Evidence on the Incentive Properties of Share Contracts

Luís H. B. Braido*
University of Chicago

February 18, 2002

Abstract

Ever since Adam Smith, economists have argued that share contracts do not provide proper incentives. This paper uses tenancy data from India to assess the existence of missing incentives in this classical example of moral hazard. Sharecroppers are found to be less productive than owners, but as productive as fixed-rent tenants. Also, the productivity gap between owners and both types of tenants is driven by sample-selection issues. An endogenous selection rule matches tenancy contracts with less-skilled farmers and lower-quality lands. Due to complementarity, such a matching affects tenants' input choices. Controlling for that, the contract form has no effect on the expected output. Next, I explicitly model farmer's optimal decisions to test the existence of non-contractible inputs being misused. No evidence of missing incentives is found.

Keywords: econometric test, agency theory, moral hazard, tenancy data, selection bias. JEL Classification: C52, D82, O12, Q15.

*I am thankful for helpful comments from Pedro Carneiro, Rodrigo Cerda, Pierre-André Chiappori, Mark Duggan, Maitreesh Ghatak, Milton Harris, D. Gale Johnson, Steven Levitt, Derek Neal, Lars Stole, and seminar participants at the University of Chicago. Financial support from CNPq-Brazil is gratefully acknowledged. URL: home.uchicago.edu/~lhbraido; email: l-braido@uchicago.edu.

1 Introduction

Moral hazard is the term used to describe situations where individuals change non-contractible behaviors in response to changes in their personal insurance. Theoretical modeling of those situations is one of the most active areas of research in economics, and many mathematical models have been in dispute for the profession's attention. The models vary from the standard textbook case with one principal, one agent, and two possible levels of effort, to more complex scenarios with intertemporal features (Townsend, 1982), random devices (Prescott and Townsend, 1984), double-sided incentives (Bhattacharyya and Lafontaine, 1995), and non-exclusive relationships (Bisin and Guaitoli, 2000, and Braido, 2001).

In spite of the elegance of using mathematical tools to model human behavior, the beauty of that is mostly due to the possibility of performing empirical tests. This paper uses tenancy data from India, collected by the International Crops Research Institute for Semi-Arid Tropics (ICRISAT), to empirically assess the existence of missing incentives in one of the classical examples of moral hazard: the landlord-tenant relationship.

Consider a situation where a landlord (principal) hires a tenant (agent) to manage a farm. The level of effort exerted by the tenant is unobservable and affects the farm's expected output. Since agricultural activities are subject to random shocks (such as climatic changes and plagues), it is not possible to infer the tenant's dedication by the farm's outcome. Therefore, the landlord must provide incentives to induce the tenant to voluntarily choose a desirable level of effort. The theoretical literature argues that the ideal compensation contract must provide incentives by making the tenant's salary conditional on the farm's output.

Farms are usually cropped under three basic contract forms: ownership (where the plot is cropped by its owner); fixed-rent tenancy (where the tenant pays an upfront rent and collect the entire revenue); and sharecropping tenancy (where the landlord supplies the land, the tenant bears the costs of labor and non-labor inputs, and they share the output).[1] Owners and fixed-rent tenants bear the marginal costs and receive the marginal benefit of their actions. Therefore, their plots must achieve the maximum expected output. Share contracts balance effort incentives and risk sharing (i.e., the landlord insure tenants at the cost of reducing effort incentives). Consequently, sharecropped farms would tend to be less productive than those owned or rented.

A first goal of this paper is to test if the expected output is affected by the tenancy contract in the way predicted by theory. Controlling for the area cropped,

[1] In many cases, the landlord shares the cost of some inputs.

sharecroppers are found to be less productive than owners, but as productive as fixed-rent tenants (contradicting the theoretical predictions). Moreover, the productivity gap between owners and both types of tenants is driven by observable variables. Sharecroppers and fixed-rent tenants usually cultivate lands with lower value. Due to complementarity, they would naturally use less of all other inputs (including managerial effort). Controlling for observable inputs, one finds no productivity difference among owned, sharecropped, and rented lands.

It is important to notice that, typically, the optimal input choice depends non-linearly on fixed factors (such as the quality of land). Therefore, introducing the value of land in the regression does not capture the indirect effects of this fixed factor on the optimal use of other inputs.

Sample selection is an important issue in the data set, since privately observed characteristics of lands and households are not expected to be orthogonal to the contract choice. Accounting for this, I use a subsample of households cropping the same product under different contract forms in the same year and season. I find that the contract form has no effect on the expected output, which suggests that share contracts provide enough incentives to induce tenants to choose the first-best level of any existing unobservable action.[2]

A second issue raised in this paper is the existence of misused inputs. In all villages studied, sharecroppers bear alone the cost of some inputs. Although observable for the researcher, it might be very costly for the landlord to monitor the farm. In that case, sharecroppers would tend to misuse these inputs, since they face distorted marginal incentives (i.e., they share the marginal benefit and bear alone the marginal cost).

It is shown that sharecroppers use less of labor and non-labor inputs per area cropped than owners. Previous works have interpreted this as evidence of moral hazard. However, it is noticed that fixed-rent tenants also use less inputs per area cropped than owners, contradicting the moral hazard interpretation. I suggest that, since sharecroppers and fixed-rent tenants use lands with lower quality, complementarity among inputs would explain the evidence. Then, I explicitly model farmers' optimal decisions and show that the degree of complementarity inherent in the Cobb-Douglas production function is able to justify sharecroppers' input choices as optimal. Once again, the results suggest the inexistence of missing incentives associated with share contracts.

Since Adam Smith, share contracts have been condemned by many economists

[2]Inexistence of hidden actions would be another possible interpretation. However, the absence of plots cultivated on a fixed-salary basis would clearly favor the interpretation that there is a hidden-action issue that is overcome by the share contract.

because of its lack of incentives. In spite of this, these contracts have prevailed over the last five centuries and still accounts for an important fraction of agricultural leases in developing and developed countries.[3] The literature on moral hazard argues that the lack of incentives is compensated by the risk-sharing properties of these contracts. The results in this paper suggest that no such a lack of incentives is present in the Indian villages studied.

Dynamic incentives may be a theoretical explanation for these findings. As stressed by Johnson (1950), landlords provide strong indirect incentives by granting only short-term leases. Moving is costly for tenants (especially if there is risk of unemployment), and landlords tend to renew those leases based on relative performance (i.e., by comparing sharecropper's output with those of adjoining farms). Moreover, landlords and tenants are sometimes very close to each other in small villages, which would simplify the monitoring activities and make tenants concerned about their reputation.

The remainder of this paper is organized as follows. Section 2 briefly reviews the related empirical literature. Section 3 discusses the methodology and describes the data set. Section 4 introduces a simple log-linear econometric model and presents the OLS results. Section 5 uses a difference regression model to take selection bias into account. Section 6 shows that sharecroppers use less input than owners due to complementarity, rather than imperfect monitoring. Section 7 presents a sensitivity analysis, and section 8 serves as a conclusion.

2 Literature Review

Many recent articles have focused on testing the empirical predictions of models with imperfect information (adverse selection and moral hazard). Tests for models of adverse selection (hidden information) are usually based on data from different insurance markets. Evidence from automobile insurance contracts is found in Puelz and Snow (1994), Dionne and Vanasse (1992), Dionne and Doherty (1994), Richaudeau (1999), and Chiappori and Salanié (2000). In this same vein, Chiappori, Durand, and Geoffard (1998), and Cardon and Hendel (2001) use data on health insurance; and Hendel and Lizzeri (2001) uses data on life insurance.

On the other hand, empirical studies on moral hazard (hidden action) have mostly focused on tenancy data. Closely related to this paper, Shaban (1987) uses

[3] Share contracts are largely used throughout the United States of America. In the state of Illinois, there are numerous large farms with values of 1.5 million dollars that are share rented. (I thank D. Gale Johnson for this note.)

a subsample of the ICRISAT's village level studies to show that mixed sharecroppers (those who also own some land) use statistically more of all inputs in their own lands. This suggests the existence of monitoring problems. One cannot forget however that complementarity between land and other inputs might be another source of explanation for this (which is precisely one of the contributions of this work). Shaban's paper also shows that the average per acre production of sharecropped plots is lower than the one in owned plots. Variables accounting for the quality of land are linearly introduced in the regressions, but non-labor and labor inputs are not. (As mentioned before, the quality of land have non-linear effects on the amount of other inputs used.)

In a different line, Laffont and Matoussi (1995) access Tunisian data and show that sharecroppers are less productive than owners and fixed-rent tenants. They define a log-linear specification for the production function, where the plot's area, the cost of non-labor inputs, and family and hired labor (in days) are used as regressors. Information on the household's characteristics and the type of crop are used, but no control for the quality of land is available. Also, sample-selection issues are not fully considered.

Cheung (2002) provides a historical survey of sharecropping studies. A large number of aggregate statistics from Asian countries are suggested as evidence that the percentage share and area cropped are competitively determined in the market and that investments leading to higher rental annuities are always enforced by the landlord.

Other related references include Bandiera (1999), who presents evidence on the relationship between the form and the duration of contracts, in 19th century Sicily; Ackerberg and Botticini (2001), who use data from early Renaissance Tuscany to study whether the endogenous contract choice is affected by landlords' and agents' characteristics and crop's riskiness; and Pandey (2001), who uses Northern Indian villages to study how share contracts change when technology varies.

3 Preliminaries

3.1 Testable Implications

The data set contains farms that are owned, rented (on a fixed-rent basis), and sharecropped. The theoretical literature on moral hazard (e.g., Holmström, 1979) provides testable implications regarding the conditional expected output of plots cropped under each of these three contract forms. First, owners and fixed-rent tenants must be equally productive. Second, under the usual assumptions that the production function is first-order stochastically increasing in a real-valued hidden action,[4] owners and fixed-rent tenants must be strictly more productive than sharecroppers. Therefore, I test if the contract form affects the conditional expected output in the way predicted by theory.

Topic 1. *What is the effect of the contract form on the conditional expected output?*

An important methodological consideration must be made here. Theoretical models on moral hazard do not distinguish between actions that are unobservable (such as managerial effort) and actions that are only observable at prohibitive monitoring costs. However, such a distinction is important for empirical research. Many actions that might be non-observed by the landlord (principal) are usually available in the data set (i.e., they are observed by the researcher). As a consequence, procedures to test the importance of hidden actions must differ from those to test the existence of monitoring problems.

In particular, some empirical works have ignored variables such as the amount of non-labor and labor inputs used by tenants, since it is not clear that those variables are monitorable. However, by disregarding those variables, one ignores important complementarity effects. Share contracts are usually associated with lower-quality lands, which would naturally affect the choice of all other inputs (due to complementarity). Typically, the optimal amount of each input is a non-linear function of the amount of fixed factors (such as the quality of land and the farmer's ability). Therefore, introducing those fixed inputs in the regression is not sufficient to capture the indirect effects that they have over production.

Remark 1. *Differences in households' and plots' characteristics impact, in a non-linear way, the optimal choice of all other inputs. Also, information about many potentially non-monitorable inputs may be available for the researcher. Therefore, procedures intending to test the importance of hidden actions must differ from those used to test the existence of imperfect monitoring.*

The existence of imperfect monitoring is another important topic studied in this paper. In section 6, I explicitly model the production function and farmers' first-order conditions to test if sharecroppers use an efficient level of non-labor and

[4]The assumption that the hidden action takes value in the real line is intended to avoid considerations about corner solutions (where the first-best and the second-best level of effort would coincide).

labor inputs (i.e., I test if plots' expected marginal productivity equals marginal cost regardless of the contract form).

Topic 2. *Are sharecroppers' input choices optimal?*

3.2 Data Description

The data set used is part of the longitudinal village level studies (VLS) conduced by the International Crops Research Institute for Semi-Arid Tropics (ICRISAT), in India. The study was conduced from 1975 to 1984 in villages intended to represent major agroclimatic zones of India.

Initially, six villages were selected in two different states. They are: Aurapalle and Dokur (in the state of Andhra Pradesh); Kanzara, Kinkheda, Shirapur, and Kalman (in the state of Maharashtra Akola). Later, in 1980, the villages of Boriya and Rampura (in the state of Gujarat) were also included in the study.

The sample is divided into four categories (large, medium, and small farmers, and landless workers) with ten households randomly selected in each category. Random replacement within each category occurs whenever a household emigrates from the village. Resident investigators collected information on farming activities in each of the plots cultivated by the selected households. The schedule used, PS files, contains information on the value of output, type of tenancy contract, area cropped, value of land, irrigated area, value of labor and non-labor inputs, village, season, year, and cropping patter. Table 1 describes the variables used and Table 2 presents the summary statistics. Details about the data collection method can be found in Jodha, Asokan, and Ryan (1977), and Binswanger and Jodha (1978).

[INSERT TABLE 1]

[INSERT TABLE 2]

4 Econometric Specification

Consider the standard Cobb-Douglas technology:

$$y_i = A_i \prod_{k=1}^{K} x_{ik}^{\alpha_k} \exp\left(\varepsilon_i\right), \tag{1}$$

where y_i represents the value of plot i's output; x_{ik} is the value of input k used in plot i; A_i accounts for observable characteristics of the plot and household who cultivates it; and ε_i is an unobserved error term (which accounts for possible hidden actions as well as households' unobserved abilities, lands' unobserved characteristics, climatic shocks, plagues, etc.).

The log-linear version of the production function is:

$$\ln(y_i) = \ln(A_i) + \sum_{k=1}^{K} \alpha_k \ln(x_{ik}) + \varepsilon_i. \tag{2}$$

As already mentioned, the error term ε_i captures the effect of hidden actions on production and the economic theory predicts that those actions are correlated with the tenancy contract. Dummy variables are used to capture the effect of the contract form on the output. Namely, those variables are the ownership dummy (i.e., d_i^o such that $d_i^o = 1$ if plot i is owned and $d_i^o = 0$ otherwise), and the fixed-rent dummy (i.e., d_i^f s.t. $d_i^f = 1$ if plot i is rented and $d_i^f = 0$ otherwise). It is assumed that the unobserved error is such that:

$$\varepsilon_i = \bar{\varepsilon} + \delta_1 d_i^o + \delta_2 d_i^f + u_i, \tag{3}$$

where $\bar{\varepsilon}$ is a constant term; δ_1 and δ_2 measure the mean effect of the respective contract form on production; and u_i accounts for other unobserved variables. (The constant term, $\bar{\varepsilon}$, allows us to assume that $E(u_i) = 0$.)

From (2)-(3), one has:

$$\ln(y_i) = \delta_1 d_i^o + \delta_2 d_i^f + \sum_{k=1}^{K} \alpha_k \ln(x_{ik}) + \ln(A_i) + \bar{\varepsilon} + u_i. \tag{4}$$

The standard moral hazard theory predicts that $\delta_1 = \delta_2 > 0$ (i.e., owners and fixed-rent tenants are equally productive, and they both are strictly more productive than sharecroppers). Then, one must obtain a consistent estimate for δ_1 and δ_2, and test their statistical significance.

4.1 OLS Estimates

In the absence of selection bias, i.e., under the assumption that u_i is orthogonal to the covariates, the ordinary least square method (OLS) consistently estimates δ_1 and δ_2.

Many variables in the ICRISAT's data set are available to be used as covariates. Village, year, and season dummies account for the technological factor, $\ln(A_i)$. The estimated value of each acre of land and the irrigated are account for the quality of land (a fixed factor). The other productive factors include the area cropped and the value of non-labor and labor inputs. Moreover, clusters are used to account for the fact that the observations are not be independently drawn among the plots cropped by the same household. Table 3 summarizes the OLS results.

[INSERT TABLE 3]

Regression (a) shows that, controlling for the village, year, season, and area cropped, owners are more productive than sharecroppers and renters. This already contradicts the theoretical prediction that sharecroppers should be less productive than fixed-rent tenants. Moreover, the other regressions show that the productivity difference between owners and the two types of tenants is explained by observable variables, such as the value of land, irrigated area, and the value of non-labor and labor inputs.

Regressions (b) shows that adding the value of land and the irrigated area reduces considerably the productivity gap between owners and tenants. In (c)-(e), one observes that there is no productivity difference between owners and tenants when the value of non-labor and labor inputs are added as control.

Result 1. *Sharecroppers are less productive than owners, but as productive as fixed-rent tenants (contradicting the theoretical predictions). Moreover, controlling for observable variables, the contract form does not affect the conditional expected output.*

5 Accounting for Ability Bias

One can always model a random variable as a linear function of some covariates plus an unobserved error (by definition of the error term). However, it is not always the case that one can assume that such an error is independent of the covariates, which is a necessary condition for consistency of OLS. The bias caused by non-randomly selected samples is known in the literature as selection bias (see Heckman, 1979).

For the problem studied here, the contract form as well as the other covariates are endogenously chosen. Therefore, one would expect that privately observed characteristics of households were strongly correlated with these choices. For instance, due to credit market imperfections, owners tend to be richer than tenants.

Therefore, one would expect owners to be more skilled and to crop the best plots. In that scenario, the OLS method would overestimate the parameter δ_1.

A unique characteristic of the data set is the presence of households cropping multiple plots of the same product, under different contract forms, in the same year and season. By comparing the output of plots cropped by the same household, one accounts for ability bias (i.e., the bias caused by the fact that household's skills might not be independent of the contract form). Unfortunately, the quality of plots cropped by the same household under each contract form is not homogeneous. As already mentioned, this affects their optimal input choices, as well as the optimal level of effort, in a monotonic but non-linear way (i.e., better lands are associated with more inputs and more effort, but the quality of land is not collinear to these variables).

The subsample of mixed tenants is divided in three categories: (i) mixed owner & sharecropper (i.e., households cropping the same product in owned and sharecropped plots, in the same year and season); (ii) mixed owner & fixed-rent tenant; and (iii) mixed fixed-rent tenant & sharecropper. The analysis is concentrated on the subsample of mixed owner & sharecropper, since it is relatively large (1,194 plots from 338 households) and allows us to identify the parameter δ_1. Unfortunately, the size of the subsample of mixed owner & fixed-rent tenant is very small (which restricts the analysis), and there are only 8 observations of mixed fixed-rent tenant & sharecropper. Table 4 describes the three subsamples.

[INSERT TABLE 4]

5.1 Mixed Owner & Sharecropper

Initially, let us consider the subsample of mixed owner & sharecropper. An observation is now defined by a household cropping the same product in a certain year and season. Index these observations by h, and let O_h (respectively, S_h) be the number of plots owned (respectively, sharecropped) by h. Also, define $\mathbb{O}_h$ and $\mathbb{S}_h$ as the respective sets of those plots.

Next, define the difference operator, Δ_h (or Diff$^{o\text{-}s}$), to be such that for any generic variable Z:

$$\text{Diff}^{o\text{-}s} Z = \Delta_h Z = \frac{\sum_{i \in \mathbb{O}_h} Z_i}{O_h} - \frac{\sum_{i \in \mathbb{S}_h} Z_i}{S_h}.$$

In words, $\Delta_h Z$ defines the difference between the average value of Z in the owned and sharecropped plots of h. Applying that operator on (4), one gets:

$$\Delta_h \ln(y) = \delta_1 + \sum_{k=1}^{K} \alpha_k \Delta_h \ln(x_k) + \nu_h, \tag{5}$$

where $\nu_h = \frac{\sum_{i \in \mathbb{O}_h} u_i}{O_h} - \frac{\sum_{i \in \mathbb{S}_h} u_i}{S_h}$.

As usual, grouped data presents heterocedasticity due to the difference in the number of elements in each group. Whenever $var(u_i) = \sigma^2$, one has:

$$Var(\nu_h) = \left(\frac{1}{O_h} + \frac{1}{S_h}\right) \sigma^2.$$

Although the OLS estimator remains unbiased and consistent, heterocedasticity would cause inefficiency. This problem would be easily solved if one divides each observation by $\sqrt{\frac{1}{O_h} + \frac{1}{S_h}}$ (GLS procedure). Moreover, clusters are recommended since there are observations drawn from the same household (in different seasons, year, etc). Table 5 summarizes the clustered GLS results.

[INSERT TABLE 5]

By comparing coefficients in Tables 3 and 5 one observes that correcting for the ability bias reduces the estimates for δ_1. The results are consistent with those from section 4. Controlling for observable variables, there is no productivity gap between owned and sharecropped plots of the same household.

5.2 Mixed Owner & Fixed-Rent Tenant

Now, let us consider the subsample of households who owns and rent plots of the same product in the same year and season. Similarly to last section, the difference operator is defined to be such that:

$$\text{Diff}^{o\text{-}f} Z = \hat{\Delta}_h Z = \frac{\sum_{i \in \mathbb{O}_h} Z_i}{O_h} - \frac{\sum_{i \in \mathbb{F}_h} Z_i}{F_h},$$

where Z is a generic variable; h indexes the observations; O_h (respectively, F_h) is the number of plots owned (respectively, rented) by h; and $\mathbb{O}_h$ and $\mathbb{F}_h$ as the respective sets of those plots.

Applying that operator on (4), one gets:

$$\hat{\Delta}_h \ln(y) = (\delta_1 - \delta_2) + \sum_{k=1}^{K} \alpha_k \hat{\Delta}_h \ln(x_k) + \hat{\nu}_h, \tag{6}$$

where $\hat{\nu}_h = \frac{\sum_{i \in \mathbb{O}_h} u_i}{O_h} - \frac{\sum_{i \in \mathbb{S}_h} u_i}{S_h}$ and $Var(\hat{\nu}_h) = \left(\frac{1}{O_h} + \frac{1}{F_h}\right)\sigma^2$.

In Table 6, the constant term identifies the term $(\delta_1 - \delta_2)$. One cannot reject the hypothesis that owned and rented plots are equally productive. One must however be careful when interpreting those results, since the sample size is very small. (This implies a large standard deviation for the proposed estimator, so that the null hypothesis would hardly be rejected).

[INSERT TABLE 6]

Result 2. *This section takes the ability bias into account. The results are consistent with those from section 4; suggesting that plots cropped under the three tenancy contracts are equally productive.*

6 Complementarity vs. Imperfect Monitoring

For all villages studied, share contracts are such that the tenant alone bears the cost of some inputs. This creates a distortion in the intensive margin (i.e., one bears the entire marginal cost and receives only a fraction of the marginal revenue), which would induce non-monitored sharecroppers to use less than the optimal level of non-labor and labor inputs. Sharecroppers indeed use less of those inputs per area cropped than owners, as shown by regressions (a) and (b) in Table 7. However, this may not be related to incentive problems, since fixed-rent tenants also use less inputs per area cropped than owners, and about as much as sharecroppers (see those same regressions). Moreover, sharecropping and fixed-rent contracts are both associated with lower-quality lands − see regression (c) in Table 7. Therefore, complementarity among factors would explain why both types of tenants use less of those inputs.

[INSERT TABLE 7]

As mentioned before, an important methodological contribution of this paper is to note that procedures used to test the existence of hidden actions must differ from those used to test the existence of monitoring problems. This section models farmers' optimal decisions and test if a standard degree of complementarity would be able to justify sharecroppers' choices of inputs.

Efficient Input Level

The farmer's ability and the quality of land are fixed factors. Also, the size of the farm is a decision made in the extensive margin (at the time of buying or renting the farm). Therefore, in each season, farmers choose the amount of labor and non-labor inputs. Since output and factors are measured in monetary units, the profit maximization problem faced by owners and fixed-rent tenants is:

$$\max_{x_{i3},x_{i4}} E\left\{y_i - x_{i1} - x_{i2} - c\right\},$$

where $y_i = A_i \prod_{k=1}^{K} x_{ik}^{\alpha_k} \exp(\varepsilon_i)$, x_{i1} and x_{i2} are the value of non-labor and labor inputs, and c stands for the rent (in the case of fixed-rent tenants) or the opportunity cost of the farm (in the case of owners).

The necessary and sufficient first-order conditions are:

$$E\left\{\alpha_j A_i x_{ij}^{\alpha_j - 1} \prod_{k \neq j} x_{ik}^{\alpha_k} \exp(\varepsilon_i)\right\} = 1,\ j \in \{1, 2\}.$$

Alternatively, the above conditions can be rewritten as:

$$E\left\{\alpha_j \frac{y_i}{x_{ij}}\right\} = 1,\ \ j \in \{1, 2\}. \tag{7}$$

Non-Monitored Choices of Sharecroppers

In many villages, the landlord also shares the cost of some inputs, in which case there is no marginal distortion to be studied. However, when sharecroppers bear alone the cost of outputs, and if there is no informal agreement regarding the amount of inputs to be used, sharecroppers would maximize:

$$\max_{x_{i3},x_{i4}} E\left\{s_i y_i - x_{i1} - x_{i2}\right\},$$

where $y_i = A_i \prod_{k=1}^{4} x_{ik}^{\alpha_k} \exp(\varepsilon_i)$ and s_i is the fraction of output received by the sharecropping tenant.

The necessary and sufficient conditions for the maximum are:

$$E\left\{s_i\alpha_j\frac{y_i}{x_{ij}}\right\} = 1,\ j \in \{1,2\}\,. \tag{8}$$

Since $0 < s_i < 1$ (by definition of sharecropping), the existence of monitoring problems would imply a higher expected productivity, $E\left\{\alpha_j\frac{y_i}{x_{ij}}\right\}$, in sharecropped plots.

6.1 Econometric Test

Whenever complementarity explains tenants' input choices, the expected marginal productivity, $E\left\{\alpha_j\frac{y_i}{x_{ij}}\right\}$, should be the same across the different contracts. On the other hand, if monitoring is indeed a problem, one should observe a larger expected marginal productivity in the sharecropped plots.

Notice that the coefficient α_j may differ across households, years, seasons, and cropping patterns. For that reason, I restrict the analysis to the subsample of mixed tenants. It is implicitly assumed that α_j is the same for each household cropping the same product in a certain year and season. Therefore, one can use the ratio $\frac{y_i}{x_{ij}}$ to test the existence of monitoring imperfections.

Let us model the output-input ratio as a constant associated with the contract form plus an error term and, then, test if these constants are the same across contracts. Thus:

$$\frac{y_i}{x_{ij}} = c_1d_i^o + c_2d_i^f + c_3d_i^s + \eta_i, \tag{9}$$

where c_1, c_2, and c_3 are constants; d_i^o, d_i^f, and d_i^s are the dummy variables for the tree contract forms (ownership, fixed rent, and sharecropping); and η_i is a error term with zero mean and constant variance.

Remark 2. *Under the null hypothesis that there is no monitoring problems, one must have $c_1 = c_2 = c_3$. The alternative hypothesis is $c_1 = c_2 < c_3$ (i.e., if sharecroppers were not monitored, their expected marginal productivity would be higher).*

Mixed Owner & Sharecropper

By using the subsample of mixed owner & sharecropper, one can identify the term $(c_1 - c_3)$. Apply the operator Δ_h, as defined in section 5.1, on (9) to get:

$$\Delta_h \tfrac{y_i}{x_{ij}} = (c_1 - c_3) + \Delta_h \eta_i,$$

where $var\left(\Delta_h \eta_i\right) = \left(\frac{1}{O_h} + \frac{1}{S_h}\right) var(\eta_i)$.

Table 8 presents the GLS estimations. The estimates for $(c_1 - c_3)$ are non-significant, so that one cannot reject the hypothesis of perfect monitoring (i.e., the marginal productivity of non-labor and labor inputs are equal in owned and sharecropped plots of the same household).

[INSERT TABLES 8]

Mixed Owner & Fixed-Rent Tenant

Let us use now the subsample of mixed owner & fixed-rent tenant to identify the term $(c_1 - c_2)$. As in section 5.2, apply the operator $\hat{\Delta}_h$ on (9), so that:

$$\hat{\Delta}_h \tfrac{y_i}{x_{ij}} = (c_1 - c_2) + \hat{\Delta}_h \eta_i,$$

where $var\left(\Delta_h \eta_i\right) = \left(\frac{1}{O_h} + \frac{1}{F_h}\right) var(\eta_i)$.

Table 9 shows that one cannot reject that the marginal productivity of non-labor and labor inputs are equal in owned and rented plots of the same household (i.e., $c_1 = c_2$).

[INSERT TABLES 9]

Result 3. *No evidence of monitoring problems is found in the data set. The type of complementarity inherent in the Cobb-Douglas production function is able to justify sharecroppers' input choices.*

7 Sensitivity Analysis

This paper finds no missing incentives associated with share contracts, and this result drastically differs from those in the current literature. As stated before, this paper is closely related to the one by Shaban (1987). We assess similar questions, with a similar data set, and obtain opposite conclusions. It is natural then to have some considerations about this.

Many methodological choices in this work differ from those made by Shaban (1987). First, in order to account for complementarity among the plot's size, land's quality, and other inputs, I estimate a Cobb-Douglas production function (while Shaban uses a linear regression model for the output per area cropped). Second, I argue that non-labor and labor inputs must be taken into account, since complementarity implies that those choices are non-linearly affected by the quality of land (which is not randomly assigned to each contract form). Third, by using the benefit of addressing the same problem more than one decade later, I am able to access a larger number of years (from 1975 to 1984). Finally, my definition of mixed tenant is finer, which generates a more homogeneous sample.

Regarding this last difference, I compare plots of the same product cropped by the same household in a certain year and season, while Shaban does not control for the cropping pattern. This section is intended to show that the results are not sensitive to the definition of mixed tenants.

7.1 Mixed* Tenants

Let us use an asterisk to represent another possible way to aggregate the data. Mixed* tenants are those cropping multiple plots under different contracts in the same year and season (without controlling for the cropping pattern). As before, the sample is divided in three categories: (i) mixed* owner & sharecropper; (ii) mixed* owner & fixed-rent tenant; and (iii) mixed* fixed-rent tenant & sharecropper. This new grouping criteria generates more observations in each of these subsamples, which allows us to analyze them all.

7.1.1 Mixed* Owner & Sharecropper

Table 10 presents some characteristics of the subsample of households cropping owned and shared plots in a certain year and season.

[INSERT TABLE 10]

As in section 5, let us estimate the difference regression model in order to identify the parameter δ_1. Table 11 presents the GLS results. Mainly, when one does not control for the cropping pattern, one gets larger estimates for δ_1 (which indicates that owners crop product with higher value). However, as before, these estimates are non-significant when observable inputs are used as covariates.

[INSERT TABLE 11]

Village Dummies

This new subsample is large enough to allow one to see the mean effect of the share contract across the different villages (notice however, from Table 10, that the number of observations is very small for some villages). In order to do that, let us replace the constant term with village dummies (see Table 12).

[INSERT TABLE 12]

For the villages of Aurapalle (A), Dokur (B), Shirapur (C), Boriya (G), and Ramputa, the productivity difference between owned and sharecropped lands is not statistically significant even without controlling for the quality of land and level of inputs. For the villages of Kalman (D) and Kanzara (E), the productivity gap is not significant when one controls for observable inputs. The results are not conclusive for the 26 observations from the village of Kinkheda (F).

7.1.2 Mixed* Owned & Fixed-Rent Tenant

As in section 5, one can identify the term $(\delta_1 - \delta_2)$ through the set of households who own and rent plots in the same year and season. The composition of this subsample is described in Table 13 and the results are in Table 14. Controlling only for the area cropped, owned lands are more productive than those rented. Similarly to the previous subsection, this productivity gap is driven by observable variables. The results suggest that owned plots are apparently more productive than sharecropped lands due to the same reasons why they seem to be more productive than rented fields. Mainly, both types of tenants crop lower quality lands and, due to complementarity, they use less of the other inputs.

[INSERT TABLE 13]

[INSERT TABLE 14]

7.1.3 Mixed* Fixed-Rent Tenants & Sharecroppers

Finally, there is a very small subsample of households cropping lands under fixed-rent and share contracts (in the same year and season). Let us now define:

$$\text{Diff}^{f\text{-}s}\ Z = \bar{\Delta}_h Z = \frac{\sum_{i \in \mathbb{F}_h} Z_i}{F_h} - \frac{\sum_{i \in \mathbb{O}_h} Z_i}{O_h},$$

so that:

$$\bar{\Delta}_h \ln(y) = \delta_2 + \sum_{k=1}^{K} \alpha_k \bar{\Delta}_h \ln(x_k) + \bar{\nu}_h, \tag{10}$$

where $\bar{\nu}_h = \frac{\sum_{i \in \mathbb{F}_h} u_i}{F_h} - \frac{\sum_{i \in \mathbb{S}_h} u_i}{S_h}$ and $Var(\bar{\nu}_h) = \left(\frac{1}{F_h} + \frac{1}{S_h}\right)\sigma^2$.

Table 15 describes the sample. The regressions in Table 16 show that there is no productive difference between rented and sharecropped plots cultivated by those mixed* tenants.

[INSERT TABLE 15]

[INSERT TABLE 16]

8 Conclusion

In this paper I test the existence of missing incentives in one of the classical examples of moral hazard: the landlord-tenant relationship.

First, I test how expected output of farms is affected by the tenancy contract. Sharecroppers are less productive than owners, but as productive as fixed-rent tenants (which contradicts the moral hazard predictions). Also, I show that the productivity gap between owners and both types of tenants is driven by sample-selection issues and observable variables. An endogenous selection rule matches tenancy contracts with less-skilled farmers and lower-quality lands. Due to complementarity, such a matching also affects tenants' choices of labor and non-labor inputs. I use a subsample of households cropping the same product under different contract forms in the same year and season, to account for selection bias and show that the contract form has no effect on the expected output.

Second, I test for the existence of inputs being misused. It is shown that sharecroppers use less of labor and non-labor inputs per area cropped than owners. However, it is noticed that fixed-rent tenants also use less of labor and non-labor inputs than owners, contradicting the moral hazard interpretation. Then, I model farmer's optimal decisions to show that, since sharecroppers and fixed-rent tenants use lands with lower quality, complementarity among inputs is capable of explaining why both types of tenants use relatively less inputs than owners.

References

[1] **Ackerberg, Daniel A. and Botticini, Maristella.** "Endogenous Matching and the Empirical Determinants of Contract Form." *Journal of Political Economy, 2001,* forthcoming.

[2] **Bandiera, Oriana.** "On the Structure of Tenancy Contracts: Theory and Evidence from 19th Century Rural Sicily." Mimeo*,* London School of Economics, 1999.

[3] **Banerjee, Abhijit, Gertler, Paul, and Ghatak, Maitreesh.** "Empowerment and Efficiency: Tenancy Reform in West Bengal." *Journal of Political Economy,* Forthcoming, 2001.

[4] **Bhattacharyya, Sugato and Lafontaine, Francine.** "Double-Sided Moral Hazard and the Nature of Share Contracts." *Rand Journal of Economics,* Winter 1995, 26 (4), 761-781.

[5] **Binswanger, Hans P. and Jodha, N.S.** "Manual of Instructions for Economic Investigators in ICRISAT's Village Level Studies." Hyderabad: International Crops Research Institute for Semi-Arid Tropics, 1978.

[6] **Bisin, Alberto and Guaitoli, Danilo.** "Moral Hazard and Non-Exclusive Contracts." Mimeo, New York University, 2000.

[7] **Braido, Luís H.B.** "General Equilibrium with Endogenous Financial Design and Moral Hazard." Mimeo, University of Chicago, 2001.

[8] **Cardon, James and Hendel, Igal.** "Asymmetric Information in Health Insurance: Evidence from NMES." *Rand Journal of Economics, 2001,* forthcoming.

[9] **Cheung, Steven N.S.** "Sharecropping." In "Famous Fables of Economics: Myths of Market Failures," edited by Daniel F. Spulber, Blackwell Publishers Ltd, Oxford, U.K., 2002.

[10] **Chiappori, Pierre-André, Durand, Franck, and Pierre-Yves Geoffard.** "Moral Hazard and the Demand for Physician Services: First Lessons from a French Natural Experiment." *European Economic Review,* May 1998, 42 (3-5), 499-511.

[11] **Chiappori, Pierre-André and Salanié, Bernard.** "Testing for Asymmetric Information in Insurance Markets." *Journal of Political Economy,* February 2000, 108 (1), pp. 56-78.

[12] **Dionne, Georges and Doherty, Neil A.** "Adverse Selection, Commitment, and Renegotiation: Extensions to and Evidence from Insurance Markets." *Journal of Political Economy,* April 1994, 102 (2), 209-235.

[13] **Dionne, Georges and Vanasse, Charles.** "Automobile Insurance Ratemaking in the Presence of Asymmetrical Information." *Journal of Applied Econometrics,* April-June 1992, 7 (2), 149-165.

[14] **Jodha, N.S., Asokan, M. and Ryan, J.C.** "Village Study Methodology and Resource Endowment of the Selected Villages in ICRISAT's Village Level Studies." Economics Program Occasional Paper no. 16. Hyderabad: International Crops Research Institute for Semi-Arid Tropics, 1977.

[15] **Johnson, D. Gale.** "Resource Allocation under Share Contracts." *Journal of Political Economy*, April 1950, 58 (2), 111-123.

[16] **Heckman, James J.** "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models." *The Annals of Economic and Social Measurement*, Fall 1976, 5 (4), pp. 475-492.

[17] **Heckman, James J.** "Dummy Endogenous Variables in a Simultaneous Equation System." *Econometrica*, July 1978, 46 (6), pp. 931-961.

[18] **Heckman, James J.** "Sample Selection Bias as a Specification Error." *Econometrica*, January 1979, 47 (1), pp. 153-162.

[19] **Heckman, James J. and Robb, Richard Jr. "**Alternative Methods for Evaluating the Impact of Interventions: An Overview." *Journal of Econometrics*, October-November 1985, 30 (1-2), pp. 239-267.

[20] **Hendel, Igal and Lizzeri, Alessandro.** "Optimal Dynamic Contracts: Evidence from Life Insurance." Mimeo, Princeton University, 2001.

[21] **Holmström, Bengt R.** "Moral Hazard and Observability." *Bell Journal of Economics*, Spring 1979, 10 (1), pp. 74-91.

[22] **Laffont, Jean-Jacques and Matoussi, Mohamed S.** "Moral Hazard, Financial Constraints and Sharecropping in El Oulja." *Review of Economic Studies,* July 1995, 62 (3), 381-399.

[23] **Pandey, Priyanka.** "Effects of Technology on Incentive Design of Share Contracts." Mimeo, Pennsylvania State University, 2001.

[24] **Prescott, Edward C. and Townsend, Robert M.** "Pareto Optima and Competitive Equilibria with Adverse Selection and Moral Hazard." *Econometrica*, January 1984, 52 (1), pp. 21-46.

[25] **Puelz, Robert and Snow, Arthur.** "Evidence on Adverse Selection: Equilibrium Signaling and Cross-Subsidization in the Insurance Market." *Journal of Political Economy,* April 1994, 102 (2), pp. 236-257.

[26] **Richaudeau, Didier.** "Automobile Insurance Contracts and Risk of Accident: An Empirical Test Using French Individual Data", *The Geneva Papers on Risk and Insurance Theory,* June 1999, 24 (5), pp. 97-114.

[27] **Shaban, Radwan A.** "Testing between Competing Models of Sharecropping." *Journal of Political Economy*, October 1987, 95 (5), pp. 893-920.

[28] **Townsend, Robert M.** "Optimal Multiperiod Contracts and the Gain of Enduring Relationships under Private Information." *Journal of Political Economy*, December 1982, 90 (6), pp. 1166-1186.

TABLE 1. Data Description

Variable	Description
Output	Value of main output and byproducts (in Rupees, R$)
Ownership Dummy	1 if plot is owned (82.6%); 0 otherwise
Fixed-Rent Dummy	1 if plot is rented on a fix-rent basis (2%); 0 otherwise
Area Cropped	Area of the plot actually cultivated (in acres)
Value of Land (per acre)	Per acre estimated value of the plot, in 100R$
Irrigated Area	Total irrigated area in the plot
Non-Labor Input	Value of seeds, fertilizers, pesticides, organic and inorganic manures, plus rental value of owned and hired bullock, and other machineries (in R$)
Labor Input	Value of family and hired labor according to the village wages for males, females, and children (in R$)
Planting Season Dummies	35.2% planted from June to October; 59.2% from November to February; 5.3% from March to May; .2% perennial crops; .1% missing data
Village Dummies	14% Aurepalle; 5.2% Dokur; 21.1 Shirapur; 15.9% Kalman; 14% Kanzara; 5.4% Kinkheda; 9.1% Boriya; 15.3% Rampura
Year Dummies	1975 (11%); 1976 (11.2%); 1977 (10.8%); 1978 (9.5%); 1979 (9.2%); 1980 (9.6%); 1981 (10.5%); 1982 (9.7%); 1983 (9.3%); 1984 (9.2%)
Cropping Pattern	Qualitative variable (with 1,031 different codes) describing all products cropped in a certain plot

Note: Data from the International Crops Research Institute for Semi-Arid Tropics (ICRISAT).

TABLE 2. Summary Statistics (Entire Sample)

Variable	Mean	Min	Max	St. Dev.	Sample Size
Output	901.3	0	22,768.8	1,338.6	11,517
Area Cropped	1.8	0	25	2.0	11,517
Value of Land (per acre)	33.7	0	160	24.4	11,517
Irrigated Area	.31	0	9	.67	11,516
Non-Labor Input	346	0	7,217.5	518.6	11,517
Labor Input	175.7	0	2,709.4	211.4	11,517

TABLE 3. Regression Model (Entire Sample)

Clustered OLS
Dependent Variable: Log Output

	(a)	(b)	(c)	(d)	(e)
Ownership Dummy (δ_1)	**.31***	**.17***	.06	-.01	-.01
Robust t-statistic	(4.85)	(3.33)	(1.45)	(-.46)	(-.53)
Robust Std. Err.	(.06)	(.05)	(.04)	(.03)	(.03)
Fixed-Rent Dummy (δ_2)	-.05	-.02	-.07	-.07	-.07
Robust t-statistic	(-.39)	(-.15)	(-.62)	(-.78)	(-.81)
Robust Std. Err.	(.14)	(.14)	(.11)	(.08)	(.08)
Log Area Cropped	**.68***	**.68***	**.30***	**.05***	**.05**
Log Value of Land (per acre)		**.56***	**.32***	**.19***	**.18***
Irrigated Area		**.50***	**.11***	**.09***	**.07***
Log Non-Labor Input			**.66***		**.07***
Log Labor Input				**1.0***	**.96***
Village, Planting Season, and Year Dummies	Yes	Yes	Yes	Yes	Yes
Constant	**6.9***	**6.3***	**1.7***	**1.2***	**.65**
Sample Size	*10,704*	*10,701*	*10,687*	*10,701*	*10,687*
R^2	***.41***	***.51***	***.65***	***.76***	***.76***

Note: Number of clusters equals 275. The marks *** (respectively, ** and *) denotes significance at 1% (respectively, 5% and 10%) level.

TABLE 4. Sample Characteristics (Mixed Tenants)

	Number of Households	Number of Plots
Mixed Owner & Sharecropper	338	609 owned; 585 sharecropped
Mixed Owner & Fixed-Rent Tenant	54	84 owned; 59 rented
Mixed Fixed-Rent Tenant & Sharecropper	8	8 rented; 10 sharecropped

TABLE 5. Difference Regression (Mixed Owner & Sharecropper)

Clustered GLS
Independent Variable: Diff$^{o\text{-}s}$ Log Output

	(a)	(b)	(c)	(d)	(e)
Constant (δ_1)	**.15****	.13*	.06	-.06	-.01
Robust t-statistic	(2.29)	(2.69)	(.89)	(-1.25)	(-.23)
Robust Std. Err.	(.07)	(.11)	(.07)	(.05)	(.05)
Diff$^{o\text{-}s}$ Log Area Cropped	**.89*****	**.89*****	**.53*****	-.23	-.04
Diff$^{o\text{-}s}$ Log Value of Land (per acre)		**.47*****	**.41****	.25	**.26****
Diff$^{o\text{-}s}$ Irrigated Area		.18*	.06	.03	.16*
Diff$^{o\text{-}s}$ Log Non-Labor Input			**.48*****		**-.77*****
Diff$^{o\text{-}s}$ Log Labor Input				**1.4*****	**1.9*****
Sample Size	*338*	*338*	*338*	*338*	*338*
R^2	***.23***	***.25***	***.29***	***.54***	***.59***

Note: Number of clusters equals 82. The marks *** (respectively, ** and *) denotes significance at 1% (respectively, 5% and 10%) level.

TABLE 6. Difference Regression (Mixed Owner & Fixed-Rent Tenant)

Clustered GLS
Independent Variable: Diff $^{o\text{-}f}$ Log Output

	(a)	(b)	(c)	(d)	(e)
Constant (δ_1 - δ_2)	.16	.12	-.07	.11	.19
Robust t-statistic	(.74)	(.41)	(-.22)	(.68)	(1.12)
Robust Std. Err.	(.22)	(.11)	(.07)	(.16)	(.17)
Diff $^{o\text{-}f}$ Log Area Cropped	**1.2*****	**1.1****	.06	-.59*	-.34
Diff $^{o\text{-}f}$ Log Value of Land (per acre)		.37	.27	-.26	-.30
Diff $^{o\text{-}f}$ Irrigated Area		.04	-.09	-.09	-.04
Diff $^{o\text{-}f}$ Log Non-Labor Input			**1.2****		-.54
Diff $^{o\text{-}f}$ Log Labor Input				**2.4*****	**2.7*****
Sample Size	*54*	*54*	*54*	*54*	*54*
R^2	***.16***	***.16***	***.28***	***.70***	***.72***

Note: Number of clusters equals 29. The marks *** (respectively, ** and *) denotes significance at 1% (respectively, 5% and 10%) level.

TABLE 7. Productive Inputs (Entire Sample)

Clustered OLS

	(a) Log Non-Labor Input Per Area Cropped	(b) Log Labor Input Per Area Cropped	(c) Log Value of Land (per acre)
Ownership Dummy	**.42*** **	**.43*** **	**.16*** **
Robust t-statistic	(6.09)	(5.89)	(3.94)
Robust Std. Err.	(.07)	(.07)	(.04)
Fixed-Rent Dummy	.06	.04	-.08
Robust t-statistic	(.64)	(.40)	(-1.40)
Robust Std. Err.	(.10)	(.10)	(.06)
Village, Planting Season, and Year Dummies	Yes	Yes	Yes
Constant	**4.1*** **	**3.9*** **	**3.1*** **
Sample Size	*11,485*	*11,503*	*11,515*
R^2	***.37***	***.36***	***.59***

Note: Number of clusters equals 275. The marks *** (respectively, ** and *) denotes significance at 1% (respectively, 5% and 10%) level.

TABLE 8. Marginal Productivity (Mixed Owner & Sharecropper)

Clustered GLS

	Diff $^{o\text{-}s}$ Output / Non-Labor Input	Diff $^{o\text{-}s}$ Output / Labor Input
Constant (c_1-c_3)	-.08	.02
Robust t-statistic	(-.44)	(.19)
Robust Std. Err.	(.18)	(.11)
P-value	(.66)	(.85)
Sample Size	*338*	*338*

Note: Number of clusters equals 82.

TABLE 9. Marginal Productivity (Mixed Owner & Fixed-Rent Tenant)

Clustered GLS

	Diff $^{o\text{-}f}$ Output / Non-Labor Input	Diff $^{o\text{-}f}$ Output / Labor Input
Constant (c_1-c_2)	-.08	.15
Robust t-statistic	(-.27)	(.55)
Robust Std. Err.	(.30)	(.28)
P-value	(.79)	(.59)
Sample Size	*54*	*54*

Note: Number of clusters equals 29.

TABLE 10. Sample Characteristics (Mixed* Owner & Sharecropper)

	Number of Households	Number of Owned Plots	Number of Sharecropped Plots
Aurapalle (A)	4	10	7
Dokur (B)	33	70	61
Shirapur (C)	123	562	433
Kalman (D)	84	417	340
Kanzara (E)	54	239	145
Kinkheda (F)	26	65	51
Boriya (G)	78	217	206
Rampura (H)	26	273	230
TOTAL	454	1,853	1,473

TABLE 11. Difference Regression (Mixed* Owner & Sharecropper)

Clustered GLS
Independent Variable: Diff$^{o\text{-}s}$ Log Output

	(a)	(b)	(c)	(d)	(e)
Constant (δ_1)	**.41*****	**.29*****	.03	-.04	-.02
Robust t-statistic	(3.69)	(2.69)	(.34)	(-.60)	(-.30)
Robust Std. Err.	(.11)	(.11)	(.09)	(.06)	(.07)
Diff$^{o\text{-}s}$ Log Area Cropped	**.56*****	**.66*****	.13	-.12	-.10
Diff$^{o\text{-}s}$ Log Value of Land (per acre)		**.71*****	**.36****	**.21****	**.23****
Diff$^{o\text{-}s}$ Irrigated Area		**.60*****	.08	-.03	.002
Diff$^{o\text{-}s}$ Log Non-Labor Input			**1.0*****		-.18
Diff$^{o\text{-}s}$ Log Labor Input				**1.4*****	**1.6*****
Sample Size	*454*	*454*	*454*	*454*	*454*
R^2	***.10***	***.18***	***.39***	***.61***	***.61***

Note: Number of clusters equals 103. The marks *** (respectively, ** and *) denotes significance at 1% (respectively, 5% and 10%) level.

TABLE 12. Village Effects (Mixed* Owner & Sharecropper)

Clustered GLS
Independent Variable: Diff$^{o\text{-}s}$ Log Output

	(a)	(b)	(c)	(d)	(e)
Aurapalle (A)	.62	.70	.21	-.06	-.04
Robust t-statistic	(1.08)	(1.35)	(.45)	(-.13)	(-.08)
Robust Std. Err.	(.58)	(.52)	(.47)	(.45)	(.46)
Dokur (B)	.03	-.09	-.12	**-.20****	-.20
Robust t-statistic	(.13)	(-.32)	(-.80)	(-2.23)	(-1.76)
Robust Std. Err.	(.25)	(.29)	(.16)	(.09)	(.11)
Shirapur (C)	.34	.25	.16	-.04	-.05
Robust t-statistic	(1.28)	(1.18)	(.88)	(-.32)	(-.43)
Robust Std. Err.	(.26)	(.21)	(.18)	(.12)	(.12)
Kalman (D)	**.76*****	**.63*****	.18	-.03	-.01
Robust t-statistic	(3.14)	(2.66)	(.96)	(-.34)	(-.11)
Robust Std. Err.	(.24)	(.24)	(.19)	(.10)	(.10)
Kanzara (E)	**.96*****	**.69****	.31	.30	.34
Robust t-statistic	(2.96)	(2.04)	(1.21)	(1.44)	(1.52)
Robust Std. Err.	(.33)	(.34)	(.26)	(.21)	(.23)
Kinkheda (F)	**.56****	**.51****	.12	.23*	.28*
Robust t-statistic	(2.39)	(2.20)	(.84)	(1.85)	(1.92)
Robust Std. Err.	(.23)	(.23)	(.14)	(.12)	(.14)
Boriya (G)	-.07	-.08	-.22	-.20*	-.19*
Robust t-statistic	(-.42)	(-.45)	(-1.31)	(-1.79)	(-1.67)
Robust Std. Err.	(.18)	(.17)	(.17)	(.11)	(.11)
Rampura (H)	.33	.15	-.19	-.10	-.06
Robust t-statistic	(.87)	(.49)	(-1.06)	(-.53)	(-.26)
Robust Std. Err.	(.38)	(.30)	(.18)	(.19)	(.22)
Diff$^{o\text{-}s}$ Log Area Cropped	**.57*****	**.66*****	.17	-.12	-.10
Diff$^{o\text{-}s}$ Log Value of Land (per acre)		**.67*****	**.34****	**.20****	**.22****
Diff$^{o\text{-}s}$ Irrigated Area		**.58*****	.08	-.05	-.01
Diff$^{o\text{-}s}$ Log Non-Labor Input			**.98*****		-.21
Diff$^{o\text{-}s}$ Log Labor Input				**1.4*****	**1.6*****
Sample Size	*454*	*454*	*454*	*454*	*454*
Adjusted R^2	***.14***	***.21***	***.40***	***.62***	***.62***

Note: Number of clusters equals 103. The marks *** (respectively, ** and *) denotes significance at 1% (respectively, 5% and 10%) level.

TABLE 13. Sample Characteristics (Mixed* Owner & Fixed-Rent Tenant)

	Number of Households	Number of Owned Plots	Number of Rented Plots
Aurapalle (A)	26	75	31
Dokur (B)	4	24	5
Shirapur (C)	2	8	3
Kalman (D)	2	12	2
Kanzara (E)	26	168	38
Kinkheda (F)	1	3	1
Boriya (G)	35	97	64
Rampura (H)	35	141	48
TOTAL	124	528	192

TABLE 14. Difference Regression (Mixed* Owner & Fixed-Rent Tenant)

Clustered GLS
Independent Variable: $\text{Diff}^{o\text{-}f}$ Log Output

	(a)	(b)	(c)	(d)	(e)
Constant (δ_2 - δ_1)	**.42****	**.30****	.17	.10	.13
Robust t-statistic	(2.46)	(1.74)	(1.10)	(.75)	(1.01)
Robust Std. Err.	(.17)	(.18)	(.15)	(.13)	(.13)
$\text{Diff}^{o\text{-}f}$ Log Area Cropped	**1.0*****	**.89*****	.31	-.41	-.35
$\text{Diff}^{o\text{-}f}$ Log Value of Land (per acre)		**.59****	.38	.04	.05
$\text{Diff}^{o\text{-}f}$ Irrigated Area		**.47*****	-.06	**-.23****	-.08
$\text{Diff}^{o\text{-}f}$ Log Non-Labor Input			**.94*****		**-.49****
$\text{Diff}^{o\text{-}f}$ Log Labor Input				**2.0*****	**2.4*****
Sample Size	*124*	*124*	*124*	*124*	*124*
R^2	***.11***	***.17***	***.29***	***.62***	***.64***

Note: Number of clusters equals 50. The marks *** (respectively, ** and *) denotes significance at 1% (respectively, 5% and 10%) level.

TABLE 15. Sample Characteristics (Mixed* Fixed-Rent Tenant & Sharecropper)

	Number of Households	Number of Rented Plots	Number of Sharecropped Plots
Aurapalle (A)	0	0	0
Dokur (B)	2	3	2
Shirapur (C)	0	0	0
Kalman (D)	0	0	0
Kanzara (E)	12	20	32
Kinkheda (F)	1	1	1
Boriya (G)	6	8	13
Rampura (H)	11	21	37
TOTAL	32	53	85

TABLE 16. Difference Regression (Mixed* Fixed-Rent Tenant & Sharecropper)

Clustered OLS
Independent Variable: $\text{Diff}^{f\text{-}s}$ Log Output

	(a)	(b)	(c)	(d)	(e)
Constant (δ_2)	.05	-.15	-.20	.05	.16
Robust t-statistic	(.16)	(-.47)	(-.67)	(.18)	(.78)
Robust Std. Err.	(.30)	(.32)	(.30)	(.26)	(.21)
$\text{Diff}^{f\text{-}s}$ Log Area Cropped	.32	.33	-.01	-.46	-.53
$\text{Diff}^{f\text{-}s}$ Log Value of Land (per acre)		$.88^{*}$	.62	-.08	-.26
$\text{Diff}^{f\text{-}s}$ Irrigated Area		$\mathbf{.64}^{**}$	-.18	-.04	.27
$\text{Diff}^{f\text{-}s}$ Log Non-Labor Input			$\mathbf{.96}^{**}$		-.68
$\text{Diff}^{f\text{-}s}$ Log Labor Input				$\mathbf{1.6}^{***}$	$\mathbf{2.2}^{***}$
Sample Size	*32*	*32*	*32*	*32*	*32*
R^2	***.02***	***.14***	***.32***	***55***	***.58***

Note: Number of clusters equals 12. The marks *** (respectively, ** and *) denotes significance at 1% (respectively, 5% and 10%) level.