CIRPÉE
Centre interuniversitaire sur le risque, les politiques économiques et l'emploi

Cahier de recherche/Working Paper **07-01**

The Response to Incentives and Contractual Efficiency: Evidence from a Field Experiment

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Janvier/January 2007

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This paper circulated previously as "The Response of Worker Effort to Piece Rates: Evidence from a Field Experiment". The authors gratefully acknowledge research support from SSHRC. Shearer also acknowledges support from FQRSC and the Canada Research Chair in Social Policies and Human Resources at the Université Laval. For helpful comments and useful suggestions, the authors thank Uwe Sunde, and Lawrence Kahn. They also thank seminar participants at the HEC Montréal, the Université Laval, and the University of North Carolina at Chapel Hill as well as participants at the First Annual IZA Workshop on Behavioral and Organizational Economics (Bonn), the Society of Labor Economics Second World Congress (San Francisco) and the Atelier en Économie du Travail (UQAM).

Abstract:
We investigate the efficiency of piece-rate contracts using data from a field experiment, conducted within a tree-planting firm. During the experiment, the piece rate paid to planters was exogenously increased. Regression methods yield an estimate of the elasticity of output with respect to changes in the piece rate of 0.39. Regression methods are limited in their ability to predict the performance of alternative contracts. Therefore, we apply structural methods to interpret the experimental data. Our structural estimate of the elasticity is 0.37, very close to the regression estimate. Importantly, our structural model is identified without imposing profit maximization. This allows us to evaluate the optimality of the observed contract. We simply measure the profit distance between the observed contract and the profit-maximizing contract, evaluated at the structural parameter estimates. We estimate this distance to be negligible, suggesting that the observed contract closely approximates the expected-profit maximizing contract under asymmetric information. Under complete information, expected profits would increase by approximately fourteen percent, holding expected utility constant.

Keywords: Incentives, Contractual Efficiency, Field Experiments

JEL Classification: J33, J41, C93

1. Introduction and Motivation

Worker performance under different contracts plays 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; see, for example, Hart and Holmström (1987), Holmström and Milgrom (1990), Milgrom and Roberts (1992), and Baker (1992). In the related and recently-developed field of personnel economics — see, for example, Lazear (1998) — compensation systems are considered policy instruments of the firm which can be used to improve the performance of workers and the profits of firms. Recently, researchers have used data from payroll records 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), Haley (2003), Copeland and Monnet (2003), Shearer (2004), as well as Bandiera, Barankay, and Rasul (2004).[1]

Despite the growing number of data sets available for analyzing incentive models, little is known of the efficiency of observed contracts within firms. Do observed contracts maximize profits? At one level, the answer is obviously no. Optimal contracts take into account all relevant information and are typically complicated, nonlinear functions; see Holmström (1979). Observed contracts, on the other hand, are often simple, linear functions of output; see Stiglitz (1991). Explanations of these differences typically involve the added costs of implementing complicated contracts; see, for example, Holmström and Milgrom (1990) as well as Ferrall and Shearer (1999). The relevant empirical question is perhaps: Do observed contracts maximize profits within a subset of easily-implemented — local — alternatives? However, even this question can be difficult to answer. Reduced-form econometric methods cannot recover the structural parameters that would permit one to compare the profit performance of

[1] For reviews of this literature, see Prendergast (1999) and Chiappori and Salanié (2003).

different contracts, while structural econometric methods typically impose profit maximization to obtain identification of technological and preference parameters. While imposing the hypothesis of profit maximization allows one to compare profits across contracts, the optimality of the observed contract is maintained, so cannot be tested.

Evaluating the local optimality of observed contracts requires identifying structural parameters without imposing profit maximization. One strategy is to obtain econometric identification using only a subset of the constraints implied by a complete economic model. In economic models of contracts, researchers typically impose multiple constraints on the firm's choice of a contract. For example, in the standard principal-agent model, the firm chooses a contract to maximize expected profits subject to incentive compatibility as well as a participation constraint. Below, we show that it is possible to identify the parameters of an empirical principal-agent model using a subset of these constraints, excluding expected-profit maximization on the part of the firm. This strategy allows us to calculate expected profits conditional on the estimated parameters and to compare the profits of the observed contracts with other, local alternatives.

Our data come from a field experiment conducted within a tree-planting firm operating in British Columbia, Canada. Workers in this firm are typically paid piece rates: A worker'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.

Previous work by Paarsch and Shearer (1999 and 2000) has used structural econometric methods to solve for endogeneity problems in non-experimental contractual data. Here, we exploit experiments. Experiments provide a simple, yet powerful way to solve endogeneity problems (Burtless, 1995). As in Shearer (2004) we apply both unrestricted and structural econometric methods to the experimental data. However, whereas Shearer (2004) was primarily concerned with comparing productivity under piece rates and fixed wages, exploiting his structural model to generalize experimental results to nonexperimental settings, here we seek to test the profit-maximization hypothesis.

Our 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), while 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 generated 197 observations on daily productivity, 109 at regular piece rates and 88 at treatment piece rates.

We begin our analysis of these data using regression methods. These methods provide an unrestricted estimate of the treatment effect of increasing the piece rate. We estimate the elasticity of worker productivity with respect to experimental changes in the piece rate to be 0.39. We also investigated the importance of potentially confounding factors, such as weather, fatigue, and endogenous participation, but found them to be unimportant, both economically and statistically.

The regression estimates have no direct interpretation in terms of economic fundamentals. What is more, they are limited in their ability to predict behaviour under alternative contracts, not observed in the experiment; see Wolpin (1995). To undertake such a comparison, we turned to structural methods. We used information gathered during extensive discussions with firm managers to guide our modelling of worker and firm decision-rules over effort and the contract. We model the choice of contract as satisfying a worker's participation constraint, subject to optimal effort choices on the part of workers. This allows us to capture the correlation between planting conditions and the piece rate, without imposing expected-profit maximization. Incorporating these decision rules into the estimation strategy admits identification of the model's parameters and estimation via the methods of maximum likelihood. The maximum-likelihood estimate of the elasticity of output with respect to the piece rate is 0.37, very close to the unrestricted regression estimate.

We evaluated contractual performance at the maximum-likelihood estimates of the structural model, comparing expected profits realized under the observed contract with those attainable under alternative contracts. The observed contract is a constrained, linear contract; the base wage is set to zero. To test the hypothesis that this contract maximizes expected profits, we derived the optimal, unconstrained, linear contract, consisting of a piece rate and a base wage. We found that this contract would have a negligible effect on firm expected profits. This suggests that the observed contract is a close approximation to the expected-profit maximizing contract, at least among a local set of alternative contracts.

Our results also suggest that the firm foregoes large gains by failing to tailor its contracts to individual abilities, pointing to the likely importance of intertemporal commitment, once worker types are revealed. In particular, introducing an individual-specific base wage into the contract would increase the firm's expected profits by approximately fourteen percent, leaving workers indifferent between the base-wage contract and the observed contract. Expected profits would increase by approximately forty-five percent were the firm to use the base-wage contract to capture rents from the workers.

Our 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. Institutional Details

2.1. 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.

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, and 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. A worker's productivity depends on his/her effort level as well as the terrain on which he/she is planting. 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*. Because seedlings must be planted directly in the soil, screefing simplifies planting. Sites that are relatively flat, that are free of rocks, or that have been screefed are much easier to plant than sites that are very steep or have not been screefed. The typical density of seedlings is between 1200 and 1800 stems per hectare, an inter-tree spacing of about 2.4 to 2.8 metres.[2] Depending on the conditions and effort, an average planter can plant between 700 and 1100 trees per day, about half an hectare.

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

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 late summer. Before the bidding, 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 worker 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 area-based schemes are used, albeit infrequently. An area-based scheme is one under which workers are paid in proportion to the area of land they plant in a given day, assuming a particular seedling density.

2.2. Experimental Firm

Our data were collected at a medium-sized, tree-planting company. This company is divided into four contracting units, each under the control of a separate manager. Each manager is responsible for bidding on contracts, hiring workers, and setting piece rates. Essentially, each manager runs an independent firm. Our data are from one of these firms.

At any time, each manager employs between ten and twenty planters. The planters work under the supervision of foremen, approximately one foreman per ten planters. The foremen are responsible for supplying trees to the planters as well as monitoring the quality of planting. Trees that are poorly planted have a lower survival rate than those that are planted well. Depending on the land tenure arrangement, the quality of planting is evaluated by either the government or a timber-harvesting firm, once the contract is completed. Lower-than-acceptable quality subjects the firm to fines. Therefore, the firm monitors its planters closely; poorly-planted trees must be replanted at the planter's expense.[3]

Workers in this firm are typically paid piece rates. Daily earnings are strictly proportional to the number of trees planted on a particular day; no base wage is included in the contract. Blocks to be planted are divided into *plots*, each allocated to an individual worker for planting. For each block, the firm decides on a piece rate. This rate takes into account the expected number of trees that a worker can plant in a day and the expected wage the firm wants to pay. Steep, rocky, unprepared terrain slows the planter down, rendering planting more difficult. Consequently, for a given piece rate workers prefer to plant in easy terrain since they can earn more money for less effort. To induce workers to plant trees in difficult terrain the firm increases the piece rate, satisfying a participation constraint.

It is important to note that under non-experimental conditions the piece rate is the same for all plots in an entire block. No systematic matching of workers to planting conditions occurs in this firm so, even though planters may be heterogeneous, the piece rate received is independent of planter characteristics.

3. Experimental Design

The experiment took place on three separate blocks, over a three-month period. During the experiment, each homogeneous 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 be planted under the treatment piece rate. The treatment piece rate represented an increase of between eight and twenty percent above the regular piece rate.

[3] Problems concerning quality are relatively rare; none is present in our experimental data.

Two limitations in the design of the experiment warrant discussion. First, in order to avoid any possible Hawthorne effects, the experimental change in the piece rate was presented to the workers within the context of the normal daily operations of the firm.[4] To accomplish this, the firm presented the treatment blocks as separate blocks on which planting conditions had changed since the original bid.[5] While this was convincing to the workers, 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. Blocks, large enough to accommodate all workers at once, are typically planted sequentially. This ensures that all workers are planting under similar conditions on the same day. 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 regular 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

$$\tilde{p} = \begin{cases} p > r & \text{for treatment-group observations} \\ r & \text{for control group observations,} \end{cases}$$

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

[4] 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 lighting 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.

[5] This sometimes happens when the block has been unexpectedly prepared, screefed.

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 ($CAD)	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:

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

where Y_{ij} represents trees planted by individual i on block j, r_j represents the piece rate received per tree planted on block 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 the 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_{ij} in equation (4.1).[6] This correlation will result in biased and inconsistent 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

[6] The way in which the firm chooses the piece rate as a function of planting conditions generates this correlation; see Section 2.2.

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	0.03	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

treatment group it was about 26 cents per tree. On average, the control group planted 888 seedlings per day, while the treatment group planted 1012 seedlings.

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

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

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 block; *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 block 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 equation (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 over 0.41.[7]

[7] 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 concentrated on two, weather and fatigue.

5.1. Role of Weather

To control for weather, we collected data on daily rainfall as well as the maximum daily-temperature for the days and the 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.[8] This suggests that macro-weather shocks are not playing a major role.

5.2. The Role of Fatigue

Another, potentially confounding, element that could influence the ANOVA results is worker fatigue. Since the piece rate was increased only after planting was completed

[8] 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			

at the regular rate, workers may, in general, be more tired on treatment-rate days than on control-rate days. We chose to proxy fatigue by cumulative days worked since the last day of rest. From Tables 3 and 4, average cumulative-days-worked are 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 cumulative-days-worked directly into the conditional mean function for productivity and used regression analysis. These results

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			

are presented in Table 7.

Cumulative-days-worked have 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

Table 8
Cumulative-Days-Worked and Participation

	Participation		
Cumulative-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

sample-selection problem. Counteracting this, the experimental increase in the piece 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 planters. Furthermore, since everyone involved in the experiment received the same piece rate on a given day, we know what piece rate a planter forwent by her or his absence.

To investigate the importance of participation decisions in our sample, we document, 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 Table 9, we document that participation decisions are almost identical between treatment and control groups. The participation rates are 97.8 percent and 98.2 percent, respectively, suggesting that the experimental variation in the piece rate had

Table 9
Participation in Treatment and Control Groups

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

a negligible effect on participation.

As a final indication of the importance of participation in our results, we estimated a Probit model linking participation to cumulative-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:

$$P_{it}^{*} = \delta_0 + \delta_1 Days_{it} + \delta_2(\log \widetilde{p} - \log r) + U_{it}, \tag{5.2}$$

estimated using the experimental sample. Here, δ_1 captures the effect of cumulative-days-worked $Days_{it}$ on participation decisions, while δ_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. No evidence exists suggesting 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.[9]

[9] We have also estimated a complete structural model incorporating participation decisions and

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

Independent Variable	Coefficient	Std. Error	p-Value
Constant	2.102	0.354	0.000
Cumulative-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

Above, we have provided 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 when contracts change. Effort levels are sensitive to contracts and must be predicted as contracts change. 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, concentrating on the marginal benefit of introducing a base wage. Importantly, we estimate the structural model without imposing the assumption of expected-profit maximization: To wit, contracts are only chosen to ensure the marginal worker's par-

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 have omitted these results from the paper.

ticipation.[10] We then "test" for the optimality of the observed contract by solving for the optimal base-wage contract (given the estimated structural parameters) and comparing would-be expected profits to those earned under the observed contract.

6.1. Productivity

To begin, 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 has the following 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 assume further a utility function separable in I and E having the following form:

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

[10] This is consistent with the manner in which the firm chooses the piece rate; see section 2.

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 is 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 (or marginal) worker in the firm. The worker with the 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 the marginal worker'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 equation (6.3) into equation (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 equation (6.3), yielding the following empirical specification in terms of random variables:

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

6.4. Identification Results

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

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

or

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

Theorem 1: Identification

Part a)

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 b)

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 a)

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 b)

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 $[\log(\kappa_1) - \log(\kappa_i)]$.

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.[11] In the absence of such variation, when $\tilde{p}_j$ equals r_j, identifying γ requires a measure of alternative utility, $\bar{u}$ and the estimated value of γ will be sensitive to any such measure.[12]

6.5. Empirical Results

We estimated equation (6.7) using the experimental data. The results are presented in Table 11, column (a). The estimate of the elasticity of effort with respect to the piece rate γ is 0.33 and its estimated standard error is 0.09. The value of the logarithm of the likelihood function is 29.25.

The experimental estimate of γ is statistically significant, though substantially smaller than that of Paarsch and Shearer (1999) or Haley (2003). 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 yields an estimate of $\bar{u}$ of \$85.31, considerably larger than that imposed by Paarsch and Shearer (1999) or Haley (2003). 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.

6.6. Correlated Weather Shocks and Perception Errors

Increased flexibility can be obtained in the structural model by introducing daily

[11] Note that the restrictions embodied in equation (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.

[12] This was the identification strategy followed by Paarsch and Shearer (1999) as well as Haley (2003).

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

weather-shocks W and perception errors ν. Perception errors capture the possibility that the firm may misjudge actual planting conditions on a given block. Let daily output be given by

$$Y = ESW$$

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] Furthermore, we assume that the value of W

[13] We place a subscript on average weather-shocks W_j 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.

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

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

Optimal effort is

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

Substituting into productivity and taking logarithms yields

$$\log Y_i = \gamma \log r - \gamma \log \kappa_i + (\gamma + 1) \log S + (\gamma + 1) \log W. \tag{6.9}$$

The piece rate is chosen to satisfy

$$\frac{r_j^{\gamma+1} \exp[(\gamma+1)\tilde{\mu}_j + 0.5(\gamma+1)^2(\sigma_j^2 + \sigma_\nu^2)] \exp[(\gamma+1)\mu_{Wj} + 0.5(\gamma+1)^2\sigma_W^2]}{(\gamma+1)\kappa_h^\gamma} = \bar{u}. \tag{6.10}$$

Substituting equation (6.10) into equation (6.9) yields

$$\begin{aligned} \log Y_{ijt} = & \log \bar{u} + \log(\gamma+1) - \log r_j + \gamma(\log \kappa_h - \log \kappa_i) - \\ & 0.5(\gamma+1)^2 \left(\sigma_j^2 + \sigma_W^2 + \sigma_\nu^2\right) + \gamma(\log \tilde{p}_j - \log r_j) + \varepsilon_{ijt} \end{aligned} \tag{6.11}$$

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

$$
\begin{aligned}
\mathcal{E}(\varepsilon_{ijt}) &= 0 \\
\mathcal{E}(\varepsilon_{itj}\varepsilon_{itj}) &= (\gamma+1)^2(\sigma_j^2 + \sigma_W^2 + \sigma_\nu^2) \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{i'j't}) &= (\gamma+1)^2\sigma_W^2 \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{i'jt'}) &= (\gamma+1)^2\sigma_\nu^2 \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{ij't'}) &= 0 \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{i'jt}) &= (\gamma+1)^2(\sigma_W^2 + \sigma_\nu^2) \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{ijt'}) &= (\gamma+1)^2\sigma_\nu^2 \\
\mathcal{E}(\varepsilon_{ijt}\varepsilon_{ij't}) &= (\gamma+1)^2\sigma_W^2.
\end{aligned}
\tag{6.12}
$$

Estimates of different versions of equation (6.11) are presented in Table 11 — columns (b), (c), and (d). In column (b), we admit 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 37.68. In column (c), we present estimates of the model without weather shocks, but admitting 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 41.07. Finally, in column (d), we present estimates of the model admitting both perception errors and weather shocks; *i.e.*, σ_W and σ_ν are both positive. Here, the estimate of γ is 0.37 and the value of the logarithm of the likelihood function increases to 44.37.[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. Here, we do so simply to provide the reader with some feeling for how much better the models fit when perception errors and daily weather-shocks are included.

by their inclusion. At the same time, the estimated effort elasticity is reasonably stable, ranging from 0.33 to 0.44.

6.7. 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 concentrated 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 placed the 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 affect the estimate of worker reaction to incentives. This is not surprising since identification of this parameter comes mainly through the exogenous change in the piece rate. This highlights the benefits of small-scale experiments. As always, however, 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 Firm Profits

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 — provide incentives for effort and guarantee 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 introducing a base wage into the contract would affect firm profits. Initially, we restrict the alternative contract to be independent of worker type (as is the observed contract), extending this later to allow the firm to condition on worker ability.

Information Assumption 1.

The firm can write contracts on the set $\{\mu, \sigma^2, \kappa_h, f_K(\kappa_i), \gamma\}$,

where $f_K(\kappa_i)$ is the distribution of ability levels in the firm. Throughout, we assume that individual type is independent of productivity and daily weather-shocks.

The base-wage contract includes a base wage B and a piece rate R and, for block j, takes the following form:

$$I = B_j + R_j Y.$$

As with the observed piece-rate contract, the base-wage contract is independent of worker type. This is consistent with two scenarios: First, the firm cannot observe worker type κ_i; second, the firm can observe worker type, but cannot write (or refrains from writing) a contract on it. 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 ensure the marginal worker continues to participate in this firm. This ensures that the distribution of types will not change under the new 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 (6.10),

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

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

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

Solving for a B that guarantees participation of the marginal worker yields

$$B_j(R_j) = \bar{u}\left[1 - \frac{R_j^{(\gamma+1)}}{r_j^{(\gamma+1)}}\right]. \tag{7.1}$$

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

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

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

$$\hat{R} = \frac{\gamma}{(\gamma+\lambda)}P \tag{7.3}$$

where

$$\lambda = \frac{\mathcal{E}\left(\frac{1}{\kappa_i^{\gamma}}\right) - \left(\frac{1}{\kappa_h^{\gamma}}\right)}{\mathcal{E}\left(\frac{1}{\kappa_i^{\gamma}}\right)} < 1 \tag{7.4}$$

given κ_h equals $\max\{\kappa_1, \kappa_2, \ldots, \kappa_n\}$.[15]

Two special cases of the optimal contract imply that incentives are independent of the distribution of worker type $f_K(\kappa_i)$. First, if workers are homogeneous (κ_i is the same for all i), then λ is zero and $\hat{R}$ equals P. Under these circumstances, the firm's marginal return to increasing the piece rate is independent of worker type and the firm can use the base wage to recover the surplus generated by high-powered incentives. This is the standard solution with risk-neutral agents. Second, if the participation constraint does not bind (so $\kappa_h \to \infty$), then λ is one and the firm maximizes profits by setting $\hat{R}$ equal to $[P \times \gamma/(\gamma + 1)]$, equating the firm's marginal revenue of increasing the piece rate to its marginal cost.[16] In the presence of heterogeneous workers, a

[15] If the firm can observe individual ability, but cannot write a contract on κ_i, then the firm's expected profits are

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

The optimal piece rate is then given by

$$\hat{R} = \frac{\gamma}{(\gamma + \lambda)}P,$$

where

$$\lambda = \frac{\sum_{i=1}^{n}\left(\frac{1}{\kappa_i^{\gamma}}\right) - n\left(\frac{1}{\kappa_h^{\gamma}}\right)}{\sum_{i=1}^{n}\left(\frac{1}{\kappa_i^{\gamma}}\right)}.$$

[16] More generally, this solution satisfies the condition

$$\frac{P - \hat{R}}{\hat{R}} = \frac{1}{\gamma} \tag{7.5}$$

which is a variant of the monopolist's price-markup equation. Here, the firm controls the piece rate and sets the markup to be equal to the inverse elasticity of effort.

common base wage and a binding participation constraint, the firm's marginal return to increasing the piece rate is type-dependent; the optimal contract must balance incentives across types.

The optimal base-wage is given by substituting $\hat{R}$ into equation (7.1), yielding expected profits per worker under the base-wage contract

$$\pi^{(B,R)} = (P - \hat{R})\frac{\hat{R}^{\gamma}}{r^{\gamma+1}}\bar{u}(\gamma+1)\mathcal{E}\left[\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\right] - \bar{u}\left[1 - \left(\frac{\hat{R}}{r}\right)^{\gamma+1}\right]. \tag{7.6}$$

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

$$\pi^{r} = \frac{(P-r)}{r}\mathcal{E}\left[\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\right]\bar{u}(\gamma+1). \tag{7.7}$$

We calculated expected profits under the assumption that the marginal individual is in the experiment. This assumption is reasonable given the structure of the firm. Recall that the piece rate on a given contract is chosen by the manager responsible for that contract. In effect, each manager operates his own independent firm within the company, setting piece rates and hiring workers. Since the experiment was completed on one such "firm," it is not unreasonable to assume that the marginal worker is present.[17]

In Table 12 (a), we present a summary of contractual performance on each experimental block, evaluated at the estimates from Table 11 (d); *i.e.*, admitting daily weather-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 price per tree planted received by the firm. In the third column we present the optimal piece rate under the base-wage contract. In the fourth column, we present the base-wage paid under the base-wage contract; in the fifth column, we present expected profits under the actual piece-rate contract; in the sixth column, we present expected

[17] If the marginal individual were not in the data set, then the analysis would still go through, with a slight change in interpretation; *viz.*, by redefining the base wage to satisfy the expected utility of the highest-cost individual in the sample, we can calculate the profits accruing from rendering that individual indifferent between contracts.

profits under the base-wage contract; and, in the seventh column, we present the percent increase in expected profit by switching to the base-wage contract.

We estimate the increase in expected profits to be less than one percent in all three cases. This suggests that the actual contract, which sets the base wage to zero on all blocks, is very close to being the optimal linear contract; to a first approximation, the firm's choice of contracts is maximizing expected profits. We now turn to evaluating the importance of information over worker type on contracts and profits.

7.1. Information over Worker Type

To consider the importance of information to firm profits, we relax the restriction prohibiting the firm to condition the contract on worker type.

Information Assumption 2.

The firm can write contracts on the set $\{\mu, \sigma^2, \kappa_h, \kappa_i, \gamma\}$,

If the firm can condition on worker type, then the optimal contract is to sell the rights to plant trees on a particular block of land to each worker. Since workers earn rents under the current contract, a base-wage contract will have two effects: First, it will allow the firm to tailor the contract to each individual; second, it will allow the firm to capture rents. To decompose the importance of each element in the contract, we distinguish two cases: First, we impose that the base-wage contract ensures *each* worker obtains her or his current level of utility, equal to

$$\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma} \bar{u}.$$

We call these contracts *constant-utility contracts.* Any increase in expected profits from the base-wage contract under these conditions is attributed to conditioning on individual type; second, we allow the firm to reduce the base wage to capture *all* of the rent from each worker, ensuring that each worker earns the alternative utility level, $\bar{u}$. We call these contracts *alternative-utility contracts.*

Table 12 (a)

Base-Wage Contract Expected Profits

Block	Rate Paid	Price	Optimal Rate	Base Wage	π^r	$\pi^{(B,R)}$	Percent Increase
I	0.18	0.33	0.16	14.45	166.84	168.09	0.7%
II	0.23	0.43	0.20	13.35	170.95	172.01	0.6%
III	0.23	0.47	0.22	3.23	207.88	207.94	0.0%

Table 12 (b)

Constant-Utility Base-Wage Contract Expected Profits

Block	Rate Paid	Optimal Rate	Base Wage	π^r	$\pi^{(B,R)}$	Percent Increase
I	0.18	0.33	−189.15	166.84	189.15	13.4%
II	0.23	0.43	−194.23	170.95	194.23	13.6%
III	0.23	0.47	−241.54	207.88	241.54	16.2%

Table 12 (c)

Alternative-Utility Base-Wage Contract Expected Profits

Block	Rate Paid	Optimal Rate	Base Wage	π^r	$\pi^{(B,R)}$	Percent Increase
I	0.18	0.33	−248.00	166.84	248.00	48.6%
II	0.23	0.43	−253.15	170.95	253.15	48.1%
III	0.23	0.47	−300.39	207.88	300.39	44.5%

Case A: Constant-Utility Contracts

The base wage that keeps worker i indifferent between the piece-rate contract and the base-wage contract is given by

$$B_{ij}(R) = \bar{u}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\left[1 - \frac{R^{(\gamma+1)}}{r^{(\gamma+1)}}\right]. \tag{7.8}$$

Therefore, expected profits per worker are given by

$$(P-R)R^{\gamma}\bar{u}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\frac{(\gamma+1)}{r^{\gamma+1}} - \bar{u}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\left[1-\left(\frac{R}{r}\right)^{\gamma+1}\right]. \tag{7.9}$$

Maximizing expected profits over R yields the standard solution

$$\begin{aligned} \hat{R}_j &= P_j \\ B_{ij} &= \bar{u}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\left[1-\left(\frac{P_j}{r_j}\right)^{\gamma+1}\right]. \end{aligned} \tag{7.10}$$

The firm sells the rights to plant on block j to the workers. Each worker pays a fee that depends on her or his cost of effort. Since the piece rate is equal to the price the firm receives per tree planted, profits per worker are equal to $-B_{ij}$.

The relative performance of the constant-utility base-wage contract is presented in Table 12 (b). By introducing a base wage, expected profits would increase by approximately fourteen percent.

Case B: Alternative-Utility Contracts

The firm can capture all of the rent that each worker earns by setting the base wage equal to

$$B_{ij}(R) = \bar{u}\left[1 - \left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\frac{R^{(\gamma+1)}}{r^{(\gamma+1)}}\right]. \tag{7.11}$$

The optimal contract is then given by

$$\begin{aligned} \hat{R}_j &= P_j \\ B_{ij} &= \bar{u}\left[1 - \left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\left(\frac{P}{r}\right)^{\gamma+1}\right]. \end{aligned} \tag{7.12}$$

We calculated the expected profits associated with each of these contracts in Table 12 (c). If the firm were to capture all of the rents workers earn, then expected profits would increase by between forty-four and forty-nine percent.

8. Discussion and Conclusions

Economists are increasingly turning to experiments to gather data concerning individual behaviour. Experiments allow for the exogenous 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; see, for example, French (1953). Field experiments provide a simple, yet powerful, tool for analyzing the effects of different personnel policies within the firm.

We have analyzed data from one such field experiment which was designed to measure the reaction of workers to changes in piece-rate incentives. Experimental variation in the piece rate allows for the direct measurement of reactions within an unrestricted framework. Our results suggest that workers do react to incentives. We estimate 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) as well as 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 (2000), and Shearer (2004) have also found, incentives do matter.

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 point to the importance of worker heterogeneity within the firm as a determinant of contractual performance. Indeed, if heterogeneity is ignored, then the observed contract is locally optimal – adding a base wage would have a negligible effect on expected profits. In contrast, conditioning the base wage on worker type would increase expected profits substantially. This raises the question of why contracts are independent of worker type. One possible explanation is that the firm does not know worker type. However, given the nature of the work and the fact that the firm gathers worker productivity records for payroll purposes, this does not seem to be plausible. An alternative explanation deals with contracting 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. We find that the firm forgoes a fourteen percent increase in expected profits by ignoring heterogeneity. One interpretation is that these results provide a lower bound to the cost of implementing such a contract. Further benefits are predicted were the firm to use the base wage to extract rents from each worker. However, under such circumstances, workers would have an incentive to mis-represent their abilities. This points to intertemporal commitment as an important determinant of observed contracts: The firm commits to refrain from using information over worker type in order to induce high-ability workers to reveal their type.

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 may be 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. Dynamic elements are also highlighted within the contracting environment. We have identified the firm's commitment to ignore worker type as important in implementing the observed contract. The firm may also have incentive to change the contract as information concerning planting conditions are revealed. Extending empirical models to explicitly incorporate learning over conditions and commitment will provide insight into the empirical importance of these issues.

Figure 1

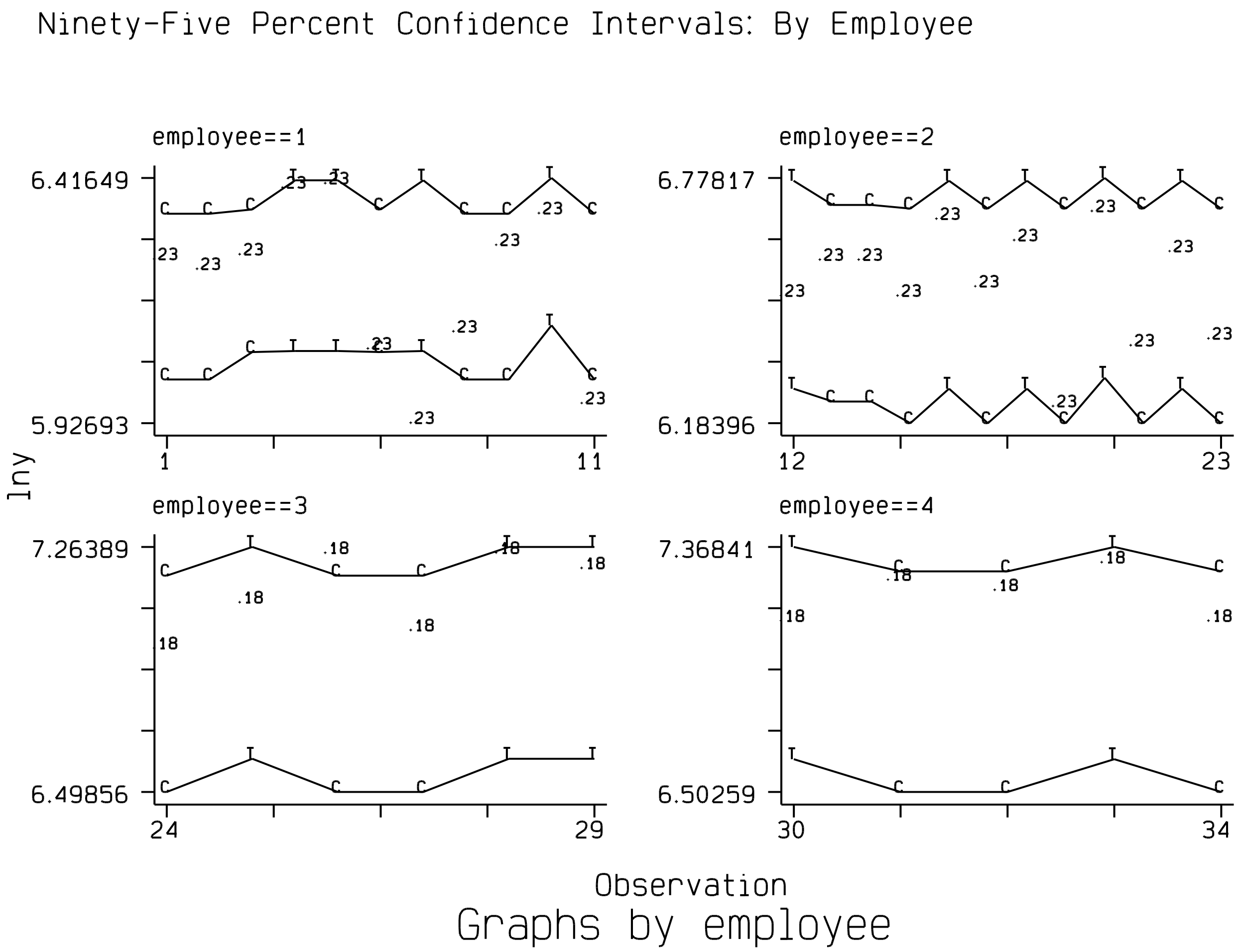

Ninety-Five Percent Confidence Intervals: By Employee
employee==1
employee==2
employee==3
employee==4
6.41649
5.92693
6.77817
6.18396
7.26389
6.49856
7.36841
6.50259
1
11
12
23
24
29
30
34
lny
Observation
Graphs by employee

Figure 1 (continued)

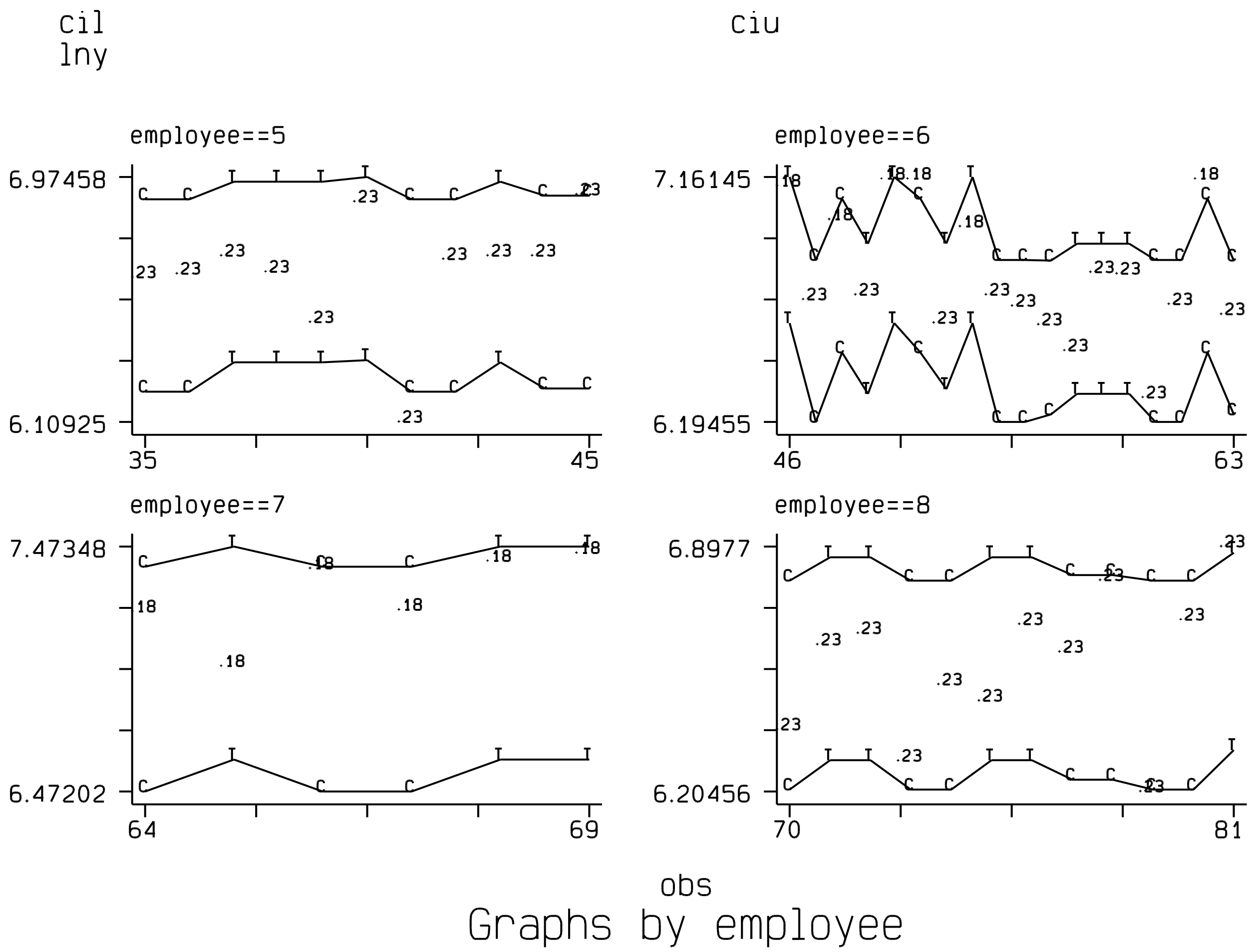


Figure 1 (continued)

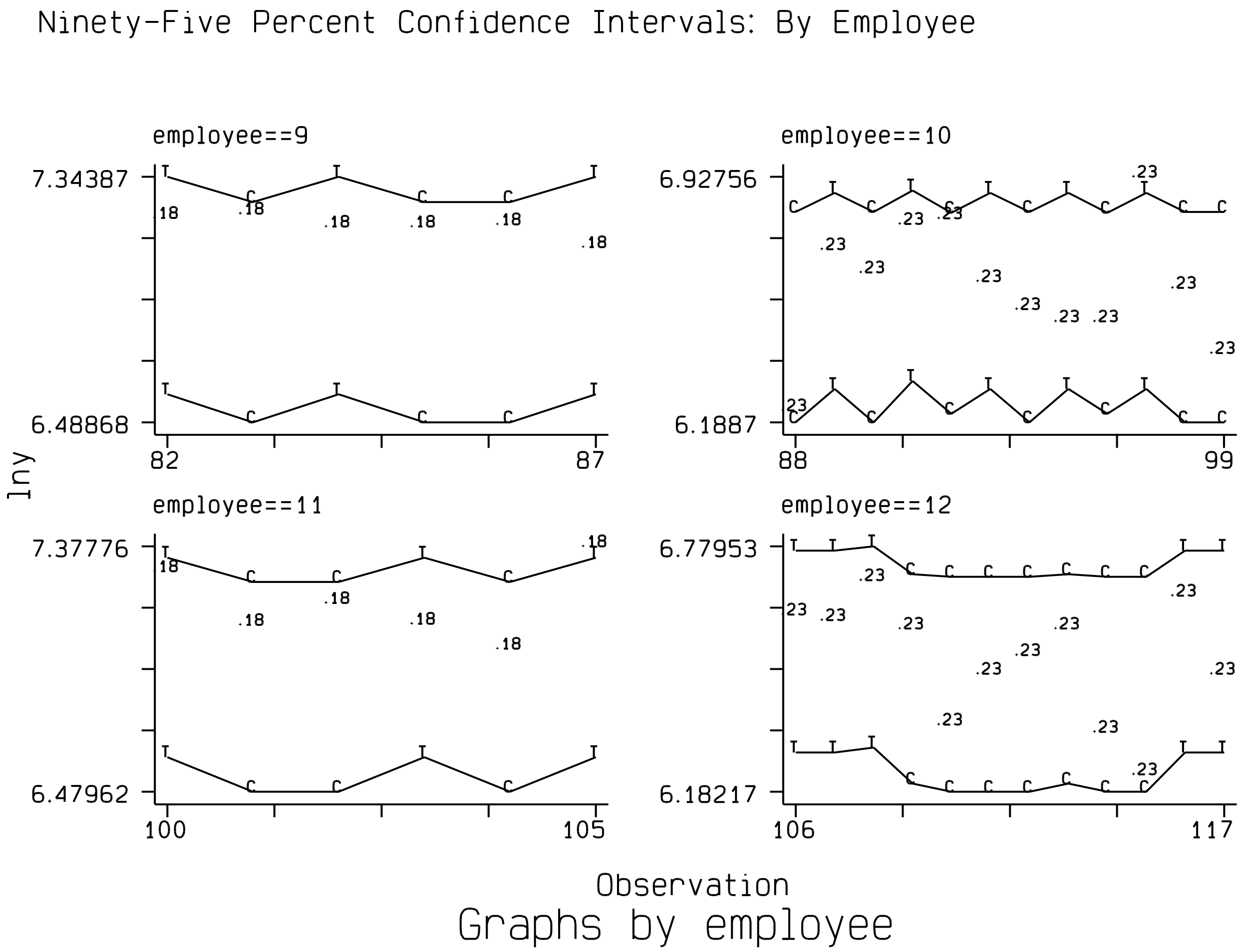


Figure 1 (continued)

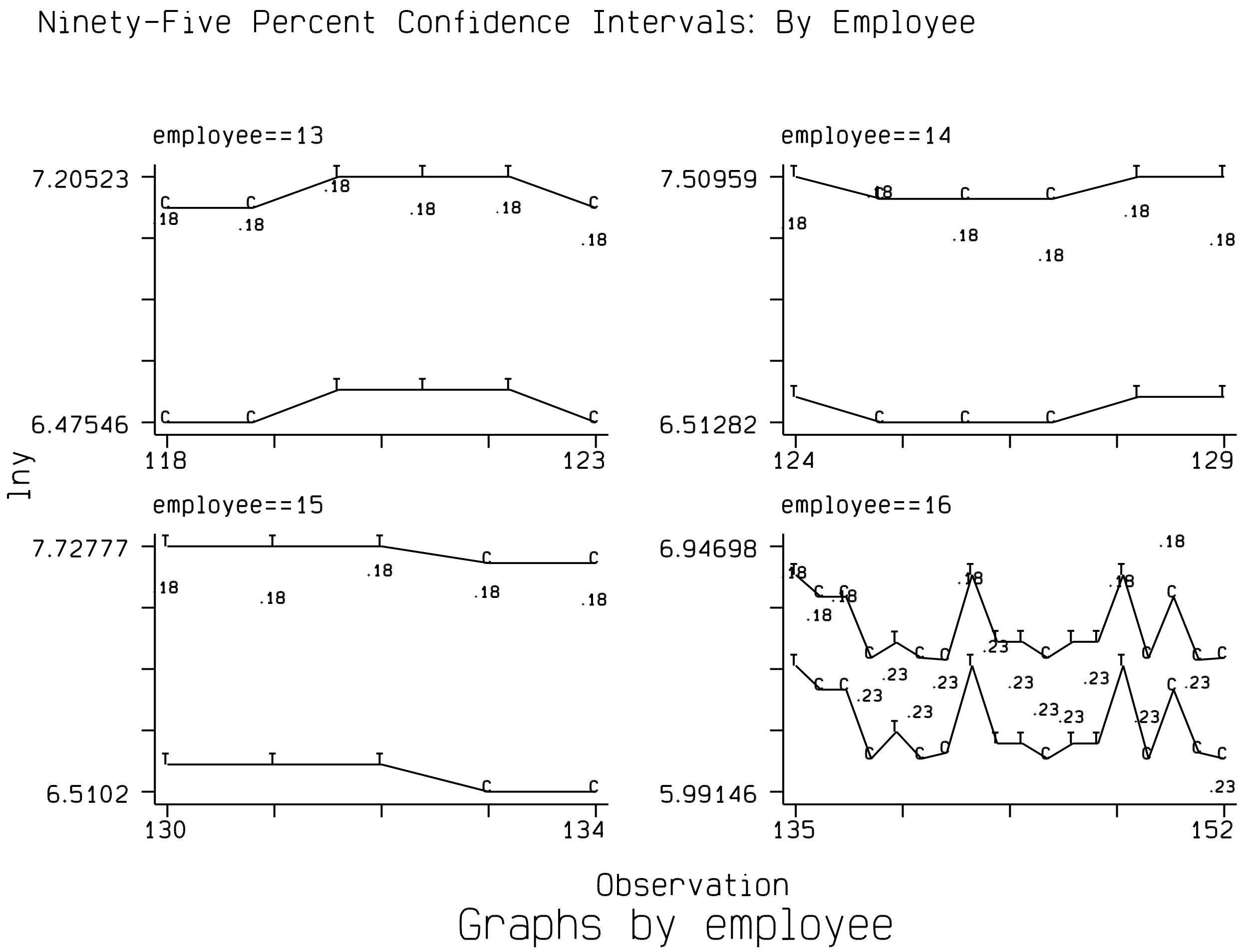
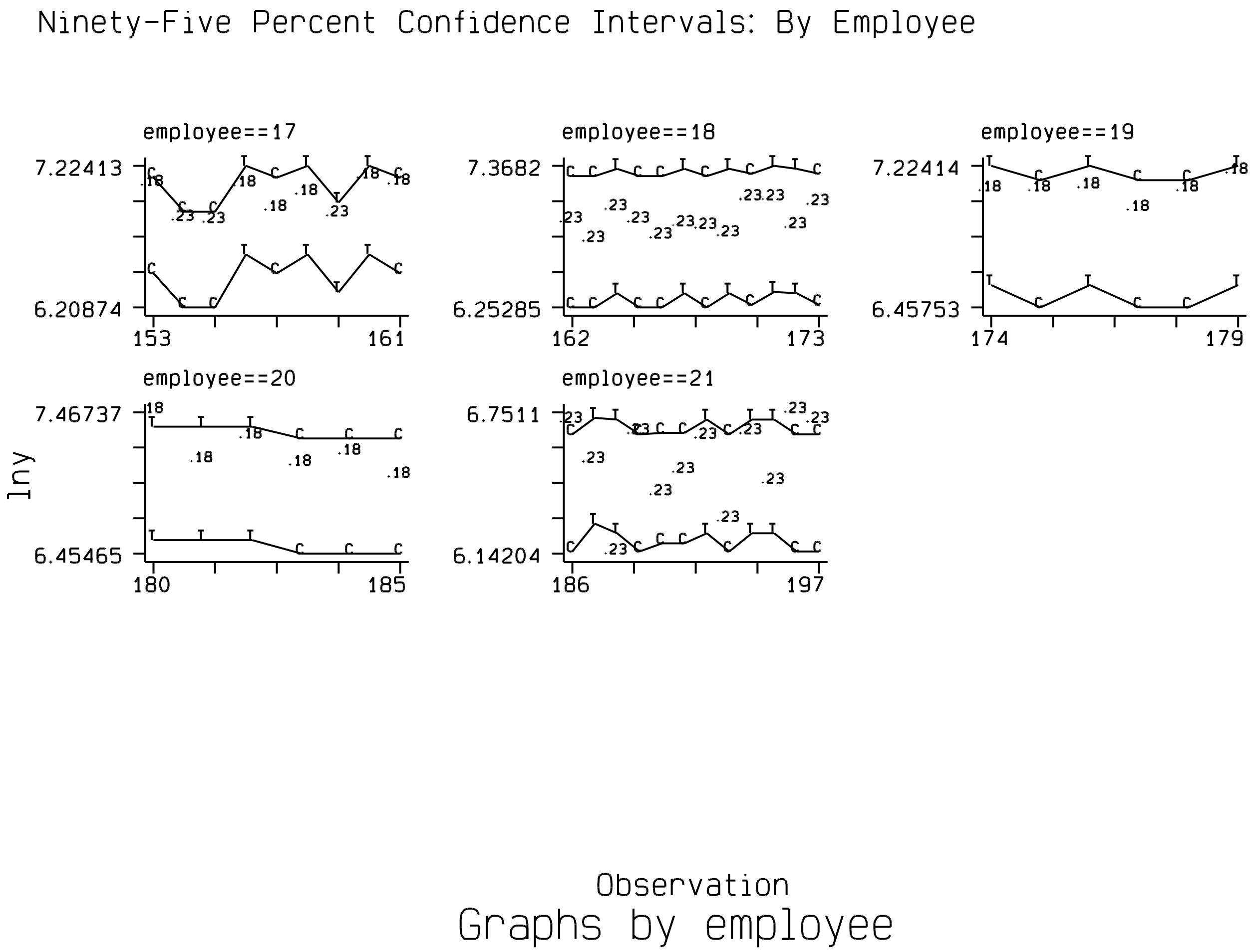


Figure 1 (continued)



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