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Abstract

This paper explores the effects of monitoring in contracts between an exporting firm and small agricultural producers in Madagascar. Building on a theoretical framework that incorporates both adverse selection and moral hazard, I test for the effect of monitoring of the agents by the principal on productivity, all the while including an estimate of agent-specifc technical inefficiency in the regression used to conduct my test, which obviates the identification problem usually encountered when using cross-sectional data in applied contract theory. Empirical results show that the inclusion of such a technical inefficiency estimate has important implications both for applied contract theory and for policy.

Keywords: monitoring, supervision, development economics, agricultural economics, contract theory, applied contract theory, principal-agent models.

JEL Classication Codes: D86, L24, 012, 013, Q12.

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1 Introduction

Do incentives matter in bilateral contracting? This question has preoccupied economists ever since the so-called information revolution of the 1970s, which saw economic theorists take into account problems in which certain agents have more information than others and, as a consequence, incentive questions (Stiglitz, 2000). Thus, ever since the seminal papers of Akerlof (1970), Spence (1973) and Rothschild and Stiglitz (1976), the question of how agents should and do respond to incentives in bilateral contracting situations has very much been a central preoccupation of economists.

Yet, there has been a considerable lag between theory and practice. Although the field of applied contract theory is rapidly growing, it was virtually nonexistent until the 1980s (Salanié, 1997; Chiappori and Salanié, 2003). Moreover, the empirical evidence so far on contracts has been mixed, with some authors finding that incentives indeed matter, and some authors finding that they do not (Prendergast, 1999). As such, the question is still very much open to debate. Furthermore, there has been little work done on whether the monitoring of agents by the principal can reduce the extent of the posited moral hazard problem, with the notable exceptions of Frisvold (1994) and Hubbard (2000), who find that supervision of hired labor by members of the household increases productivity in India and that monitoring devices do make a difference in the trucking industry, respectively.

This paper contributes to the literature on applied contract theory by testing whether monitoring matters in crop-growing contracts between an exporting firm and small farmers (the principal and the agents, respectively) in Madagascar. In this setting, the principal (i) provides the agent with inputs to be used on plots on which green vegetables are grown; and (ii) agrees to buy the agent's output of green vegetables in exchange for a fixed price. Thus, the principal provides in-kind seasonal credit in exchange for the agent's production of green vegetables, which is then exported to Europe. Based on a simple theoretical model incorporating both adverse selection and moral hazard as well as supervision, I test whether monitoring by the principal has any effect on the agent's productivity on contracted plots. In this setting, both an agent's type – his exogenously given level of technical ability – and the effort he endogenously provides contribute in determining his output of green vegetables. Less technically able agents are less likely to produce high outputs, as are agents who shirk and provide a sub-optimal amount of effort. It is therefore important, when testing the effect of monitoring in these contracts, to control for adverse selection, i.e., to control for the agents' types.

The nature of the data facilitates going beyond the identification problem that has traditionally plagued empirical work on contracts, i.e., using a cross-section of contracts, it is generally not possible to identify whether the source of any observed departure from Pareto-efficiency is due to adverse selection, moral hazard, or both (Chiappori and Salanié, 2000; 2003). In my case, each agent owns at least two plots: (i) a contracted plot on which rice is grown during the main agricultural season and green vegetables are grown during the counter-season;[1] and (ii) a non-contracted plot on which only rice is grown. The non-contracted plot provides a natural control for household-specific, plot-invariant technical inefficiency, thus summarizing exogenous agent productivity. This in turn provides control for adverse selection in testing for the effect of monitoring on agent productivity on the contracted plot.

The rest of the paper is organized as follows. In section 2, I present a formal theoretical model that incorporates both adverse selection and moral hazard as well as supervision. Section 3 briefly presents summary statistics for the data. In section 4, I derive an empirical framework which allows me to test for the effect of monitoring. Section 5 presents estimation results, the results of the statistical hypothesis test, as well as a discussion of those results. I conclude in section 6 by briefly discussing the policy implications of the empirical results and by pointing to directions for future research.

2 Theoretical Framework

In this section, I adapt a simple principal-agent model of bilateral contracting incorporating adverse selection and moral hazard (Bolton and Dewatripont, 2005), which highlights the key features of my data. The principal contracts with each agent individually and provides inputs (seeds, mineral fertilizer, and phytosanitary products) to be used to grow green vegetables on a contracted plot. In exchange for those inputs, the principal promises to buy the

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[1] In the data, the main agricultural season begins in November, and most of the rice is harvested between the months of March and May. The counter-season usually begins in July and ends in October.

agent's output of green vegetables at a fixed price, minus the value of the input advance. The principal thus provides in-kind seasonal credit to the agent. The model builds on those of Picard (1987) and Guesnerie et al. (1988), who characterize optimal contracts under adverse selection and moral hazard and adverse selection with risk-neutral agents, and on those of Page (1991) and Theilen (2003), who consider the same scenario but with risk-averse agents. The difference here is that there are two types of agents as well as two possible outputs, whereas both Page and Theilen treat both these variables as continuous. The assumptions made here are made for tractability, but the basic results and intuitions remain.

Let $y \in \{0, Y\}$ be the two possible outputs on the contracted plot. The agent has ability $\theta \in \{\theta_L, \theta_H\}$, where $\theta_L < \theta_H$. The principal's prior is that the agent has ability θ_H with probability β and has ability θ_L with probability $(1-\beta)$. An agent with ability θ who supplies effort e then generates Y with probability θe, at cost $\psi(e) = \frac{ce^2}{2}$. This is thus a model of probabilistic crop failure, with the probability of crop failure a function of both endogenous effort e and exogenous ability θ.

The principal's problem is to offer a contract – or a menu of contracts, depending on whether there is adverse selection, moral hazard, or both – (a_i, r_i), where a_i is the input advance offered to an agent of type $i \in \{L, H\}$ and r_i is the reimbursement due by an agent of type $i \in \{L, H\}$ to the principal. The principal faces a limited liability constraint, in the sense that $r_i \in [0, Y]$, i.e., the agent cannot reimburse more than the total value of the output grown on the contracted plot. Finally, assume without any loss of generality that (a_i, r_i) is such that r_i is paid only if $y = Y$.

The agent's payoff is then

$$(1) \quad \theta_i e(Y - r_i) + a_i - \frac{ce^2}{2}, \; i \in \{L, H\}.$$

From the first-order condition of the agent's maximization problem, we have that

$$(2) \quad e^* = \frac{\theta_i (Y - r_i)}{c},$$

from which the following moral hazard proposition immediately obtains.

Proposition 1 *Agent effort is decreasing in the reimbursement he must give the principal and does not depend on the advance he receives from the principal. That is,* $\frac{\partial e^*}{\partial r_i} < 0$ *and* $\frac{\partial e^*}{\partial a_i} = 0$.

Proof: Taking the derivatives of e^* with respect to r_i and a_i yields, respectively

$$\frac{\partial e^*}{\partial r_i} = -\frac{\theta_i}{c} < 0 \tag{3}$$

and

$$\frac{\partial e^*}{\partial a_i} = 0. \blacksquare \tag{4}$$

Thus, the agent's optimal effort does not depend on the input advance a_i but varies negatively with the reimbursement r_i. Thus, the higher the reimbursement due to the principal, the lower the agent's effort. Given optimal effort, the agent's maximized payoff is

$$\frac{[\theta_i(Y - r_i)]^2}{2c} + a_i. \tag{5}$$

The principal then chooses the contract terms (a_i, r_i) so as to maximize his profit, given the agent's optimal choice of effort.

$$\max_{(a_i, r_i)} \left\{ \beta \Big[\frac{\theta_H^2 (Y - r_H) r_H}{c} - a_H \Big] + (1 - \beta) \Big[\frac{\theta_L^2 (Y - r_L) r_L}{c} - a_L \Big] \right\} \tag{6}$$

subject to

$$\frac{1}{2c}\big[\theta_i(Y - r_i)\big]^2 + a_i \geq \frac{1}{2c}\big[\theta_i(Y - r_j)\big]^2 + a_j \ \forall i \neq j, \forall i \in \{L, H\} \ \text{(IC)} \tag{7}$$

and

$$\frac{1}{2c}\big[\theta_i(Y - r_i)\big]^2 + a_i \geq 0 \ \forall i \in \{L, H\}, \ \text{(IR)} \tag{8}$$

where the first constraint is the agent's incentive compatibility (IC) constraint and the second constraint denotes the agent's individual rationality (IR) constraint, with the agent's reservation payoff normalized to zero without loss of generality. I now turn to characterizing what happens when the principal can perfectly monitor the agent's effort and, as a result, expects there to be only adverse selection. In order to give the two polar cases of unenforceable effort with adverse selection and perfectly enforceable effort and adverse selection, I also characterize what happens when the principal cannot monitor the agent's effort. The appendix presents the case where there is only moral hazard for completeness.

2.1 Adverse Selection and Enforceable Effort

In the data, the principal hires supervisors to monitor the agent's effort level on the contracted plot, so that it is in theory possible for the principal to enforce $\hat{e}$, his preferred level of effort, which I assume to be such that $\hat{e} > e^*$.[2] This is admittedly a very strong assumption, and I will model the case where supervision is imperfect below, but for now the principal's maximization problem becomes

$$\max_{(a_i, r_i)} \left\{ \beta(\theta_H \hat{e} r_H - a_H) + (1-\beta)(\theta_L \hat{e} r_L - a_L \right\} \tag{9}$$

subject to

$$\theta_i \hat{e}(Y - r_i) + a_i \geq \theta_i \hat{e}(Y - r_j) + a_j \ \forall i \neq j, \forall i \in \{L, H\} \text{ (IC)} \tag{10}$$

and

$$\theta_i \hat{e}(Y - r_i) + a_i - \frac{c\hat{e}^2}{c} \geq 0 \ \forall i \in \{L, H\}. \text{ (IR)} \tag{11}$$

From this framework, I can state the following about the shape of the contracts observed.

Proposition 2 *When the principal can enforce his preferred level of effort but cannot observe the agent's type, both types provide their total output as reimbursement to the principal and each type receives an input advance that is just enough to cover his cost of effort. That is,* $r_H = r_L = Y$, *and* $a_H = a_L = \frac{c\hat{e}^2}{2}$.

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[2] Note that I do not consider the case where the principal must supervise the supervisors. Holmstrom (1982) considers moral hazard in teams and finds that supervisors must be made residual claimants on the principal's profit in order to be effective in their work. Given data limitations, such considerations are beyond the scope of this paper.

Proof: Given that the choice variables enter the principal's maximization problem linearly, we cannot use the usual maximization techniques to solve for the optimal menu of contracts. Instead, note that the principal cannot observe the agent's type but can enforce his preferred level of effort. In this case, the principal should set the reimbursement to be as high as possible, i.e., $r_H = r_L = Y$. But then, in order for both the IC and IR constraints to bind, the principal must set $a_H = a_L = \frac{c\hat{e}^2}{2}$. ■

The intuition behind this result is simple: when the principal can enforce his preferred level of effort but cannot observe the agent's type, he receives all of the agent's output, part of which serves to reimburse the input advance, which is just high enough to cover the agent's cost of effort. This is indeed the contract shape observed in the data: the principal buys all of the agent's output and provides him with seeds, mineral fertilizer, and phytosanitary products that can be used on the contracted plot for growing green vegetables. Note that this also implies – because of the principal-agent structure of the problem – that the exporting firm extracts all the gains from contracting. Although Inoue and Vukina (2007, forthcoming) develop a method to test for the principal's monopsony power in agency contracts, testing for the validity of this assumption is beyond the scope of the paper.

2.2 Adverse Selection and Moral Hazard

When the principal does not know the type of agent he faces and cannot enforce his preferred level of effort, his problem becomes

$$(12)\quad \max_{(a_i,r_i)} \left\{\beta\left[\frac{\theta_H^2(Y-r_H)r_H}{c} - a_H\right] + (1-\beta)\left[\frac{\theta_L^2(Y-r_L)r_L}{c} - a_L\right]\right\}$$

subject to

$$(13)\quad \frac{\theta_H^2(Y-r_H)^2}{2c} + a_H = \frac{\theta_H^2(Y-r_L)^2}{2c} + a_L \text{ (IC)},$$

and

$$(14)\quad \frac{\theta_L^2(Y-r_L)^2}{2c} + a_L = 0 \text{ (IR)}.$$

From this framework, we can state the following about the shape of the contracts observed.

Proposition 3 *When the principal cannot observe the agent's type and cannot enforce his preferred level of effort, the high-type agent provides no reimbursement while the low-type agent provides a positive reimbursement, and the low type must pay a fee to the principal while the high type either pays a fee to the principal that is smaller than the low type or receives an input advance. That is,* $r_H = 0$*,* $r_L = \frac{\beta(\theta_H^2-\theta_L^2)Y}{\beta(\theta_H^2-\theta_L^2)+(1-\beta)\theta_L^2}$*,* $a_H = \frac{\theta_H^2}{2c}\left[Y - \frac{\beta(\theta_H^2-\theta_L^2)Y}{\beta(\theta_H^2-\theta_L^2)+(1-\beta)\theta_L^2}\right]^2 - \frac{\theta_L^2}{2c}\left[Y - \frac{\beta(\theta_H^2-\theta_L^2)Y}{\beta(\theta_H^2-\theta_L^2)+(1-\beta)\theta_L^2}\right]$*, and* $a_L = -\frac{\theta_L^2}{2c}\left[Y - \frac{\beta(\theta_H^2-\theta_L^2)Y}{\beta(\theta_H^2-\theta_L^2)+(1-\beta)\theta_L^2}\right]$*.*

Proof: Using the IR constraint to solve for a_L and then the IC constraint to solve for a_H allows to rewrite the principal's problem only as a function of r_H and r_L. Then, taking first-order conditions and solving yields $r_H = 0$ and $r_L = \frac{\beta(\theta_H^2-\theta_L^2)Y}{\beta(\theta_H^2-\theta_L^2)+(1-\beta)\theta_L^2}$. Using these optimal reimbursements, we can then solve for the input advances, which yield $a_L = -\frac{\theta_L^2}{2c}\left[Y - \frac{\beta(\theta_H^2-\theta_L^2)Y}{\beta(\theta_H^2-\theta_L^2)+(1-\beta)\theta_L^2}\right] < 0$ and $a_H = \frac{\theta_H^2}{2c}\left[Y - \frac{\beta(\theta_H^2-\theta_L^2)Y}{\beta(\theta_H^2-\theta_L^2)+(1-\beta)\theta_L^2}\right]^2 - \frac{\theta_L^2}{2c}\left[Y - \frac{\beta(\theta_H^2-\theta_L^2)Y}{\beta(\theta_H^2-\theta_L^2)+(1-\beta)\theta_L^2}\right] > a_L$. ■

Note that the two scenarios presented above are figurative "bounds" on reality since they represent the two polar cases, i.e., the case where monitoring is perfect and the principal's preferred level of effort is thus perfectly enforceable but there is adverse selection as well as the case where the principal's preferred level of effort is unenforceable and there is adverse selection. Reality, however, most likely lies in between these two polar cases, i.e., there is adverse selection, but monitoring is imperfect. If monitoring is imperfect, one should expect it to have a positive effect on agent productivity. If, however, monitoring is perfect, one should expect it to have little or no impact on agent productivity given that agents produce at a level that is optimal for the principal.

2.3 Adverse Selection, Moral Hazard, and Imperfect Supervision

Suppose now that the principal can choose to supervise the agent at rate $s \in [0, 1]$, where $s = 0$ means that the principal does not monitor the agent, and $s = 1$ means that the agent's effort is perfectly enforced. Supervision, however, is costly and incurs a cost of $\phi(s) = \frac{ks^2}{2}$. In this case, the agent's effort will be a convex combination of $\hat{e}$, the principal's preferred level of effort, and of e^*, the agent's optimal effort when there is no monitoring. That is, $\tilde{e_i}$, agent i's effort under imperfect supervision, is such that

$$(15)\quad \tilde{e_i} = s\hat{e} + (1-s)e^*,$$

and this experession is such that

$$(16)\quad \tilde{e_i} \equiv s\hat{e} + (1-s)\frac{\theta_i(Y-r_i)}{c}.$$

Based on this last expression, I can derive the following two propositions.

Proposition 4 *Agent effort is increasing in the amount of supervision. That is,* $\frac{\partial \tilde{e}}{\partial s} > 0$.

Proof: Recall that I assumed above that $\hat{e} > e^*$, which implies that $\frac{\partial \tilde{e}}{\partial s} = \hat{e} - e^* > 0$. ■

Proposition 5 *Output is increasing in the level of supervision. That is,* $\frac{\partial \Pr(y=Y)}{\partial s} > 0$.

Proof: Recall that $\Pr(y = Y) = \theta_i e$. Thus, with imperfect supervision,

$$(17)\quad \Pr(y = Y) = \theta_i\Big[s\hat{e} + (1-s)\frac{\theta_i(Y-r_i)}{c}\Big],$$

so that

$$(18)\quad \frac{\partial \Pr(y = Y)}{\partial s} = \theta_i[\hat{e} - e^*] > 0.$$

The likelihood of observing the high output is thus increasing in the level of supervision. ■

The principal's maximization problem changes considerably when one incorporates supervision, as it becomes a combination of both the moral hazard and adverse selection and the pure adverse selection problems. Having derived the paper's main testable implication above, I merely present the principal's full maximization problem for completeness, as solving for it would require solving for nine endogenous variables in nine equations and wouldn't add much to this paper other than length and implications that I unfortunately cannot test for given the limitations of the data. Thus, the principal solves

$$\max_{(a_i, r_i, s)_{i=L,H}} \left\{ \beta \left[\theta_H \tilde{e}_H r_H - a_H \right] + (1-\beta) \left[\theta_L \tilde{e}_L r_L - a_L \right] \right\} \tag{19}$$

subject to

$$\theta_H \tilde{e}_H (Y - r_H) + a_H \geq \theta_H \tilde{e}_L (Y - r_L) + a_L \text{ (IC}_H\text{)}, \tag{20}$$

$$I(s=1)\theta_L \tilde{e}_L (Y - r_L) + a_H \geq \theta_L \tilde{e}_L (Y - r_H) + a_H \text{ (IC}_L\text{)}, \tag{21}$$

$$I(s=1)\theta_H \tilde{e}_H (Y - r_H) + a_H \geq 0 \text{ (IR}_H\text{), and} \tag{22}$$

$$\theta_L \tilde{e}_L (Y - r_L) + a_L \geq 0 \text{ (IR}_L\text{)}, \tag{23}$$

where $I(s=1)$ is an indicator variable equal to one if supervision is equal to one and zero otherwise. This ensures that the problem is a combination of the moral hazard and adverse selection and of the pure adverse selection problems.

Given the increased use of production contracts between exporting firms and small agricultural producers in developing countries (Reardon and Timmer, 2005), whether monitoring allows to enforce effort or, at the very least, whether it allows to increase productivity at the margin is of increasing importance to development economics. I now turn to devising an empirical framework which allows me to first control for unobserved heterogeneity between agents, i.e., control for the agents' types, and then to test for the effect of monitoring.

3 Data and Descriptive Statistics

The data were collected by a joint Cornell University-Katholieke Universiteit Leuven team in four *fivondronana*[3] in the Lac Alaotra region of Madagascar between the months of June and August 2004. Each of the 200 sample households had entered a contract with Lecofruit, a firm that exports fresh produce to the European market. The former are thus the agents and the

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[3] A *fivondronana* is a Malagasy administrative unit that is smaller than a province but which encompasses many communes, which in turn encompass many villages.

latter the principal. Each selected household was selected based on the stratification criterion of owning at least two plots: (i) a rice plot on which rice was grown during the agricultural season and on which a contracted crop (green beans, cucumbers, leeks, or snow peas) was grown during the agricultural counter-season; and (ii) a rice plot on which rice was grown during the agricultural season and on which a non-contracted crop was grown during the agricultural counter-season. For some households in the sample, data on an additional plot was collected. This additional plot was selected based on its close topographical similarity to the contracted plot. Data were collected at the household-, contract-, and plot-level. The end result is a sample of 200 households and 487 plots.

Table 1: Summary Statistics for All Sample Plots

Variable	**Mean**	**Std. Dev.**	**N**
Rice Yield (Kg/Are)	50.442	22.422	482
Labor (Person-Hour/Are)	12.996	10.978	478
Cultivated Area (Ares)	9.622	12.004	482
Seeds (Kg/Are)	2.019	1.564	480
Phytosanitary Products (Ariary/Are)	4.499	74.709	482
Fertilizer (Ariary/Are)	21.24	147.072	479
Manure (Carts/Are)	0.14	1.292	480
Compost (Carts/Are)	0.022	0.131	480
Duration of Cultivation Season (Months)	4.728	0.568	482
Cyclone Dummy	0.316	0.465	487
Age (Years)	37.276	10.493	485
Male Dummy	0.732	0.443	485
Education (Completed Years)	6.509	2.329	479
Fivondronana 1 Dummy	0.246	0.431	487
Fivondronana 2 Dummy	0.244	0.43	487
Fivondronana 3 Dummy	0.246	0.431	487
Fivondronana 4 Dummy	0.259	0.438	487

Table 1 presents summary statistics for all the plots in the sample (plots used uniquely for rice production, plots used for rice production and contracted counter-seasonal production, and plots used for rice production and non-contracted counter-seasonal production). Rice yields average 5 tons[4] per

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[4] 1 ton = 1000 kg.

hectare,[5] a number that is much greater than the national average in Madagascar. Although the average rice yield in Madagascar is around 2 tons per hectare, Lac Alaotra is the country's most fertile rice-producing region, with average rice yields in the region much higher than the national average (Randrianarisoa, 2003).

The average plot size was just under 10 ares and required respectively 13 person-hours of work, 2 kilograms of seeds, less than US$0.01[6] of phytosanitary products,[7] a little over US$0.01 of fertilizers, 0.14 carts[8] of manure, and 0.02 carts of compost per are. Note that the average duration of rice cultivation was about five months, and that a little under a third of the households in the sample declared that their rice production had been affected by one of the two cyclones that hit Madagascar in 2004.

The average agent was 37 years old and had 6.5 years of formal education, while almost three-quarters of the agents were male. Finally, the sample plots were distributed nearly uniformly across the four *fivondronana*.

Table 2 presents summary statistics for the contracted plots.[9] The average yield for green vegetables[10] was 12.2 tons per hectare. A little under 65 percent of the area cultivated by all the agents was used to grow green beans, 33 percent was used to grow cucumbers, and 2 percent was used to grow leeks. The remainder of the area cultivated, less than 1 percent of the area cultivated, was in snow peas. The average area cultivated under contract covered about 1.5 ares and required 164 person-hours of work, 1.7 kilograms of seeds, US$11 of phytosanitary products, US$8 of fertilizer, 0.14 carts of manure, and 1.8 carts of compost per are. Contract vegetable cropping is thus

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[5] 1 hectare = 100 ares.

[6] US$1 ≈ 2,000 ariary at the time the data was collected.

[7] Phytosanitary products include all chemicals used to eliminate pests and diseases.

[8] These farmers think about organic fertilizers in terms of the number of cartloads used, hence this measure.

[9] Although there are 200 contracted plots in the sample, there are over 330 observations given that more than one crop might be grown on a given contracted plot. This unfortunately does not allow me to include household-plot fixed effects in the contracted plot production functions estimated in section 5.

[10] To get more efficient estimates, I aggregate over four types of contracted crops: green beans, cucumbers, leeks and snow peas. Crop heterogeneity is controlled for in the second-stage analysis by using crop dummies.

considerably more intensive in purchased inputs (fertilizer and phytosanitary products) than rice. The number of visits by a supervisor during the counter-season averaged about 11, but there was considerable variance in the number of times an agent was supervised, since 65 agents were not visited at all. Also note that the expenditures in terms of phytosanitary products and fertilizers were much higher for the contracted crops than they were for rice. This reflects the fact that the principal provides the agents with these inputs as a result of European Union standards for imported produce.

Table 2: Summary Statistics for Contracted Plots Only

Variable	**Mean**	**Std. Dev.**	**N**
Green Vegetables Yield (Kg/Are)	122.027	63.218	339
Cultivated Area (Ares)	1.478	6.485	339
Seeds (Kg/Are)	1.723	16.473	336
Phytosanitary Products (Ariary/Are)	22562.532	15021.393	339
Fertilizer (Ariary/Are)	16527.125	13808.623	339
Manure (Carts/Are)	0.135	0.376	332
Compost (Carts/Are)	1.836	0.816	334
Labor (Person-Hour/Are)	164.409	52.716	332
Technical Inefficiency ($\hat{u}_i$)	0.195	0.128	337
Monitoring (Visits per Year)	10.795	11.178	327
Age (Years)	38.499	10.63	337
Education (Completed Years)	6.346	2.329	332
Male Dummy	0.733	0.443	337
Green Bean Dummy	0.646	0.479	339
Cucumber Dummy	0.33	0.471	339
Leek Dummy	0.021	0.142	339
Fivondronana 1 Dummy	0.242	0.429	339
Fivondronana 2 Dummy	0.251	0.434	339
Fivondronana 3 Dummy	0.248	0.432	339
Fivondronana 4 Dummy	0.254	0.436	339

4 Empirical Strategy

In order to test whether monitoring by the principal affects the productivity of agents, I proceed in two steps. The first step is to estimate coefficients of technical inefficiency for each agent, which I use to control for their type, θ, since the theoretical model of section 4.1 assumes that agents differ by their unobservable level of productivity. The second step is to estimate a production function for the contracted crop and, after instrumenting for the frequency of monitoring, since it might be affected by the (expected) level of output, testing whether the estimated marginal effect of monitoring on output, and thus on effort, is zero. Rejecting the null hypothesis would mean that monitoring does affect agent productivity, i.e., that monitoring reduces opportunistic behavior (Williamson, 1985), but also that monitoring is imperfect, i.e., an increase in monitoring could increase productivity. Alternatively, not rejecting the null hypothesis would mean that monitoring has little to no effect on productivity, and therefore that the principal can perfectly monitor the agents and enforce his preferred level of effort. In other words, not rejecting the null would mean that it is likely that monitoring can lead the agents to producing at the optimal level.

The survey design allows to use rice production on all plots (both contracted and non-contracted) to estimate a panel data stochastic frontier production function, i.e., an econometric model that allows to estimate household-specific, plot-invariant coefficients of technical inefficiency. Assuming a translog functional form, the specification of the model is such that (Kumbhakar and Lovell, 2000)

$$\ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln \tilde{x}_{kit} + \frac{1}{2} \sum_{k=1}^{K} \sum_{m=1}^{K} \gamma_{km} \ln \tilde{x}_{kit} \ln \tilde{x}_{mit}$$

(24)

$$+ \sum_{j=1}^{J} \beta_j z_{jit} + \sum_{\ell=1}^{L} \beta_\ell z_{\ell i} - u_i + v_{it},$$

where $i \in 1, ..., N$ indexes the agents, $t \in 1, 2, 3$ represents the plot, y is the yield (kg/are), x denotes the K inputs thought to affect the level of output, z_j denotes the J plot characteristics available to control for plot heterogeneity, z_ℓ

denotes the L agent characteristics available to control for agent heterogeneity, u is a non-negative measure of technical inefficiency whose distribution is truncated normal, and v is an error term with mean zero and variance σ_v^2. A tilde ($\tilde{}$) denotes a variable that's been normalized by dividing by its mean prior to taking logarithms, since a translog is a local second-order approximation at the sample mean. Note that in this specification, technical efficiency in rice production is invariant across plots: an agent growing rice on two different plots is assumed to be equally efficient on both plots. That is, I use u only to recover agent-specific but plot-invariant unobservable characteristics that affect productivity, thereby operationalizing θ from section 4.1.

Once I have obtained agent-specific estimates of technical inefficiency $\hat{u}_i$, I can then estimate a contracted crop Cobb-Douglas production function,[11] such that

$$(25)\quad \ln q_i = \gamma_0 + \sum_{k=1}^{K} \gamma_k \ln x_{ki} + \sum_{j=1}^{J} \gamma_j z_{ji} + \sum_{\ell=1}^{L} \gamma_\ell z_{\ell i} + \gamma_s \ln s_i + \gamma_u \hat{u}_i + \epsilon_i$$

where q denotes the yield of green vegetables on the contracted plot, x denotes the K inputs thought to affect the yield of green vegetables, z_j denotes the J plot characteristics available to control for plot heterogeneity, z_ℓ denotes the L agent characteristics available to control for agent heterogeneity, s_i denotes the frequency of monitoring,[12] $\hat{u}_i$ denotes the agent's coefficient of technical inefficiency on rice plots,[13] and ϵ_i denotes an error term with mean zero and variance σ_ϵ^2. Note that the specification in equation 25 treats monitoring as an input in the production process by taking its natural logarithm. The null hypothesis of interest is thus H_0: $\gamma_s = 0$, versus the alternative hypothesis

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[11] In an earlier version of this paper, I assumed a translog functional form. I explain in detail in section 5 why I had to abandon this more flexible functional form, but in short, it was because it posed a degrees of freedom problem in the instrumenting strategy I ultimately settle upon in section 5.4.

[12] Since the frequency of monitoring is likely endogenous – agents who are more technically inefficient, and thus who have lower expected yields, will be monitored more intensively – I instrument for it using distance from the village. Sections 5.2 and 5.4 present results for the instrumenting regression and discuss the validity of my instrument.

[13] I assume that technical inefficiency is not crop-specific, i.e., an agent who is relatively more efficient at cultivating rice will also be relatively more efficient at cultivating other crops.

H_1: $\gamma_s > 0$. Rejecting the null hypothesis would lead one to conclude that monitoring is effective in enforcing the principal's preferred level of effort and in reducing moral hazard, thereby increasing yields.

This empirical strategy allows me to resolve the usual identification problem discussed in the introduction: once adverse selection is controlled for by including estimates of individual technical inefficiency in production function, I can isolate the prospective effect of moral hazard.

Additionally, note that it would be informative to test proposition 1, i.e., to test whether agent effort is decreasing in the reimbursement due to the principal and whether input advances affect effort, by estimating an equation of the form

$$(26) \quad \mathbf{e}_i = f(\theta_i, Y_i, r_i, \mathbf{c}_i) + \omega_i,$$

where $\mathbf{e}$ is a vector of "efforts" (i.e., labor and input intensities), θ is the estimate of technical inefficiency, Y is yield, r is reimbursement, $\mathbf{c}$ is a vector of marginal effort costs (i.e., wage and input prices), and ω is the error term. Given that yield is endogenous in this regression and that the data did not include any valid instrument for it, and given that wage and input prices were only collected where agents had to hire in labor and purchase inputs, it is unfortunately impossible to estimate such a regression.

5 Results and Analysis

This section presents the estimation results for the econometric models outlined in section 4.3. I first present the results of the stochastic frontier production function for rice that yields estimates of each agent's type θ, as proxied by his technical inefficiency. I then present estimation results for a regression of the number of monitoring visits on its instruments and then use the instrumented monitoring regressor in the contracted plot production function to test my core hypothesis.

Table 3: Estimation Results for the Stochastic Rice Production Frontier

Variable	**Coefficient**	**(Std. Err.)**
Manure	0.138^{**}	(0.063)
Seeds Squared	0.006	(0.007)
Phytosanitary Products Squared	0.000	(0.011)
Fertilizer Squared	0.000	(0.005)
Manure Squared	0.022^{***}	(0.006)
Compost Squared	0.055^{***}	(0.021)
Labor Squared	-0.144^{**}	(0.060)
Cultivated Area Squared	0.008	(0.022)
Seeds*Phytosanitary Products	-0.008	(0.018)
Seeds*Fertilizer	0.005	(0.012)
Seeds*Manure	0.012	(0.010)
Seeds*Compost	-0.011	(0.028)
Seeds*Labor	-0.078^{*}	(0.047)
Seeds*Cultivated Area	-0.031	(0.028)
Phytosanitary Products*Fertilizer	0.000	(0.004)
Phytosanitary Products*Manure	0.006	(0.006)
Phytosanitary Products*Compost	-0.011	(0.012)
Phytosanitary Products*Labor	-0.041	(0.025)
Phytosanitary Products*Cultivated Area	-0.033	(0.020)
Fertilizer*Manure	-0.003	(0.003)
Fertilizer*Compost	0.002	(0.011)
Fertilizer*Labor	0.006	(0.017)
Fertilizer*Cultivated Area	0.003	(0.011)
Manure*Compost	0.006	(0.007)
Manure*Labor	0.014	(0.020)
Manure*Cultivated Area	0.031^{**}	(0.014)
Compost*Labor	0.055	(0.036)
Compost*Cultivated Area	0.074^{**}	(0.036)
Labor*Cultivated Area	0.031	(0.061)
Relationship Length	-0.041	(0.035)
Cyclone	-0.116^{***}	(0.044)
Age	0.016	(0.014)
Age Squared	0.000	(0.000)
Male	0.007	(0.047)
Education	0.018^{*}	(0.009)
Intercept	0.219	(1.081)
N	463	
Log-Likelihood	-157.101	
$\chi^2(58)$	760.484	
p-value	0.000	

5.1 Stochastic Rice Production Frontier

Table 3 presents the estimation results for the stochastic translog[14,15] rice production frontier.[16] Since the average agent in the sample owns 2.4 rice plots (e.g., a rice plot on which contracted counter-seasonal crops are grown, a rice plot on which non-contracted counter-seasonal crops are grown, and in some cases a rice plot on which no counter-seasonal crop is grown), I can estimate a panel data, plot-invariant stochastic frontier. Note that phytosanitary products might be endogenous to yield, given that these inputs are applied in response to shocks. Unfortunately, the data set does not include a good instrument for the phytosanitary products used in rice production. Considering that these inputs were applied in less than 1 percent of cases, however, the endogeneity problem is most likely muted, so I do not worry about it in what follows.

The interpretation of the results for the inputs follow the mean elasticities presented in table 4. As the cultivated area increases, yield decreases. This indicates that the well-known inverse farm size–productivity relationship holds in these data (for an application to Madagascar, see Barrett, 1996). The mean elasticities for phytosanitary products, manure, and labor are positive, indicating that these inputs have a positive effect on yield. The mean elasticities for fertilizer and compost, for their part, are negative, indicating that these inputs have a negative effect on yield. Going back to table 3, the two cyclones that hit Madagascar in early 2004 had the expected negative effect on rice yields. Finally, an agent's education has a positive effect on his rice yield, which suggests that more educated individuals are also generally more productive.

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[14] For many observations, the value of one or more inputs was equal to zero. Since the translog production function uses the logarithm of the observed output and input values, I rescaled all of the output and input values by adding 0.001 to each observation, following MaCurdy and Pencavel (1986) and Jacoby (1993). This rescaling also applies to the Cobb-Douglas production functions estimated below.

[15] Some of the non-interacted, non-squared inputs were dropped by STATA due to collinearity.

[16] Note that for brevity, the estimated coefficients for the plot-level characteristics – cultivated area, sources of irrigation, soil color and texture, fertility, change in fertility over the last year, type and variety of the rice grown – as well as the *fivondronana* dummies were omitted from table 4.3 but they are available upon request.

Table 4: Estimated Elasticities

Variable	**Elasticity**
Seeds	0.015
Phytosanitary Products	0.015
Fertilizer	-0.001
Manure	0.016
Compost	-0.153
Labor	0.069
Cultivated Area	-0.291

The estimated coefficient of technical inefficiency $\hat{u}_i$ had a mean equal to 0.197 with a standard deviation of 0.133. In other words, the average agent was about 20 percent inefficient in rice production. Figure 1 presents a plot of the kernel density estimates of this estimate.

The estimated coefficients of the stochastic rice production frontier presented here, however, are only instrumental in that they yield agent-specific estimates of technical inefficiency, which I use to control for the unobserved heterogeneity associated with agent type θ and therefore for adverse selection. I next instrument for endogenous monitoring of effort before coming to the core regression and hypothesis test of interest.

5.2 Instrumenting for Endogenous Monitoring Frequency

In order to properly instrument for the number of monitoring visits from Lecofruit received by an agent during the counter-season, one needs to use a variable that is uncorrelated with yield on the contracted plot yet correlated with the number of monitoring visits. Fortunately, the data include the distance between an agent's house and his plot, in walking minutes. Since the houses in the village are very close to one another and villages tend to be small in Lac Alaotra (they are practically hamlets, by American standards), and since the person hired by Lecofruit to monitor its agents is co-resident in the village, it makes sense to use this distance measure as my instrument. Presumably, nearby plots are trivially monitorable (e.g., the supervisor may be able to monitor them during the course of other, regular affairs). More-

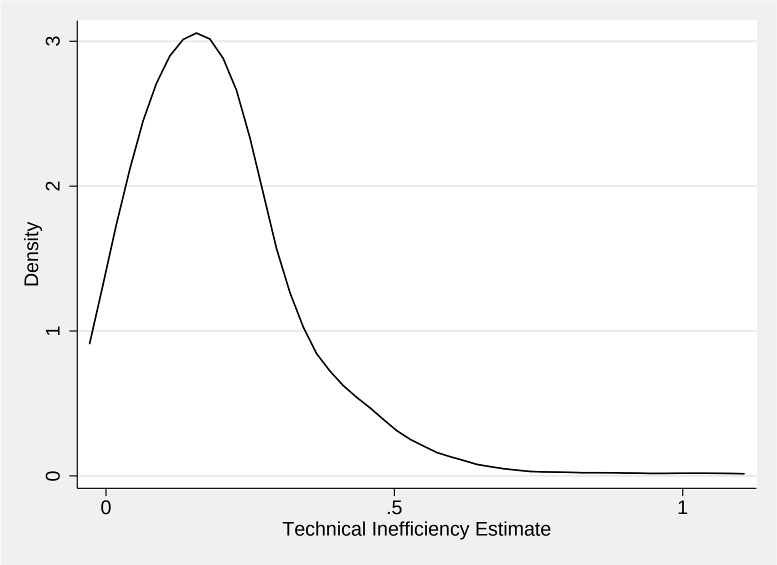

Figure 1: Kernel Density Estimate of Technical Inefficiency.

over, the geography in Lac Alaotra is such that villages are on higher ground, with most fertile plots in valley bottoms and irrigated perimeters not immediately by the village. Thus, explicit monitoring visits are more necessary for more distant plots. I thus use the distance between the agent's house and his plot and its square as instruments. Additionally, I use the length of the relationship between the principal and the agent as an instrument, i.e., the number of years they have been contracting together. On the one hand, this variable likely affects the level of monitoring if one assumes that the amount of information agents reveal about themselves is an increasing function of time. On the other hand, there is no *a priori* reason why relationship length should affect yield on contracted plots.

Recall from table 2 that the number of monitoring visits is a non-negative integer with mean equal to 10.8 and variance equal to about 125. The number of monitoring visits is equal to zero in about one sixth of the cases. It would therefore be preferable to estimate a zero-inflated negative binomial (ZINB) regression given the prevalence of zero outcomes in the dependent variable and its count data nature (Cameron and Trivedi, 1998). The ZINB regression estimates a two-stage model: (i) in the first stage, a logit model

Table 5: Estimation Results for the Instrumenting Regression

Variable	**Coefficient**	**IRR**	**(Std. Err.)**
Distance from House	0.054^{***}	1.056	(0.006)
Distance from House Squared	-0.001^{***}	0.999	(0.000)
Relationship Length	-0.024^{**}	0.976	(0.010)
Seeds	0.047	1.048	(0.039)
Phytosanitary Products	-0.136^{***}	0.873	(0.031)
Fertilizer	0.144^{***}	1.155	(0.031)
Manure	0.058^{***}	1.060	(0.018)
Compost	0.248^{***}	1.281	(0.051)
Labor	0.072	1.074	(0.118)
Cultivated Area	0.242	1.274	(0.153)
Technical Inefficiency	0.300	1.350	(0.276)
Age	0.068^{***}	1.071	(0.025)
Age Squared	-0.001^{***}	0.999	(0.000)
Education	-0.009	0.991	(0.016)
Male	-0.057	0.944	(0.081)
Fivondronana 2	-0.998^{***}	0.369	(0.114)
Fivondronana 3	-0.787^{***}	0.455	(0.112)
Fivondronana 4	-0.562^{***}	0.570	(0.114)
Intercept	1.102	–	(0.831)
N			364
Log-likelihood			-1178.554
$\chi^2(34)$			255.700
p-value			0.000
Pseudo-R^2			0.105

is fitted to determine whether the dependent variable will be equal to zero or whether it will be strictly positive; (ii) in the second stage, a negative binomial regression is used to study the determinants of the dependent variable, conditional on the fact that the dependent variable is strictly positive (Pohlmeier and Ulrich, 1995).[17]. However, since the instrumenting strategy I ultimately adopt would pose a degrees of freedom problem with the ZINB regression, I settle for a simple negative binomial regression.

Table 5 presents the estimated coefficients as well as incidence rate ratios[18] for the negative binomial instrumenting regression. Note that my three instruments are highly significant: the relationship between frequency of monitoring and distance between the house of the agent and his plot exhibiting a concave relation, and relationship length has, as posited above, a negative effect on frequency of monitoring.

5.3 Contracted Plot Production Function

In this section, I estimate two specifications of the contracted plot production function: (i) a specification in which technical inefficiency is included; and (ii) a specification in which technical inefficiency is omitted. In each specification, monitoring is treated as an input in the Cobb-Douglas production function, i.e., the variable of interest is the natural logarithm of the instrumented frequency of monitoring. Standard errors were bootstrapped in both cases.

Tables 6 and 7 present the estimation results. In the interest of brevity, these results omit the estimated coefficients for the plot-level controls, as well as for the *fivondronana* dummies, but those are available upon request. Additionally, note that the amount of phytosanitary products used on the plot might be endogenous to yield considering that these products are applied as a response to shocks. The data do not include a valid instrument for the amount of phytosanitary products used, but since these inputs were applied

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[17] A negative binomial regression is similar to a Poisson regression, except that it allows for overdispersion in the dependent variable, i.e., for a variance that is greater than the mean.

[18] The incidence rate is the predicted count at the sample mean, i.e., $\hat{y}$. The incidence rate ratio denotes the change in the expected count $E(y)$ for a one-unit increase in the explanatory variable x_k, i.e., e^{β_k}. It is thus conceptually similar to a probit marginal effect.

Table 6: Estimation Results for the Contracted Plots

Variable	**Coefficient**	**(Std. Err.)**
Seeds	0.064	(0.117)
Phytosanitary Products	-0.276	(0.225)
Fertilizer	0.256	(0.232)
Manure	0.044	(0.027)
Compost	0.147^{*}	(0.087)
Labor	0.400^{**}	(0.197)
Cultivated Area	-0.323	(0.382)
Age	0.010	(0.028)
Age Squared	0.000	(0.000)
Education	-0.031^{*}	(0.018)
Male	-0.042	(0.077)
Technical Inefficiency	-0.814^{**}	(0.432)
Monitoring	-0.114	(0.127)
Intercept	2.276^{*}	(1.286)
N	376	
R^2	0.403	
$\chi^2(32)$	238.81	
p-value	0.000	

Table 7: Estimation Results for the Contracted Plots (Technical Inefficiency Omitted)

Variable	**Coefficient**	**(Std. Err.)**
Seeds	0.074	(0.079)
Phytosanitary Products	-0.285	(0.227)
Fertilizer	0.264	(0.235)
Manure	0.042	(0.027)
Compost	0.168^{*}	(0.100)
Labor	0.383^{*}	(0.212)
Cultivated Area	-0.323	(0.382)
Age	0.021	(0.021)
Age Squared	0.000	(0.000)
Education	-0.032	(0.020)
Male	-0.042	(0.097)
Monitoring	-0.200	(0.131)
Intercept	2.332^{**}	(1.135)
N	376	
R^2	0.392	
$\chi^2(31)$	255.80	
p-value	0.000	

in only 17 percent of cases, the endogeneity problem is likely muted.

In table 5, the frequency of monitoring is not statistically significant. Yet, it becomes almost significant in table 6 when technical inefficiency is omitted from the right-hand side of the contracted crop production function, i.e., when adverse selection is not controlled for, supervision almost has a negative marginal effect on yield. This offers a good indication of the importance of controlling for the agents' types when testing for the effect of monitoring. The results, even though they are not statistically significant, are counter to the predictions of the theoretical model of section 2, according to which monitoring should have a positive marginal effect on yield. Thus, it appears that something more is at play in these data.

5.4 Re-Instrumenting for Endogenous Monitoring Frequency

Note that the relationship between frequency of monitoring and the distance between the agent's house and his plot was concave in the instrumenting regression above. This is a puzzling result, since one should expect the frequency of monitoring to be strictly decreasing in the distance between the village, where the supervisor resides, and the village. It is thus likely that the frequency of monitoring is measured with error. That is, nearer plots might be trivially monitorable, in the sense that the supervisor does not need to leave the village to supervise them, whereas the decreasing relation between frequency of monitoring and distance from the village holds for plots that are further away from the village.

Unfortunately, the data do not include a valid instrument to correct for this measurement error problem. All hope is not lost, however, if one is willing to make a potentially heroic assumption regarding which plots might be trivially monitorable and which plots might not be. Thus, for the purposes of capturing what is – in theory – the right relation between monitoring and distance, I re-estimate the negative binomial instrumenting regression on the sub-sample of plots which are more than 15 minutes away from the village. Although the turning point (the distance at which monitoring switches from being increasing to decreasing in distance) is at 27 minutes of walking distance between the agent's house and his plot in the results of the first instrumenting regression in table 5, I choose this particular distance given that it offers a good trade-off between capturing the fact that monitoring is decreasing in distance, i.e., the strictly negative part of the concave relationship above, and the number of degrees of freedom, i.e., the higher the assumption about which plots might be trivially monitorable, the lower the number of degrees of freedom.

Table 8 presents the estimation results for this sub-sample instrumenting regression.[19] Note that among the three instruments, only the square of the distance between the agent's house and his plot is significant at any of the usual significance levels, whereas the distance itself is borderline significant. In this case, the relationship between frequency of monitoring and distance is convex. However, the relationship switches from decreasing to increasing in only 21 cases in the data, i.e., for distances that are above 48 minutes, which represent only a third of the data. Additionally, note that the incidence rate ratio for the square of the distance is equal to one. In other words, although the effect of the squared distance is statistically significant, it has an infinitesimal impact on the dependent variable.

Note that this new instrumenting strategy is what prevents me from estimating a ZINB regression for the instrumenting regressions and from estimating a translog specification of the contracted plot production function: with only 60 observations in the restricted sample, (i) there aren't enough zero observations on the right-hand side of the instrumenting regression to estimate a ZINB regression; and (ii) the translog would mean that all the interaction terms from the second-stage regression would have to be included in the ZINB regression, which would leave few degrees of freedom.

5.5 Contracted Plot Production Function Redux

In this section, I re-estimate the two specifications of the contracted plot production function using the instrumenting strategy outlined in the last section. Once again, standard errors were bootstrapped. Tables 9 and 10 present the new estimation results. In the interest of brevity, the results omit the estimated coefficients for the plot-level controls, as well as for the *fivondronana*

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[19] The difference in degrees of freedom between tables 5 and 8 is due to STATA dropping plot-level controls due to collinearity.

Table 8: Estimation Results for the Instrumenting Regression (Restricted Sample)

Variable	**Coefficient**	**IRR**	**(Std. Err.)**
Distance from House	-0.030	0.971	(0.021)
Distance from House Squared	0.000**	1.000	(0.000)
Relationship Length	0.013	1.013	(0.047)
Seeds	-0.283	0.754	(1.508)
Phytosanitary Products	-0.517***	0.596	(0.075)
Fertilizer	0.416***	1.515	(0.092)
Compost	-6.842***	0.001	(1.211)
Labor	1.031	2.804	(0.632)
Cultivated Area	0.162	1.176	(0.413)
Technical Inefficiency	4.143***	62.977	(1.149)
Age	0.835***	2.304	(0.175)
Age Squared	-0.010***	0.989	(0.002)
Education	-0.136	0.873	(0.163)
Male	-0.362	0.696	(0.468)
Fivondronana 2	3.040*	20.908	(1.626)
Fivondronana 3	2.208	9.096	(1.757)
Fivondronana 4	3.159	23.537	(2.175)
Intercept	-18.889***	–	(5.226)
N			60
Log-likelihood			-135.692
$\chi^2(28)$			151.30
p-value			0.000
Pseudo-R^2			0.358

Table 9: Estimation Results for the Contracted Plots

Variable	**Coefficient**	**(Std. Err.)**
Seeds	0.093	(0.115)
Phytosanitary Products	-0.229	(0.209)
Fertilizer	0.218	(0.215)
Manure	0.042*	(0.025)
Compost	0.896	(1.266)
Labor	0.394	(0.294)
Cultivated Area	-0.317	(0.376)
Age	-0.085	(0.155)
Age Squared	0.001	(0.002)
Education	0.003	(0.027)
Male	-0.005	(0.110)
Technical Inefficiency	-1.509*	(0.915)
Monitoring	0.115	(0.184)
Intercept	3.573	(3.880)
N	310	
R^2	0.438	
$\chi^2(32)$	119.60	
p-value	0.000	

Table 10: Estimation Results for the Contracted Plots (Technical Inefficiency Omitted)

Variable	**Coefficient**	**(Std. Err.)**
Seeds	0.003	(0.100)
Phytosanitary Products	-0.401*	(0.237)
Fertilizer	0.357	(0.237)
Manure	0.044*	(0.025)
Compost	-1.382**	(0.664)
Labor	0.732***	(0.259)
Cultivated Area	-0.258	(0.345)
Age	0.194**	(0.081)
Age Squared	-0.002**	(0.001)
Education	-0.040*	(0.022)
Male	-0.098	(0.085)
Monitoring	-0.218**	(0.097)
Intercept	-2.763	(2.127)
N	310	
R^2	0.369	
$\chi^2(31)$	101.84	
p-value	0.000	

dummies, but those are available upon request.

The results are considerably more interesting this time around. When the coefficient of technical inefficiency is included in the production function, monitoring is not significantly different from zero, but it has the right sign. Using Andrews' (1989) inverse power function method, I find that the elasticity of yield with respect to monitoring is less than 0.66 at the 5 percent significance level, but that there is no evidence that it is lower than 0.36. In other words, on average, one more monitoring visit implies an increase in yield that is less than 7.5 kg/are (or 11.1 kg of additional output, on average) of green vegetables at the 5 percent significance level, but there is no evidence that the increase is less than 4.1 kg/are (or 6.5 kg of additional output, on average).[20] Thus, even though monitoring is not statistically significant, it is still economically significant in the sense that it does sensibly increase yields at the margin.

Also note that when the coefficient of technical inefficiency is omitted from the production function, I obtain the perverse result that monitoring is statistically significant and has a negative effect on yield, i.e., monitoring backfires. This result, when contrasted with the result obtained when technical inefficiency is included in the production function, illustrates the importance of controlling both for adverse selection and moral hazard when conducting empirical work on contracts using cross-sectional data.

6 Conclusion

I have tested for the effects of monitoring in contracts between a large exporting firm and small agricultural producers in Madagascar. Using estimated technical inefficiency in rice production to control for unobserved agent heterogeneity – essentially, the individual types that might give rise to adverse selection – allows me to obviate the usual identification problem encountered

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[20] These yields are obtained as follows: at the mean of the explanatory variables, one more monitoring visit represents a 9.26 percent increase in monitoring, which is multiplied by the numbers obtained via the inverse power function method, which are bounds on the elasticity of yield with respect to monitoring. These bounds are then multiplied by the average yield to obtain an average marginal effect of monitoring, and these yields are multiplied by the size of the average plot to obtain changes in total output.

when conducting applied contract-theoretic work using cross-sectional data. My empirical results indicate that monitoring has a positive, statistically insignificant effect on yields, but that the effect is economically significant nonetheless: one more monitoring visit implies an increase in yield that is between 4.1 and 7.5 kg/are, on average, at the 5 percent significance level.

Additionally, and of greater interest for those doing applied work on contracts, my results empirically demonstrate the importance of controlling both for adverse selection and moral hazard when conducting applied work on contracts using cross-sectional data. When omitting the agent-specific coefficient of technical inefficiency, the empirical results indicate that supervision has a negative, statistically significant effect on yields, a result that is counter to both economic theory and intuition.

Even though additional monitoring visits may have an economically significant positive effect on yields, it is not immediately obvious that Lecofruit should monitor its agents more intensively. If the marginal cost of monitoring exceeds its marginal benefit, then Lecofruit should not increase the level of supervision. In an industry in which both the fixed and proportional transactions costs (Key et al., 2000; Bellemare and Barrett, 2006) associated with marketing output are significant and in which local competition is heavy, profit margins are likely low, which may mean that increased monitoring of the agents is simply not worth it.

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A Appendix

A.1 Moral Hazard Only

When the principal knows the type of agent he faces but cannot enforce his preferred level of effort, his problem is to

$$(27) \quad \max_{(a_i, r_i)} \left\{ \frac{\theta_i^2 (Y - r_i) r_i}{c} - a_i \right\}$$

subject to

$$(28) \quad \frac{1}{2c} \big[\theta_i (Y - r_i) \big]^2 + a_i \geq 0 \ \forall i \in \{L, H\}. \ \text{(IR)}$$

From this framework, we can state the following about the shape of the contracts observed.

Proposition 6 *When the principal can observe the agent's type but cannot enforce his preferred level of effort, both types provide nothing as reimbursement to the principal and each type pays an up-front fee proportional to his type in order to work for the principal. That is,* $r_H = r_L = 0$*, and* $a_i = -\frac{\theta_i^2 Y^2}{2c}$.

Proof: Using the IR constraint, we substitute for a_i in the principal's maximization problem, which yields the following first-order condition:

$$(29) \quad -\frac{\theta_i r_i^*}{c} = 0,$$

from which it is obvious that the value of r_i that maximizes the principal's objective function is such that $r_i^* = 0$. Plugging that value into the IR constraint yields $a_i^* = -\frac{\theta_i^2 Y^2}{2c}$ ■

Once again, the intuition behind the result is simple: when the principal can observe the type of the agent but cannot enforce his preferred level of effort, he charges a type-dependent up-front fee for the agents who wish to work for him but gets nothing further. This is analogous to a fixed rent contract in the long-standing agrarian contracts literature.