Economics Letters 108 (2010) 345–348

Contents lists available at ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Sorting, incentives and risk preferences: Evidence from a field experiment

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ARTICLE INFO

Article history:
Received 5 March 2009
Received in revised form 29 May 2010
Accepted 16 June 2010
Available online 23 June 2010

Keywords:
Risk aversion
Sorting
Incentive contracts
Field experiments

JEL classifications:
J33;
M52;
C93

ABSTRACT

We conducted experiments within a firm to measure the risk preferences of workers who face substantial daily income risk. We find that these workers are significantly more risk-tolerant than individuals from the broader population. This is consistent with sorting: risk-tolerant workers are attracted to high-risk occupations.

1. Introduction

Moral hazard models posit that individuals react to incentives, and optimal contracts must balance incentives with risk sharing. Recent empirical work has thus focussed attention on the role of risk and the risk preferences of workers in determining observed contracts (Prendergast, 2000). If risk is important within the contracting environment then observed contracts will vary with risk in predictable ways, giving empirical content to the agency model. However, many studies of actual contracts have failed to detect a role for risk that is consistent with theoretical predictions; see, for example, Allen and Lueck, 1992. These studies conclude that transaction costs prevent the implementation of optimal contracts, and thus are important determinants of contract choices.[1]

A major difficulty facing empirical work on contracts is that risk preferences are unobservable. Unobservability greatly complicates testing economic theory (Chiappori and Salanié, 2003). Comparative static results are conditional on unobservable preferences. If workers sort themselves across contracts on the basis of specific preferences, then regression methods seeking to measure the effects of risk on contracts will confound changes in risk with changes in unobserved preferences. This can bias the coefficient estimates and, in turn, downplay the importance of risk and sorting as an explanation of contract choice determination relative to transaction costs (Ackerberg and Botticini, 2002).

This paper considers the empirical validity of the sorting hypothesis. We exploit preference-revealing experiments, originally proposed by Holt and Laury (2002), to identify the risk preferences of the employees of a tree-planting firm in British Columbia, Canada. These workers are paid piece rates and face substantial daily earnings risk due to random planting conditions. We find that a significant proportion of these workers (between 39% and 46%) is risk loving or risk neutral, proportions that are significantly higher than those found in the broader Canadian population by Dave et al. (2008). These results are consistent with the sorting hypothesis: occupations with higher income risks attract workers with greater risk tolerance.

2. Experimental design and income risk

Our experiment was conducted within a medium sized tree-planting firm in British Columbia. This firm pays its planters piece rates; daily earnings for a planter are determined by the product of the piece rate and the number of trees the planter planted on that day. Blocks of land to be planted typically contain between 20 and 30 planter-days of work, with some lasting over 100 planter-days. For each block, the firm decides on a piece rate. All workers planting on the same block receive the same piece rate. No matching of workers to planting conditions occurs.[2] Planting

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[1] A related literature uses reported earnings and occupational data instead of contractual data to infer the relationship between risk and preferences. See Bonin et al. (2007) for a recent example.

[2] See Bellemare and Shearer (2009) for a more detailed description of the manner in which piece rates are determined.

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doi:10.1016/j.econlet.2010.06.010

Table 1
Decisions and payoffs in the low stakes treatment. Payoffs in the high stakes treatment correspond to the payoffs of the table multiplied by 2.

Decision	Lottery A	Lottery B	Expected payoff difference
1	1/10 of \$20.00, 9/10 of \$16.00	1/10 of \$38.50, 9/10 of \$1.00	\$11.70
2	2/10 of \$20.00, 8/10 of \$16.00	2/10 of \$38.50, 8/10 of \$1.00	\$8.30
3	3/10 of \$20.00, 7/10 of \$16.00	3/10 of \$38.50, 7/10 of \$1.00	\$5.00
4	4/10 of \$20.00, 6/10 of \$16.00	4/10 of \$38.50, 6/10 of \$1.00	\$1.60
5	5/10 of \$20.00, 5/10 of \$16.00	5/10 of \$38.50, 5/10 of \$1.00	−\$1.80
6	6/10 of \$20.00, 4/10 of \$16.00	6/10 of \$38.50, 4/10 of \$1.00	−\$5.10
7	7/10 of \$20.00, 3/10 of \$16.00	7/10 of \$38.50, 3/10 of \$1.00	−\$8.50
8	8/10 of \$20.00, 2/10 of \$16.00	8/10 of \$38.50, 2/10 of \$1.00	−\$11.80
9	9/10 of \$20.00, 1/10 of \$16.00	9/10 of \$38.50, 1/10 of \$1.00	−\$15.20
10	10/10 of \$20.00	10/10 of \$38.50	−\$18.50

Table 2
Cumulative distributions of the number of times lottery A in Table 1 is chosen before crossing over to play lottery B. Table reports distributions for the low and high stakes treatments conducted in the firm. The last column presents the cumulative distribution estimated by Dave et al. (2008) for the entire population. "All" refers to the entire sample in each treatment. "Consistent" refers to the sub-samples of subjects in each treatment who made consistent answers.

		Tree-planting firm				Population	
		Low stakes		High stakes		High stakes	
Number of A decisions	$U=\frac{x^{1-r}}{1-R}$	All	Consistent	All	Consistent	All	Consistent
0–1	$r<-0.95$	0.098	0.142	0.076	0.102	0.016	0.017
2	$-0.95<r<-0.49$	0.117	0.171	0.091	0.124	0.021	0.019
3	$-0.49<r<-0.15$	0.235	0.257	0.212	0.245	0.059	0.053
4	$-0.15<r<0.15$	0.392	0.457	0.424	0.449	0.167	0.157
5	$0.15<r<0.41$	0.726	0.800	0.727	0.714	0.295	0.271
6	$0.41<r<0.68$	0.902	0.886	0.849	0.857	0.527	0.496
7	$0.68<r<0.97$	0.941	0.914	0.924	0.918	0.738	0.722
8	$0.97<r<1.37$	0.941	0.914	0.969	0.959	0.857	0.841
9–10	$1.37<r$	1	1	1	1	1	1
Sample size		51	35	66	49	881	806

conditions vary across and within blocks. For example, while a given block may appear uniform on the surface, some parts of the block can be characterized by rocky soil under the surface, making planting more difficult. Given the firm cannot completely know the undersoil conditions for the whole 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.

Our experimental design consists of two treatments: a low stakes treatment which took place in the first week of May, 2005 and a high stakes treatment which took place in the first week of May, 2006. Both treatments were identical with the exception of the payoffs: the payoffs in the high stakes treatment were twice those of the low stakes treatment. This allows us to consider the sensitivity of our results to the payoff scales.[3]

Each morning during the experiment, we met with a different crew of planters for approximately 20 min before they were transported to their planting site. We invited the planters to participate in our study, offering them a \$10 participation fee, plus an additional sum which would depend on the choices they made, and chance. Participation was voluntary.[4] Each participant was given paper instructions, a decision sheet, a clipboard, and an ink pen. We then read aloud the instructions for the experiment and explained how to fill in the decision sheet. We used an oversized copy of the decision sheet to assist us in describing the experiment.

To complete the experiment, each planter had to make 10 decisions. Each decision consisted of choosing one of two binary lotteries: a safe lottery, denoted A, which paid either a low payoff of \$16 or a high payoff of \$20, and a risky lottery, denoted B, which paid either a low payoff or \$1 or a high payoff of \$38.50.[5] Which of the high or low payoffs materialized, was determined by chance.

A summary of the decisions can be found in Table 1. For the first decision the probability of the high payoff is 10% and the expected payoff from lottery A is \$11.70 higher than for lottery B. In this case only an extreme risk seeker would prefer lottery B. 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. For the last decision, the high payoff of each lottery is paid with probability 1 (\$20 for lottery A, and \$38.50 for lottery B) — even the most risk-averse individuals will prefer lottery B at this point.[6]

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. This was to be done by drawing 2 poker chips with replacement from an opaque bag containing 10 identical chips, numbered from 1 to 10. The first number drawn selected the lottery to be played. The second number drawn determined the outcome of the selected lottery, and hence the planter's lottery earnings.

Planters were informed that their lottery earnings and participation fee would be added to their next pay check. Once we had read the instructions, participants were allowed to ask clarifying questions. We then asked each planter to make his/her decisions individually and in silence. Planters who completed their decision sheets were asked to come forward to draw their poker chips. Each daily session took on average 15 min and involved between 10 and 20 planters. Fifty-one planters participated in the low stakes treatment, 66 in the high stakes treatment.

With constant relative risk aversion for money x, the utility function is defined as $u(x)=x^{1-r}/(1-r)$ for $x>0$ where r denotes the

[3] Holt and Laury (2002) report evidence that measured risk preferences can be sensitive to payoff scales.

[4] There were no cases of planters refusing to participate in any of the treatments.

[5] These were the payoffs for the low stakes treatment — they were doubled in the high stakes treatment.

[6] The difference between the high and low payoffs in the risky lottery B (37.50\$) in the low stakes treatment is just under a one standard deviation in the observed daily earnings risk (51\$, see Section 3) for these workers. Consequently, both treatments represented considerable payoffs to the planters, and the risky lottery offers a realistic variation in daily earnings.

Table 3
Summary statistics for the 2005 planting season. Number of trees, piece rate and daily earnings are measured at the planter-day level.

Variable	Observations	Mean	Std.	Minimum	Maximum
Number of trees	1682	833.942	426.076	30	2460
Piece rate	1682	0.244	0.063	0.11	0.62
Daily earnings	1682	196.120	66.434	10.01	442.80

coefficient of relative risk aversion. This specification implies risk loving behavior for $r<0$, risk neutrality for $r=0$, and risk aversion for $r>0$.[7] 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. For example, 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 r in the interval $(-0.15, 0.15)$. The second column of Table 2 presents the interval estimate around r which is consistent with a respondent crossing over to play lottery B after having made s safe choices.

2.1. Income risk

To illustrate the importance of income risk to planters, Table 3 presents descriptive statistics for the 2005 planting season for planters who participated in the low stakes experiment. The average daily number of trees planted is 833.94, with a large standard deviation (426.08). The average daily earning is \$196.12 with a standard deviation of \$66.43. Planters have, on average, worked 21.36 days before taking part in the experiment, again with a sizeable standard deviation. Using regression analysis, it is possible to decompose the total variation in productivity into two parts: one due to differences in productivity across planters and the other reflecting differences in daily planting conditions.[8] We find that 57.1% of total variation in daily productivity can be explained by variations in day-to-day planting conditions, while 42.9% of the total variation is accounted for by productivity differences across planters. Similar results apply when we look at daily earnings. We find that only 39.2% of the total variation in daily earnings reflects variation in productivity across planters. This implies that 60.2% of the daily variation in earnings (a standard deviation of approximately 51\$) can be attributed to daily variation in planting conditions and piece rates, indicating considerable earnings variability beyond the planters' control.[9]

3. Results

Table 2 presents the cumulative distribution of the number of safe choices in the low stakes and high stakes treatments. The third column presents the cumulative distributions of the number of safe choices made in the low stakes treatment for all 51 planters who participated. The fourth column presents the cumulative distribution using only planters who gave consistent answers.[10] We find that 39.2% of tree planters have risk aversion profiles between extreme risk loving and risk neutral, and 72.6% have risk profiles between risk loving and weak risk aversion. These probabilities tend to increase when we exclude planters who gave inconsistent answers. These results show a significant level of risk tolerance among these workers. The fifth and sixth columns present the results in the high stakes experiment. We see that the proportion of planters who are either risk neutral or risk loving in the high stakes treatment slightly increases relative to the low stakes treatment (42.4%). As in the low stakes treatment, risk aversion appears to decrease when restricting the analysis to planters which gave consistent answers.

The final two columns present the population distributions reported by Dave et al. (2008) who sampled 881 individuals from across Canada. They used the Holt and Laury (2002) design with stakes corresponding to those of our high stakes treatment. The proportion of individuals who are risk neutral or risk loving in the broader population is substantially lower than for workers in our treatments (16.7% for all participants, and 15.7% for participants who gave consistent answers). We performed a chi square test of the null hypothesis that the distribution in our high stakes treatment is the same as the distribution in the broader population. The chi square test easily rejects the null hypothesis (p-value $=0.000$).[11]

4. Conclusion

This study adds to the growing body of research measuring the importance of sorting when evaluating the empirical efficiency of observed contracts. The use of experimental methods allows us to measure each individual's willingness to bear risk within a controlled environment, permitting the characterization of risk tolerance. We find that approximately 40% of the workers who have self-selected into a particular incentive-paying job are either risk neutral or risk loving. This percentage is significantly higher than in the broader population, suggesting that sorting over risk preferences is an important characteristic of labour-market contracts. Consequently, one cannot reject agency models based on the observed correlation between the incentive intensity of contracts and risk levels. The statistical analysis of the effect of risk on contracts, based on a comparison of contracts exhibiting different risk levels, must account for the sorting of workers across contracts.

Acknowledgments

We thank Sabine Kröger for comments. We acknowledge the research support from SSHRC and FQRSC and the Canada Research Chair in Social Policies and Human Resources at the Université Laval.

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[7] When $r=1$, $u(x)=\ln(x)$ is used.

[8] The decomposition is based on the following model of daily productivity y_{it}

$$y_{it} = \alpha + \mu_i + \varepsilon_{it}$$

where α is an intercept, μ_i represents fixed planter-specific, time-invariant productivity effects, and ε_{it} represents other unsystematic differences in planting conditions. Under the assumption that μ_i is independent of ε_{it}, the total variance in y_{it} is given by

$$\mathbf{V}(y_{it}) = \mathbf{V}(\mu_i) + \mathbf{V}(\varepsilon_{it}).$$

The share of the total variance due to day-to-day variation in planting conditions is simply $\mathbf{V}(\varepsilon_{it})/\mathbf{V}(y_{it})$.

[9] Similar results also apply to the 2006 planting season.

[10] Inconsistent answers consisted of planters crossing more than once between lotteries. The percentage of planters giving inconsistent answers was 31.2%. Holt and Laury (2002) report that approximately 15% of students made inconsistent decisions when first playing such an experiment.

[11] The p-value is also 0.000 when comparing distributions based only on participants who made consistent answers. Furthermore, the p-value remains the same when comparing population distributions with those of our low stakes treatment.

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