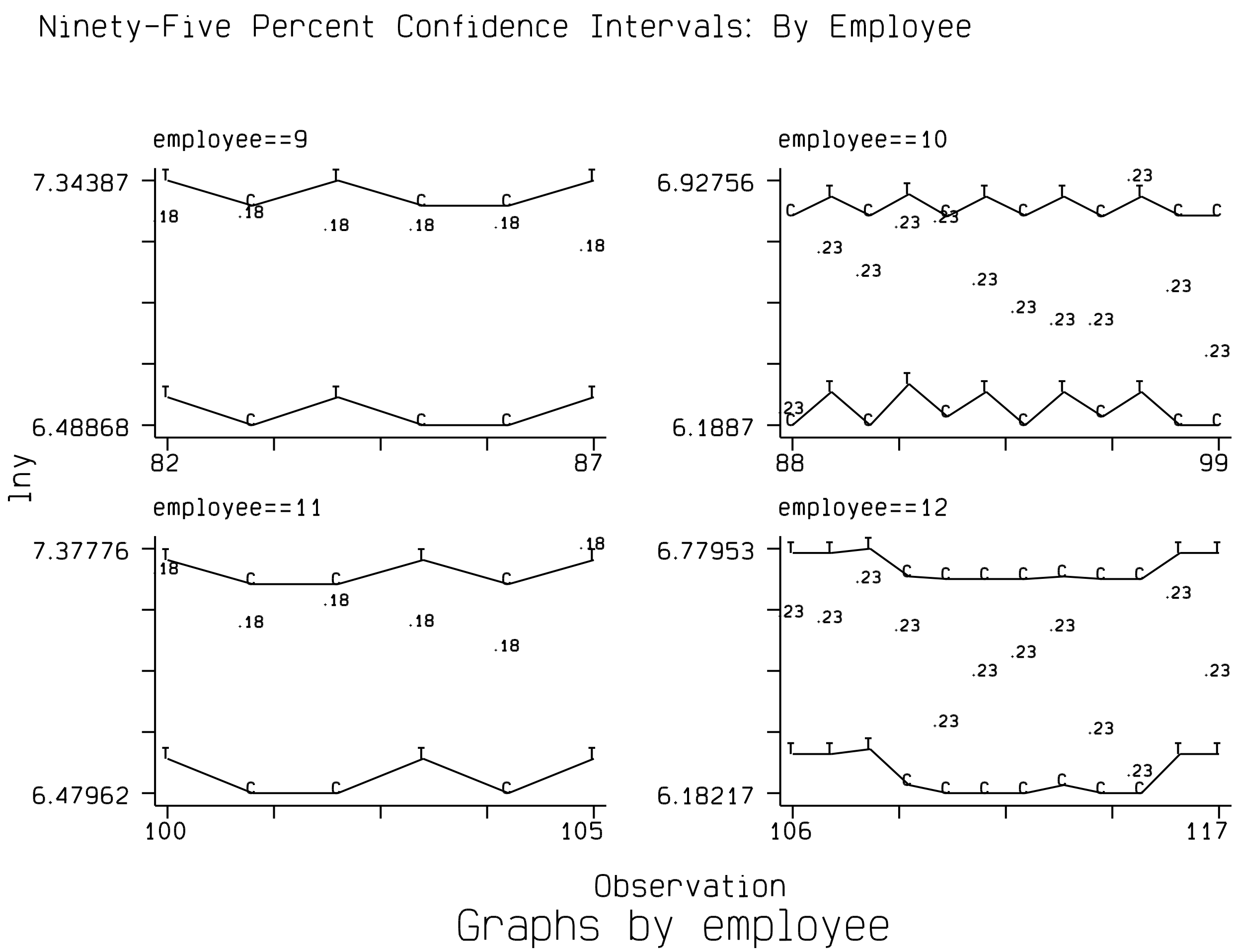


Figure 1 (continued)

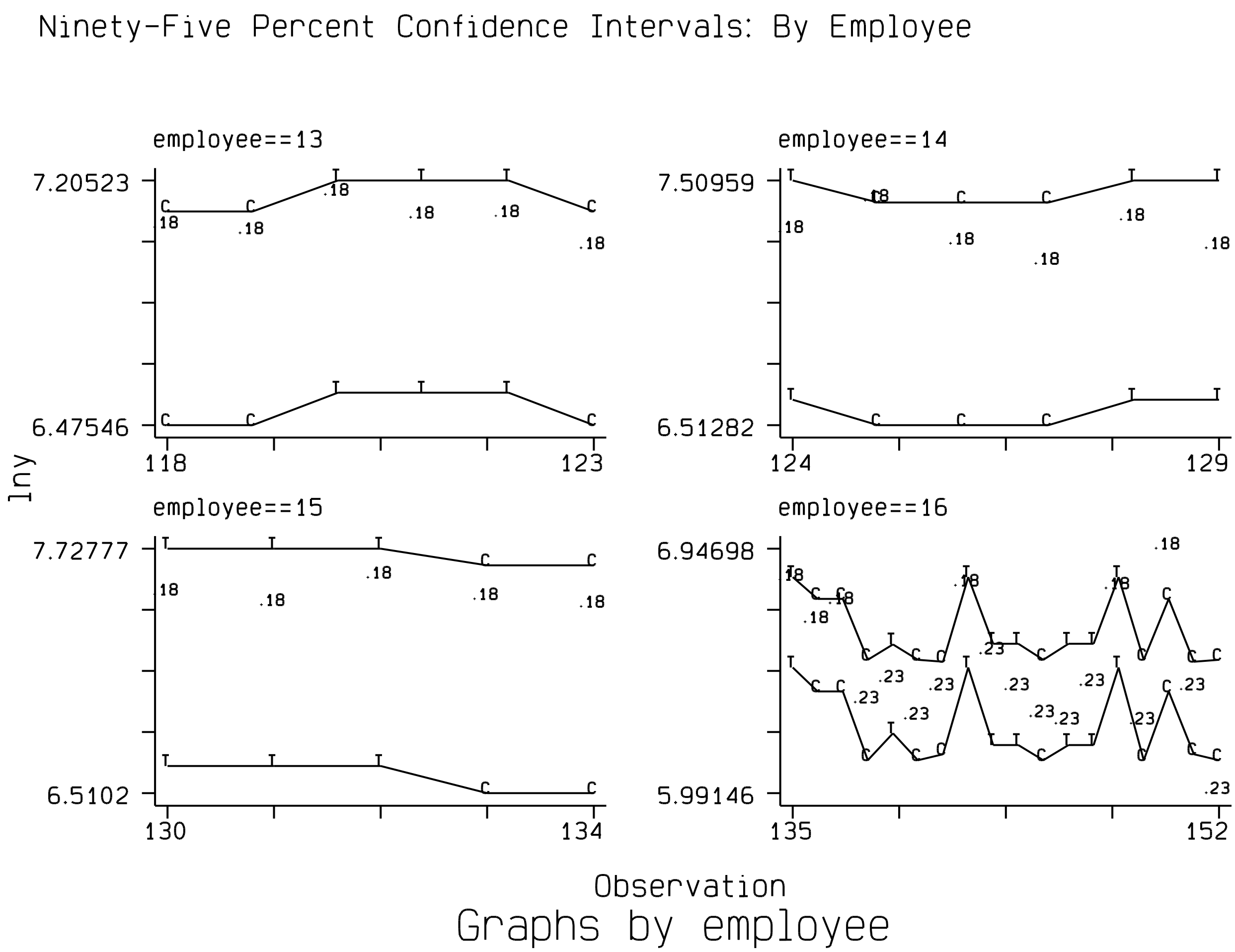
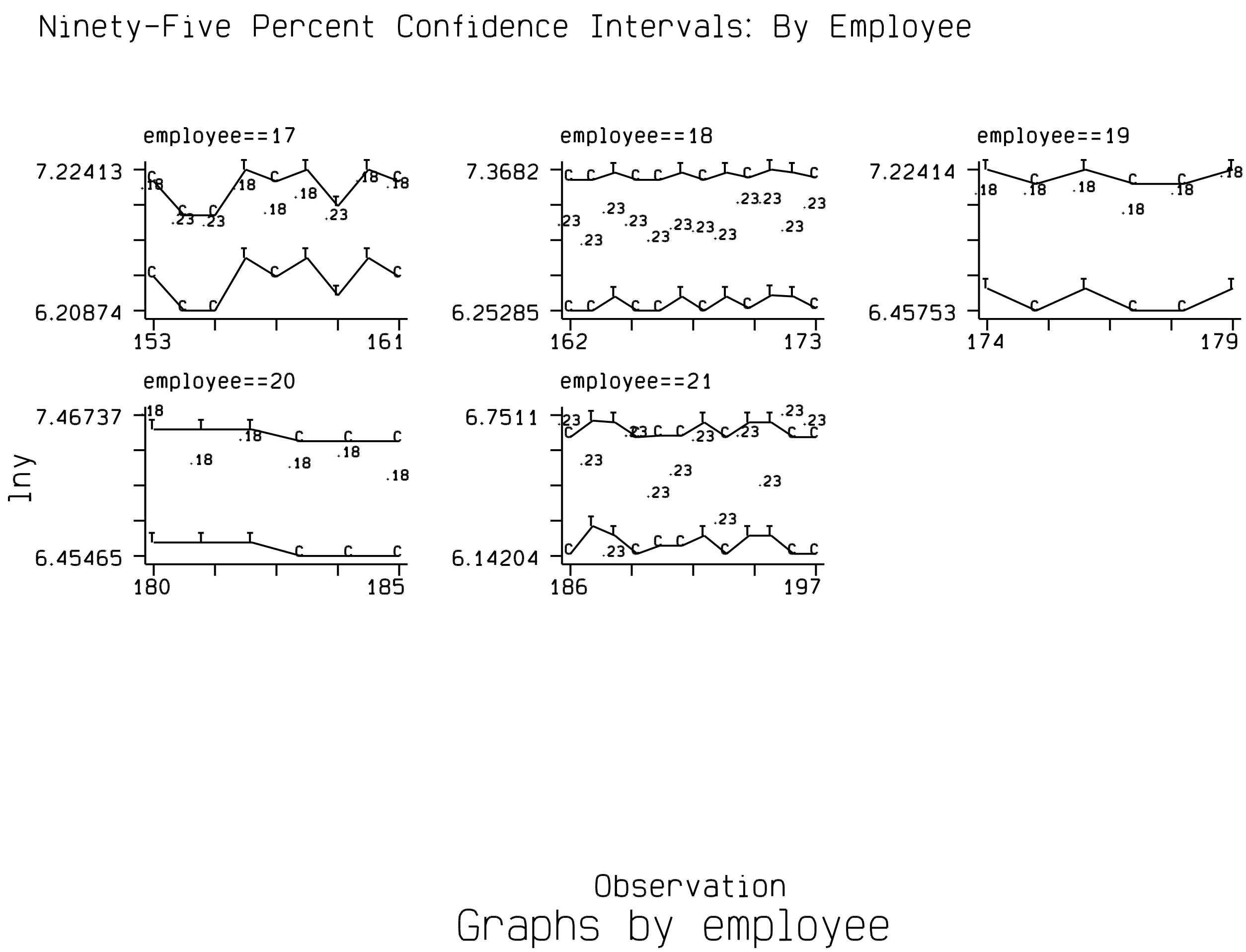


Figure 1 (continued)



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