Worker Heterogeneity and the Economic Importance of Risk and Matching: Evidence from Contractual Data and Field Experiments

Charles Bellemare* Bruce Shearer†

September 16, 2009

Abstract

We measure the importance of risk within a firm that pays its workers piece rates, exploiting data from payroll records and a series of field experiments conducted within the firm. These data are used to identify and estimate worker preferences, abilities and risk exposure. These estimates are combined to measure the workers' cost of risk: their willingness to pay to avoid risky contracts. We find that costs of risk are, on average, small (1% of daily earnings). However, these costs are found to vary substantially across workers (reaching up to 39% of daily earnings), reflecting substantial heterogeneity in worker productivity and risk tolerance. Furthermore, we measure the potential benefits to the firm of reducing risk exposure to risk-averse agents by matching workers to work conditions. We find that matching could increase overall firm profits by up to 12%.

JEL Codes: J33, M52, C93

Keywords: Risk Exposure, Matching, Agency Models.

1 Introduction

Risk and risk preferences have played an important role in the economic theory of the firm. Differences in risk-bearing ability have been used by theorists to explain the existence of firms (Knight, 1921; Kihlstrom and Laffont, 1979) as well as the form of incentive contracts; see, for example, Stiglitz (1975). Yet, in spite of its theoretical significance, little is known as to the economic importance of risk within this setting. Empirical work on contracts has focussed on the tradeoff between risk and incentives (see, for example, Allen and Lueck

*Département d'économique, Université Laval, CIRPÉE and IZA.{email: Charles.Bellemare@ecn.ulaval.ca} .

†Département d'économique, Université Laval, CIRPÉE and IZA. {email: Bruce.Shearer@ecn.ulaval.ca} .
We thank .... We acknowledge research support from SSHRC and the Canada Research Chair in Social Policies and Human Resources at the Université Laval.

(1992)). Profit maximizing contracts minimize the risk exposure of risk-averse workers by muting incentives in high-risk environments. A general inability to detect this implied tradeoff using regression methods has raised doubts over the empirical importance of risk in determining contracts, and, more generally, within firms (Prendergast (2000)).

Yet questions persist over the ability of regression models to measure the importance of risk using contractual data. Beyond problems associated with measuring risk (Laffontaine, 1992), variation in unobserved preferences can lead to selection problems (Chiappori and Salanié, 2003). Ackerberg and Botticini (2002) have argued that the failure of empirical studies to reveal a tradeoff between risk and incentives can be attributed to endogenous matching between workers and firms on the basis of unobservable preferences and/or characteristics.[1]

Perhaps the most direct measure of the importance of risk within a firm is the benefits that accrue to the firm and its workers from eliminating risk. This paper measures these benefits within a firm that pays its workers piece rates. We identify worker risk preferences, worker abilities and risk exposure within the firm, combining payroll data and preference-revealing experiments. We use our estimates to measure the net benefits of risk reduction on two levels: First, we consider the workers' cost of risk – their willingness to pay to avoid risky contracts. Second, we measure the potential benefits to the firm of reducing risk exposure to risk-averse agents by matching workers to risk levels within the firm. Matching allows the firm to increase profits by lowering payment to risk-averse workers in low-variance environments.

Our data come from a British Columbia tree-planting firm. The workers in this firm face substantial daily earnings risk due to random planting conditions. Our payroll data contain information on the contract (the piece rate paid to workers) and the daily productivity of the planters (the number of trees planted) over a period of 5 months. Planting is performed on blocks of contiguous terrain and all workers on the same block receive the same piece rate. Worker productivity depends on their effort level, but also on the soil conditions on which they are planting. Terrain containing rocky or compact soil renders planting more difficult, slowing the planters down and reducing their earnings. The firm

[1] They find a significant tradeoff after controlling for endogenous matching.

adjusts the contract according to the soil conditions on a particular block, yet has incomplete information over those conditions. Planters are therefore exposed to varying levels of planting difficulty under the same contract, and, as a result, daily income risk.

Our empirical strategy is model based. As in Ferrall and Shearer (1999), Paarsch and Shearer (1999, 2000) and Dubois and Vukina (2007), we use the structure of an agency model to interpret contractual data. When risk levels affect worker utility, this leads to compensating earnings differentials (Rosen, 1986) which can be identified from the firm's payroll data. However, when workers are heterogeneous, these differentials identify the preferences of the *marginal worker* (that worker who is indifferent across contracts) and will not identify the full cost of risk (Rees, 1975). What is more, in contractual settings, workers are compensated for their cost of effort in addition to risk.[2] Identifying the full cost of risk therefore requires estimates of the cost of effort as well as the complete distribution of risk preferences within the firm.

To calculate the cost of risk we supplement our payroll data with data from a series of field experiments conducted within the same firm. The first experiment (which we call the "piece-rate experiment") exogenously varies the piece rate paid to workers, identifying worker reaction to incentives (or the cost of effort). The second experiment (which we call the "risk-preference-revealing experiment") follows the methodology developed in Holt and Laury (2002), to identify the distribution of risk preferences of the workers who are observed in the payroll data. Combining identifying information in this way allows experimental knowledge to accumulate in building empirical models. (Heckman, Lalonde and Smith, 1999). Experiments also provide verification that the structural estimates are not overly sensitive to modelling assumptions.

Importantly, our model does not restrict risk preferences ex-ante but allows them to be determined empirically. Our results suggest that the marginal individual in this firm is risk loving. The experimental evidence confirms the presence of risk-loving workers in the firm – approximately 8% of the workers display risk preferences consistent with our estimate of the marginal worker's preferences. It also reveals considerable heterogeneity in risk

[2]This distinguishes empirical work on risk within the context of moral hazard from the context of adverse selection (Cohen and Einav, 2007).

preferences – approximately half of workers display risk aversion, while the remaining half is either risk neutral or risk loving.

Our parameter estimates suggest that, on average, risk is of minor importance to the workers of this firm. Even where risk levels are at their highest observed values, the average cost of risk (as measured by the difference between average earnings and certainty-equivalent earnings) is only $1.25. This represents only 1% of expected net earnings. Yet averaging hides a good deal of heterogeneity. For some workers the cost of risk attains $72.56, representing 39% of their expected net earnings. Matching workers to risk levels within the firm would benefit the firm. Reallocating relatively risk-averse worker from high-risk to low-risk environments would increase profits by up to 12%.

The rest of the paper is organized as follows. The next section provides institutional details of the tree-planting industry in British Columbia and discusses the payroll data. In Section 3, we present the structural model. Identification is discussed in Section 4. Section 5 presents the parameter estimates. In Section 6 we present the policy analysis, presenting the results on the cost of risk and the value of matching. In Section 7 we discuss our results and conclude.

2 Institutional Details

2.1 The Tree-Planting Firm

The data used in this paper were collected from a medium-sized, tree-planting firm throughout the 2006 tree-planting season. This firm is located in British Columbia, Canada and pays its planters piece rates. Daily earnings for a planter are determined by the product of the piece rate and the number of trees he/she planted on that day.

Tree planting is a simple, yet physically exhausting task. Workers are responsible for planting seedlings on recently logged blocks of land. Planters move around the block on foot, carrying seedlings to be planted in a sack that fits around their hips. To plant a tree, they a dig hole in the terrain with a special shovel, place the seedling in the hole and tamp down the earth around the seedling. A worker's productivity depends on his/her effort and the conditions of the terrain being planted. Terrain that is steep or contains compact or rocky soil is more difficult to plant, slowing the planters down.

British Columbia is a mountainous region of Canada and planting conditions can vary a great deal from block to block. Blocks of land to be planted typically contain between 20 and 30 planter-days of work with some lasting over 100 planter-days. Crews of between 10 and 15 planters work under the supervision of a foreman. For each block to be planted, the firm decides on a piece rate to be paid to the planters. The piece rate accounts for the planting conditions on that block. Blocks which are less appealing to planters (due the their steepness, for example) require higher piece rates to attract workers. The piece rate applies to all planting done on a block; no systematic matching of workers to planting conditions occurs within the firm. Workers typically meet at a central location each morning and are transported to the planting sites in trucks. Planters are then assigned to plots of land as they disembark from the truck. Thus, to a first approximation, planters were randomly assigned to planting conditions.

Conditions vary within blocks as well. For example, some parts of a given block may be characterized by rocky soil under the surface, making planting more difficult. Given the firm cannot know completely the undersoil conditions for the whole block, and given the contract is constant within each block, some planters will invariably end up working in more difficult conditions, under the same contract. These random elements expose planters to daily income risk.

2.2 Payroll Data

The payroll data contains information on the piece rate received by each planter, as well as the planter's daily productivity and earnings. We have restricted the data to contain days for which planters received the same piece rate for a complete day of planting.[3] This eliminates the need to aggregate trees and piece rates under different planting conditions. Furthermore, the model we estimate in Section 4 contains individual-specific and block-specific effects. In order to estimate these effects we restricted our sample to include indi-

[3]This eliminates 2497 observations from the data.

viduals and blocks that had at least 15 observations on them.[4]

The summary statistics for these data are presented in Table 1. The top half of the table presents descriptive statistics by planter-day observations of which there are 3709. The piece rate received by planters ranges between \$0.14 and \$0.35, with an average of 0.23.[5] Average daily productivity is 920 trees planted and average earnings are equal to \$197. The standard deviation in daily earnings is equal to \$65.64.

Figure 1A plots the relationship between the piece rate and average natural logarithm of productivity. The downward sloping connected line represents the fitted values from a regression of the log of productivity on the piece rate. The downward slope reflects the manner in which piece rates are set: as conditions become more difficult, slowing the planters down, the firm increases the piece rate. Piece rates also vary depending on the time of the year. According to the firm manager the competition for planters varies across the planting season, affecting the piece rate that must be paid by the firm. This is evident in Figure 1B which plots piece rates paid during the different months of the year. Piece rates were higher in the summer and fall months than in the spring.[6]

To consider whether or not workers of different abilities plant under different conditions, we use average daily earnings per worker (averaged over the whole planting season) as a proxy for ability. In Figure 2 we plot the average ability of the planters versus the piece rates paid, for each month of planting. These graphs show no discernible relationship between piece rates and average earnings, reinforcing the firm's claim that they do not systematically match workers to conditions on the basis of worker ability.[7]

[4] This step eliminates another 850 observations from our data set. Descriptive statistics including those observations are very similar to those we report in the paper and are available upon request.

[5] All monetary figures are in Canadian dollars.

[6] A regression of the piece rate on average productivity and monthly dummy variables shows that the coefficients on the monthly dummies are statistically significantly different from zero – the p-value is equal to 0.0003.

[7] A statistical analysis of these data can be performed by estimating the following regression for each month of planting

$$r_{it} = \beta_0 + \beta \overline{y}_i + \epsilon_{it}, \tag{1}$$

where r_{it} denotes the piece-rate paid to worker i on date t and $\overline{y}_i$ captures the productivity of planter i, defined as the average earnings of the planter (averaged over the entire season). Consistent with Figure 2 we find little evidence to suggest that the firm systematically matches workers to piece rates/conditions based on (1). The

Risk

The bottom half of Table 1 presents summary statistics by block, of which there are 68.[8] We note that blocks display considerable heterogeneity; their size varies from between 16 planting days to 207, with an average of 54.54. The average daily trees planted ranges between 552.14 and 1586.57. The average daily earnings ranges between \$143.56 and \$247.78. The standard deviation of daily trees planted ranges between 118.36 and 639.58. In order to gage the importance of daily earnings risk to individuals we decomposed the variation in daily earnings into variation within and between individual planters. To do so, we ran the regression

$$W_{it} = \mu_0 + \mu_i + \varepsilon_{it}$$

where W_{it} represents the earnings of individual i on day t, μ_i is an individual-specific effect and μ_0 is a constant. The proportion of the total variance in earnings due to within-planter variation, $\boldsymbol{V}(\varepsilon_{it})/\boldsymbol{V}(W_{it})$, is calculated to be 50%. This suggests that considerable earnings variability is beyond the planters' control.

As a preliminary investigation of the relationship between risk and the contract we plot, Figure 3A, the piece rate paid on contract j versus the standard deviation of the natural logarithm of daily output on contract j. The graph shows a negative relationship between the standard deviation of output on a particular block and the piece rate. The solid line represents the fitted values from a regression of the piece rate on the standard deviation of output. The numbers beside each point denote the number of observations on the block. The estimated slope coefficient is $-.149$ with a p-value of 0.001, suggesting that high-variance environments are characterized by lower piece rates.[9] This correlation is consistent with a risk-neutral firm optimally muting incentives in risky environments when contracting with risk-averse workers; see, for example, Milgrom and Roberts (1992), Cahuc and Zilberger (2004). However Figure 3B seemingly contradicts this story. Risk-averse workers should require a risk premium for working in risky environments.

coefficient on $\overline{y}_i$ is statistically significant(at the 5% level) for only 3 of the seven months and among these three significant coefficients, two are positive and one is negative; the results of these regressions are available on request.

[8] A block is defined by the piece rate paid to planters in a given month.

[9] Conditioning on month does not significantly alter these results.

3 Model

3.1 Technology

Daily productivity of worker i on block j is determined by worker effort, E_{ij}, and a productivity shock, S_{ij}

$$Y_{ij} = E_{ij} S_{ij}. \tag{2}$$

The productivity shock represents planting conditions such as hardness and steepness of the ground. We assume that $\ln(S_{ij})$ follows a normal distribution with mean μ_j and variance σ_j^2.

Workers are paid piece rates; their daily earnings W_{ij} are strictly proportional to the number of trees planted; *ie*, $W_{ij} = r_j Y_{ij}$, where r_j denotes the piece-rate paid to all workers planting on block j.

3.2 Utility

Workers are assumed to have CRRA utility functions defined over earnings on block j, W_{ij}, and effort, E_{ij},

$$U(W_{ij}, E_{ij}) = \begin{cases} \frac{1}{\delta_i}\left[W_{ij} - C(E_{ij})\right]^{\delta_i} & \text{if } W_{ij} \geq C(E_{ij}); \\ -\infty & \text{otherwise,} \end{cases} \tag{3}$$

where $C(E_{ij}) = \frac{\kappa_i}{\eta} E_{ij}^{\eta}$ denotes individual i's cost of effort and δ_i denotes the risk-aversion parameter of worker i. These preferences apply under situations where the worker chooses effort as a function of S_{ij}, a timing sequence that we justify below within this setting. An advantage of this specification is that it separates the characterization of risk preferences from the marginal return to effort. Consequently, an optimal effort solution exists under a general characterization of risk preferences.[10]

[10]The major disadvantage in using CRRA utility is the presence of wealth effects. Wealth does not affect effort decisions in this context since utility is separable. It does, however, affect expected utility and hence, potentially, the setting of piece rates. In what follows, we assume wealth to be zero. Given tree planters are typically seasonal workers and/or students with limited outside assets, this seems a reasonable assumption

3.3 Timing

For a given block, j, to be planted:

1. Nature chooses (μ_j, σ_j^2);
2. The firm observes (μ_j, σ_j^2) and chooses the piece rate, r_j;
3. The worker observes (μ_j, σ_j^2, r_j) and accepts or rejects the contract;[11]
4. Conditional on accepting the contract, the worker draws a value s_{ij} from the distribution of S_{ij} and chooses an effort level, producing Y_{ij};
5. The firm observes Y_{ij} and pays earnings W_{ij}.

Workers in this environment are randomly allocated to plant trees on a particular plot of block j – they draw a value of S_{ij}.[12] They then begin to plant trees by digging holes in the ground, revealing how difficult the terrain is for planting. Workers can then adjust their effort levels to those conditions. In this context it seems reasonable to assume that workers observe a draw s_{ij} from the distribution of S_{ij} before selecting an effort level.

3.4 Effort Choice and Output

Conditional on s_{ij}, a particular value of S_{ij}, the worker selects effort to maximize utility. This gives[13]

as a first approximation.

[11] Assuming that the firm and workers observe (μ_j, σ_j^2) abstracts from sampling error and the credible conveyance of information to workers.

[12] Recall, from Section 2.1, the firm does not match workers to conditions.

[13] Given our specification, utility is defined for $E_{ij} \in \left[0, \left(\frac{r_j s_{ij}}{\kappa_i}\right)^{\gamma}\left(\frac{\gamma+1}{\gamma}\right)^{\gamma}\right]$.

The first-order condition for utility maximization is given by

$$\left(r_j e_{ij} s_{ij} - \kappa_i \frac{\gamma}{\gamma+1} e_{ij}^{\frac{\gamma+1}{\gamma}}\right)^{(\delta_i - 1)} (r_j s_{ij} - \kappa_i e_{ij}^{\frac{1}{\gamma}}) = 0. \tag{4}$$

This can be satisfied at two solutions;

$$e_{ij}^1 = \left[\frac{r_j s_{ij}}{\kappa_i}\right]^{\gamma},$$

and

$$e_{ij}^2 \in \left\{0, \left(\frac{\gamma}{\gamma+1}\right)^{\gamma}\left[\frac{r_j s_{ij}}{\kappa_i}\right]^{\gamma}\right\}.$$

$$e_{ij} = \left[\frac{r_j s_{ij}}{\kappa_i}\right]^{\gamma}, \tag{5}$$

where

$$\gamma \equiv \frac{1}{\eta - 1}.$$

Substituting from (5) into (2) and taking logarithms gives the logarithm of daily productivity,

$$\ln(Y_{ij}) = \gamma \ln(r_j) - \gamma \ln(\kappa_i) + (\gamma + 1)\ln(s_{ij}), \tag{6}$$

where, by random sampling, $\ln(s_{ij}) \sim N(\mu_j, \sigma_j^2)$.

The optimal effort level is independent of risk preferences. This is due to the fact that workers observe a realization of S_{ij} before selecting their effort level; there is no risk once S_{ij} is determined.[14] This is consistent with the findings presented in section 5.3 below, where we show that empirically estimated risk preferences are not significantly related to worker productivity. Note, however, that equilibrium effort will still be affected by risk through its effect on the determination of r_j (see Section 3.5, below).

The second-order-sufficient conditions for optimal effort are satisfied independently of the risk attitudes of workers, suggesting that these preferences are general enough to capture different risk attitudes among workers. In particular, the second derivative of utility with respect to effort is given by

$$\begin{aligned}\frac{\partial^2 U}{\partial E_{ij}^2} = (\delta_i - 1)\left[r_j E_{ij} s_{ij} - \kappa_i \frac{\gamma}{\gamma+1} E_{ij}^{\frac{\gamma+1}{\gamma}}\right]^{(\delta_i - 2)} \left(r_j s_{ij} - \kappa_i E_{ij}^{\frac{1}{\gamma}}\right)^2 \\ - \left[r_j E_{ij} s_{ij} - \kappa_i \frac{\gamma}{\gamma+1} E_{ij}^{\frac{\gamma+1}{\gamma}}\right]^{(\delta_i - 1)} \frac{\kappa_i}{\gamma} E_{ij}^{\frac{(1-\gamma)}{\gamma}}.\end{aligned} \tag{7}$$

Evaluating (7) at optimal effort using (5) gives

$$-\left[\frac{r_j^{\gamma+1} s_{ij}^{\gamma+1}}{\kappa_i^{\gamma}(\gamma+1)}\right]^{\delta_i - 1} \left[\frac{1}{\gamma} r_j^{1-\gamma} s_{ij}^{1-\gamma} \kappa_i^{\gamma}\right] < 0 \quad \text{if } \kappa_i > 0, \gamma > 0.$$

Simple algebra shows that indirect utility at e_{ij}^2 is equal to zero, while the indirect utility at e_{ij}^1 is positive; e_{ij}^1 is the optimal effort choice.

[14] Two conditions must be satisfied for risk preferences to affect effort: (i) effort must be chosen before uncertainty is revealed and (ii) the shock must affect the marginal productivity of effort. Models with additive shocks (as in most textbook presentations of the agency relationship) will not generate effort as a function of risk preferences.

3.5 Indirect Utility and Contracts

Substituting from (5) into (3), and using the properties of the log-normal distribution, gives the expected indirect utility of planting on a given block j for individual i,

$$
\begin{aligned}
V_{ij} &= \frac{1}{\delta_i} \frac{r_j^{\delta_i(\gamma+1)}}{(\gamma+1)^{\delta_i} \kappa_i^{\delta_i \gamma}} exp^{(\gamma+1)\delta_i \mu_j + 0.5(\gamma+1)^2 \delta_i^2 \sigma_j^2} & (8) \\
&= \frac{1}{\delta_i} \frac{1}{(\gamma+1)^{\delta_i}} [\boldsymbol{E}(W_{ij})]^{\delta_i} exp^{0.5\delta_i(\gamma+1)^2 \sigma_j^2 (\delta_i - 1)}. & (9)
\end{aligned}
$$

where[15]

$$
\boldsymbol{E}(W_{ij}) = \frac{r_j^{(\gamma+1)} exp^{(\gamma+1)\mu_j + 0.5(\gamma+1)^2 \sigma_j^2}}{k_i^{\gamma}} \tag{10}
$$

The contract must satisfy the expected utility of each planter observed working in the firm. Yet, with only one instrument in the contract and heterogeneous workers, the participation constraint of each worker cannot be satisfied with equality; some workers earn rents. Define the marginal worker, h, as that worker who is indifferent between working and staying home. Then, from (8),

$$
V_{hj} = \frac{1}{\delta_h} \frac{r_j^{\delta_h(\gamma+1)}}{(\gamma+1)^{\delta_h} \kappa_h^{\gamma \delta_h}} \exp\{(\gamma+1)\delta_h \mu_j + 0.5(\gamma+1)^2 \delta_h^2 \sigma_j^2\} = \frac{1}{\delta_h} \bar{w}^{\delta_h} \tag{11}
$$

or

$$
(\gamma+1)\mu_j = \ln(\bar{w}) - (\gamma+1)\ln(r_j) + \gamma \ln(\kappa_h) + \ln(\gamma+1) - 0.5(\gamma+1)^2 \delta_h \sigma_j^2, \tag{12}
$$

where $\bar{w}$ is the net market alternative.[16] Hence, we assume that the firm chooses r_j such that (11) is satisfied – the marginal worker is constant across contracts. As a result, the piece-rate accounts for the net alternative, the risk exposure of workers as well as the disutility of effort and the risk tolerance of the marginal worker.

[15](9) demonstrates how compensating differentials arise in the model. For example, risk-averse workers (for whom $\delta_i < 1$) must be compensated with higher expected earnings in order to offset reductions in utility due to increased risk exposure.

[16]With heterogeneity in multiple dimensions, more that one worker can be indifferent to any contract. Under these circumstances there is a marginal group of workers and the analysis assumes that the piece-rate setting behaviour is stable; *ie,* the piece rate is set on the basis of the preferences of the same individual within the marginal group.

Given the firm's choice of r_j, the equilibrium expected earnings $\boldsymbol{E}(W^{\star}_{ij})$ for worker i on contract j can be obtained by substituting $r_j^{\gamma+1}$ from (11) into (10), resulting in

$$\begin{aligned} \boldsymbol{E}(W^{\star}_{ij}) &= \gamma\bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma} exp^{\{0.5(\gamma+1)^2\sigma^2(1-\delta_h)\}} + \bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma} exp^{\{0.5(\gamma+1)^2\sigma^2(1-\delta_h)\}} \\ &= \boldsymbol{E}\left[C(e_{ij})\right] + \bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma} exp^{\{0.5(\gamma+1)^2\sigma^2(1-\delta_h)\}} \end{aligned} \tag{13}$$

The first part of (13) represents earnings paid to compensate workers for their expected effort costs evaluated at optimal effort e_{ij} given in (5).[17] The second term represents equilibrium compensation net of effort costs.

Hedonic wage equations use earning's regressions to measure the cost of risk (Thaler and Rosen, 1976). Since individuals must be induced to take risks through higher earnings, the difference in average earnings across risk settings is the amount the individual is willing to pay to eliminate that risk. Yet, in the presence of hetergeneous preferences, earnings adjust to compensate the marginal worker for his/her differences in expected utility. Hence the measured differential only applies to the marginal worker. What is more, since effort costs change across contracts along with risk, the observed differential overstates the cost of risk to the marginal worker. Calculating the cost or risk therefore requires holding effort constant.

3.6 The Cost of Risk

To measure the importance of risk to workers, we calculate the amount the worker is prepared to pay to eliminate risk, holding effort costs constant at the levels implied by optimal worker behaviour. We define $\overline{W}_{ij}$ to be worker i's certainty equivalent income on block j, holding the expected cost of effort constant at optimal levels. Then $\overline{W}_{ij}$ provides the worker with the same level of expected utility as he/she gains from working on plot j under uncertainty, holding expected effort costs constant at the level implied by optimal behaviour; from (8), $\overline{W}_{ij}$ solves

[17] The compensation for effort costs can be derived by substituting $r_j^{\gamma+1}$ from (11) in the cost of effort function $C(\cdot)$ evaluated at the optimal effort level given in (5).

$$\frac{1}{\delta_i}\left[\overline{W}_{ij} - \boldsymbol{E}\left[C(e_{ij})\right]\right]^{\delta_i} = \frac{1}{\delta_i}\left[\frac{r_j^{(\gamma+1)}}{(\gamma+1)\kappa_i^{\gamma}} exp^{(\gamma+1)\mu_j + 0.5(\gamma+1)^2\delta_i\sigma_j^2}\right]^{\delta_i} \tag{14}$$

Substituting $r_j^{\gamma+1}$ from (11) gives

$$\overline{W}_{ij} = \bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma} exp^{0.5(\gamma+1)^2\sigma_j^2(\delta_i-\delta_h)} + \boldsymbol{E}\left[C(e_{ij})\right] \tag{15}$$

The cost of risk cr_{ij} for individual i on block j is therefore obtained by subtracting (15) from the equilibrium expected earnings (13), giving

$$cr_{ij} = \bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\left[exp^{0.5(\gamma+1)^2\sigma_j^2(1-\delta_h)} - exp^{0.5(\gamma+1)^2\sigma_j^2(\delta_i-\delta_h)}\right]. \tag{16}$$

Inspection of (16) reveals the following: First, as expected, the cost of risk is zero in the absence of risk ($\sigma^2 = 0$). Second, the cost of risk is increasing (decreasing) in σ^2 if individual i is risk averse (loving).[18] Third, the cost of risk is proportional to planting ability, given risk preferences. This is due to the fact that the moments of the earnings distribution depend on ability (relative to the marginal worker).[19]

It follows from (16) that measuring the cost of risk for individual i on block j requires estimates of

$$\bar{\omega}\left[\frac{\kappa_h}{\kappa_i}\right]^{\gamma}, (\gamma+1)^2\sigma_j^2, \delta_h, \text{and } \delta_i.$$

In section 4.1, we show that by applying our model to payroll data we can identify

$$(\gamma+1)\bar{\omega}\left[\frac{\kappa_h}{\kappa_i}\right]^{\gamma}, (\gamma+1)^2\sigma_j^2, \text{ and } \delta_h.$$

Estimating the cost of risk requires separately identifying γ and δ_i. To accomplish this we supplement our payroll data with two field experiments: one to identify γ, which

[18] Taking the derivative of the cost of risk with respect to σ^2 and rearranging gives

$$\frac{\partial cr_{ij}}{\partial \sigma^2} = 0.5\bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}(\gamma+1)^2 exp^{0.5(\gamma+1)^2\sigma_j^2(1-\delta_h)}\left[(1-\delta_h) - (\delta_i-\delta_h)exp^{0.5(\gamma+1)^2\sigma_j^2(\delta_i-1)}\right]$$

The sign of which depends on the sign of $\left[(1-\delta_h) - (\delta_i-\delta_h)exp^{0.5(\gamma+1)^2\sigma_j^2(\delta_i-1)}\right]$ which is positive when $\delta_i < 1$, zero when $\delta_i = 1$ and negative when $\delta_i > 1$.

[19] Ability affects effort, the reaction to productivity shocks and hence the variance of earnings. Recall, the contract (piece rate) is set to satisfy the marginal worker's participation constraint. As such, it takes account of his/her reaction to shocks, but not the reactions of the other workers.

we call the "piece-rate experiment" (discussed in section 4.2), and another to identify δ_i, which we call the "risk-preference-revealing" experiment (discussed in section 4.3). Each experiment was conducted within the same firm; we discuss each source of identification in turn, beginning with the payroll data.

4 Identification and estimation

4.1 Identifying $(\gamma+1)\bar{\omega}\left[\frac{\kappa_h}{\kappa_i}\right]^{\gamma}$, $(\gamma+1)^2\sigma_j^2$, and δ_h: Payroll Data

To estimate the model we allow for alternative utility, $\bar{\omega}$, to vary across months to capture seasonal changes in the piece-rate setting behaviour of the firm as shown in Figure 1. Substituting from (12) into (6) gives the logarithm of worker i's productivity on block j at month t as

$$\ln(Y_{ijt}) = \ln\bar{\omega}_t + \ln(\gamma+1) + \gamma(\ln\kappa_h - \ln\kappa_i) - \ln r_j - 0.5\delta_h(\gamma+1)^2\sigma_j^2 + \epsilon_{ijt} \qquad (17)$$

where $\epsilon_{ijt} \sim N\big(0, (\gamma+1)^2\sigma_j^2\big)$. Note, (17) is the equilibrium hedonic wage equation, regressing (the logarithm of) earnings on risk; the structure of the model serves to identify risk.

To discuss identification of δ_h, let $\boldsymbol{E}(\ln(Y_{imt}))$ and $\boldsymbol{V}(\ln(Y_{imt}))$ denote respectively the expectation and variance of log of productivity conditional on worker i planting on block m at time t. It then follows from (17) and the assumptions on ϵ_{ijt} that, for any two blocks j and k such that $\boldsymbol{V}(\ln(Y_{ijt})) \neq \boldsymbol{V}(\ln(Y_{ikt}))$,

$$\delta_h = \frac{[\boldsymbol{E}(\ln(Y_{ijt})) - \boldsymbol{E}(\ln(Y_{ikt}))] - [\ln(r_k) - \ln(r_j)]}{0.5[\boldsymbol{V}(\ln(Y_{ikt})) - \boldsymbol{V}(\ln(Y_{ijt}))]} \qquad (18)$$

Risk preferences generate an earnings differential to the marginal worker to compensate for risk. Hence, the risk aversion parameter of the marginal worker is identified from the ratio of the difference in expected log earnings to the difference in the variance across blocks in a given month.

While equation (18) makes transparent the conditions for identification of δ_h, it is not convenient for estimation of that parameter. To estimate δ_h, we first rewrite the (17) as

$$\ln(Y_{ijt}) + \ln(r_j) = a_0 + \sum_{i\neq 1}^{I} a_{1i} DI_i + \sum_{t\neq 1}^{T} a_{2t} DM_t - \delta_h \sum_{j\neq 1}^{J} a_{3j} DB_j + \epsilon_{ijt} \quad (19)$$

where $\epsilon_{ijt} \sim N(0, \tilde{\sigma}_j^2)$, DI_i indicates individual i, DM_t indicates month t, and DB_j indicates block j, and where we define

1. $a_0 = \ln\left((\gamma+1)\bar{\omega}_1 \left[\frac{\kappa_h}{\kappa_1}\right]^{\gamma}\right)$;
2. $a_{1i} = \ln\left(\left[\frac{\kappa_1}{\kappa_i}\right]^{\gamma}\right)$;
3. $a_{2t} = \ln\left(\frac{\bar{\omega}_t}{\bar{\omega}_1}\right)$;
4. $a_{3j} = 0.5\tilde{\sigma}_j^2$
5. $\tilde{\sigma}_j^2 = (\gamma+1)^2\sigma_j^2$;

where κ_1 is the normalized individual in the sample and $\bar{\omega}_1$ is the alternative in the first month of the sample. We estimate the parameters $\{a_0, a_{12}, .., a_{3J}, \tilde{\sigma}_2^2, ..., \tilde{\sigma}_J^2, \delta_h\}$ of equation (19) by maximum likelihood.[20]

The econometric model above reveals that $(\gamma+1)\bar{\omega}_t \left[\frac{\kappa_h}{\kappa_i}\right]^{\gamma}$ is identified by combining estimates of a_0, a_{1i} and a_{2t}. Furthermore, the estimate of $\tilde{\sigma}_j^2$ directly identifies $(\gamma+1)^2\sigma_j^2$. Finally, estimates of $\tilde{\sigma}^2$ and a_{3j} identify δ_h. Notice however, these risk preferences are identified without knowledge of who the marginal worker is. This is important in models with heterogeneity in multiple directions since it is not generally possible to identify the marginal worker ex-ante.[21] This, due to the fact that the average productivity of the marginal worker can be higher or lower than that of any other worker.

[20] To proceed, note that our distributional assumptions imply that the contribution to the likelihood of individual i planting on block j is given by

$$l_{ijt} = \frac{1}{\sqrt{2\pi}\tilde{\sigma}_j} \exp\left\{-\frac{\epsilon_{ijt}^2}{2\tilde{\sigma}_j^2}\right\}$$

where ϵ_{ijt} is defined in (19).

[21] This contrasts to models in which heterogeneity operates only along one dimension; see Paarsch and Shearer, 1999.

4.2 Identifying γ: The Piece-Rate Experiment

The piece-rate experiment took place on three separate blocks, over a three-month period in 2003.[22] 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 (equal to the regular piece rate plus five cents). The regular piece rates paid on these blocks were 18 cents and 23 cents, respectively. The treatment piece rates therefore represented an increase of between 21 and 27 percent above the regular piece rate; 21 planters participated in the piece-rate experiment.

To avoid any Hawthorne effects,[23] the experimental changes were presented to the workers within the context of the normal daily operations of the firm. To this effect, the firm presented the treatment and control blocks as separate blocks, with separate piece rates.[24] Note that this 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.

Let r^T and r^C denote the treatment and control piece rates, respectively. Then, from (6),

$$\ln(Y_{ij}^T) = \gamma \ln(r_j^T) - \gamma \ln(\kappa_i) + (\gamma + 1) \ln(S_{ij}) \tag{20a}$$

$$\ln(Y_{ij}^C) = \gamma \ln(r_j^C) - \gamma \ln(\kappa_i) + (\gamma + 1) \ln(S_{ij}). \tag{20b}$$

Let J^{pr} denote the number of blocks in the piece-rate experiment, and I^{pr} the number of planters. Furthermore, define $\{Db_j : j = 1, 2, ..., J^{pr}\}$ as dummy variables taking a value of 1 for block j, and 0 otherwise. Similarly, define $\{DI_i : i = 1, 2, ..., I^{pr}\}$ as dummy variables

[22] Data from this experiment were first analyzed in Paarsch and Shearer (2008). We refer the reader to that paper for a complete discussion of the experiment and the data.

[23] Hawthorne effects occur when experimental participants know that they are participating in an experiment and alter their behaviour as a consequence.

[24] A convincing explanation for the difference in piece rates was prepared invoking the fact that conditions on the treatment blocks had changed since the original bidding. This sometimes happens when the block has been unexpectedly prepared (cleared of debris) by the government. In practice, no explanation was needed as none of the planters questioned the higher piece rates.

taking a value of 1 for planter i, and 0 otherwise. Then, combining (20a) and (20b) gives

$$\ln(Y_{ij}) = a_0 + \sum_{i=2}^{I^{pr}} a_{1i} DI_i + \sum_{j=2}^{J^{pr}} a_{2j} Db_j + \gamma \left(\ln(r_j^T) - \ln(r_j^C) \right) DT_{ij} + \epsilon_{ij} \qquad (21)$$

where

$$\begin{aligned} a_0 &= -\gamma \ln(\kappa_1) + \gamma \ln(r_1^C) + (\gamma + 1) \boldsymbol{E} \left(\ln(S_{i1}) \right) \\ a_{1i} &= \gamma \left(\ln(\kappa_1) - \ln(\kappa_i) \right) \\ a_{2j} &= (\gamma + 1) \left[\boldsymbol{E} \left(\ln(S_{ij}) \right) - \boldsymbol{E} \left(\ln(S_{i1}) \right) \right] + \gamma \left(\ln(r_j^C) - \ln(r_1^C) \right) \\ \epsilon_{ij} &= (\gamma + 1) \left[\ln(S_{ij}) - \boldsymbol{E}(\ln(S_{ij})) \right] \end{aligned}$$

and

$$DT_{ij} = \begin{cases} 1 & \text{if paid treatment piece rate on block } j, \\ 0 & \text{if paid control piece rate on block } j. \end{cases}$$

The exogenous variation in the piece rate implies that the expected value of ϵ_{ij} is equal to zero, conditional on the included regressors. Hence, the model in (21) identifies γ.[25]

4.3 Identifying δ_i: The Risk-Preference-Revealing Experiment

The risk-preference-revealing experiment took place in the Spring of 2006, inspired by the experimental design exploited by Holt and Laury (2002) to determine the risk preferences of an individual. During the experiment workers were asked to make 10 decisions. Each decision consisted of choosing one of two binary lotteries. A summary of the decisions can be found in Table 3. The actual decision sheet is presented in appendix A. For each decision there is a ”safe” lottery, denoted A, which pays either a low payoff of \$16.00 or a high payoff of \$40.00, and a ”risky” lottery, denoted B, which pays either a low payoff of \$2.00 or a high payoff of \$77.00. Which of the high or low payoffs materialized, was determined by chance.

For the first decision, the probability of the high payoff for both lotteries is 10%, so only an extreme risk seeker would choose lottery B. As can be seen in the far right column of Table 3, the expected payoff difference between lotteries A and B, for the first decision, is

[25] In principal, the experimental data could also be fit to the structural model developed in Section 4. We chose not to in an effort to identify our parameters with minimum assumptions.

$23.40. The probability of winning the high payoff increases gradually as we move down the Table, increasing the relative payoff of the risky lottery B. Consequently, an individual should eventually cross over and start choosing lottery B as he/she moves down the decision sheet. In fact, for the last decision, the high payoff of each lottery is paid with probability 1 ($40 for lottery A, and $77.00 for lottery B). This means that even very risk averse individuals should choose lottery B in the last decision.

The pattern of decisions for a given planter can be related to risk preferences for a utility function with constant relative risk aversion for money δ. The payoffs for the lottery choices in the experiment are such that the crossover point from lottery A to lottery B provides an interval estimate of a subject's coefficient of relative risk aversion. The payoff numbers for the lotteries are such that a risk neutral decision pattern (four safe choices followed by six risky choices) is consistent with a constant relative risk aversion coefficient δ_i in the interval (0.85, 1.14).

After we described the decisions they would be making, planters were informed that, once their decisions were made, one of their ten decisions would be randomly chosen and played out to determine their earnings. To select which of the ten lotteries would be played, each planter would first draw a poker chip from an opaque black bag containing identical chips numbered from 1 to 10. The number drawn would select the lottery to be played. We would then replace the chip in the bag, shuffled the bag, and ask the planter to draw a chip for a second time to determine the outcome of the selected lottery, and thus the planter's lottery earnings.[26]

Planters were informed that their lottery earnings and participation fee would be added to their next pay check. After having read the instructions, participants were allowed to ask clarifying questions. We then asked each planter to make their decisions individually and in silence. Planters who completed their decision sheets were asked to come forward to draw their poker chips.

[26]For example, a planter who selected the number 4 on his first draw would play lottery A.4 if he had selected lottery A for decision 4 and B.4 if he had selected lottery B. If his second draw was in the interval 1-4, he would win $40 if he had selected lottery A and $77.00 if he had selected lottery B. If his second draw was in the interval 5-10, he would win $32 if he had selected lottery A and $2 if he had selected lottery B.

5 Results

5.1 Parameter estimates from Payroll Data

The risk-preference coefficient δ_h is estimated to be 2.73, with a p-value essentially equal to zero. The estimated values of $\tilde{\sigma}_j^2$ range between 0.02 and 0.34 with an average of 0.08.[27] This suggests that the marginal worker is risk loving; for a given set of average conditions, the marginal worker prefers contracts on which the variance is high.

Somewhat ironically, the negative correlation between the variance of output and the piece rate observed in Figure 1 confirms the standard model's predictions for the wrong reasons. In the standard model, workers are risk averse and the firm reduces the incentive intensity in risky environments (for a given output price) to reduce the costs of implementing incentives. Here, the output price varies across contracts, offsetting changes in cost. The firm reduces incentives in risky environments because the risk-loving marginal worker requires lower average earnings to induce his/her participation.

To consider the fit of the model, we calculated ninety-five and ninety-nine percent confidence intervals for the average logarithm of predicted daily productivity on each contract. These are presented in Figures 4 and 5 as the solid lines. The average observed logarithm of productivity on each contract is given by the dashed line connecting the dots.

The graphs suggest that the model captures the general features of the data very well. The model replicates the negative correlation between average productivity and the piece rate. What is more, observed average productivity lies within the 95% confidence interval for 13 of the 22 contracts (59%) and it lies within the 99% confidence interval for 15 of the 22 contracts (68%).

5.2 The Piece-Rate Experiment

Table 2 presents the summary statistics of the piece-rate experiment averaged over all planters in both treatment and control conditions. The average daily number of trees planted under the control conditions is 888.95, with a relatively high standard deviation. Under the treatment conditions, the average number of trees planted climbs to 1012.39.

[27] A full table of results is available from the authors on request.

This reflects a 13.9% increase in planter productivity relative to the control conditions, a change consistent with the higher piece-rates paid in the treatment conditions.[28]

The estimate of γ from (21) is equal to 0.39.[29] A statistical test of the null hypothesis that γ is equal to zero is rejected at all levels of statistical significance – the p-value is essentially equal to zero.

5.3 The Risk-Preference-Revealing Experiment

The results of the risk-preference-revealing experiment are presented in Table 7 under the heading "High payoff scale". Along with the range of the estimated risk-preference parameter, based on the number of safe choices made by the worker, we present the cumulative distribution of individuals by category. Some individuals provided inconsistent answers during the experiment. The second column under the heading "High payoff scale" gives excluding inconsistencies. Overall we find substantial heterogeneity in risk preferences. Close to one fourth of all workers made decisions revealing risk loving behavior (3 safe choices or less), and a little more than half of the workers made decisions revealing various degrees of risk aversion (5 or more safe choices).

We note that 7-8% of the workers in this firm display risk preferences which are consistent with our estimate of δ_h (the risk preferences of the marginal worker) obtained from applying our structural model to the payroll data. While it is impossible to identify who the marginal worker is from the experimental data, this consistency is encouraging; it provides a certain degree of independent validation of the structural results and suggests that they are not overly sensitive to our modelling assumptions.

An important issue when eliciting risk preferences is whether the measured distribution of preferences is sensitive to the payoff scale of the lotteries used (see Holt and Laury, 2002). To assess the importance of scaling, we compare the results of the current experiment with those of a similar experiment conducted one year earlier (in 2005), in the same firm. The experiment in the preceding year was identical to the current experiment ex-

[28]This pattern holds conditionally as well – productivity is higher under the treatment piece rate for each block; see Paarsch and Shearer (2008), Table 2.

[29]Paarsch and Shearer (2008) also estimate a value of γ of 0.39 using the same data.

cept that the lottery payoffs were one-half of those used in the current experiment.[30] 51 workers participated in the previous experiment. The payoff scale should not affect the distribution of measured risk preferences, conditional on preferences being of the CRRA type. Results for all workers and only those who gave consistent answers are reported in the second two columns of Table 7 under the heading "Low payoff scale". We find that the distribution of risk preferences is broadly similar to the high payoff scale experiment. In particular, the proportion of risk loving workers remains above 20% while close to half of the workers reveal being risk averse. These results suggest that the measured distribution of risk preferences is relatively robust to the scaling of the payoffs in the experiment.[31]

Finally, it is of interest to analyze whether risk preferences are related to worker productivity. To proceed, we regressed worker productivity $\ln(Y_{it})$ on a set of dummy variables for each piece-rate value present in the data and an individual fixed effect μ_i, capturing worker intrinsic productivity. We then regressed the estimated fixed effect $\tilde{\mu}_i$ on the number of safe decisions taken in the risk experiment. We find that the effect of the risk preference variable on productivity is not significantly different from zero (p-value = 0.901).[32] This suggests that risk preferences are not significant determinants of worker productivity, consistent with our structural model.

[30] Lottery A paid either $20 or $16, while lottery B paid either $38.50 or $1.

[31] It is also of interest to note that these workers display significantly lower degrees of risk aversion than do individuals from the overall Canadian population. Dave, Eckel, Johnson, and Rojas (2008) present results of risk-preference revealing experiments on individuals sampled from across Canada with payoffs corresponding to our high payoff scale experiment. They found a much lower proportion of individuals displaying risk neutral or risk loving preferences; the differences are statistically significant (Bellemare and Shearer, 2009). These results are consistent with the hypothesis that workers match to firms on the basis of their risk preferences : risk-tolerant workers are attracted to high-risk occupations.

[32] Adding a quadratic term in the number of safe choices does not alter the result: the linear and quadratic effects of the risk preference variable on productivity are jointly insignificant (p-value = 0.883).

6 Counterfactual Analysis

6.1 The Importance of Risk to Workers

To measure the cost of risk for the workers in this firm, we evaluated (16) at the estimated parameter values for the highest and lowest variance block during the May 2006 planting season. The corresponding estimated values of $\tilde{\sigma}_j^2 = (\gamma+1)^2\sigma_j^2$ were 0.257 and 0.017 respectively. The results are presented in Figure 6. The average cost of risk on the high-variance block (top left graph) is equal to \$1.26. Yet, there is considerable heterogeneity with values ranging from -\$38.73 to \$72.56, reflecting heterogeneity in planting abilities and risk preferences. The costs of risk as a proportion of expected earnings on the high variance block reveal a similar heterogeneity (top right graph): the proportions vary from -15% to 40%, with an average proportion of 1.1%. Unsurprisingly, there is a very small variance in the costs of risks across planters on the low-risk block (bottom left graph), with an average close to zero. As a result, the costs as a proportion of expected earnings are negligible (bottom right graph).

6.2 The Benefits of Matching

The heterogeneity in risk preferences suggests that there are potential gains from matching workers to planting conditions within the firm. To measure these benefits we consider the change in profits that the firm could induce from a redistribution of risk among its workers. First, we consider how worker utility would change if the piece-rate paid on block j would change from r_j to $\tilde{r}_j$. From (8) worker i's indirect utility from planting on plot j at the new piece-rate $\tilde{r}_j$ is given by

$$V_{i,j}(\tilde{r}_j; r_j, \mu_j, \sigma_j^2) = \frac{1}{\delta_i}\frac{\tilde{r}_j^{\delta_i(\gamma+1)}}{(\gamma+1)^{\delta_i}\kappa_i^{\delta_i\gamma}} exp^{(\gamma+1)\delta_i\mu_j + 0.5(\gamma+1)^2\delta_i^2\sigma_j^2} \tag{22}$$

But from (11)

$$exp^{\{(\gamma+1)\mu_j\}} = \frac{\bar{\omega}(\gamma+1)\kappa_h^{\gamma} exp^{-0.5\delta_h(\gamma+1)^2\sigma_j^2}}{r_j^{\gamma+1}},$$

which depends on the initial piece-rate r_j. Combining, gives

$$V_{i,j}(\tilde{r}_j; r_j, \mu_j, \sigma_j^2) = \frac{1}{\delta_i}\left[\left(\frac{\tilde{r}_j}{r_j}\right)^{(\gamma+1)} \bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma} exp^{0.5(\gamma+1)^2\sigma_j^2(\delta_i-\delta_h)}\right]^{\delta_i}.$$

Now, consider two planting plots, denoted H and L, with $\sigma_H^2 > \sigma_L^2$. Let r_H and r_L denote the piece rates the firm currently pays on these plots. If the firm instead paid $\tilde{r}_L$ on plot L and allowed workers to choose the plot on which they plant, only those workers for whom $V_{i,L}(\tilde{r}_L; r_L, \mu_L, \sigma_L^2) > V_{i,H}(r_H; r_H, \mu_H, \sigma_H^2)$ would choose to plant on plot L; *ie*, whenever

$$\left(\frac{\tilde{r}_L}{r_L}\right)^{(\gamma+1)} exp^{0.5(\gamma+1)^2\sigma_L^2(\delta_i-\delta_h)} > exp^{0.5(\gamma+1)^2\sigma_H^2(\delta_i-\delta_h)}.$$

or

$$\left(\frac{\tilde{r}_L}{r_L}\right)^{(\gamma+1)} > exp^{0.5(\gamma+1)^2(\delta_i-\delta_h)(\sigma_H^2-\sigma_L^2)}. \tag{23}$$

The potential gains to matching can be seen from (23) – the firm can reduce the piece rate paid to workers for whom $\delta_i < \delta_h$ on plot L while increasing their utility vis-à-vis plot H. Notice that these gains can only be realized if workers are heterogeneous with respect to risk preferences and risk is important – otherwise (23) is only satisfied if $\tilde{r}_j > r_j$, increasing costs for the firm. Of course, whether or not actual gains are realized will depend on the change in behaviour of the workers who self select onto plot L. As the piece rate changes, their effort levels will change affecting firm profits. We now turn to calculating the effect on profits.

Solving (23) for δ_i gives the set $\Delta(\tilde{r}_L)$ of workers who will choose to plant on plot L as a function of $\tilde{r}_L$:

$$\Delta(\tilde{r}_L) = \{\delta_i : \delta_i < \delta^*(\tilde{r}_L)\}. \tag{24}$$

where the threshold value $\delta^*(\tilde{r}_L)$ is given by

$$\delta^*(\tilde{r}_L) = \delta_h + \frac{2(\ln(\tilde{r}_L) - \ln(r_L))}{(\gamma+1)(\sigma_H^2 - \sigma_L^2)} \tag{25}$$

6.3 The Firm's Gains from Matching

To calculate the gains from matching, we first consider the increase in firm daily profits which can result by allowing workers to sort across a high variance block H and a low variance block L. We proceed with the blocks used in Section 6.1 to estimate the costs of risk. The piece rates paid on these blocks are $r_H = 0.14$ and $r_L = 0.35$. Note, r_H and r_L both satisfy (11), giving firm daily profits per worker

$$\frac{(P_j - r_j)}{r_j}\bar{\omega}(\gamma+1)\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma} exp^{0.5(\gamma+1)^2\sigma_j^2(1-\delta_h)}, \quad j \in H, L. \tag{26}$$

In the absence of matching, workers are randomly distributed across blocks and profits are given by (26). Under matching, the firm chooses $\tilde{r}_L$ to maximize

$$\begin{aligned} &\sum_{\delta_i \in \Delta(\tilde{r}_L)} (P_L - \tilde{r}_L)\frac{\tilde{r}_L^{\gamma}}{r_L^{(\gamma+1)}}\bar{\omega}(\gamma+1)\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma} exp^{0.5(\gamma+1)^2\sigma_L^2(1-\delta_h)} + \\ &\sum_{\delta_i \notin \Delta(\tilde{r}_L)} \frac{(P_H - r_H)}{r_H}\bar{\omega}(\gamma+1)\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma} exp^{0.5(\gamma+1)^2\sigma_H^2(1-\delta_h)}. \end{aligned} \tag{27}$$

To calculate profits we set $P_j = 2 \times r_j$, in accordance with firm practice.[33] Notice as well, from section 3,

$$exp^{a_0 + a_{1i} + a_{2t}} = \bar{\omega}_t(\gamma+1)\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma},$$

so profits are identified on each block. Given $\delta^*(\tilde{r}_L)$ and the profits on both blocks, we also need to use the experimental data on risk preferences for each worker to identify individuals below and above $\delta^*(\tilde{r}_L)$. Recall that the experiment described in section 5.3 identifies for each worker a range of parameter values for the risk-preference parameter δ_i. We perform our calculation by choosing the mid-point of the appropriate interval for each worker.[34]

We calculate the profits obtained under matching to those obtained under random allocation at the maximum-likelihood estimates. We find that profits under matching are maximized by reducing the current piece-rate of \$0.35 on r_L to \$0.31. At this reduced piece-rate, the firm could increase profits by approximately 13.4% relative to the profits made without matching. Doing so would select the more risk-averse workers to that plot, leaving only the risk-loving workers on the high-variance block. In effect, only those workers with $\delta_i > \delta^* = 1.318$ would plant on the high-variance block. From Table 7 this represents 10% of the workforce.

[33] Interviews with firm managers revealed that the price the firm receives per tree planted is typically twice the piece rate paid to workers.

[34] Choosing the lower or upper bounds of the intervals provides almost identical results.

7 Discussion and Conclusions

We have measured the importance of risk within a firm that pays its workers piece rates. Our measure is based on the willingness to pay to avoid risk. Our results indicate that the average cost of risk is low in this firm – less than 1% of expected earnings. This is consistent with selectivity and matching in the labour market; workers who are relatively risk loving are attracted to firms paying piece rates. Yet workers are shown to be heterogeneous in ability as well as risk, implying that risk-averse workers are also present in the firm. Indeed the cost of risk can attain up to 39% of expected earnings for some (risk-averse) planters.

Our results have implications for economic interpretations of the determinants of contracts. Agency theory suggests that optimal contracts balance risk-sharing and incentives. Yet our results suggest that transaction (or implementation) costs play an important role as well. In the absence of such costs, the firm could gain by matching individual workers to risk levels, reducing the risk exposure of risk-averse workers within the firm. Yet the firm does not implement matching, forgoing the increase in profits. This suggests there are (unmodelled) costs of matching that render it unprofitable in practice. For example, the size of the blocks to be planted may not sustain the workforce implied by the matching equilibrium. Our counterfactual calculations assume that there is no constraint from the size of the blocks – all workers interested in working on a given block, on a given day, can be accommodated. Yet size constraints may render matching impossible. Alternatively, the firm may be constrained in time. The need to plant blocks before a specific deadline may impose that firms forgo the benefits of matching and allocate workers to plots independent of their risk preferences. Finally, the matching contract may require information that the firm does not have. The observed contract only requires that the firm know the risk preferences of the marginal worker and the distribution of planter abilities, which are easily observable from planter output. Under the matching contract, however, the expected profit on a particular block depends on the matching equilibrium, requiring knowledge of the joint distribution of risk preferences and abilities. The cost of obtaining this information may simply be prohibitive for the firm.

More generally, this paper highlights the complementarities between econometrics and experiments for empirical work in economics. Preference-revealing experiments can be used to confirm the estimates of structural parameters that are identified within structural models but may be sensitive to functional form assumptions (such as the risk preferences of the marginal worker). Experiments can also provide supplementary information over parameters not identified by econometric models (such as the risk preferences of the infra-marginal workers).

Variable	Mean	Std. deviation	Minimum	Maximum
By individual-day (3709 observations)				
Number of trees	920.31	381.75	30	2780
Regular piece rate	0.23	0.05	0.14	0.35
Daily earnings	197.15	65.64	7.5	547.50
By block (68 observations)				
Planting days	54.54	40.35	16	207
Average daily trees planted	877.27	230.16	552.14	1586.57
Piece rate	0.24	0.05	0.14	0.35
Average daily earnings	198.43	21.10	143.56	247.78
Standard dev. earnings	62.54	13.47	37.31	98.62
Standard dev. trees planted	279.90	102.09	118.36	639.58

Table 1: Descriptive statistics of the payroll data.

Control Sample: 109 Observations				
Variable	Average	Std. Deviation Gift	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
Treatment Sample: 88 Observations				
Variable	Average	Std. Deviation Gift	Minimum	Maximum
Number of Trees	1012.39	351.23	375	1965
Piece Rate	0.26	0.02	0.23	0.28
Daily Earnings	254.56	68.98	105.00	451.95

Table 2: Summary Statistics: Piece-Rate Experiment

Decision	Lottery A	Lottery B	Expected payoff difference
1	1/10 of $40.00, 9/10 of $32.00	1/10 of $77.00, 9/10 of $2.00	$23.40
2	2/10 of $40.00, 8/10 of $32.00	2/10 of $77.00, 8/10 of $2.00	$16.60
3	3/10 of $40.00, 7/10 of $32.00	3/10 of $77.00, 7/10 of $2.00	$10.00
4	4/10 of $40.00, 6/10 of $32.00	4/10 of $77.00, 6/10 of $2.00	$3.20
5	5/10 of $40.00, 5/10 of $32.00	5/10 of $77.00, 5/10 of $2.00	-$3.60
6	6/10 of $40.00, 4/10 of $32.00	6/10 of $77.00, 4/10 of $2.00	-$10.20
7	7/10 of $40.00, 3/10 of $32.00	7/10 of $77.00, 3/10 of $2.00	-$17.00
8	8/10 of $40.00, 2/10 of $32.00	8/10 of $77.00, 2/10 of $2.00	-$23.60
9	9/10 of $40.00, 1/10 of $32.00	9/10 of $77.00, 1/10 of $2.00	-$30.40
10	10/10 of $40.00	10/10 of $77.00	-$37.00

Table 3: High payoff scale matrix of the lottery experiment.

		High payoff scale		Low payoff scale	
Nbr. safe choices s	$U = x^{\delta}$	All	Consistent	All	Consistent
0-1	$\delta_i > 1.95$	0.085	0.109	0.098	0.142
2	$1.49 < \delta_i < 1.95$	0.102	0.130	0.117	0.171
3	$1.14 < \delta_i < 1.49$	0.237	0.261	0.235	0.257
4	$0.854 < \delta_i < 1.14$	0.458	0.478	0.392	0.457
5	$0.589 < \delta_i < 0.854$	0.763	0.739	0.726	0.800
6	$0.324 < \delta_i < 0.589$	0.864	0.870	0.902	0.886
7	$0.029 < \delta_i < 0.324$	0.915	0.913	0.941	0.914
8	$-0.368 < \delta_i < 0.029$	0.966	0.957	0.941	0.914
9-10	$\delta_i < -0.368$	1	1	1	1
Sample size		59	46	51	35

Table 4: The first column presents the number of safe choices made in the experiment. The second column presents the interval around the coefficient of relative risk aversion δ_i which is consistent with a given number of safe choices. Table reports distributions for the high and low stakes treatments conducted in the firm. Note that the numbers of planters under high stakes differ slightly from Bellemare and Shearer (2009) since some were not matched to the payroll records. "All" refers to the entire sample in each treatment. "Consistent" refers to the sub-samples of subjects in each treatment who made consistent answers.

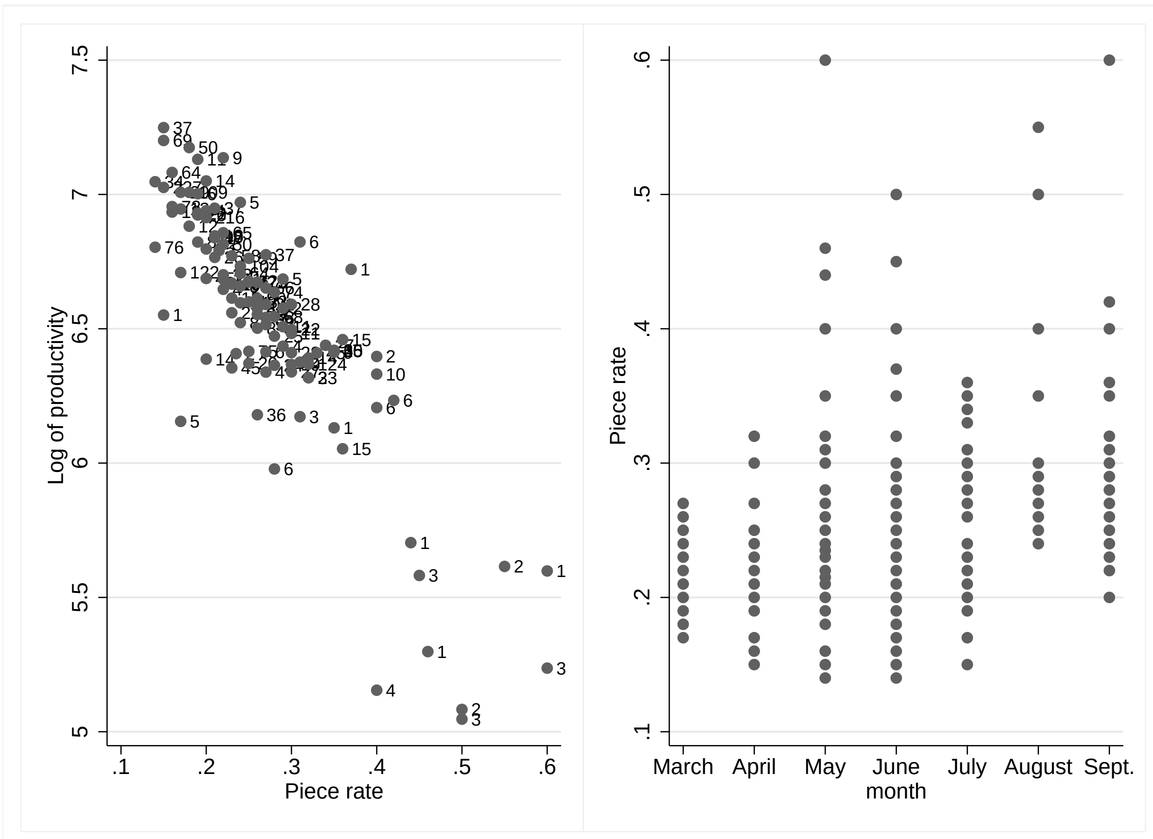

Figure 1: Figure 1A (left) presents the log of productivity as a function of the piece-rates. Figure 1B (right) presents the piece-rates as a function of the months of the planting season. Numbers in both graphs represent the number of observations for each point.

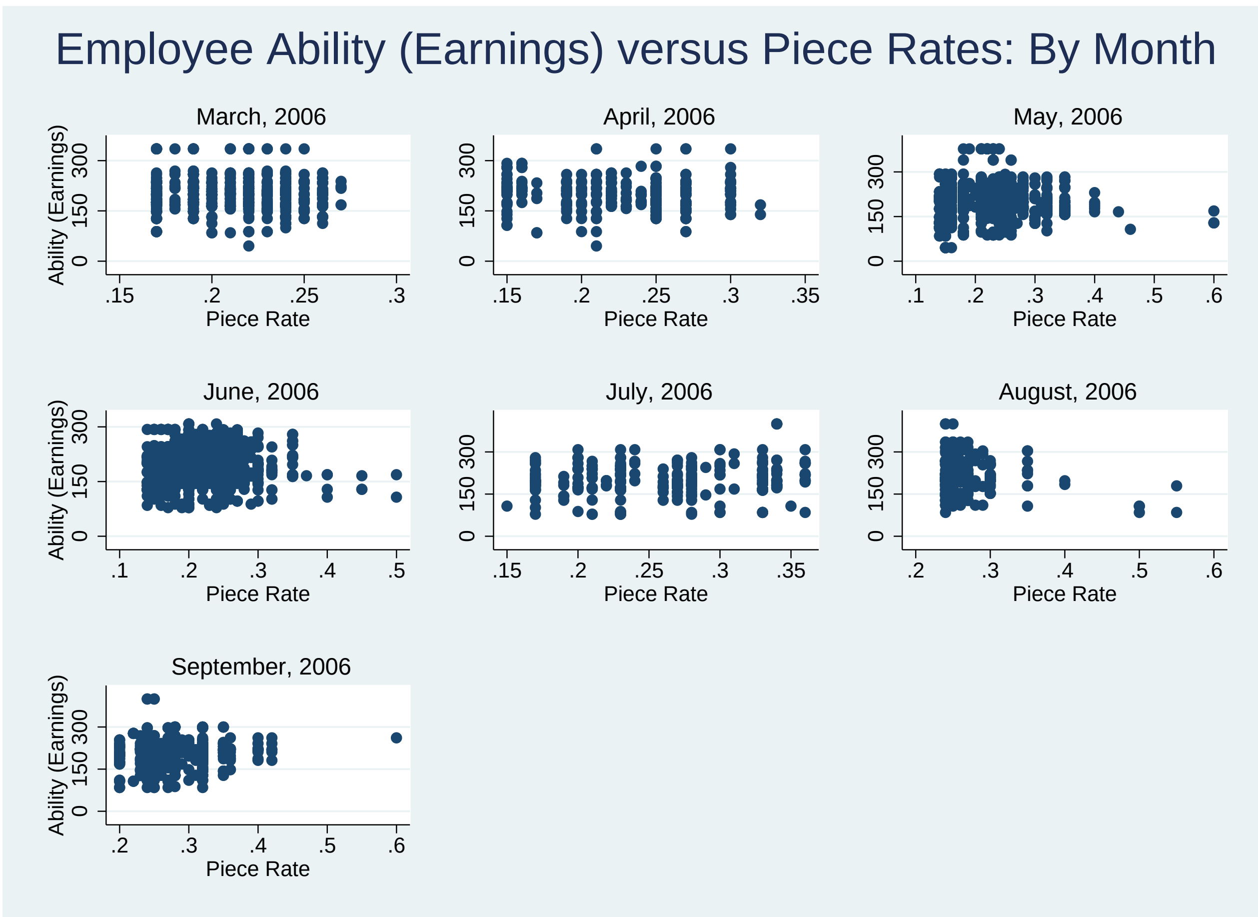
Employee Ability (Earnings) versus Piece Rates: By Month
March, 2006
April, 2006
May, 2006
June, 2006
July, 2006
August, 2006
September, 2006
Ability (Earnings)
Piece Rate
0
150
300
.15
.2
.25
.3
.35
.1
.4
.5
.6

Figure 2:

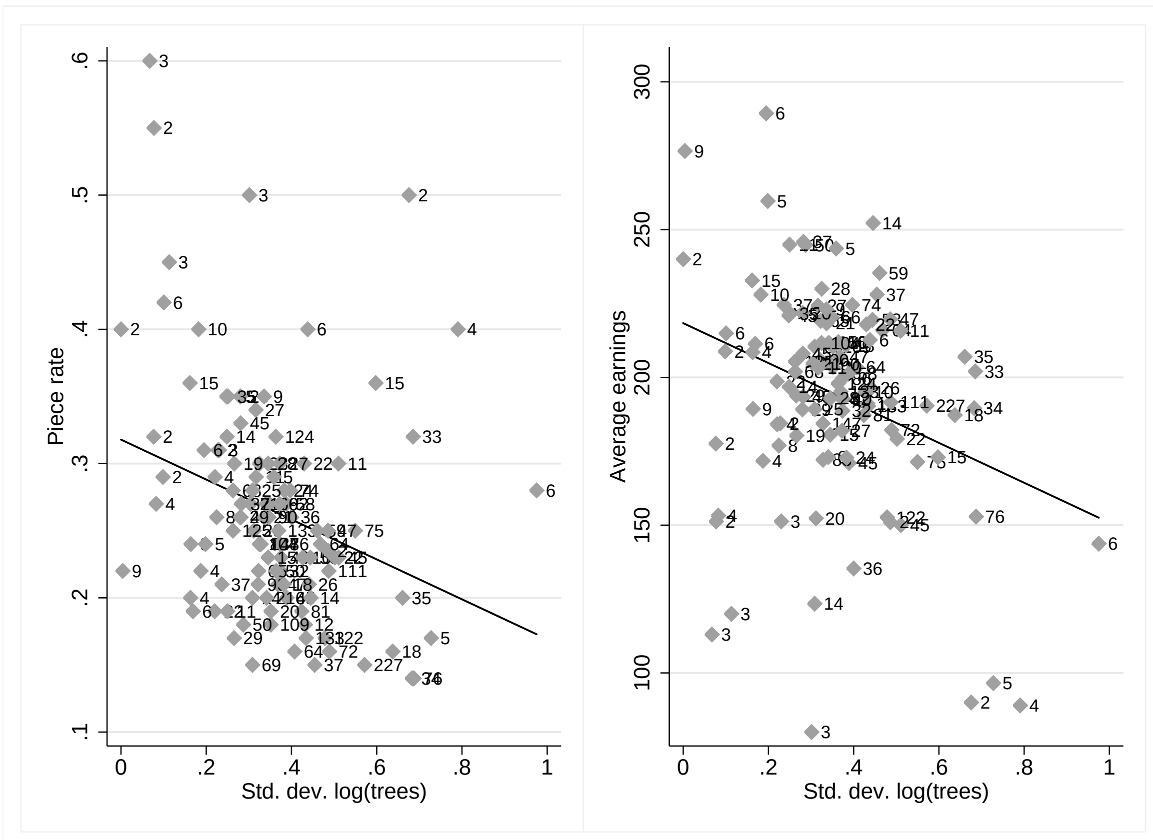

Figure 3: Figure 3A (left) presents piece rates as a function of the standard deviations of the log of productivity and the estimated regression function. Figure 3B (right) presents average earnings as a function of the standard deviations of the log of productivity and the estimated regression function. Numbers in both graphs represent the number of observations for each point.

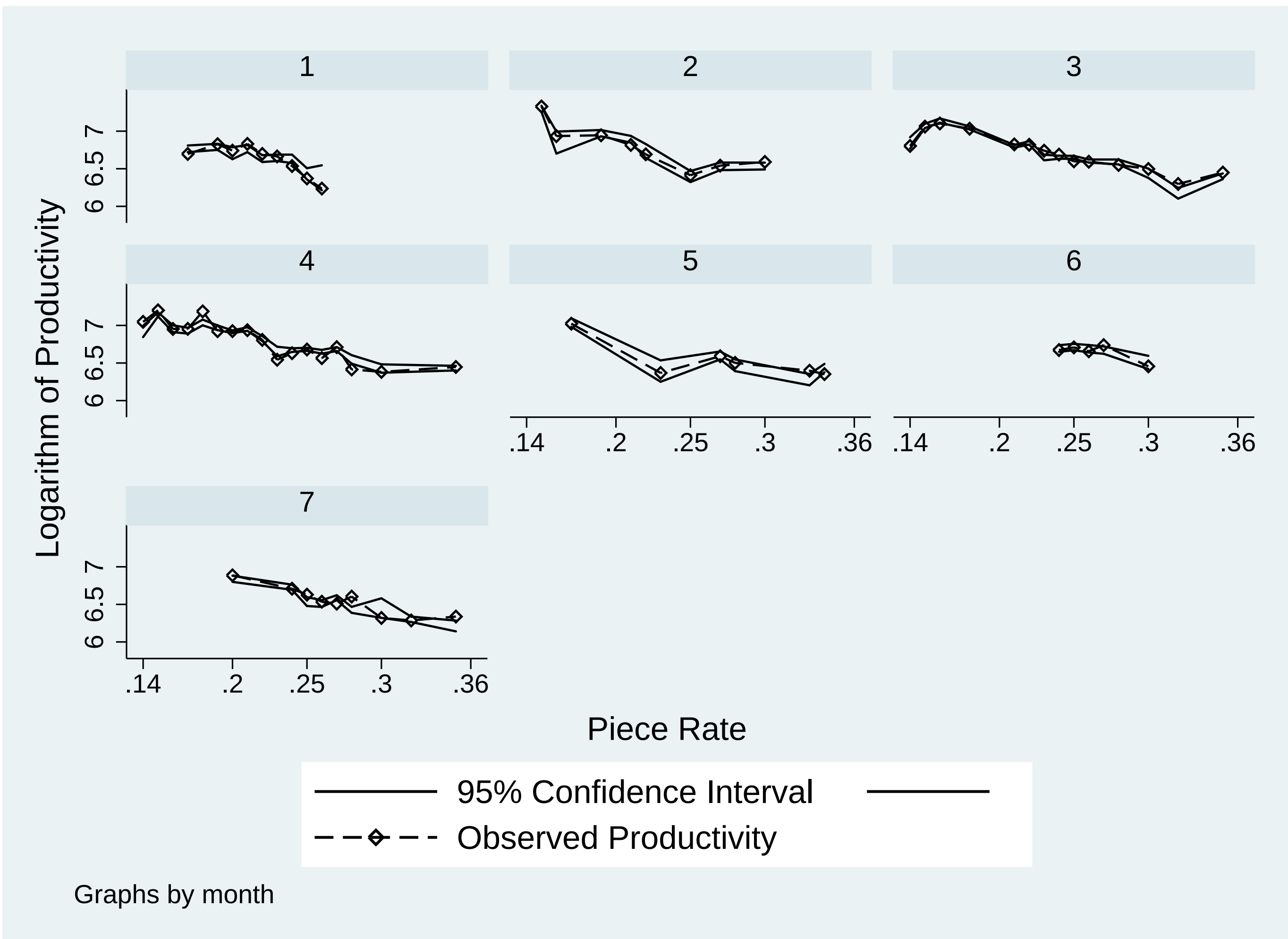
1
2
3
4
5
6
7
Logarithm of Productivity
6 6.5 7
.14 .2 .25 .3 .36
Piece Rate
95% Confidence Interval
Observed Productivity
Graphs by month

Figure 4:

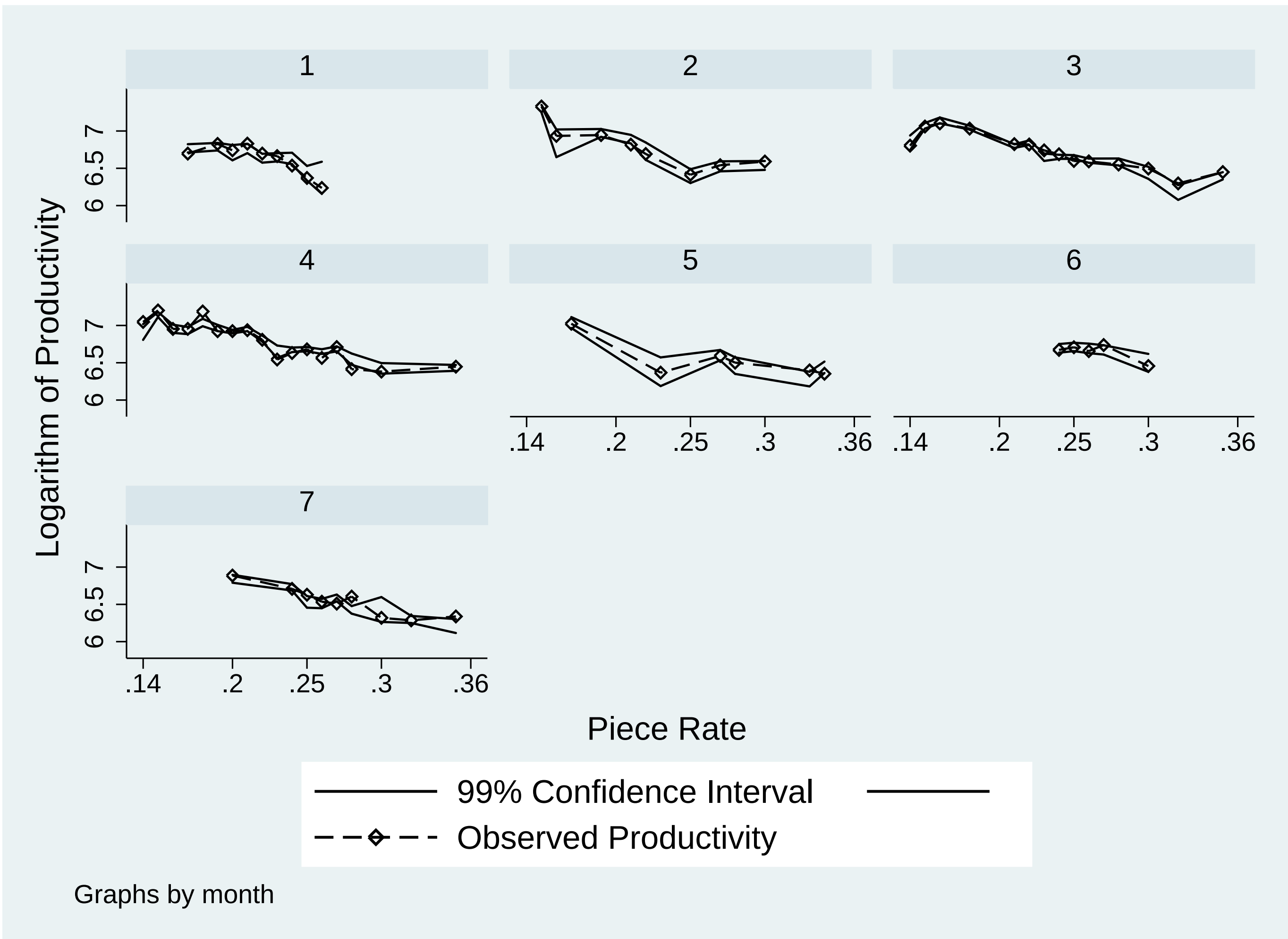
1
2
3
4
5
6
7
Logarithm of Productivity
6 6.5 7
.14 .2 .25 .3 .36
Piece Rate
99% Confidence Interval
Observed Productivity
Graphs by month

Figure 5:

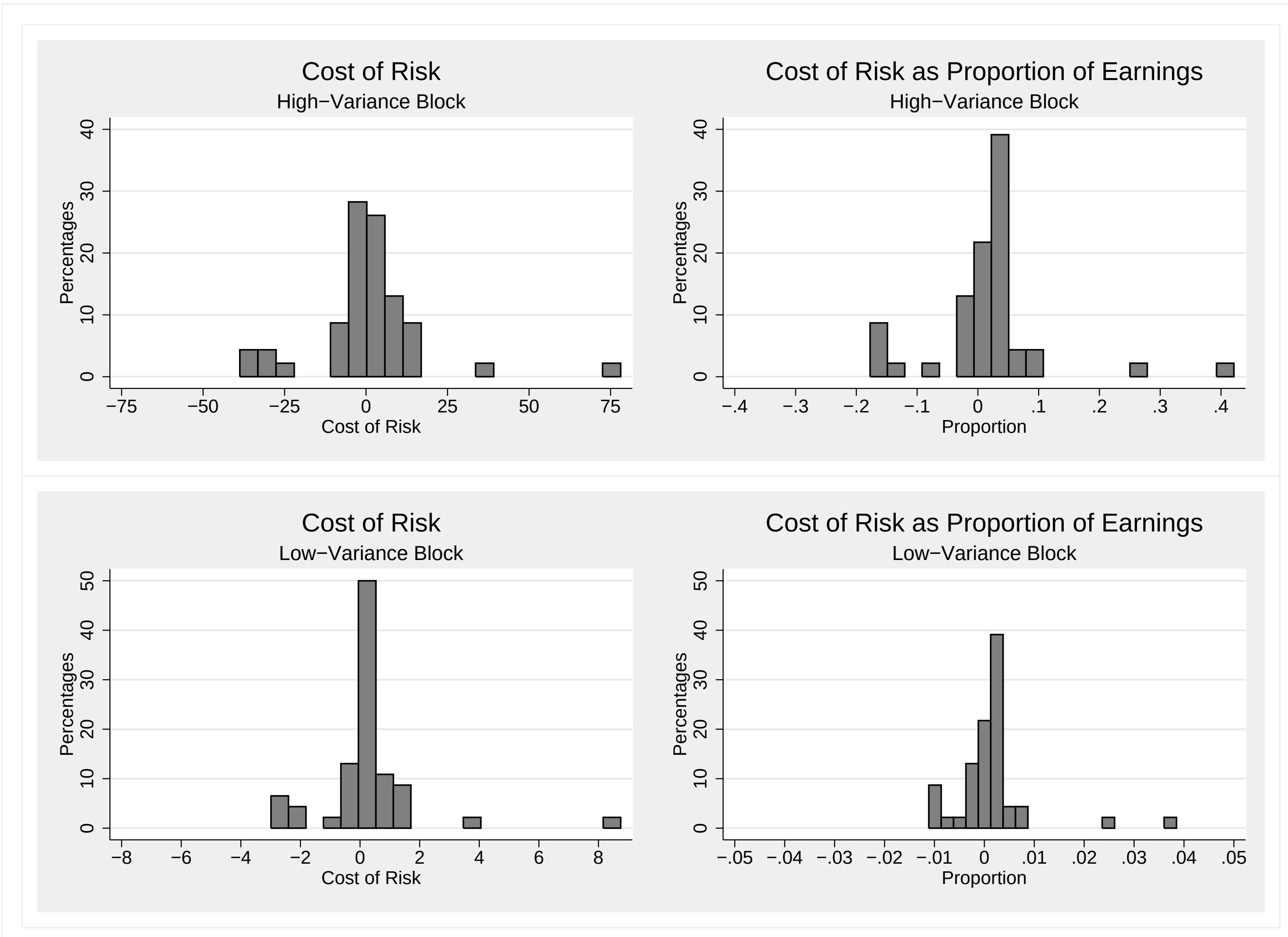

Figure 6: Distribution of the Costs of Risk (first graph column) and the costs of risk as a proportion of worker expected earnings (second graph column) on the high and low variance blocks .

References

ACKERBERG, D., AND M. BOTTICINI (2002): "Endogeneous Matching and the Empirical Determinants of Contract Form," *Journal of Political Economy*, 110, 564–591.

ALLEN, D., AND D. LUECK (1992): "Contract Choice in Modern agriculture: Cash Rent versus Cropshare," *Journal of Law and Economics*, 35.

BELLEMARE, C., AND B. SHEARER (2009): "Gift Giving and Worker Productivity: Evidence from a Firm Level Experiment," *forthcoming, Games and Economic Behavior*.

CAHUC, P., AND A. ZYLBERBERG (2004): *Labor Economics*. MIT Press, Cambridge, U.S.A.

CHIAPPORI, P., AND B. SALANIÉ (2003): *Testing Contract Theory: a Survey of Some Recent Work*vol. Advances in Economics and Econometrics - Theory and Applications , Eighth World Congress, M. Dewatripont, L. Hansen and P. Turnovsky eds., pp. 115–149. Cambridge University Press, Cambridge.

COHEN, A., AND L. EINAV (2007): "Estimating Risk Preferences from Deductible Choice," *American Economic Review*, 97.

DAVE, C., C. ECKEL, C. JOHNSON, AND C. ROJAS (2008): "Eliciting Risk Preferences: When is Simple Better ?," *CBEES Working paper*.

DUBOIS, P., AND T. VUKINA (2007): "Optimal Incentives under Moral Hazard and Heterogeneous Agents: Evidence from Production Contracts Data," *mimeo GREMAQ*.

FERRALL, C., AND B. SHEARER (1999): "Incentives and Transactions Costs Within the Firm: Estimating and Agency Model using Payroll Records," *Review of Economic Studies*, 66, 309–338.

HECKMAN, J., R. LALONDE, AND J. SMITH (1999): *The Economics and Econometrics of Active Labor Market Programs*vol. Handbook of Labor Economics , Vol. IV chapter 31, O. Ashenfelter and D. Card eds. Elsevier North-Holland.

HOLT, C., AND S. LAURY (2002): "Risk Aversion and Incentive Effects," *American Economic Review*, 92.

KIHLSTROM, R., AND J. LAFFONT (1979): "A General Equilibrium Entrepreneurial Theory of Firm Formation Based on Risk Aversion," *Journal of Political Economy*, 87, 719–748.

KNIGHT, F. H. (1921): *Risk, Uncertainty and Profit, 1964 Edition*. Augustus M. Kelley, New York.

LAFONTAINE, F. (1992): "Agency Theory and Franchising: Some Empirical Results," *RAND Journal of Economics*, 23, 263–283.

MILGROM, P., AND J. ROBERTS (1992): *Economics, Organization and Management*. Prentice Hall, U.S.A.

PAARSCH, H., AND B. SHEARER (1999): "The Response of Worker Effort to Piece Rates: Evidence from the British Columbia Tree-Planting Industry," *Journal of Human Resources*, 34, 643–667.

——— (2000): "Piece Rates, Fixed Wages and Incentive Effects: Evidence from Payroll Data," *International Economic Review*, 41, 59–92.

——— (2008): "The Response to Incentives and Contractual Efficiency: Evidence from a Field Experiment," *forthcoming, European Economic Review*.

REES, A. (1975): *Compensating wage differentials*vol. Essays on Adam Smith, A. Skinner and T. Wilson, eds. Oxford University Press, Oxford.

ROSEN, S. (1986): *The Theory of Equalizing Differences*vol. Handbook of Labor Economics , Vol. I chapter 31, O. Ashenfelter and R. Layard eds. Elsevier North-Holland.

STIGLITZ, J. (1975): "Incentives, Risk, and Information: Notes Towards a Theory of Hierarchy," *Bell Journal of Economics*, 6, 552–579.