Multidimensional heterogeneity and the economic importance of risk and matching: evidence from contractual data and field experiments

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We measure the cost of risk and the benefits of matching heterogeneous workers to risk levels within a firm that pays its workers piece rates. The workers of this firm are heterogeneous in two dimensions: risk preferences and ability. Our results suggest that workers' willingness to pay to avoid risk is heterogeneous. It can attain 40% of their expected net earnings but averages to only 1%. Moreover, the benefits to the firm of matching are relatively small: profits are predicted to increase by only 2.3%, 4% if we restrict attention to cases where matching is possible. Although labor-market sorting contributes to this result (the workers in this firm are relatively risk tolerant), it is not the primary cause. More important is the relative homogeneity of risk conditions in this firm that give rise to limited opportunities for matching.

1.   Introduction

■   Risk and risk preferences have played an important role in the economic analysis of contracts. Differences in risk-bearing ability between the firm and workers have been used by theorists to explain the form of incentive contracts (Stiglitz, 1975; Holmstrom, 1979). Empirical studies have concentrated on measuring the importance of risk in contractual settings (e.g., Allen and Lueck, 1992; Lafontaine, 1992), often with disappointing results (Prendergast, 2000). Recent work has stressed the importance of heterogeneous risk preferences and the sorting of workers across risk environments (Ackerberg and Botticini, 2002; Chiappori and Salanié, 2003; Bonin et al., 2007). Sorting reduces the cost of risk in the economy—and the measured effect of risk on contracts— if risk-tolerant workers are attracted to risky settings.

Yet sorting does not preclude risk as an important source of contracting costs when worker heterogeneity is extended to multiple dimensions. In such circumstances, sorting can be based on factors other than risk preferences.[1] The cost of risk will then depend on the risk preferences of workers and the risk levels to which they are exposed. What is more, if the firm performs multiple tasks, or contracts across different risk settings, then matching workers to different risk environments within the firm may be profitable.

In this article, we measure the cost of risk to workers and the derived benefits to matching within a firm that pays its workers piece rates. We exploit payroll data and preference-revealing experiments to identify risk exposure along with worker heterogeneity in two dimensions: risk preferences and ability. We use our estimates to calculate the workers' willingness to pay to avoid risk. We also calculate how profits would increase if the firm offered a menu of contracts to the workers, inducing matching across risk settings within the firm. Finally, we exploit our model to identify the relative importance of labor-market sorting and risk exposure in determining the measured cost of risk within the firm.

Our data come from a British Columbia tree-planting firm. The workers in this firm face substantial daily earnings variation 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 five months in 2006. 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 in which they are planting. Terrain containing rocky or compact soil renders planting more difficult, slowing the planters down and reducing their earnings. The firm 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 (2009), 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) that 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") was completed in 2003.[3] It exogenously varied 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") was conducted in 2006. It followed 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.[4] 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.

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[1] Dohmen and Falk (2011) find that ability explained a large proportion of sorting into payment schemes in a laboratory experiment. Lazear (2000) finds that sorting on ability explained a large proportion of the observed change in productivity that accompanied a change in compensation systems in a firm.

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

[3] Data from this experiment are extensively analyzed in Paarsch and Shearer (2009).

[4] An analysis of the relationship between measured risk preferences and earnings using these data has appeared in Bellemare and Shearer (2010).

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

Our results suggest that matching heterogeneous workers to risk levels can substantially affect profits within the firm studied, particularly when risk levels vary considerably across work sites. Under such circumstances, reallocating risk-averse workers from high-risk to low-risk environments would increase expected profits by up to 15%. Driving this result is the fact that the cost of risk (as measured by the difference between average earnings and certainty-equivalent earnings) can attain 39% of expected earnings for some (risk-averse) workers on high-risk work sites. Differences in risk levels are, however, typically limited within this particular firm, reducing the average increase in firm profits from matching to less than 2.5%. Sorting on risk preferences appears to be of minor importance in explaining this result. If the distribution of risk preferences in the firm replicated that found in broader populations, the benefits to matching would increase by less than one percentage point.

The rest of the article 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

□ **The tree-planting firm.** The data used in this article 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. There is no team production in this firm — 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 that are less appealing to planters (due to 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

TABLE 1 Descriptive Statistics of the Payroll Data

Variable	Mean	Standard 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 deviation earnings	62.54	13.47	37.31	98.62
Standard deviation trees planted	279.90	102.09	118.36	639.58

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.

The labor market in this industry is fluid. There are no unions, and the planters do not sign employment contracts with the firm. They are free to leave the firm at any time if they are not satisfied with the work conditions. In this setting, participation is closely approximated by a daily decision. We will concentrate on this decision in our modelling framework.

☐ **Payroll data.** The payroll data contain information on the piece rate received by each planter, as well as the planter's daily productivity and earnings over a period of five months in 2006. We have restricted the data to contain days for which planters received the same piece rate for a complete day of planting.[5] 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 individuals and blocks with at least 15 observations on them.[6]

The summary statistics for these data are presented in Table 1. The top part 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.[7] Average daily productivity is 920 trees planted and average earnings are equal to $197. The standard deviation in daily earnings is large (equal to $65.64), implying substantial daily earnings variability.[8] Part of this variability is due to variation in individual ability, effort, and planting conditions across blocks; our empirical model will take account of these factors.

Figure 1A plots the relationship between the piece rate and average natural logarithm of productivity. The negative relationship 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 generally higher in the summer and fall months than in the spring.[9]

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

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[5] This eliminates 2497 observations from the data.

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

[7] All monetary figures are in Canadian dollars.

[8] The standard deviation of earnings exceeds $90 on certain blocks.

[9] 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.

FIGURE 1

PIECE-RATE SETTING BEHAVIOR
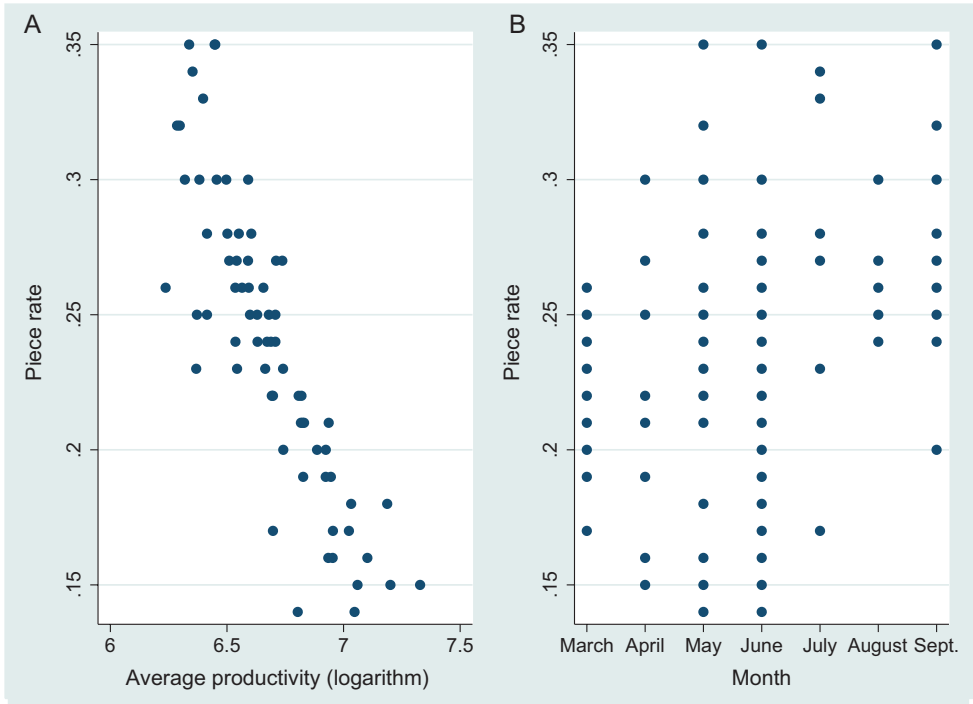
Note: Figure 1A presents the relationship between the average natural logarithm of productivity and the piece rate paid to workers. Figure 1B presents the piece rate as a function of the month of the planting season.

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.[10]

3. Model

☐ **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.

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[10] 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 coefficient on $\overline{y}_i$ is statistically significant (at the 5% level) for only three 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.

FIGURE 2

EMPLOYEE ABILITY AS A FUNCTION OF THE PIECE RATES FROM MARCH TO SEPTEMBER 2006
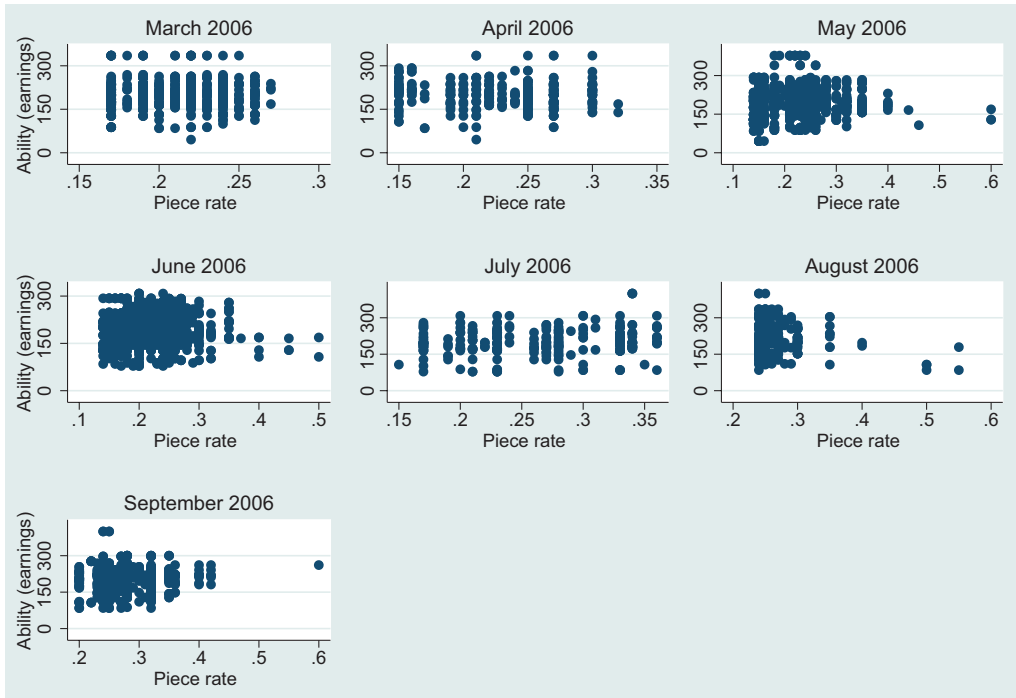
Note: Employee ability is given by the daily earnings of each planter averaged over the entire 2006 season.

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

□ **Utility.** Workers are assumed to have constant absolute risk aversion (CARA)[11] utility functions defined over earnings on block j, W_{ij}, and effort, E_{ij},

$$U(W_{ij}, E_{ij}) = \begin{cases} \dfrac{1}{\delta_i}[W_{ij} - C(E_{ij})]^{\delta_i} & \text{if } W_{ij} > C(E_{ij}); \\ -\infty & \text{otherwise,} \end{cases} \quad (3)$$

where $C(E_{ij}) = \frac{\kappa_i}{\eta} E_{ij}^{\eta}$ denotes individual i's cost of effort. Here, κ_i allows for individual-specific ability in tree planting and η measures the curvature of the function. The parameter δ_i denotes the risk-preference parameter of worker i. 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.[12]

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[11] Additive shocks and CARA preferences present an alternative structure within which to analzse risk preferences and contracts. See, for example, Dubois and Vukina (2009). Developing statistical tools to test between models with additive and multiplicative shocks is an important area of future research for agency models.

[12] The major disadvantage in using CARA utility is the presence of wealth effects. Wealth does not affect effort decisions in this context because 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.

☐ **Timing.** For a given block, j, to be planted:

(i) nature chooses (μ_j, σ_j^2);
(ii) the firm observes (μ_j, σ_j^2) and chooses the piece rate r_j;
(iii) the worker observes (μ_j, σ_j^2, r_j) and accepts or rejects the contract[13];
(iv) 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}; and
(v) 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}.[14] 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.[15]

☐ **Effort choice and output.** Conditional on s_{ij}, the worker selects effort to maximize utility. It follows that optimal effort is given by[16]

$$e_{ij} = \left[\frac{r_j s_{ij}}{\kappa_i}\right]^{\gamma}, \tag{4}$$

where

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

Substituting from (4) into (2) and taking logarithms gives

$$\ln(Y_{ij}) = \gamma \ln(r_j) - \gamma \ln(\kappa_i) + (\gamma + 1)\ln(s_{ij}), \tag{5}$$

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.[17] Note, however, that equilibrium effort will still be affected by risk through the participation constraint and the determination of r_j (see 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

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

$$- \left[r_j E_{ij} s_{ij} - \kappa_i \frac{\gamma}{\gamma + 1} E_{ij}^{\frac{\gamma+1}{\gamma}}\right]^{(\delta_i - 1)} \frac{\kappa_i}{\gamma} E_{ij}^{\frac{(1-\gamma)}{\gamma}}. \tag{6}$$

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

[14] Recall, from Section 2, the firm does not match workers to conditions.

[15] We also assume that workers receive one shock per day. This implies that planting conditions are identical on all parts of the block that they plant.

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

[17] 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.

Evaluating (6) at optimal effort, (4), gives

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

☐ **Indirect utility and contracts.** Substituting from (4) 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,

$$V_{ij} = \frac{1}{\delta_i}\frac{r_j^{\delta_i(\gamma+1)}}{(\gamma+1)^{\delta_i}\kappa_i^{\delta_i\gamma}}\exp^{(\gamma+1)\delta_i\mu_j+0.5(\gamma+1)^2\delta_i^2\sigma_j^2} \tag{7}$$

$$= \frac{1}{\delta_i}\frac{1}{(\gamma+1)^{\delta_i}}[\mathbf{E}(W_{ij})]^{\delta_i}\exp^{0.5\delta_i(\gamma+1)^2\sigma_j^2(\delta_i-1)}, \tag{8}$$

where[18]

$$\mathbf{E}(W_{ij}) = \frac{r_j^{(\gamma+1)}\exp^{(\gamma+1)\mu_j+0.5(\gamma+1)^2\sigma_j^2}}{k_i^{\gamma}}. \tag{9}$$

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. The firm could, in principle, capture some of these rents by offering a menu of piece rates to workers. In accordance with the practices of the firm, we do not analyze the possibility of offering more than one piece rate on a given block.

Define the marginal worker, h, as that worker who is indifferent between working and staying home. Then, from (7),

$$V_{hj} = \frac{1}{\delta_h}\frac{r_j^{\delta_h(\gamma+1)}}{(\gamma+1)^{\delta_h}\kappa_h^{\gamma\delta_h}}\exp\left\{(\gamma+1)\delta_h\mu_j+0.5(\gamma+1)^2\delta_h^2\sigma_j^2\right\} = \frac{1}{\delta_h}\bar{w}^{\delta_h} \tag{10}$$

or

$$(\gamma+1)\mu_j = \ln(\bar{w}) - (\gamma+1)\ln(r_j) + \gamma\ln(\kappa_h) + \ln(\gamma+1) - 0.5(\gamma+1)^2\delta_h\sigma_j^2, \tag{11}$$

where $\bar{w}$ is the net market alternative.[19] Hence, we assume that the firm chooses r_j on each block such that (10) 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.

Given the firm's choice of r_j, the equilibrium expected earnings $\mathbf{E}(W_{ij}^\star)$ for worker i on contract j can be obtained by substituting $r_j^{\gamma+1}$ from (10) into (9), resulting in

$$\mathbf{E}(W_{ij}^\star) = \gamma\bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\exp^{\{0.5(\gamma+1)^2\sigma^2(1-\delta_h)\}} + \bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\exp^{\{0.5(\gamma+1)^2\sigma^2(1-\delta_h)\}}$$

$$= \mathbf{E}\left[C(e_{ij})\right] + \bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^{\gamma}\exp^{\{0.5(\gamma+1)^2\sigma^2(1-\delta_h)\}}. \tag{12}$$

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[18] Equation (8) 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.

[19] More than 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 behavior is stable; that is, the piece rate is set on the basis of the preferences of the same individual within the marginal group.

The first part of (12) represents earnings paid to compensate workers for their expected (optimal) effort costs.[20] The second term in (12) represents equilibrium compensation for the marginal worker's cost of risk, prorated to individual i's ability.[21]

Notice that if the marginal worker does not care about risk, then expected earnings collapses to

$$\mathbf{E}(W_{ij}^\star) = (\gamma + 1)\bar{\omega} \left(\frac{\kappa_h}{\kappa_i}\right)^\gamma,$$

which is constant across contracts (and independent of risk). This provides a direct test of whether risk determines contracts. Recall that workers receive daily shocks to productivity and earnings. One possible scenario in these circumstances is that shocks average out over time and only average earnings matter. Our empirical model nests this scenario as a special case: when $\delta_h = 1$.

□ **The cost of risk.** Hedonic wage equations use earnings regressions to measure the cost of risk (Thaler and Rosen, 1976). As 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 heterogeneous preferences, earnings adjust to compensate the marginal worker for his/her differences in expected utility (Rees, 1975). Also, because effort costs change across contracts along with risk, the observed differential compensates for both changes in effort costs and risk. Calculating the cost of risk in this setting therefore requires measuring the earnings that are required to compensate for risk, holding effort constant.

To measure the cost of risk to workers on a given contract, we calculate the amount a worker is prepared to pay to eliminate risk on that contract, holding expected effort costs constant at optimal levels. We define $\overline{W}_{ij}$ to be worker i's certainty equivalent income on block j. 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 behavior. From (7), $\overline{W}_{ij}$ solves

$$\frac{1}{\delta_i}\left[\overline{W}_{ij} - \mathbf{E}[C(e_{ij})]\right]^{\delta_i} = \frac{1}{\delta_i}\left[\frac{r_j^{(\gamma+1)}}{(\gamma+1)\kappa_i^\gamma}\exp^{(\gamma+1)\mu_j+0.5(\gamma+1)^2\delta_i\sigma_j^2}\right]^{\delta_i}. \tag{13}$$

Substituting $r_j^{\gamma+1}$ from (10) gives

$$\overline{W}_{ij} = \bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \exp^{0.5(\gamma+1)^2\sigma_j^2(\delta_i-\delta_h)} + \mathbf{E}[C(e_{ij})]. \tag{14}$$

The cost of risk cr_{ij} for individual i on block j is therefore obtained by subtracting (14) from the equilibrium expected earnings (12), giving

$$cr_{ij} = \bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \left[\exp^{0.5(\gamma+1)^2\sigma_j^2(1-\delta_h)} - \exp^{0.5(\gamma+1)^2\sigma_j^2(\delta_i-\delta_h)}\right]. \tag{15}$$

Inspection of (15) 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

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[20] The compensation for effort costs can be derived by substituting $r_j^{\gamma+1}$ from (10) in the cost of effort function $C(\cdot)$ evaluated at the optimal effort level given in (4).

[21] To see this, notice that for the marginal individual, the second term is equal to

$$\bar{\omega}\exp^{[0.5(\gamma+1)^2s^2(1-\delta_h)]}, \tag{16}$$

evaluated at $s^2 = \sigma_j^2$, the variance on block j. The difference between (16) evaluated at $s^2 = \sigma_j^2$ and at $s^2 = 0$ (in the absence of risk) represents the cost of risk to the marginal worker on block j (see (15)).

i is risk averse (loving).[22] 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).[23]

It follows from (15) that measuring the cost of risk for individual i on block j requires estimates of

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

In Section 4, we show that by applying our model to payroll data, we can identify

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

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 we call the "piece-rate experiment" (discussed in Section 4), and another to identify δ_i, which we call the "risk-preference-revealing" experiment (discussed in Section 4). 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

□ **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 behavior of the firm, as shown in Figure 1. Substituting from (11) into (5) gives the logarithm of worker i's productivity on block j at month t as

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

where $\epsilon_{ijt} \sim N(0, (\gamma+1)^2\sigma_j^2)$. 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 $\mathbf{E}(\ln(Y_{imt}))$ and $\mathbf{V}(\ln(Y_{imt}))$ denote, respectively, the expectation and the variance of the logarithm 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 $\mathbf{V}(\ln(Y_{ijt})) \neq \mathbf{V}(\ln(Y_{ikt}))$,

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

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.

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[22] 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 $[(1-\delta_h) - (\delta_i - \delta_h)\exp^{0.5(\gamma+1)^2\sigma_j^2(\delta_i-1)}]$, which is positive when $\delta_i < 1$, zero when $\delta_i = 1$, and negative when $\delta_i > 1$.

[23] 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.

Although 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 (17) as

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

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

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

Here, 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 $\{a_0, a_{12}, \ldots, a_{3J}, \tilde{\sigma}_2^2, \ldots, \tilde{\sigma}_J^2, \delta_h\}$ of equation (19) by maximum likelihood.[24]

The econometric model above reveals that $(\gamma + 1)\bar{\omega}_t[\frac{\kappa_h}{\kappa_i}]^\gamma$ 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, that these risk preferences are identified without knowledge of who the marginal worker is. This is important in models with heterogeneity in multiple directions because it is not generally possible to identify the marginal worker *ex ante*.[25] This is due to the fact that the average productivity of the marginal worker can be higher or lower than that of any other worker.

□ **Identifying γ and risk preferences: experimental data.** Identifying γ and the full distribution of risk preferences δ_i requires that we supplement our payroll data with information from other sources. We use experiments, conducted within the same firm, to identify γ and the δ_is. We then extrapolate the results from these experiments to our payroll data.

□ **The piece-rate experiment.** The piece-rate experiment took place on three separate blocks, over a three-month period in 2003.[26] 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, and 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,[27] 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.[28]

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[24] 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).

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

[26] Data from this experiment were first analyzed in Paarsch and Shearer (2009). The maintained assumption of our model is that γ does not vary across time and individuals. This allows us to estimate γ using data from 2003.

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

[28] 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

Let r^T and r^C denote the treatment and control piece rates, respectively. Then, from (5),

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

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

Let J^{pr} denote the number of blocks in the piece-rate experiment, and I^{pr} the number of planters. Furthermore, define $\{Db_j : j = 1, 2, \ldots, J^{pr}\}$ as dummy variables taking a value of 1 for block j, and 0 otherwise. Similarly, define $\{DI_i : i = 1, 2, \ldots, I^{pr}\}$ as dummy variables taking a value of 1 for planter i, and 0 otherwise. Then, combining (20a) and (20b) gives

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

where

$$a_0 = -\gamma \ln(\kappa_1) + \gamma \ln\left(r_1^C\right) + (\gamma + 1)\mathbf{E}\left(\ln(S_{i1})\right)$$

$$a_{1i} = \gamma \left(\ln(\kappa_1) - \ln(\kappa_i)\right)$$

$$a_{2j} = (\gamma + 1)[\mathbf{E}(\ln(S_{ij})) - \mathbf{E}(\ln(S_{i1}))] + \gamma\left(\ln\left(r_j^C\right) - \ln\left(r_1^C\right)\right)$$

$$\epsilon_{ij} = (\gamma + 1)[\ln(S_{ij}) - \mathbf{E}(\ln(S_{ij}))]$$

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.[29]

□ **The risk-preference-revealing experiment.** The risk-preference-revealing experiment took place in May 2006, inspired by the experimental design exploited by Holt and Laury (2002) to determine the risk preferences of an individual.[30] 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 $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,

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prepared (cleared of debris) by the government. In practice, no explanation was needed, as none of the planters questioned the higher piece rates.

[29] In principle, 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.

[30] May is typically the busiest period for the firm. Its workforce during this period is typically made up of both students, working for summer jobs, and career planters (who typically plant throughout the whole season). Consequently, there is no reason to believe that our sample is more homogeneous, in terms of risk preferences, than it would be at another period of the season.

TABLE 2   Summary Statistics: Piece-Rate Experiment

Variable	Average	Standard Deviation Gift	Minimum	Maximum
Control Sample: 109 Observations				
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				
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 3   High Payoff Scale Matrix of the Lottery 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

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 10 decisions would be randomly chosen and played out to determine their earnings. To select which of the 10 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, shuffle the bag, and ask the planter to draw a chip for a second time to determine the outcome of the selected lottery and the planter's lottery earnings.[31]

Extrapolation. Our approach to identification combines estimates from different experiments to estimate parameters otherwise not identified from the economic model and the payroll data. We have done so within the context of a very simple economic model that assumes parameters are constant across time, settings, and in some cases individuals. This allows us to apply the estimated values of γ and δ from separate field experiments directly to the payroll data, which enables us to perform the counterfactual welfare calculations of the cost of risk and the benefits of

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[31] 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. Bellemare and Shearer (2010) provide a further discussion of this experiment.

matching. These are admittedly strong simplifying assumptions that merit scrutiny on the part of the reader.[32] Relaxing them may lead to improved models of worker behavior that generalize more accurately across experimental environments. Nevertheless, our view is that the results based on these simplifying assumptions are of interest and deserve attention.

One immediate concern is that γ may be individual specific. If so, and if the sample of workers has changed between the different settings, then the value of γ that was estimated in the piece-rate experiment may not apply to the workers in the payroll data. Mitigating these concerns is the fact that one third of the workers who participated in the piece-rate experiment are present in the payroll data. Moreover, the composition of the workforce is similar in the two settings. The average age was 34 in the piece-rate experiment and 33 in the payroll data, whereas the proportion of males was .80 in the piece-rate experiment and .67 in the payroll data. This suggests that the average response to incentives obtained in the piece-rate experiment can serve as a reasonable approximation to the response in 2006.[33]

Similar issues arise with respect to the risk preferences. We assume that the risk preferences identified from the lottery experiment apply to the daily work decisions of these workers. Although we do not claim to have perfectly calibrated the earnings or risk levels between the lottery and the payroll data, we note that the lottery represents considerable earnings for the workers, who earn on average $200 per day.[34] We also note that our previous research (Bellemare and Shearer, 2010) shows that the distribution of risk preferences among these workers is not sensitive to scale effects (changes in the amount of money available from the lottery). Finally, we note that the difference in earnings between the high and low payouts in the risky lottery is $75.00, just larger than the standard deviation of daily earnings in the payroll day as reported in Table 1 ($66.00). This suggests that the the risk lottery offers a realistic representation of the daily variation in earnings faced by these workers. Given these facts, we feel that the preferences measured in the lottery are a reasonable approximation to the risk preferences of workers.

5. Results

☐ **Parameter estimates from payroll data.** The risk-preference coefficient δ_h is estimated to be 2.73 and the estimated standard error is 0.403, giving a p value (for the hypothesis $H_o : \delta_h = 0$) essentially equal to zero.[35] The estimated values of $\tilde{\sigma}_j^2$ range between 0.02 and 0.34 with an average of 0.08.[36] 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.

To consider the fit of the model, we calculated 95% and 99% confidence intervals for the average logarithm of predicted daily productivity on each contract. The observed average productivity lies within the 95% confidence interval for 13 of the 22 contracts (59%) and within the 99% confidence interval for 15 of the 22 contracts (68%). The 99% intervals are shown in Figure 3 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, replicating the negative correlation between average productivity and the piece rate.

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[32] Given the nonlinearities involved in calculating the benefits to matching, it is not possible to sign analytically the bias that may result from the violation of these assumptions.

[33] It is worth noting that a common value of γ does not restrict the effort response to incentives to be the same across workers. This is because our costs of effort function depends on κ_i, which varies across planters. It does, however, restrict the elasticity of effort with respect to the piece rate to be constant.

[34] Expected earnings from the lottery depend on the choices the participant makes. However, the participant can guarantee themselves $32.00 by selecting the low-risk lottery at each alternative. Given participation took 20–30 minutes of their time, this represents considerably more than they could expect to make in in a similar amount of time planting trees.

[35] A test of the hypothesis that $\delta_h = 1$, implying that risk has no effect on contracts, is also rejected at all standard significance levels.

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

FIGURE 3

NINETY-NINE PERCENT CONFIDENCE INTERVALS
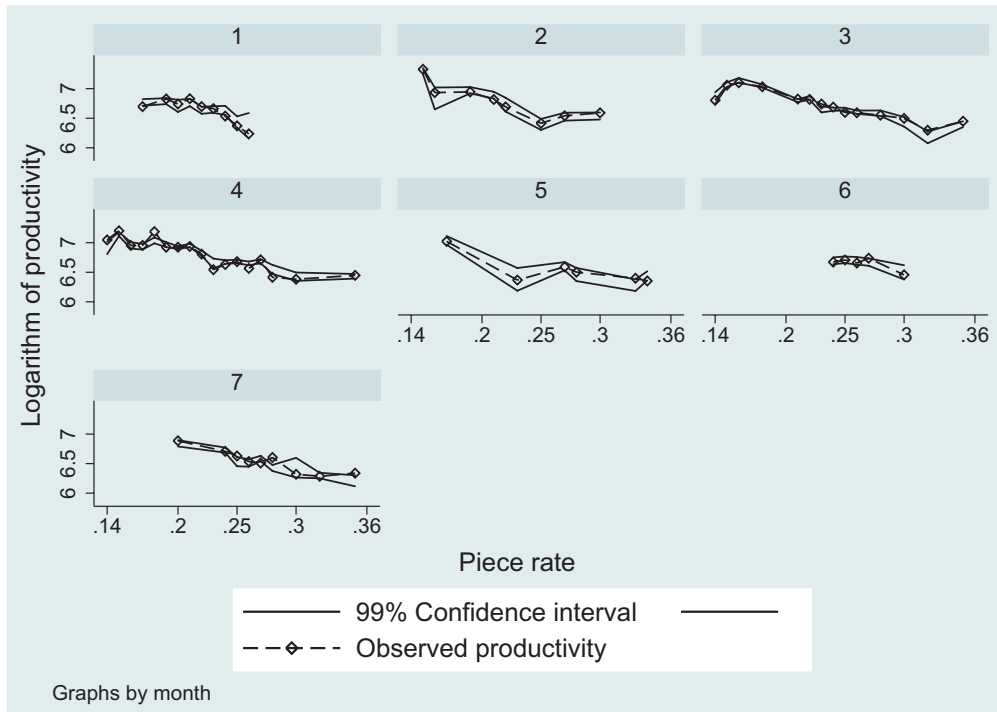
Note: 99% confidence intervals (solid lines) and observed productivity (empty dots). Computations are based on estimates using only the payroll data.

☐ **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. 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.

The estimate of γ from (21) is equal to 0.39. 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.

☐ **The risk-preference-revealing experiment.** The results of the risk-preference-revealing experiment are presented in Table 4 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 (13) individuals provided inconsistent answers during the experiment.[37] The second column under the heading "high payoff scale" gives results, excluding inconsistencies. Overall, we find substantial heterogeneity in risk preferences. Close to one fourth of all workers made decisions revealing risk-loving behavior (three safe choices or fewer), and a little more than half of the workers made decisions revealing various degrees of risk aversion (five or more safe choices).

We note that 7%–8% of the workers in this firm display risk preferences that are consistent with our estimate of δ_h (the risk preferences of the marginal worker) obtained from applying our

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[37] We eliminated these individuals from the sample.

TABLE 4   Risk-Preference-Revealing Experiment Results

Number of safe choices s	$U = x^\delta$	Tree-Planting Firm				Population	
		High Payoff Scale		Low Payoff Scale		High Payoff Scale	
		All	Consistent	All	Consistent	All	Consistent
0–1	$\delta_i > 1.95$	0.085	0.109	0.098	0.142	0.016	0.017
2	$1.49 < \delta_i < 1.95$	0.102	0.130	0.117	0.171	0.021	0.019
3	$1.14 < \delta_i < 1.49$	0.237	0.261	0.235	0.257	0.059	0.053
4	$0.854 < \delta_i < 1.14$	0.458	0.478	0.392	0.457	0.167	0.157
5	$0.589 < \delta_i < 0.854$	0.763	0.739	0.726	0.800	0.295	0.271
6	$0.324 < \delta_i < 0.589$	0.864	0.870	0.902	0.886	0.527	0.496
7	$0.029 < \delta_i < 0.324$	0.915	0.913	0.941	0.914	0.738	0.722
8	$-0.368 < \delta_i < 0.029$	0.966	0.957	0.941	0.914	0.857	0.841
9–10	$\delta_i < -0.368$	1	1	1	1	1	1
Sample size		59	46	51	35	881	806

Note: 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 that is consistent with a given number of safe choices. The table reports distributions for the high- and low-stakes treatments conducted in the firm. The last two columns present the cumulative distribution estimated by Dave, Eckel, Johnson, and Rojas (2010) for the entire population. "All" refers to the entire sample in each treatment. "Consistent" refers to the subsamples of subjects in each treatment who made consistent answers.

structural model to the payroll data. Although 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 except that the lottery payoffs were one half of those used in the current experiment.[38] Fifty-one workers participated in the previous experiment. The payoff scale should not affect the distribution of measured risk preferences, conditional on preferences being of the CARA type. Results for all workers and only those who gave consistent answers are reported in the second two columns of Table 4 under the heading "low payoff scale." We find that the distribution of risk preferences is broadly similar to the high payoff scale experiment.[39] In particular, the proportion of risk-loving workers remains above 20%, whereas 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 (local) rescaling of the payoffs in the experiment.[40] It is also of interest to compare the risk preferences of these workers to those of individuals sampled from a broader population. The final column presents the results of Dave, Eckel, Johnson, and Rojas (2010), who conducted 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. 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.

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

[39] Invariance to rescaling is generally inconsistent with CARA preferences, which predict increased aversion to risk as stakes are increased (Holt and Laury, 2002).

[40] Although larger changes may bring about changes in preferences over risk, we feel that the scales considered are relevant for investigating behavior in tree planting, where workers typically earn approximately $200 per day.

6. Policy analysis

□ **The importance of risk to workers.** To measure the cost of risk for the workers in this firm, we evaluated (15) 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 4. The average cost of risk on the high-variance block (top left graph) is equal to \$1.26 and the standard deviation is 17.35. There is considerable heterogeneity, with values ranging from $-\$38.73$ to \$72.56, reflecting heterogeneity in planting abilities and risk preferences. Yet the majority of values are concentrated around the mean: the interquartile range of the cost of risk $(-5.05, 6.1)$. 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).

□ **The benefits of matching.** The heterogeneity in risk preferences suggests that there are potential gains to the firm from matching workers to contracts based on risk conditions and preferences. In this section, we analyze these benefits. We first present our formal analysis within the context of two available contracts. Extending to multiple contracts (which we do to compute the gains) is straightforward.

Measuring the benefits to matching is complicated by the fact that observed contracts vary in both μ_j and σ_j^2. To isolate the potential benefits accruing from differences in risk and risk preferences, we consider the change in profits that the firm could earn from matching across contracts that differ only in the risk parameter σ^2.[41] To do so, we use our model to generate contracts that differ in risk, holding μ constant at μ_0. From (10),

$$r_j^{(\gamma+1)} \exp^{(0.5(\gamma+1)^2 \delta_h \sigma_j^2)} = \bar{\omega} \kappa_h^{\gamma} (\gamma + 1) \exp^{-(\gamma+1)\mu_j} \equiv \tilde{\mu}_j. \tag{22}$$

We set $\tilde{\mu}_0$ at the level of $\tilde{\mu}_j$ on the low-variance contract in the data (for which $r_j = 0.35$ and $(\gamma + 1)^2 \sigma_j^2 = 0.018$). This gives a value of $\tilde{\mu}_0 = 0.24$. We then use (22) to generate piece rates $\hat{r}_j$ that are consistent with the estimated variances and $\tilde{\mu}_0$; that is,

$$\hat{r}_j^{(\gamma+1)} = \exp^{-(0.5(\gamma+1)^2 \delta_h \sigma_j^2)} \tilde{\mu}_0. \tag{23}$$

The generated contracts for the month of May 2006 are given in Table 5. The table also shows the value of the risk parameter, σ_j^2, and the original contract, r_j. We show in Appendix B that the choice of blocks from which to calculate $\tilde{\mu}_0$ is immaterial to our results. Whereas it will alter the value of $\tilde{\mu}_0$ and the generated piece rates, matching profits and worker expected utility are unaffected.

To study the benefits of matching, we first consider how worker utility would change on block j if the piece rate paid on that block were changed from $\hat{r}_j$ to $\tilde{r}_j$, holding conditions constant at μ_0, σ_j^2. From (7), worker i's indirect utility from planting on plot j at the piece rate $\tilde{r}_j$ is given by
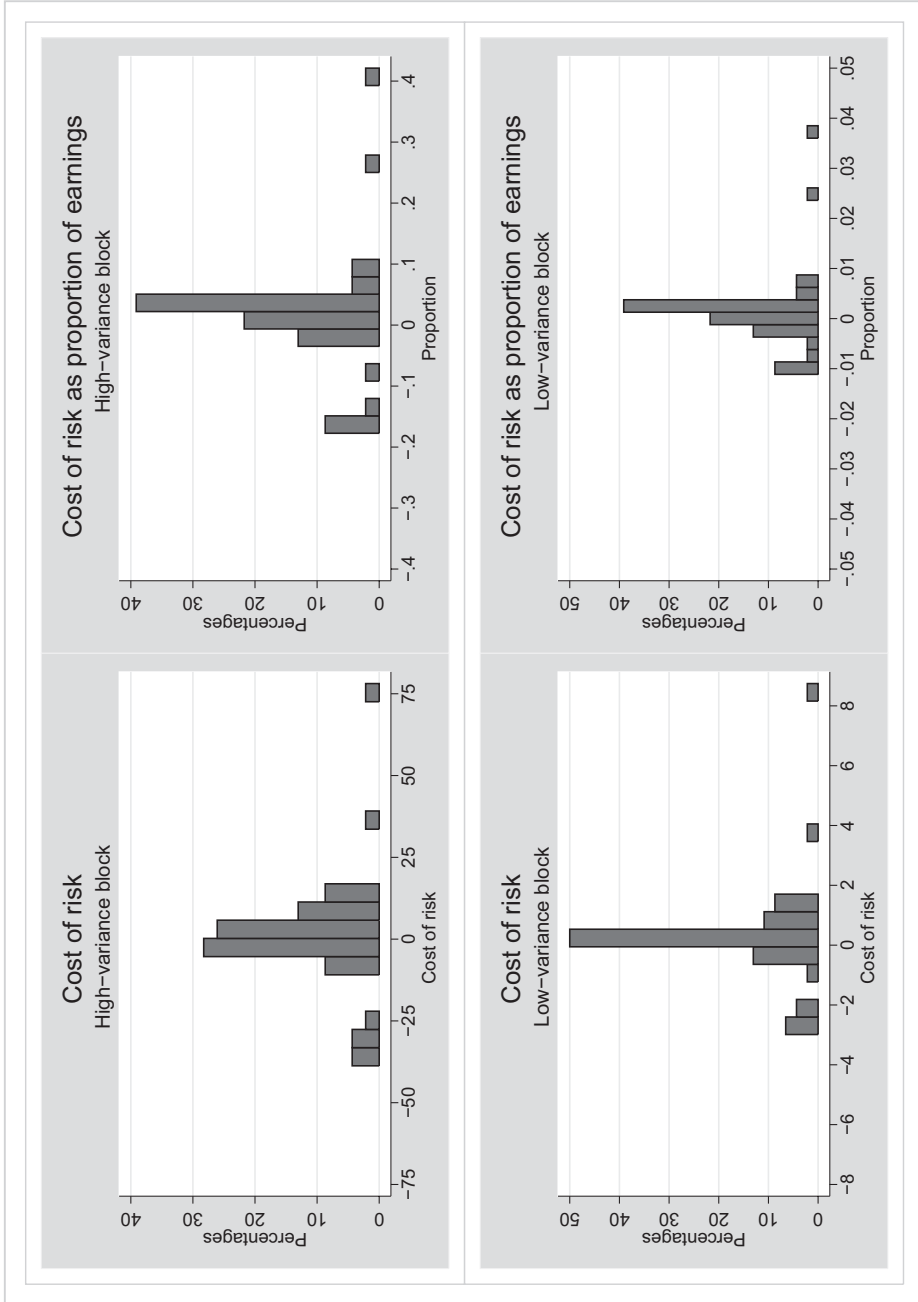
$$V_{i,j}(\tilde{r}_j; \hat{r}_j, \tilde{\mu}_0, \sigma_j^2) = \frac{1}{\delta_i} \frac{\tilde{r}_j^{\delta_i(\gamma+1)}}{(\gamma + 1)^{\delta_i} \kappa_i^{\delta_i \gamma}} \exp^{(\gamma+1)\delta_i \mu_0 + 0.5(\gamma+1)^2 \delta_i^2 \sigma_j^2}. \tag{24}$$

But from (10),

$$\exp^{\{(\gamma+1)\mu_0\}} = \frac{\bar{\omega}(\gamma + 1)\kappa_h^{\gamma} \exp^{-0.5\delta_h(\gamma+1)^2 \sigma_j^2}}{\hat{r}_j^{\gamma+1}}, \tag{25}$$

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[41] From (15), and footnote 22, this alters the cost of risk to workers and hence the benefits of matching.

FIGURE 4

THE COST OF RISK

Note: 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.

TABLE 5   Original and Generated Contracts with Constant $\bar{m}u$ for the Month of May 2006

Variance σ_j^2	Original Contract r_j	Generated Contract $\hat{r}_j$
0.25732	0.14000	0.27675
0.21506	0.32000	0.28846
0.10284	0.15000	0.32203
0.069655	0.23000	0.33268
0.068638	0.16000	0.33302
0.057580	0.25000	0.33665
0.056098	0.28000	0.33714
0.042678	0.30000	0.34160
0.041691	0.24000	0.34194
0.039515	0.26000	0.34267
0.033015	0.21000	0.34486
0.028588	0.18000	0.34636
0.026214	0.22000	0.34717
0.017924	0.35000	0.35000

which depends on the piece rate $\hat{r}_j$. Combining with (24) gives

$$V_{i,j}\left(\tilde{r}_j; \hat{r}_j, \mu_j, \sigma_j^2\right) = \frac{1}{\delta_i}\left[\left(\frac{\tilde{r}_j}{\hat{r}_j}\right)^{(\gamma+1)}\bar{\omega}\left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \exp^{0.5(\gamma+1)^2\sigma_j^2(\delta_i-\delta_h)}\right]^{\delta_i}. \tag{26}$$

☐ **Matching with two available blocks.** Now, consider a planting day for which two planting blocks are available. These are denoted H and L, with $\sigma_H^2 > \sigma_L^2$. Let $\hat{r}_H$ and $\hat{r}_L$ denote the piece rates the firm would pay on these plots at μ_0. If the firm instead paid $\tilde{r}_L$ on plot L and allowed workers to choose the plot on which they plant, workers for whom

$$V_{i,L}\left(\tilde{r}_L; \hat{r}_L, \mu_0, \sigma_L^2\right) > V_{i,H}\left(r_H; r_H, \mu_0, \sigma_H^2\right) \tag{27}$$

would choose to plant on plot L. With two blocks available, this is equivalent to

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

or

$$\left(\frac{\tilde{r}_L}{\hat{r}_L}\right)^{(\gamma+1)} > \exp^{0.5(\gamma+1)^2(\delta_i-\delta_h)(\sigma_H^2-\sigma_L^2)}. \tag{28}$$

The potential gains to matching can be seen from (28). The right-hand side of (28) is less than one if $\delta_i < \delta_h$. Hence, the firm can reduce the piece rate paid to these workers on block L, $\tilde{r}_L$, whereas 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, (28) is only satisfied if $\tilde{r}_L > \hat{r}_L$, increasing costs for the firm. Of course, whether or not actual gains are realized will depend on the change in behavior 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 (28) for δ_i gives the set $\Delta(\tilde{r}_L)$ of workers who will choose to plant on plot L as a function of $\tilde{r}_L$:

$$\Delta(\tilde{r}_L) = \{\delta_i : \delta_i < \delta^*(\tilde{r}_L)\}, \tag{29}$$

where the threshold value $\delta^*(\tilde{r}_L)$ is given by[42]

$$\delta^*(\tilde{r}_L) = \delta_h + \frac{2(\ln(\tilde{r}_L) - \ln(\hat{r}_L))}{(\gamma + 1)(\sigma_H^2 - \sigma_L^2)}. \tag{30}$$

The gains from matching are calculated by comparing the firm's expected daily profits that result from allowing workers to sort across a given high-variance block H and the low-variance block L.[43] We denote these profits $\pi_{t,H,L}^m$. We then calculate the profits from randomly allocating workers across these two blocks, denoted $\pi_{t,H,L}^{nm}$. We denote the expected profit increase to matching workers between these two blocks $\pi_{t,H,L}$.

To illustrate, consider the two blocks used in Section 6 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 (10), giving daily profits for worker i on block j equal to

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

To calculate the profits from not matching workers, we randomly allocate workers to block H and block L. Profits are then given by

$$\pi_{t,H,L}^{nm} = \sum_{i \in \mathcal{H}} \pi_{i,H}^{nm} + \sum_{i \in \mathcal{L}} \pi_{i,L}^{nm}, \tag{31}$$

where $i \in \mathcal{H}$ denotes the set of workers who are randomly allocated to plant on block H and $i \in \mathcal{L}$ denotes the set of workers who are randomly allocated to plant on block L.

Under matching, the firm chooses $\tilde{r}_L$ to maximize

$$\pi_{t,H,L}^m = \sum_{\delta_i \in \Delta(\tilde{r}_L)} (P_L - \tilde{r}_L)\frac{\tilde{r}_L^\gamma}{\hat{r}_L^{(\gamma+1)}}\bar{\omega}(\gamma + 1)\left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \exp^{0.5(\gamma+1)^2\sigma_L^2(1-\delta_h)}$$

$$+ \sum_{\delta_i \notin \Delta(\tilde{r}_L)} \frac{(P_H - r_H)}{r_H}\bar{\omega}(\gamma + 1)\left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \exp^{0.5(\gamma+1)^2\sigma_H^2(1-\delta_h)}. \tag{32}$$

The increase in expected profit from matching between block j and L is then given by

$$\pi_{t,H,L} = \frac{\left(\pi_{t,H,L}^m - \pi_{t,H,L}^{nm}\right)}{\pi_{t,H,L}^{nm}}. \tag{33}$$

To calculate profits, we set $P_j = 2 \times \hat{r}_j$. 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 identifies for each worker a range of parameter values for the risk-preference parameter δ_i. We perform our calculation by choosing the midpoint of the appropriate interval for each worker.[44]

☐ **Matching with J available blocks.** To generalize to the case where J_t blocks are to be planted on day t, let $\hat{\mathbf{r}} = (\hat{r}_1, \hat{r}_2, \ldots, \hat{r}_{J_t})$ denote the vector of piece rates on the J_t blocks that

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[42] Equation (30) can be generalized to solve for workers' preferred blocks if γ is heterogeneous. Under such circumstances, (30) can be solved for δ^* for all planters with a given value of γ. Solving for the matching equilibrium then requires iterating over different values of γ in the sample for each $\tilde{r}_L$.

[43] We take as given the observed firm practice of paying the same contract to all workers planting on the same block.

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

solve (23). Furthermore, let $\tilde{\mathbf{r}} = (\tilde{r}_1, \tilde{r}_2, \ldots, \tilde{r}_{J_t})$ denote the vector of piece rates paid on those blocks. Generalizing (27), define

$$\Delta(j, \tilde{\mathbf{r}}) = \{\delta_i : V(i, j, \tilde{r}_j, \hat{r}_j) > V(i, j', \tilde{r}_{j'}, \hat{r}_{j'}) \, \forall j' \neq j\} \tag{34}$$

to be the set of workers, defined by their risk preferences, who prefer block j at piece-rate vector $\tilde{\mathbf{r}}$. Finally, let H denote $j : \sigma_j^2 \geq \sigma_{j'}^2 \quad \forall j' \in J_t$, the block with the highest variance from the available J_t blocks, and let $\tilde{\mathbf{r}}_{\tilde{H}}$ denote the subvector of $\tilde{\mathbf{r}}$ that excludes $\tilde{r}_H$. The profits from matching are given by

$$\pi_{t,J_t}^m = \sum_{j \neq H} \left\{ \sum_{\delta_i \in \Delta(j, \tilde{\mathbf{r}})} (P_j - \tilde{r}_j) \frac{\tilde{r}_j^\gamma}{\hat{r}_j^{(\gamma+1)}} \bar{\omega}(\gamma + 1) \left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \exp^{0.5(\gamma+1)^2 \sigma_j^2 (1-\delta_h)} \right\}$$

$$+ \sum_{\delta_i \in \Delta(H, \tilde{r})} \frac{(P_H - r_H)}{r_H} \bar{\omega}(\gamma + 1) \left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \exp^{0.5(\gamma+1)^2 \sigma_H^2 (1-\delta_h)} . \tag{35}$$

Under matching, the firm chooses $\tilde{\mathbf{r}}_{\tilde{H}}$ to maximize (35).

The profits from not matching are given by

$$\pi_{t,J_t}^{nm} = \sum_{j=1}^{J_t} \left\{ \sum_{i \in j} \pi_{i,j}^{nm} \right\}, \tag{36}$$

where

$$\pi_{i,j}^{nm} = \frac{(P_j - r_j)}{r_j} \bar{\omega}(\gamma + 1) \left(\frac{\kappa_h}{\kappa_i}\right)^\gamma \exp^{0.5(\gamma+1)^2 \sigma_j^2 (1-\delta_h)} .$$

The percentage gain from matching on day t is then given by

$$\pi_{t,J_t} = \frac{(\pi_{t,J_t}^m - \pi_{t,J_t}^{nm})}{\pi_{t,J_t}^{nm}}, \tag{37}$$

and the gains to matching over a period of T planting days are given by the average of the daily gains,

$$\sum_{t=1}^{T} \frac{1}{T} \pi_{t,J_t}. \tag{38}$$

☐ **Calculating the gains to matching.** To calculate the profit gain to matching within the firm, we calculate (37) across different planting days throughout the planting season, taking the available piece rates as given on each day. As such, we reproduce the actual distribution of piece rates that are available for matching workers within the firm on different planting days. In practice, the blocks on which the planters work are grouped together based on geographic location. These blocks are all accessible from a common site (the camp or the hotel at which the planters are staying). We consider a planting day to be a date on which planting occurred at one or more piece rates within one of these geographic regions. This ensures that matching was geographically possible across piece rates (the different blocks were accessible to the planters). It also renders the number of planting days greater than the number of separate dates on which work was performed in the firm.

To calculate the benefits to matching, we used the distribution of piece rates on planting days from the month of May 2006.[45] This distribution is presented in Table 6. Notice that of the 86 planting-contract days during this month, 37 days (43%) featured only one piece rate and hence

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[45] The month of May is typically the busiest time for planting during the season. The average number of blocks planted per day in this month was 1.90, compared to 1.71 for the 2006 season.

TABLE 6   Distribution of Matching Opportunities

Contracts per Day	Number of Occurrences	Percent
1	37	43.02
2	25	29.07
3	19	22.09
4	5	5.81

FIGURE 5

DISTRIBUTION OF THE BENEFITS TO MATCHING ACROSS ALL BLOCKS PLANTED DURING THE 2006 SEASON
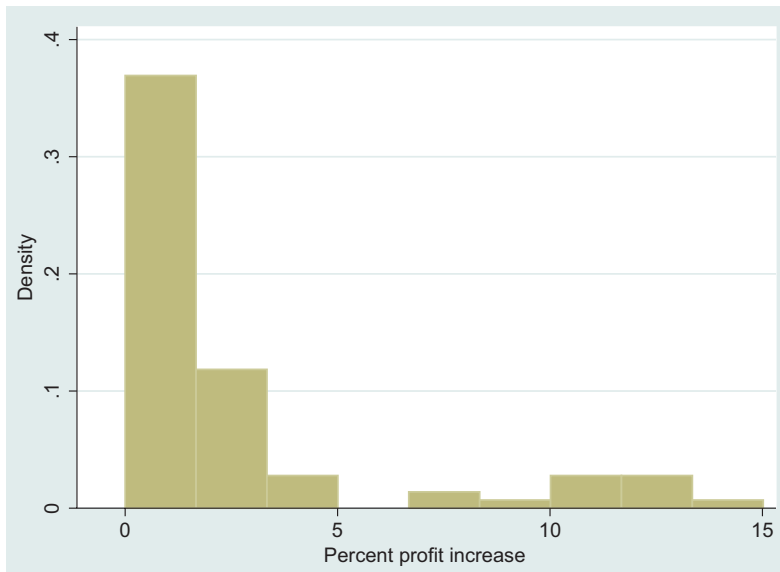
no matching possibilities. Of the remaining days, 25 (29%) featured two contracts, 19 (22%) featured three contracts, and 5 (6%) featured four contracts.

For each planting day, we ordered the blocks available according to the block variance σ_j^2. We then allow the firm to vary $\tilde{\mathbf{r}}_{\bar{H}}$ to maximize (35) subject to workers choosing the block on which they want to work. To complete the maximization problem, we discretized the values of $\tilde{\mathbf{r}}_{\bar{H}}$ and performed a grid search over the discrete alternatives, calculating the profit of each alternative.[46] We then calculated (36) resulting from a random allocation of planters across blocks. In all cases, we assume that all workers are available for all contracts on a given planting day.[47]

The results are shown graphically in Figure 5. The average increase in profits from matching is on the order of 2.3%. This is relatively small in economic terms, yet statistically significant:

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[46] We allowed for 299 different piece rates on each block, ranging between the unconstrained profit-maximizing piece rate $\gamma/(\gamma+1)P$ and the generated piece rate $\hat{r}_j$ (which satisfies the participation constraint). The number of replications was chosen based on calculation time and how the number of discrete values affected results. With 299 values for each block, we evaluate the profit function $299^3 = 26,730,899$ iterations for planting days with four piece rates available. Running the complete program to calculate profits on each planting day in the month of May takes 2 hours on a Lenovo M90P desktop computer. Simulating confidence intervals using 99 draws of the estimated parameters takes just over 8 days. Increasing the number of piece-rate values in the grid search to 399 gives no perceptible change in our results—the average profit increase over all contracts is 2.28% rather than 2.3%—whereas increasing the computing time to 4 hours and 45 minutes.

[47] If certain types of workers were not available on certain days, then the benefits of matching would decrease. In this sense, we can interpret our estimates as an upper bound to the benefits of matching within this firm.

FIGURE 6

DISTRIBUTION OF THE VARIANCES ACROSS ALL BLOCKS PLANTED DURING THE 2006 SEASON
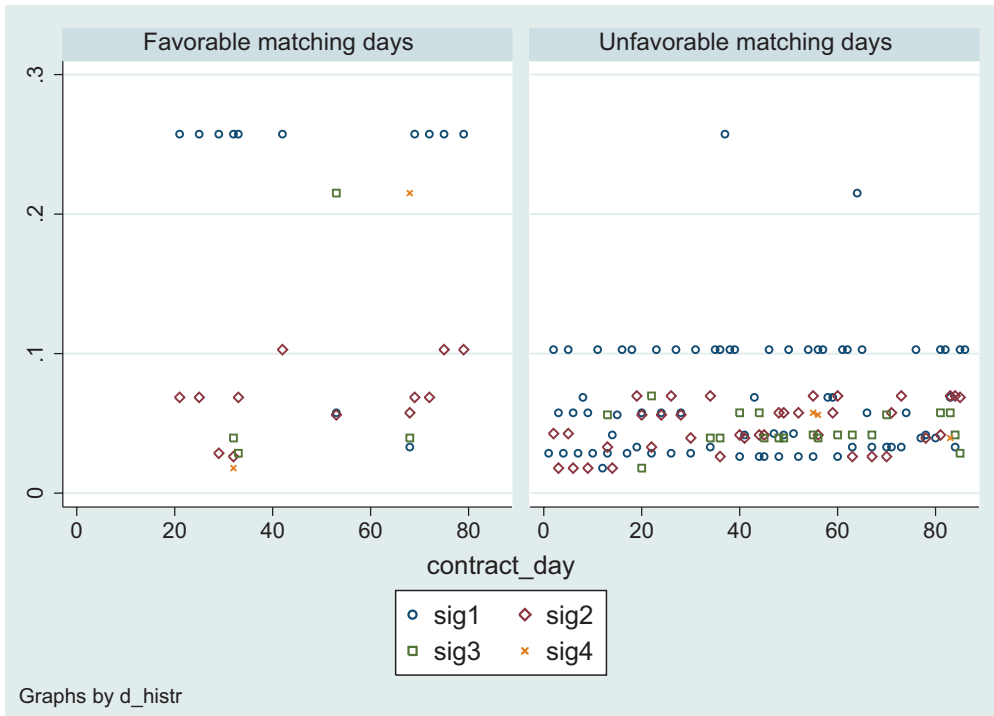
Note: Left and right graphs present results for profitable and unprofitable days, respectively.

the simulated 95% confidence interval is (1.8%, 3.1%).[48] This average increase in profits nearly doubles to 4% if we limit consideration to days in which matching was possible (i.e., days on which more than one block was planted). What is more, for some planting days, the profit increase from matching attains 15%. This suggests that matching can have substantial benefits under certain conditions, although those conditions do not occur very often within this particular firm.

The histogram of percent increases in profits due to matching suggests two broad groups of planting days: those for which the gains to matching are economically modest (less than 5%) and those for which the gains to matching are economically more significant (greater than 5%); we refer to the latter as profitable matching days. To characterize the conditions that lead to significant gains to matching, we compare the variability in planting conditions (and hence the opportunities for matching) between profitable and unprofitable planting days. In Figure 6, we graph the distribution of daily block conditions (the variances on the different blocks planted on a particular day) that are available for planting on profitable and unprofitable days. The results are quite striking and accord with intuition: profitable matching days are days for which σ_j^2 varied considerably across the available blocks. For days on which matching led to significant gains in profit, the variance of σ_j^2 across blocks was equal to 0.12, six times higher than for days on which the gains to matching were modest (for which the variance of σ^2 is .02).

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[48] The confidence interval is derived by simulation. In particular, we take 99 random draws from the joint distribution of $(\gamma, \{\kappa_i : i = 1, \ldots, N\}, \{(\mu_j, \sigma_j^2) : j = 1, \ldots, J\})$ and evaluate the matching benefits for each draw. We keep $\delta_i : i = 1, \ldots, N$ fixed throughout, as their distributional properties are unknown. The confidence interval is derived from the variance of the matching benefits across all draws.

□ **Capacity constraints to matching.** The estimates provided in the previous section were generated ignoring capacity constraints, essentially assuming that blocks can accommodate as many workers as want to plant on them. If blocks have limited capacity, then these estimates may overstate the benefits of matching. To consider this, we limit the number of workers who can plant on a given block, on a given day, to the number of planting days available on that block, on that day. We do so for both the matching solution and the no-matching solution, where workers are randomly allocated. Given we assume that all workers are available to plant on every day, we prorate the constraint on a given block as the proportion of planter-days on that block relative to total number of planter-days for all blocks available on the same day. If blocks j and k were planted on day t with d_j and d_k planter-days available, respectively, and if N is the number of planters in the firm, then $n_j \leq C_j \equiv (d_j/(d_j + d_k)) \times N$ and $n_k \leq C_k \equiv (d_k/(d_j + d_k)) \times N$ are the constraints imposed on the number of planters allocated to blocks j and k.

Note, because the firm does not change the piece rate on block H, the planters are all willing to plant on this block. On the other blocks, the firm reduces the piece rate below that which satisfies the marginal worker's participation constraint, taking advantage of the fact that workers who are less risk loving than the marginal worker will still plant on those blocks at reduced piece rate, as the variance is lower. For blocks $j \neq H$, the piece rate is below the regular piece rate (which solves the participation constraints by assumption). We therefore never force a worker to move from block H, as we cannot be sure that his/her participation constraint is satisfied.

To take account of these capacity constraints, we calculate each worker's preference ordering over the J available blocks given $\tilde{\mathbf{r}}$. We then calculate the number of workers who prefer each block, n_j. If $n_j > C_j$ (too many workers select block j), then $n_j - C_j$ of these workers are randomly chosen to change blocks. If $J = 2$, these workers are moved to block H. If $J = 3$, these workers are moved to their second-choice block, if there is space to accommodate them; otherwise, they are moved to their third choice. In this way, there can never be an overload (too many workers) on block $j \neq H$. There can, however, be an overload on block H. If this occurs, we consider that no matching solution exists under the capacity constraints, and we calculate profits to be those from random allocation under observed piece rates—there is no gain to matching in this case. If $J = 4$, workers are moved to their second, third, and fourth choice, as in the case of $J = 3$.

Imposing capacity constraints reduces the firm's ability to match workers to conditions and hence reduces the potential profits from matching. Our results are presented in Figure 7. They suggest that the effects of constraints are economically significant, cutting the average percentage gains to matching to less than 1% (0.6%). The maximum profit increase is 5%. The benefits to matching are almost exactly 1% (1.004%) on days when matching was possible.

□ **The importance of risk preferences.** The relatively small benefits to matching within this firm may be due to labor-market sorting, leading to risk-tolerant workers being attracted to the firm, or the low frequency to which workers are exposed to high-risk environments. To investigate the relative importance of labor-market sorting on risk preferences, we shift the distribution of risk preferences to mimic that found in the Canadian population. We do this by randomly excluding/replicating workers in each risk class to render the proportion of workers in that class equal to that of the population.[49] We then recalculate the benefits to matching workers across risk levels observed in the firm given the population distribution of risk preferences. Doing so increases the benefits to matching within the firm, but only slightly. The distribution of the returns to matching is presented in Figure 8. Matching would increase profits by 2.67% (4.69%

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[49] For example, from Table 4, there are that 11% of the firm's workers (five workers) are in the most risk-loving class, whereas only 2% of the population are found in that risk class. If 2% of the workers were in this risk class, we would expect to find one worker. We therefore randomly eliminate four of the five workers we find in that risk class. Similarly, only 1% of workers are in the most risk-averse class, versus 16% of the population. If 16% of the workers were in this risk class, we would expect to find seven workers there. We therefore randomly replicate the two workers who are in this class to add five extra workers.

FIGURE 7

DISTRIBUTION OF THE CONSTRAINED BENEFITS TO MATCHING ACROSS ALL BLOCKS PLANTED
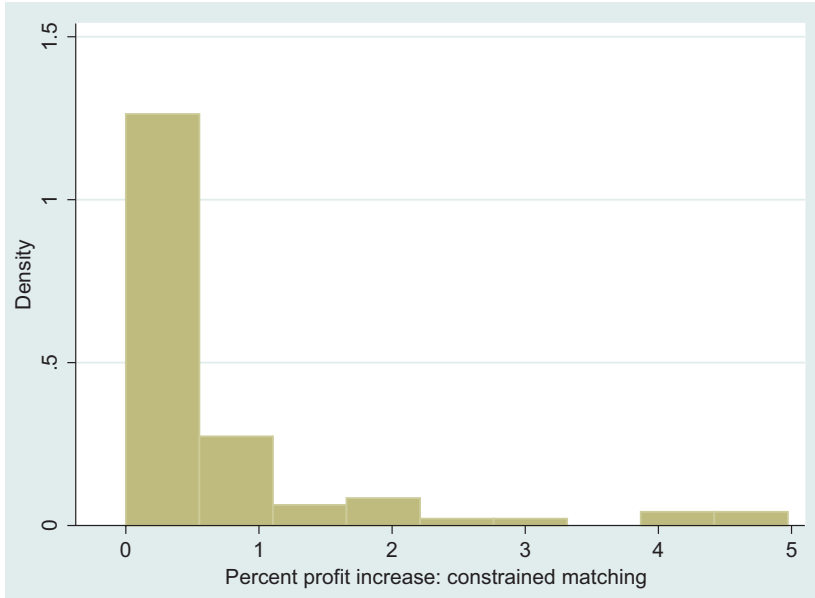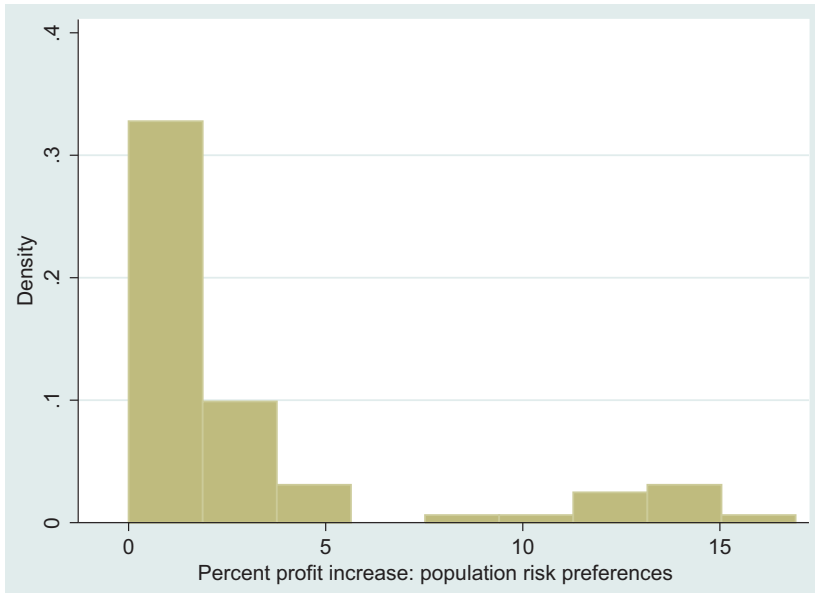DURING THE 2006 SEASON

FIGURE 8

DISTRIBUTION OF THE BENEFITS TO MATCHING ACROSS ALL BLOCKS PLANTED DURING THE 2006
SEASON USING POPULATION RISK PREFERENCES

if we restrict attention to days when matching is possible). This represents an increase of less than 1% vis-à-vis the actual distribution of risk preferences in the firm. This suggests that the minor importance of risk within the firm is caused by the low frequency with which workers are exposed to high-risk environments; it is not due to sorting on risk preferences.

7. Discussion and conclusions

■ We have measured the importance of risk within a firm that pays its workers piece rates. Our measures are based on the benefits of reducing risk exposure to the firm's workers. We found that the willingness to pay to avoid risk varies across workers, reflecting heterogeneity in risk preferences and worker ability. Overall, the cost or risk is predicted to be small: the measured willingness to pay averages to only 1% of expected net earnings, even on the riskiest contracts within the firm. Our results also suggest that the benefits to the firm from matching workers to risk environments are generally low, increasing profits by 2.3% (4% in situations where matching was possible). Taking account of congestion problems in allocating workers across different blocks reduces the estimated returns to matching to 0.6%.

We have investigated two possible explanations for the minor importance of matching within this firm. First, the workers are (on average) risk tolerant, so that risk is not important to them. This is consistent with selectivity and sorting in the labor market. Second, the conditions found within this firm are not conducive to matching. Our results suggest that the second explanation dominates. Even if the distribution of risk preferences within the firm replicated that found in the broader population, the benefits of matching would increase by less than one percentage point.

We caution that our results should not be interpreted as showing matching does not matter. Rather, they show that matching is of little importance within this particular firm. Other firms, operating in different settings, may have larger returns to matching. Indeed, our results point to where we should look for profitable opportunities for matching: where the measure of risk across working conditions is highly variable. Under such conditions, matching can increase profits by as much as 15% within this firm. Larger gains to matching might be expected in different contexts. For example, in situations where workers cannot observe production shocks before they choose their effort level, effort will generally depend on the worker's risk preferences. This will increase the variability of output, likely resulting in higher returns to matching. Matching might also bring more important welfare gains across firms with different risk exposure than within a given firm, as in the current study. Finally, matching might be more important for managers than for blue-collar workers. Recent work by Gayle and Miller (2009) shows that risk and risk preferences play an important role in determining managerial compensation contracts. Calculating the empirical gains to matching in such settings would be an interesting direction for future research.

Our results also have implications for the study of incentive contracts. It is well known that real-world contracts rarely resemble their theoretical counterparts (*e.g.*, Stiglitz, 1991). What is more, observed contracts often do not vary as established theories would suggest (Allen and Lueck, 1992). Although the effects of heterogeneity and sorting have been recognized within the context of these debates (Ackerberg and Botticini, 2002), our results point to the importance of multidimensional heterogeneity and the possible bunching of types within contractual settings. In such cases, it is not clear that any testable relationship between risk and contracts can be established *ex ante*. Further characterization of the implications of multidimensional heterogeneity for optimal contracts may lead to new and important insights into the relationship between theoretical and real-world contracts.[50]

Finally, this article highlights the complementarities between econometrics and experiments for empirical work in economics. Experiments can provide supplementary information over parameters not identified by econometric models. They can also provide over-identifying information, confirming the estimates of structural parameters that are identified within structural

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[50] Rochet and Stole (2003) provide an account of the theoretical literature on multidimensional sorting.

models but may be sensitive to functional form assumptions. In turn, econometrics can provide information not found in experiments. The cost of risk depends on preferences and risk exposure. Experiments can provide information on risk preferences, but may have difficulty replicating (or even identifying) the risk levels that workers face in the actual economy.

Appendix A

This appendix contains the decision sheet for the risk-preference-revealing experiment.

	Option A	My choice is A	Option B	My choice is B
Decision 1	$40.00 if chip is 1 $32.00 if chip is 2 to 10		$77.00 if chip is 1 $2.00 if chip is 2 to 10	
Decision 2	$40.00 if chip is 1 to 2 $32.00 if chip is 3 to 10		$77.00 if chip is 1 to 2 $2.00 if chip is 3 to 10	
Decision 3	$40.00 if chip is 1 to 3 $32.00 if chip is 4 to 10		$77.00 if chip is 1 to 3 $2.00 if chip is 4 to 10	
Decision 4	$40.00 if chip is 1 to 4 $32.00 if chip is 5 to 10		$77.00 if chip is 1 to 4 $2.00 if chip is 5 to 10	
Decision 5	$40.00 if chip is 1 to 5 $32.00 if chip is 6 to 10		$77.00 if chip is 1 to 5 $2.00 if chip is 6 to 10	
Decision 6	$40.00 if chip is 1 to 6 $32.00 if chip is 7 to 10		$77.00 if chip is 1 to 6 $2.00 if chip is 7 to 10	
Decision 7	$40.00 if chip is 1 to 7 $32.00 if chip is 8 to 10		$77.00 if chip is 1 to 7 $2.00 if chip is 8 to 10	
Decision 8	$40.00 if chip is 1 to 8 $32.00 if chip is 9 to 10		$77.00 if chip is 1 to 8 $2.00 if chip is 9 to 10	
Decision 9	$40.00 if chip is 1 to 9 $32.00 if chip is 10		$77.00 if chip is 1 to 9 $2.00 if chip is 10	
Decision 10	$40.00 if chip is 1 to 10		$77.00 if chip is 1 to 10	

Appendix B

Below we show that the choice of blocks from which to calculate $\tilde{\mu}_0$ has no effect on our results

Note that the generated contracts ensure workers the same level of expected utility as they get under observed contracts:

$$E\left[U_{i,j}\left(\hat{r}_j, \mu_0, \sigma_j^2\right)\right] = \frac{1}{\delta_i}\left[\frac{\hat{r}_j^{\gamma+1}}{(\gamma+1)\kappa_i^{\gamma}}\exp^{(\gamma+1)\mu_0+0.5(\gamma+1)^2\sigma_j^2\delta_i}\right]^{\delta_i}$$

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

$$= E\left[U_{ij}\left(r_j, \mu_j, \sigma_j^2\right)\right]. \tag{B1}$$

Similarly, profits are unchanged by the use of the generated contract (as long as the price P_j is twice the piece rate paid to workers).[51] To see this, note that under the observed contracts, expected profits of individual i on block j are given by

$$E\left[\pi_{ij}\left(r_j, \mu_j, \sigma_j^2\right)\right] = (P_j - r_j)\frac{r_j^{\gamma}}{\kappa_i^{\gamma}}E[S^{(\gamma+1)}]$$

$$= (P_j - r_j)\frac{r_j^{\gamma}}{\kappa_i^{\gamma}}\exp^{(\gamma+1)\mu_j+0.5(\gamma+1)^2\sigma_j^2}$$

$$= \frac{(P_j - r_j)}{r_j}\bar{\omega}(\gamma+1)\left[\frac{\kappa_h}{\kappa_i}\right]^{\gamma}\exp^{0.5(\gamma+1)^2\sigma_j^2(1-\delta_h)}, \tag{B2}$$

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[51] We specify the price to be twice the piece rate paid to workers, in accordance with firm practice as revealed through interviews with firm managers.

where (B2) follows from the fact that

$$\exp^{[(\gamma+1)\mu_j]} = \frac{\bar{\omega}(\gamma+1)\kappa_h^{\gamma}\exp^{-0.5\delta_h(\gamma+1)^2\sigma_j^2}}{r_j^{\gamma+1}}, \tag{B3}$$

from (10).

Under the generated contracts, expected profits are given by

$$E\left[\pi_{ij}\left(\hat{r}_j, \mu_0, \sigma_j^2\right)\right] = (P_j - \hat{r}_j)\frac{\hat{r}_j^{\gamma}}{\kappa_i^{\gamma}}E\left[S^{(\gamma+1)}\right]$$

$$= (P_j - \hat{r}_j)\frac{\hat{r}_j^{\gamma}}{\kappa_i^{\gamma}}\exp^{(\gamma+1)\mu_0+0.5(\gamma+1)^2\sigma_j^2}$$

$$= \frac{(P_j - \hat{r}_j)}{\hat{r}_j}(\gamma+1)\left[\frac{\kappa_h}{\kappa_i}\right]^{\gamma}\exp^{0.5(\gamma+1)^2\sigma_j^2(1-\delta_h)} \tag{B4}$$

$$= E\left[\pi_{ij}\left(r_j, \mu_j, \sigma_j^2\right)\right], \tag{B5}$$

where (B4) follows from the fact that

$$\exp^{[(\gamma+1)\mu_0]} = \frac{\bar{\omega}(\gamma+1)\kappa_h^{\gamma}\exp^{-0.5\delta_h(\gamma+1)^2\sigma_j^2}}{\hat{r}_j^{\gamma+1}}, \tag{B6}$$

from (10).

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