

Evidence on the Incentive Properties of Share Contracts

Luis H. B. Braido *Getulio Vargas Foundation*

Abstract

Ever since Adam Smith, share contracts have been condemned for their lack of incentives. Sharecropping tenants face incentives to undersupply productive inputs since they receive only a fraction of the marginal revenue. The empirical literature reports that lands under sharecropping are indeed less productive and employ inputs less intensively than those operated by owners. This paper shows that (1) sharecropping and fixed-rent tenancy are both associated with low-quality lands, (2) plots under sharecropping and fixed rent present (on average) the same unconditional productivity, (3) controlling for observed land quality and input use, their average productivities are also identical to those of owner-operated plots, and (4) the input choices satisfy the same profit maximization conditions for all land contracts. These results challenge the conventional wisdom connecting sharecropping to incentive distortions. They support an alternative view that farmers optimally employ more input resources into good-quality lands, which are typically managed by owners.

1. Introduction

Throughout time, lands have been cultivated under three basic contract forms: (1) ownership, in which the field is managed by its owner, (2) fixed-rent tenancy, in which the tenant pays a rent upfront to the landowner, bears all input costs, and retains the final output, and (3) sharecropping tenancy, in which the landlord supplies the land, the tenant bears most input costs, and they share the final

This paper is based on an essay from my Ph.D. dissertation at the University of Chicago. I am thankful for comments from Juliano Assunção, Pedro Carneiro, Rodrigo Cerda, Pierre-André Chiappori, Carlos E. da Costa, Bev Dahlby, Mark Duggan, Maitreesh Ghatak, Milton Harris, D. Gale Johnson, Steven Levitt, Derek Neal, Sam Peltzman (the editor), Lars Stole, anonymous referees, and participants in various meetings organized by the Center for Economic Studies and Institute for Economic Research (CESifo; Venice 2003), the Econometric Society (Washington, D.C., 2003, São Paulo 2002), the Brazilian Society of Econometrics (SBE; Nova Friburgo 2002), and the Latin American and Caribbean Economic Association (LACEA; Madrid 2002). Financial support from the Brazilian National Council for Scientific and Technological Development (CNPq) is gratefully acknowledged.

[*Journal of Law and Economics*, vol. 51 (May 2008)]

© 2008 by The University of Chicago. All rights reserved. 0022-2186/2008/5102-0012\$10.00

output.¹ Classical authors such as Adam Smith, Anne R. J. Turgot, John S. Mill, and Alfred Marshall condemned sharecropping tenancy for its lack of incentives. Since sharecropping tenants bear most of the marginal costs and receive a smaller fraction of the marginal revenue, they face incentives to undersupply productive inputs and managerial effort.²

The modern theory of moral hazard presents a rationale for the use of share contracts despite their incentive disadvantage (see Stiglitz 1974; Holmström 1979; Grossman and Hart 1983). In this literature, sharecropping is viewed as a constrained efficient contract that balances incentives and risk sharing. By sharing production risk, landlords insure tenants at the cost of reducing incentives for performance. Similarly to classical authors, the static moral hazard theory predicts that the final output should be higher if the land contract is ownership or fixed rent instead of sharecropping (holding fixed all characteristics of the household and land).

On the other hand, there are theories predicting that similar farms cultivated under ownership, fixed rent, and sharecropping should be equally productive. Cheung (1969, 2002) argues that landlords are able to perfectly monitor tenants' activities, especially in small villages where they have social relations. In an alternative vein, Johnson (1950) argues that dynamic incentives compensate for the low incentive power of share contracts. Sharecropping leases usually have short durations, and landlords renew these leases on the basis of relative performance, by comparing the sharecropper's performance with those of adjoining owned and rented farms. Therefore, moving costs and risk of unemployment should act in the extensive margin and induce sharecroppers to behave properly. Furthermore, recent models show that infinite repetition of the principal-agent relationship would approximately lead to first-best outcomes (see Rubinstein and Yaari 1983; Radner 1985).³

The empirical side of this debate does not seem to support first-best theories (based on monitoring or dynamic incentives) and apparently makes the case for the classical prediction that share contracts distort incentives and reduce land productivity. In an influential work, Shaban (1987) shows that farmers who simultaneously own and sharecrop multiple plots are more productive and em-

¹ In many cases, the sharecropping landlord shares the cost of some inputs at the same rate used to share the output. However, there are always some inputs (such as owned bullock, family labor, and managerial effort) that are provided by the sharecropper. In the sharecropping plots studied in this paper, family labor accounts for about 54 percent of the labor costs and owned bullocks for about 47 percent of the nonlabor costs.

² These authors have also condemned tenancy contracts (both sharecropping and fixed rent) for inducing the tenants (who face tenure instability) to make suboptimal levels of land-specific investments that take time to mature. Adam Smith was the most critical among them; Mill and Marshall, for instance, acknowledge different mechanisms available for landlords to mitigate those issues. Potential holdup problems associated with long-term land-specific investments are not discussed in this paper. For references on this topic, see Johnson (1950), Banerjee, Gertler, and Ghatak (2002), Dubois (2002), Jacoby, Li, and Rozelle (2002), Jacoby and Mansuri (2002), and Bandiera (2002).

³ First-best results could also be approximated in finite-horizon models when one works with the epsilon-equilibrium concept defined by Radner (1981).

ploy inputs more intensively in the fields they own. Other papers in the literature present similar results, as discussed in Section 2. However, this literature has ignored an important selection issue that may be driving these findings. Contracts are endogenous, and owner-operated lands are typically better. Therefore, regressions comparing output and input use across land contracts tend to overestimate the impact of ownership. This paper presents robust evidence that the productivity disadvantage of sharecropping is strongly related to this land quality selection problem.

I access the same data source used by Shaban (1987)—namely, the Indian Village Level Studies conducted by the International Crops Research Institute for Semi-Arid Tropics (ICRISAT).⁴ The analysis starts by replicating the stylized fact that sharecropped lands are less productive and employ inputs less intensively than owner-operated fields. Regressions show that owner-operated fields are around 40 percent more productive than those under sharecropping and fixed rent. Owned plots are also 17 percent more valuable and use about 40 percent more of nonlabor and labor inputs than leased plots. Productivity, land value, and input use are not statistically different across plots leased under fixed rent and sharecropping.

Next I model the log output (expressed in monetary units per acre) as a function of dummy variables for each land contract and other control variables—namely, (1) controls for land and cropping characteristics (such as land value, irrigation, soil type, main crop, year, and season) and (2) household-period fixed effects, which account for unobserved characteristics of the household in each particular period (year and season). As in Shaban (1987), this conditional productivity is significantly higher in plots operated by owners relative to those managed under sharecropping. In addition, I find that this conditional productivity is statistically equal across lands under fixed rent and sharecropping. This latter finding does not support the existence of incentive problems associated with the low incentive power of share contracts since, like owners, fixed-rent tenants retain 100 percent of the final output.

There are theory and evidence—summarized in Section 4—relating tenancy to lower quality lands. Regardless of the particular motivation for that correlation, if land quality and inputs were complements, then owner-operated farms would naturally employ inputs more intensively and, consequently, be more productive. This suspicion is confirmed by the fact that the productivity advantage of owned lands vanishes when I introduce nonlabor and labor inputs as control variables into the log-output regression. Lands under sharecropping and fixed rent present lower unconditional productivity essentially because they are of lower quality and use inputs less intensively.

This result suggests that the productivity disadvantage of sharecropping is not

⁴The entire International Crops Research Institute for Semi-Arid Tropics sample is analyzed throughout the paper, while the particular subsample used by Shaban—composed exclusively of farmers who simultaneously own and sharecrop multiple fields—is studied in Section 7.4.

due to hidden actions (that is, actions that cannot be inferred from the input choices or other observable variables). However, it could be due to underuse of nonlabor and labor inputs. Since land quality is heterogeneous, one cannot identify input misuse simply by comparing the average amount of each input used across lands under different contracts. I then propose a structural procedure to test for efficiency of input allocation. This testing procedure is based on the fact that, in a competitive environment without externalities, Pareto optimality (or profit maximization) implies that the expected marginal productivity of each factor equals the ratio of expected input prices to expected output prices. These efficiency conditions must hold for all plots, regardless of differences in land quality and farmer ability. The empirical results do not reject the hypothesis that the expected marginal productivities are constant across farms under ownership, fixed rent, and sharecropping. The input choices do not seem to be distorted by the contract form, which casts doubts on the importance of incentive problems associated with sharecropping.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and shows that land quality is heterogeneous across owned and leased plots. Section 4 discusses alternative theories on why leased lands are associated with lands of inferior quality. The econometric model and results on land productivity are presented in Section 5. Section 6 formulates and executes the structural test for efficiency of input allocation. Robustness checks are presented in Section 7, and concluding remarks are presented in Section 8.

2. Related Literature

There are three main references in the empirical literature on sharecropping incentives (for additional references on tenancy contracting, see Braido 2006). In a pioneering work, Rao (1971) studies many different issues related to the design of land contracts and their impact on productivity. For the analysis on incentives and land productivity (p. 588), Rao uses farm-level data from the Studies in Economics of Farm Management collected by the government of India during the 1957–58 and 1958–59 cropping years in two different production zones (namely, rice and tobacco). Rao argues that there is a high correlation between land quality and the amount of different inputs used and estimates a Cobb-Douglas production function in which land quality (measured by imputed values of land resources) is the only independent variable. The results are ambiguous. The ordinary least squares (OLS) estimation shows that per-acre output is higher in owner-operated fields than in sharecropped farms, but observed land quality explains around 90 percent of the output variation. However, when Rao estimates different production functions for different farm size categories, the result is inverted. The output per unit of land is higher in sharecropped lands than in owner-operated farms of corresponding size. (This needs to be em-

phasized since unobserved land quality might be more homogeneous within farms of similar sizes.)

In another classical work, Shaban (1987) uses a subsample of the ICRISAT Village Level Studies composed of sharecropping tenants who also own some land (mixed owner-sharecropper). He shows that these farmers are more productive and use inputs more intensively in the lands they own than in the fields they rent under sharecropping. This is interpreted as evidence of incentive problems. The estimates are constructed by comparing owned and sharecropped farms for each household in a given period. Therefore, the results are free of the potential selection bias caused by unobserved heterogeneity in the household's characteristics. Land quality heterogeneity is taken into account through linear regressors such as the land value, irrigated area, and dummies for soil type.

The third main reference is Laffont and Matoussi (1995), who use 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 in which the plot's area, the cost of nonlabor inputs, and the amount of family and hired labor (measured in days) are used as regressors. Household characteristics and type of crop are used in the regressions, but no control for the quality of land is available.

Therefore, most of the existing results suggest that the low incentive power of share contracts reduces land productivity. The findings in this paper challenge this idea and support an alternative view that lower productivity of sharecropping is related to land quality selection bias.

3. Data Description

The data come from the longitudinal village-level studies conducted by ICRISAT in India.⁵ The study was conducted from 1975 to 1984 in villages intended to represent major agroclimatic zones of India. Initially, six villages were selected in two different states: Aurapalle and Dokur (in the state of Andhra Pradesh) and Kanzara, Kinkheda, Shirapur, and Kalman (in the state of Maharashtra). Later, in 1980, the villages of Boriya Becharji and Rampura (in the state of Gujarat) were also included in the study.

For each village, 10 households were randomly selected in each of the following four categories: landless workers and large, medium, and small farmers (a total of 40 households per village). Random replacement within each category occurred whenever a household emigrated from the village. Resident investigators belonging to the same linguistic group as the villagers collected information on farming activities in all plots managed by these households. The investigators had rural backgrounds, and their work was supervised by economists from ICRISAT. The interviews were conducted regularly throughout each cropping

⁵ International Crops Research Institute for Semi-Arid Tropics, Village Level Studies (<http://www.icrisat.org/gt-mpi/knowledgeBase/Databases/vls.asp>).

year, and the investigators attended local meetings in order to be close to the villagers. The villagers were informed about the purpose of the survey and the fact that ICRISAT is an independent research center. This is important because there is a general concern that official data in India underreport leasing from large to small farmers, since landowners fear the land-to-the-tiller legislation (which confers property rights on tenants after they have cultivated the land for a certain number of years). Shaban (1987, p. 898) claims that the ICRISAT database does not suffer from this problem since "it would be difficult to hide information from an investigator who lives in the village all year round and who usually gains the confidence of the villagers." Further details about the data collection can be found in Jodha, Asokan, and Ryan (1977), Singh, Binswanger, and Jodha (1985), and Walker and Ryan (1990).

The schedule used here (the PS files) contains plot-level information on farming activities and plot characteristics for all the plots of each household per year and season. The household is the primary sampling unit of this research, but the PS files contain disaggregated information on each plot of the sampled households. (For this reason, the cluster method is used to compute robust standard errors in all regressions throughout the paper.) The panel is not balanced since farmers crop different plots over time. The following variables are used in the analysis: the per-acre value of the output, dummies for the land contract (ownership, fixed rent, and sharecropping), the per-acre value of nonlabor and labor inputs, the estimated per-acre value of the plot, a dummy variable indicating the presence of irrigation, and dummies for the soil type, main crop, village, year, and season. These variables are described in Table 1.

It is important to stress how values were computed by the ICRISAT investigators. The actual value paid for seeds, fertilizers, pesticides, and manures and the rental value of rented bullocks and machinery (such as pump sets and tractors) were recorded for each plot and season. For home-produced inputs, owned bullocks, and owned machinery, the values were computed by multiplying the actual quantities employed in each plot by village-specific prices and rents. Similarly, the data set contains the actual value paid for hired labor, while the value of family labor is computed by multiplying the village wages for children, male adults, and female adults by the number of hours worked by each member. Finally, the value of the main product and by-products were recorded at prevailing village prices at the time of harvest.

According to Jodha (1981), tenants are very heterogeneous in Indian villages, and many small farmers rent their plots to larger farmers (with better resources) in exchange for advance payments. Sharecropping landlords are usually close to tenants, and the majority of those plots are leased for short periods (from one season to a year). On the other hand, most long-term leases involve fixed-rent payments to absentee landlords. There is also variation in the share of output retained by sharecroppers, which is typically between 50 and 75 percent of the

Table 1
Data Description

Variable	Description
Output	Value of main output and by-products (in rupees)
Ownership dummy	One if plot is owned (83.2%), zero otherwise
Fixed-rent dummy	One if plot is rented on a fixed-rent basis (1.9%), zero otherwise
Cropped area	Area actually cropped (in acres)
Nonlabor input	Value of seeds, fertilizers, pesticides, and organic and inorganic manures, plus the rental value of bullocks and machinery (in rupees)
Labor input	Value of family and hired labor (in rupees)
Per-acre land value	Per-acre value of the plot (in 100 rupees per acre) estimated by ICRISAT's investigators using information about potential sale value, topography, location, and so on, obtained from a village specialist
Irrigation dummy	One if the plot is irrigated (31.8%)
Soil type dummies	7.1% deep black, 34.3% medium black, 21.7% shallow black, 11.1% shallow red, 2.4% gravelly, .5% problem soil (for example, saline), 9.8% sandy soil, 1.1% other soils, 12% undefined
Cropping pattern	Qualitative variable (with 1,031 different codes) describing all products cropped in each plot
Main-crop dummies	Dummy variables constructed from the first letter of the cropping pattern code (which describes a general category for the dominant cropping product): 16.8% oilseeds, 53.2% cereals, 9.3% fiber crops, .4% garden crops, 14% pulses, .8% sugar cane, 4.2% vegetables and spices, 1.3% fodder crops
Village dummies	14.4% Aurepalle, 5.5% Dokur, 20.2% Shirapur, 15.7% Kalman, 14.6% Kanzara, 5.6% Kinkheda, 8.7% Boriya, 15.3% Rampura
Year dummies	1975 (10.9%), 1976 (11.1%), 1977 (10.3%), 1978 (9.7%), 1979 (9.5%), 1980 (9.2%), 1981 (10.6%), 1982 (9.9%), 1983 (9.5%), 1984 (9.3%)
Season dummies	35.8% planted from June to October, 58.5% from November to February, 5.5% from March to May, .2% perennial crops
Household	Village-specific numerical code that identifies the household

Note. Data are from the PS files of the Village Level Studies of the International Crops Research Institute for Semi-Arid Tropics (ICRISAT). The primary sampling unit is the household, but the observations refer to plots managed by each household in each season of the year.

total output.⁶ In normal circumstances, landlords share the costs of most non-labor inputs and some labor costs when nonfamily workers are hired for specific purposes. The fraction of each input borne by the landlord usually depends on the crop grown and the existence of soil problems. In some cases, tenants have wide discretion about the crops that are planted. However, landlords tend to determine the crop when dealing with poor sharecroppers.

There are plots that produce no output in some seasons. These are likely to be plots under rotation or temporarily abandoned after extreme shocks and are

⁶ In some cases, only the value of the main product is shared and the tenant retains the by-products. This is not particularly relevant for my analysis since by-products account for a very small fraction of the total output and the correlation between the revenue of main and secondary products is very high.

Table 2
Summary Statistics

Variable	Mean	Minimum	Maximum	SD
Per-acre output	754.1	.68	24,964	1,106
Per-acre nonlabor input	318	0	16,478.8	507.2
Per-acre labor input	150	.29	3,064	181.6
Per-acre land value	34	0	160	24.6

Note. Data are from the International Crops Research Institute for Semi-Arid Tropics Village Level Studies. $N = 10,704$.

not included in the analysis.⁷ Table 2 presents the summary statistics for the productive plots.

A special characteristic of the data set is the presence of households cropping multiple plots under different contracts in each period (season of the year). This allows one to use fixed effects to control for unobserved characteristics of the household in each particular period. On average, each household cultivates 3.86 plots per period, and about 93.6 percent of the plots are managed by farmers who cropped two or more plots in that particular period. Among the 10,704 productive plots in the sample, there are 6,876 plots managed by pure owners (that is, households who own all plots they cultivate in that specific period), 252 plots managed by pure sharecroppers (that is, tenants with all plots under sharecropping), 37 plots managed by pure renters (relative to fixed-rent contracts), 2,833 plots managed by farmers who own and sharecrop different plots in that particular period (mixed owner-sharecropper), 456 plots managed by mixed owner-renter households, five plots managed by mixed sharecropper-renter households, and 245 plots managed by farmers with lands under the three contract forms.

Table 3 presents four linear regressions for which the log of the output, land value, and labor and nonlabor inputs (measured in monetary units per acre) are used as dependent variables. In all regressions, the independent variables are dummies for the land contract, village, year, and season. From the regressions without fixed effects, one notices that owner-operated plots are approximately 42 percent more productive than lands under sharecropping and fixed rent, but these fields are also around 17 percent more valuable and employ nonlabor and labor inputs more intensively.⁸ Moreover, lands under fixed rent are less productive (−3 percent) and less valuable (−7 percent) than lands under sharecropping, but these differences are not statistically significant. The regressions that include household-period fixed effects compare the dependent variable

⁷ There are 813 plots producing no output out of 11,517 plots sampled. It would be interesting to test whether the tenancy contract affected the likelihood of a plot being abandoned. However, the data do not distinguish plots under rotation from those abandoned, and the information available is not rich enough to overcome the usual selection concerns.

⁸ Naturally, the percentage interpretation of dummy coefficients in semilogarithmic regressions is an approximation.

Table 3
Per-Acre Output, Land Value, and Inputs across Land Contracts

Log per Acre	Without Fixed Effects			With Household-Period Fixed Effects		
	Output	Land Value	Nonlabor Input	Output	Land Value	Nonlabor Input
Ownership dummy	.42**	.17**	.43**	.47**	.14**	.50**
Robust <i>t</i> -statistic	5.48	4.19	6.29	4.83	3.16	5.89
Robust standard error	.08	.04	.07	.10	.04	.08
Fixed-rent dummy	-.03	-.07	.08	.12	-.03	.20
Robust <i>t</i> -statistic	-.21	-1.25	.78	.95	-.45	1.62
Robust standard error	.15	.06	.11	.12	.07	.12
Dummies for village, year, and season	Yes	Yes	Yes	Dropped	Dropped	Dropped
<i>N</i>	10,704	10,702	10,690	10,704	10,702	10,690

Note. Results are for ordinary least squares regressions with a constant term. The cluster method is used to compute robust *t*-statistics and standard errors; this accounts for the fact that the household, rather than the plot, is the primary sampling unit. Household-period fixed effects refer to 2,773 dummy variables generated through the iteration of codes identifying the household and the period (year and season).

** Significant at the 1% level.

across farms cultivated by the same household in each period (year and season). On average, the owned plots of each household are about 47 percent more productive and 14 percent more valuable and employ nonlabor and labor inputs more intensively relative to the other lands managed by the same household in that specific period.

4. Land Quality Heterogeneity across Contracts

Owned lands are considerably more valued than those leased under sharecropping and fixed rent, as shown in Table 3. Moreover, around 34 percent of the owned lands are irrigated, while this rate drops to 24 percent for plots under fixed rent and to 20 percent for fields under sharecropping. Therefore, there seems to be a strong inverse relation between tenancy and land quality. Understanding this correlation is a central aspect of the tenancy problem, but it is beyond the scope of this paper. The research agenda on this topic is recent and has not yet reached definitive conclusions.

Adverse selection is a first possible explanation for that relation. The opportunity cost of leasing a plot increases with land quality. Hence, if landlords privately observe some soil characteristics, the competitive equilibrium in the rental market would be such that all plots with land quality below a certain threshold are leased, while the plots with land quality above that threshold are managed by their owners (see Mas-Colell, Whinston, and Green 1995, chap. 13.B). In extreme cases, only the worst type of land—the lemons—would be leased out.

An alternative view suggests that tenancy lands are endogenously worse because tenants, fearing expropriation, make suboptimal levels of land-specific investments. Dubois (2002), Jacoby, Li, and Rozelle (2002), Jacoby and Mansuri (2002), and Bandiera (2002) document the existence of underinvestment in tenancy lands resulting from holdup problems.

There are also authors who argue that good lands are less likely to be leased out because they are more sensitive to soil exploitation (see Allen and Lueck 1992, 1993; Dubois 2002). Under this theory, landlords would choose to personally manage the good-quality fields in order to assure soil conservation and protect the value of their assets.

Finally, one cannot discard the possibility of that correlation being spurious. For instance, if better lands are closer to villages, farmers could possibly prefer to own and live on those lands for motives unrelated to production.

Regardless of why good lands are predominantly owned, this affects input use and final production through channels that are not connected to the classic marginal distortion associated with the share rates. Since many land characteristics are not observed by the econometrician, this correlation causes a serious selection bias that has been ignored in the literature.

5. Land Productivity

The Cobb-Douglas production function with constant return to scale is used to model the production of each plot. This functional form allows one to extend Shaban's (1987) findings on land productivity.

Define Y_i as the amount of output produced in plot i , where i indexes the plots in each particular period (year and season), and assume that

$$Y_i = A_i K_i^{\alpha_k} L_i^{\alpha_l} T_i^{(1-\alpha_k-\alpha_l)} \exp(\varepsilon_i), \quad (1)$$

where K_i and L_i represent the amount of nonlabor and labor input used; T_i is the cropped area; A_i is a technological factor that accounts for observable household and land characteristics as well as specific effects associated with each village, year, season, and crop grown; α_k and α_l are positive parameters; and ε_i is an unobserved random term that accounts for possible hidden actions and unpredictable climatic shocks, infestations, rainfalls, and monsoon arrivals.

Under the static moral hazard theory, hidden actions captured by the error term ε_i are influenced by the incentive power of the land contract. Dummy variables for each contract are then introduced into the model. Define \mathbf{d}_i as the vector of contract dummies, and assume that

$$\varepsilon_i = \boldsymbol{\delta} \times \mathbf{d}_i + u_i, \quad (2)$$

where $\boldsymbol{\delta}$ is a vector of parameters and u_i is an error term that accounts for unpredictable productive shocks that are unrelated to the contract form.

The data set displays the monetary values for the output and inputs according to prices recorded by the ICRISAT investigators. By multiplying quantities by these recorded prices, one expresses equation (1) in monetary units as follows:

$$y_i = \left(\frac{A_i p_i}{r_i^{\alpha_k} w_i^{\alpha_l}} \right) k_i^{\alpha_k} l_i^{\alpha_l} T_i^{(1-\alpha_k-\alpha_l)} \exp(\varepsilon_i), \quad (3)$$

where p_i represents the recorded price of plot i 's output, r_i and w_i are the recorded prices for nonlabor and labor inputs, $y_i = p_i Y_i$ is the value of plot i 's output, and $k_i = r_i K_i$ and $l_i = w_i L_i$ are the value of nonlabor and labor inputs.

Constant return to scale allows one to express the model in per-acre terms, as is usual in agricultural economics. The log-linear version of the production function is then given by

$$\ln \left(\frac{y_i}{T_i} \right) = \boldsymbol{\delta} \times \mathbf{d}_i + \ln(a_i) + \alpha_k \ln \left(\frac{k_i}{T_i} \right) + \alpha_l \ln \left(\frac{l_i}{T_i} \right) + u_i, \quad (4)$$

where y_i/T_i , k_i/T_i , and l_i/T_i represent the per-acre value of output, nonlabor input, and labor input and $a_i = A_i p_i / r_i^{\alpha_k} w_i^{\alpha_l}$.

The parameters in the vector $\boldsymbol{\delta}$ represent the mean effect of each contract form on $\ln(y_i/T_i)$. The standard moral hazard theory (see Stiglitz 1974; Holmström 1979; Grossman and Hart 1983) predicts that owners and fixed-rent ten-

Table 4
Land Productivity, by Log Per-Acre Output

	(1)	(2)	(3)	(4)	(5)
Ownership dummy	.47**	.23**	.07 ⁺	-.01	-.01
Robust <i>t</i> -statistic	4.83	4.01	1.77	-.46	-.45
Robust standard error	.10	.06	.04	.03	.03
Fixed-rent dummy	.12	.03	-.04	-.07	-.07
Robust <i>t</i> -statistic	.95	.27	-.55	-1.10	-1.10
Robust standard error	.12	.10	.07	.06	.06
Log per-acre nonlabor input			.61*		-.01
Log per-acre labor input				1.03**	1.05**
Log per-acre land value		.43**	.27**	.19**	.19**
Dummies for irrigation, soil type, and main crop	No	Yes	Yes	Yes	Yes
<i>N</i>	10,704	10,702	10,688	10,702	10,688

Note. Results are for ordinary least squares regressions. The cluster method is used to compute robust *t*-statistics and standard errors; this accounts for the fact that the household, rather than the plot, is the primary sampling unit. All regressions include a constant term and 2,773 dummy variables generated through the iteration of codes identifying the household and the period (year and season).

⁺ Significant at the 10% level.

* Significant at the 5% level.

** Significant at the 1% level.

ants are equally productive and both strictly more productive than sharecroppers. Alternatively, theories based on perfect monitoring (see Cheung 1969, 2002) and on infinite-repeated games (see Rubinstein and Yaari 1983; Radner 1985) predict that lands under ownership, fixed rent, and sharecropping are equally productive. One can now test these predictions.

If $\ln(A_i)$ is perfectly measured in the data, then u_i will capture only unexpected shocks that are uncorrelated to endogenous covariates. In this case, the OLS estimator will consistently identify the parameters in equation (4). Otherwise, the error term will reflect characteristics of the land that are observed by the farmer but not by the econometrician. Then endogenously chosen variables (such as inputs and land contract) will be correlated to the error term, biasing the OLS estimator (see Zellner, Kmenta, and Drèze 1966; Hodges 1969; Mundlak 1996).

Table 4 summarizes the OLS results. The regressions include a constant term and define sharecropping to be the omitted dummy (that is, the baseline category for comparison). Fixed effects for households in each period (year and season) are used in order to control for unobserved characteristics of the household and to make results comparable to those of Shaban (1987).⁹

The regression in column 1 does not control for land characteristics and type of crop grown, while the regression in column 2 does. Land value, irrigation, soil type, and main crop account for about half of the productivity advantage of owned lands. Similar to the results of Shaban, the owned plots of each given household are approximately 23 percent more productive than their sharecropped

⁹ I have also run regressions without the fixed effects and obtained very similar results.

fields, after controlling for land characteristics.¹⁰ Lands under fixed rent are not significantly more productive than lands under sharecropping, which contradicts the distorted-incentive prediction.

The regressions in columns 3–5 introduce nonlabor and labor inputs as control variables. Conditional on input use, the productivity advantage of owned lands becomes statistically nonsignificant at the 5 percent level, which indicates that owned lands are more productive because they use inputs more intensively. Notice that the estimates for the input coefficients do not identify the Cobb-Douglas parameters, since they partially capture the omitted land quality that is correlated to input choices.

There are three key messages from these OLS regressions. First, since land quality is heterogeneous across farms under different contracts, one must be careful when interpreting differences in farm productivity as evidence of incentive problems. Land quality is not perfectly measured by variables such as land value, irrigation, and soil type. Therefore, regressing farm productivity on contract dummies—as in columns 1 and 2—generates upward-biased estimates for the coefficient of the contract form associated with the better lands (in this case, ownership). Second, the productivity disadvantage of share contracts is fully explained by observed inputs, which does not support the existence of hidden actions (that is, actions that affect productivity and cannot be inferred from observed variables). Finally, these regressions indicate that one must understand the input choices better, since they are strongly related to the productivity difference across land contracts. This goal is pursued in the next two sections.

6. Efficiency of Input Use

Owner-operated farms use nonlabor and labor inputs more intensively (see Table 3), and this explains the productivity advantage of the ownership contract over sharecropping and fixed rent (see Table 4). I develop here a structural model to test the efficiency of input allocation across farms under different contracts. The method is robust to heterogeneity in land quality and household characteristics. Moreover, as will be shown in Section 7, the test does not depend on the Cobb-Douglas format of the production function.

Consider the problem of a planner (or a landlord) who chooses the amount of labor and nonlabor inputs to be used in each plot. In a competitive environment without externalities, this problem is equivalent to maximizing the expected surplus (or profit) in each plot. In this scenario, the efficient level of each input must solve

$$\max_{K_i, L_i} \bar{p}_i E[A_i K_i^{\alpha_k} L_i^{\alpha_l} T_i^{(1-\alpha_k-\alpha_l)} \exp(\varepsilon_i)] - \bar{r}_i K_i - \bar{w}_i L_i, \quad (5)$$

¹⁰ Shaban (1987, table 3) uses a linear regression model estimated in first-difference form and finds that the owned plots of each mixed tenant are, on average, 16.3 percent more productive than their sharecropped fields.

where $(\bar{p}_i, \bar{r}_i, \bar{w}_i)$ is the vector of expected prices. (Prices are assumed to be competitive and thus independent of ε_r .)

The expected prices can potentially differ across plots because of differences in village, period, main crop grown, and farmer expectations. Moreover, they are not necessarily identical to the prices recorded by the ICRISAT investigators, namely (p_i, r_i, w_i) .

The necessary and sufficient first-order conditions for this maximization problem are

$$\bar{p}_i \alpha_k E[A_i K_i^{\alpha_k - 1} L_i^{\alpha_l} T_i^{(1 - \alpha_k - \alpha_l)} \exp(\varepsilon_i)] = \bar{r}_i, \quad (6)$$

and

$$\bar{p}_i \alpha_l E[A_i K_i^{\alpha_k} L_i^{\alpha_l - 1} T_i^{(1 - \alpha_k - \alpha_l)} \exp(\varepsilon_i)] = \bar{w}_i. \quad (7)$$

These conditions equalize the expected marginal revenue of each input to its expected marginal cost. They are equivalent to

$$\frac{\bar{r}_i K_i}{\bar{p}_i E(Y_i)} = \alpha_k, \quad (8)$$

and

$$\frac{\bar{w}_i L_i}{\bar{p}_i E(Y_i)} = \alpha_l. \quad (9)$$

If inputs were chosen efficiently, these first-order conditions should be satisfied for all plots. Regardless of differences in land quality and farmer ability, inputs should be used up to the point at which the expected marginal revenue equals the expected marginal cost. In this case, the inverse average productivities $\bar{r}_i K_i / \bar{p}_i E(Y_i)$ and $\bar{w}_i L_i / \bar{p}_i E(Y_i)$ should be constant across households and plots under different contracts.

Remark 1. In the absence of monitoring or dynamic incentives, sharecropping tenants would choose inputs by equalizing their share of the expected marginal revenue (say, s_y) to their fraction of the expected marginal costs (say, s_k and s_l). In this scenario, the sharecropping first-order conditions are $s_y \bar{p}_i \alpha_k E(Y_i) / K_i = s_k \bar{r}_i$ and $s_y \bar{p}_i \alpha_l E(Y_i) / L_i = s_l \bar{w}_i$. These conditions are distorted because s_y / s_k and s_y / s_l are typically smaller than one, since the landlords do not share the cost of many inputs (especially home-produced inputs, owned bullocks, and family labor). Therefore, the classical distortion attributed to sharecropping would imply lower levels for the inverse average productivities, namely, $\bar{r}_i K_i / \bar{p}_i E(Y_i) = \alpha_k s_y / s_k < \alpha_k$ and $\bar{w}_i L_i / \bar{p}_i E(Y_i) = \alpha_l s_y / s_l < \alpha_l$.

Expected prices are not observed by the econometrician. Therefore, an econometric specification is needed to test the validity of conditions (8)–(9):

$$\frac{\bar{p}_i}{p_i} = \mu_{\bar{p}} \exp(\eta_{\bar{p},i}), \quad (10)$$

$$\frac{\bar{r}_i}{r_i} = \mu_{\bar{r}} \exp(\eta_{\bar{r},i}), \quad (11)$$

and

$$\frac{\bar{w}_i}{w_i} = \mu_{\bar{w}} \exp(\eta_{\bar{w},i}), \quad (12)$$

where the vector $(\bar{p}_i, \bar{r}_i, \bar{w}_i)$ represents the expected prices, (p_i, r_i, w_i) stands for the prices observed by the ICRISAT investigators, and $(\eta_{\bar{p},i}, \eta_{\bar{r},i}, \eta_{\bar{w},i})$ represents random errors. (This structure also accounts for the possibility of random measurement errors in the ICRISAT prices.)

Simple algebraic manipulation of conditions (8)–(9) leads to

$$\ln(k_i) - \ln(y_i) = \gamma_k + u_{k,i}, \quad (13)$$

and

$$\ln(l_i) - \ln(y_i) = \gamma_l + u_{l,i}, \quad (14)$$

where $\gamma_k = \ln(\{\alpha_k \mu_{\bar{p}} E[\exp(u_i)]\} / \mu_{\bar{p}})$, $\gamma_l = \ln(\{\alpha_l \mu_{\bar{w}} E[\exp(u_i)]\} / \mu_{\bar{w}})$, $u_{k,i} = \eta_{\bar{p},i} - u_i - \eta_{\bar{r},i}$ and $u_{l,i} = \eta_{\bar{w},i} - u_i - \eta_{\bar{r},i}$.¹¹

The error terms $u_{k,i}$ and $u_{l,i}$ are independent of the land contract since $\eta_{\bar{p},i}$, $\eta_{\bar{r},i}$ and $\eta_{\bar{w},i}$ are shocks on prices, and u_i was defined in equation (2) as the part of ε_i that is not related to the land contract. Therefore, the vector of contract dummies (\mathbf{d}_i) can be used to measure differences in marginal productivity across contracts, as follows:

$$\ln(k_i) - \ln(y_i) = \gamma_k + \mathbf{c}_k \times \mathbf{d}_i + u_{k,i}, \quad (15)$$

and

$$\ln(l_i) - \ln(y_i) = \gamma_l + \mathbf{c}_l \times \mathbf{d}_i + u_{l,i}. \quad (16)$$

Remark 2. The exponential structure assumed in equations (10)–(12) is convenient for exposition but absolutely unnecessary. All results would still be valid if the ratios \bar{p}_i/p_i , \bar{r}_i/r_i and \bar{w}_i/w_i did assume any general distribution, as far as they were not correlated to the contract choice. This is simply because consistency of the OLS estimator does not depend on the specific distribution of the error term.

¹¹ To see this, note that equations (1) and (2) imply $E(Y_i) = Y_i \{E[\exp(u_i)] / \exp(u_i)\}$, thus conditions (8) and (9) can be written as $[(\bar{r}_i/r_i)k_i] / ((\bar{p}_i/p_i)y_i \{E[\exp(u_i)] / \exp(u_i)\}) = \alpha_k$ and $[(\bar{w}_i/w_i)l_i] / ((\bar{p}_i/p_i)y_i \{E[\exp(u_i)] / \exp(u_i)\}) = \alpha_l$.

Table 5
Econometric Test for the Profit-Maximization Conditions

	Log Nonlabor Input – Log Output (<i>N</i> = 10,690)			Log Labor Input – Log Output (<i>N</i> = 10,704)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Ownership dummy	–.05	–.05	.03	–.05	–.03	–.03
Robust <i>t</i> -statistic	–1.20	–1.16	.63	–1.16	–.68	–.93
Robust standard error	.05	.04	.04	.04	.04	.04
Fixed-rent dummy	.23	.24 ⁺	.09	.15	.18	.06
Robust <i>t</i> -statistic	1.54	1.72	1.19	1.19	1.49	.96
Robust standard error	.15	.14	.07	.12	.12	.07
Main crop dummies	No	Yes	Yes	No	Yes	Yes
Household-period fixed effects	No	No	Yes	No	No	Yes
Constant	–.87**	Yes	Yes	–1.36**	Yes	Yes

Note. Results are for ordinary least squares regressions. The cluster method is used to compute robust *t*-statistics and standard errors; this accounts for the fact that the household, rather than the plot, is the primary sampling unit. Household-period fixed effects refer to 2,773 dummy variables generated through the iteration of codes identifying the household and the period (year and season).

⁺ Significant at the 10% level.

** Significant at the 1% level.

If input choices were efficient for all land contracts, then the vectors \mathbf{c}_k and \mathbf{c}_l should be null. However, if the sharecropping marginal distortions were active, these lands should present higher expected marginal productivities and then a lower input/output ratio—that is, using sharecropping as the baseline category, the sharecropping marginal distortions would imply positive coefficients for the ownership and fixed-rent dummies.

Equations (15) and (16) are consistently estimated by OLS. Table 5 presents the results. All regressions include a constant term, and sharecropping is the baseline contract (omitted dummy). Regressions (1a) and (2a) consider the scenario in which γ_k and γ_l are fixed. Regressions (1b) and (2b) and regressions (1c) and (2c) introduce dummies for the main crop and household-period fixed effects to capture potential heterogeneity in γ_k and γ_l . The coefficients associated with the ownership dummy are negative in five of the six regressions and are always statistically nonsignificant. The coefficients associated with the fixed-rent dummy are all positive but not statistically different from zero at the 5 percent level of significance. Furthermore, in all regressions, the null assumption that both coefficients are jointly equal to zero is also never rejected at that significance level.

7. Robustness Checks

7.1. Marginal Conditions under Alternative Production Functions

The marginal and average productivities are proportional when the production function is Cobb-Douglas. This simplifies the implementation of the input tests

in Section 6 since average productivity can be measured without parametric assumptions. However, the Cobb-Douglas format is not necessary for that test. It is shown here that a similar relation between the marginal and the average productivities is valid for a broader class of homogeneous production functions.

Assume that technology exhibits constant return to scale and that the expected output of each plot is represented by

$$E(Y_i) = F_i(T_i, K_i, L_i) = T_i^{(1-\rho)} g_i(K_i, L_i), \quad (17)$$

where g_i is strictly concave, continuously differentiable, and homogeneous of degree $\rho \in (0, 1)$.¹² It is simple to show that the following condition must hold:¹³

$$\left[\frac{\bar{p}_i}{\bar{r}_i} \left(\frac{\partial F_i}{\partial K_i} \right) \right] \frac{\bar{r}_i K_i}{\bar{p}_i E(Y_i)} + \left[\frac{\bar{p}_i}{\bar{w}_i} \left(\frac{\partial F_i}{\partial L_i} \right) \right] \frac{\bar{w}_i L_i}{\bar{p}_i E(Y_i)} = \rho. \quad (18)$$

The terms $(\bar{p}_i/\bar{r}_i) (\partial F_i/\partial K_i)$ and $(\bar{p}_i/\bar{w}_i) (\partial F_i/\partial L_i)$ must equal one if inputs are chosen efficiently, as follows from conditions (6) and (7). On the other hand, if the classical sharecropping distortion is active, these terms should equal $s_k/s_y > 1$ and $s_l/s_y > 1$, respectively. Thus, this classical distortion implies that either $\bar{r}_i K_i/\bar{p}_i E(Y_i)$ or $\bar{w}_i L_i/\bar{p}_i E(Y_i)$ (or both) should be higher in sharecropping fields than in plots under ownership and fixed rent, as follows from equation (18). Therefore, the econometric test proposed in Section 6 is conceptually valid not only for Cobb-Douglas production functions but also for any technology satisfying the homogeneity condition (17).

7.2. Efficiency Test with Nonmultiplicative Productive Shocks

Efficient input allocation implies constant inverse average productivities across land contracts. This prediction is valid for any technology that satisfies the homogeneity assumption, which includes cases with nonmultiplicative shocks (such as an additive error term). However, the log-linear econometric specification proposed in Section 6 is not appropriate for those cases. An alternative empirical exercise is presented here in order to account for these possibilities.

Suppose one needs to test for conditions (8) and (9), but the right model for

¹² This family of production functions is usual in agricultural economics, where one typically models the per-acre output as a function of per-acre inputs, namely, $E(Y_i/T_i) = g_i(K_i/T_i, L_i/T_i)$. This structure encompasses the Cobb-Douglas and constant elasticity of substitution production functions and does not impose technological factors to be Hicks neutral. Note also that the deterministic and stochastic technological factors that are embedded in g_i need not be multiplicative (additive shocks, for instance, are accomplished).

¹³ Since g_i is homogeneous of degree ρ , one must have $g_i(\lambda K_i, \lambda L_i) = \lambda^\rho g_i(K_i, L_i)$, $\forall \lambda > 0$. By differentiating this equation with respect to λ and evaluating it at the point $\lambda = 1$, one obtains $(\partial g_i/\partial K_i) K_i + (\partial g_i/\partial L_i) L_i = \rho g_i(K_i, L_i)$. Then, by multiplying both sides of this condition by $T_i^{(1-\rho)}$, one finds $(\partial F_i/\partial K_i) [K_i/E(Y_i)] + (\partial F_i/\partial L_i) [L_i/E(Y_i)] = \rho$, which is equivalent to condition (18).

Table 6
Profit Maximization and Additive Production Shocks

	(1)	(2)	(3)
Ownership dummy	-.01	-.02	.06 ⁺
Robust <i>t</i> -statistic	-.19	-.60	1.79
Robust standard error	.04	.04	.03
Fixed-rent dummy	.08	.06	.02
Robust <i>t</i> -statistic	.96	.75	.52
Robust standard error	.08	.08	.05
Main crop dummies	No	Yes	Yes
Household-period fixed effects	No	No	Yes
Constant	.48**	Yes	Yes

Note. Results are for ordinary least squares regressions. The cluster method is used to compute robust *t*-statistics and standard errors; this accounts for the fact that the household, rather than the plot, is the primary sampling unit. Household-period fixed effects refer to 2,773 dummy variables generated through the iteration of codes identifying the household and the period (year and season). $N = 10,690$.

⁺ Significant at the 10% level.

** Significant at the 1% level.

$E(Y_i)$ is unknown. One could then divide one condition by another in order to obtain the following weaker testable prediction:

$$\frac{\bar{r}_i K_i}{\bar{w}_i L_i} = \frac{\alpha_k}{\alpha_l}. \quad (19)$$

If input choices are efficient, condition (19) should be satisfied in all plots. On the other hand, if input use is distorted by the share rates, the sharecropping farms would equalize the left-hand side of condition (19) to $s_k \alpha_k / s_l \alpha_l$, where s_k and s_l are the fractions of nonlabor and labor costs borne by the tenant.

If the effective share rates are such that $s_k \neq s_l$, then the sharecropping classical distortion would also be reflected in condition (19).¹⁴ Under this identifying assumption, the log-linear test derived in Section 6 can be easily adapted to test for condition (19). Table 6 presents OLS regressions for which the dependent variable is $\ln(k_i) - \ln(l_i)$ and the regressors include a constant term and dummies for ownership and fixed rent. As before, the regression in column 1 includes no control, and columns 2 and 3 introduce dummies for the main crop and household-period fixed effects. The coefficients associated with the contract dummies are not statistically significant at the 5 percent level. Moreover, the null assumption that both coefficients are jointly equal to zero is never rejected at that level of significance.

¹⁴ The data set has no information on the share rates used in each contract. However, one should expect incentive problems to more strongly affect the use of labor inputs. Family labor accounts for about 54 percent of the labor costs, and the use of this input is difficult to monitor. On the other hand, seeds, bullocks, and machinery account for about 92 percent of the nonlabor costs, and those are inputs that are possibly monitored by the landlord.

Table 7
Disaggregated Labor Input, by Fraction of Hours Worked

	Family			Hired		
	Male	Female	Child	Male	Female	Child
Ownership dummy	.33**	.16**	.016**	.22**	.26**	.003**
Robust standard error	.02	.01	.002	.01	.01	.001
95% Confidence interval	[.30, .36]	[.14, .18]	[.012, .020]	[.20, .25]	[.23, .29]	[.002, .004]
Sharecropping dummy	.37**	.14**	.011**	.23**	.24**	.003*
Robust standard error	.02	.01	.003	.03	.02	.001
95% Confidence interval	[.33, .41]	[.11, .16]	[.005, .016]	[.18, .29]	[.21, .28]	[.001, .005]
Fixed-rent dummy	.35**	.18**	.025**	.25**	.19**	.002
Robust standard error	.05	.03	.009	.05	.04	.002
95% Confidence interval	[.26, .44]	[.13, .24]	[.007, .043]	[.15, .34]	[.11, .27]	[-.001, .006]

Note. Results are for ordinary least squares regressions. The cluster method is used to compute robust *t*-statistics and standard errors; this accounts for the fact that the household, rather than the plot, is the primary sampling unit. *N* = 10,704.

* Significant at the 5% level.

** Significant at the 1% level.

7.3. Checking for Nonrandom Measurement Errors in Labor Prices

While the actual value paid for hired labor is recorded in the database, the value of family labor is computed according to average village prices for male, female, and child labor. If the opportunity cost of family labor is below the village wages, this measure will be inflated. This nonrandom measurement error could bias our previous tests if farms under different contracts presented large differences in how they mixed family and hired labor.

One must worry about this possibility because sharecropping tenants have reasons to substitute family labor by hired labor. According to Jodha (1981) and Shaban (1987, 898), landlords usually share the cost of labor hired for specific purposes but not the cost of family labor. (The landlord might consent to this input substitution.) Fortunately, the database contains disaggregated information on the number of hours worked by family members and hired workers, according to the following three categories: adult male, adult female, and child. One can then compare, for each category, the fraction of labor hours used in lands under ownership, sharecropping, and fixed rent.

Table 7 presents OLS regressions of these fractions against contract dummies. For sake of expositional clarity, the constant term (instead of the sharecropping dummy) was omitted in these regressions. The contract dummy coefficients indicate the average fraction of hours worked in lands under each contract. The null hypothesis that the dummy coefficients in each regression are statistically identical is never rejected at the 5 percent level of significance. Farms under different contracts apply, on average, similar fractions of each type of labor.

7.4. Results for the Mixed Owner-Sharecropper Subsample

I now analyze the subsample of 2,833 plots cropped by households who have owned and sharecropped plots in each particular year and season (and who had

Table 8
Land Productivity: Mixed Owner-Sharecropper Subsample

	(1)	(2)	(3)	(4)	(5)
Ownership dummy	.44**	.22**	.08 ⁺	-.02	-.02
Robust <i>t</i> -statistic	4.60	4.04	1.77	-.65	-.55
Robust standard error	.09	.05	.04	.03	.03
Log per-acre nonlabor input			.66**		-.05
Log per-acre labor input				1.1**	1.1**
Log per-acre land value		.38**	.24**	.17**	.18**
Dummies for irrigation, soil type, and main crop	No	Yes	Yes	Yes	Yes
<i>N</i>	2,833	2,831	2,830	2,831	2,830

Note. Results are for ordinary least squares regressions; the dependent variable is the log of per-acre output. The cluster method is used to compute robust *t*-statistics and standard errors; this accounts for the fact that the household, rather than the plot, is the primary sampling unit. All regressions include a constant term, household-period fixed effects, and 411 dummy variables generated through the iteration of codes identifying the household and the period (year and season).

⁺ Significant at the 10% level.

** Significant at the 1% level.

no plot under fixed rent in that period). This subsample is defined as in Shaban (1987). Since a few more years are now available in the database, the regressions here have 411 household-period units (that is, about 30 households in different years and seasons) instead of the 329 units used by Shaban.

I have run all previous regressions and obtained the same qualitative results as before. Table 8 reports the estimates of the log per-acre output regression. As before (see Table 4), the productivity gap between owners and sharecroppers is significantly reduced when observed land characteristics are introduced into the regression and vanishes when inputs are considered. Next, Table 9 tests for efficiency of input use. The results are identical to those from Table 6—that is, the null hypothesis that sharecroppers' input choices are not distorted cannot be rejected.

8. Conclusion

This paper uses tenancy data from India to test the existence of missing incentives in one of the classic examples of moral hazard: the landlord-tenant relationship. I first investigate how the expected per-acre output is affected by the tenancy contract. Sharecroppers are less productive than owners but as productive as fixed-rent tenants. The productivity gap between owners and both types of tenants is driven by observable land quality and input use. (These results hold true whether or not we control for household-period fixed effects.)

Next I test for efficiency of input use. Although there are many different reasons that would lead owners and tenants to maximize different objective functions, the empirical tests do not reject the null hypothesis that the input choices satisfy the same marginal conditions for all land contracts.

While the reduced-form model for land productivity presented in Section 5

Table 9
Profit-Maximization Conditions: Mixed Owner-Sharecropper Subsample

	Log Nonlabor Input – Log Output (N = 2,832)			Log Labor Input – Log Output (N = 2,833)		
	(1a)	(1b)	(1c)	(2a)	(2b)	(2c)
Ownership dummy	.005	–.001	.020	–.012	–.015	–.021
Robust <i>t</i> -statistic	.12	–.02	.47	–.30	–.38	–.67
Robust standard error	.05	.04	.04	.04	.04	.03
Main crop dummies	No	Yes	Yes	No	Yes	Yes
Household-period fixed effects	No	No	Yes	No	No	Yes
Constant	–.91**	Yes	Yes	–1.37**	Yes	Yes

Note. Results are for ordinary least squares regressions. The cluster method is used to compute robust *t*-statistics and standard errors; this accounts for the fact that the household, rather than the plot, is the primary sampling unit. Household-period fixed effects refer to 411 dummy variables generated through the iteration of codes identifying the household and the period (year and season).

** Significant at the 1% level.

is not free of selection problems, the structural test for input efficiency is. If inputs were chosen efficiently, the profit maximization conditions should hold for all plots, regardless of differences in land quality, farmer skill, or any other variable that is not observed by the econometrician. Moreover, the tests implemented are valid for a broad class of homogeneous production functions and are robust to different types of measurement errors, as shown in Section 7.

These results challenge the conventional wisdom that share contracts reduce incentives for optimal production decisions. One should not take the extreme view that sharecropping marginal distortions are unimportant. However, as far as statistical significance is concerned, one cannot rule out the possibility that inputs are optimally allocated for all land contracts. Increasing our capability to deal with land quality selection issues—focusing on new data and on models that address the matching between contracts and land characteristics—is an important goal for future research.

References

- Allen, Douglas W., and Dean Lueck. 1992. Contract Choice in Modern Agriculture: Cash Rent versus Cropshare. *Journal of Law and Economics* 35:397–426.
- . 1993. Transaction Costs and the Design of Cropshare Contracts. *RAND Journal of Economics* 24:78–100.
- Bandiera, Oriana. 2002. Land Tenure, Incentives and the Choice of Production Techniques in Rural Nicaragua. Unpublished manuscript. London School of Economics.
- Banerjee, Abhijit, Paul Gertler, and Maitreesh Ghatak. 2002. Empowerment and Efficiency: Tenancy Reform in West Bengal. *Journal of Political Economy* 110:239–80.
- Braido, Luis H. B. 2006. Insurance and Incentives in Sharecropping. Pp. 251–81 in *Competitive Failures in Insurance Markets*, edited by Pierre-André Chiappori and Christian Goulier. Cambridge, Mass.: MIT Press.

- Cheung, Steven N. S. 1969. *The Theory of Share Tenancy*. Chicago: University of Chicago Press.
- . 2002. Sharecropping. Pp. 190–213 in *Famous Fables of Economics: Myths of Market Failures*, edited by Daniel F. Spulber. Oxford: Blackwell.
- Dubois, Pierre. 2002. Moral Hazard, Land Fertility and Sharecropping in a Rural Area of the Philippines. *Journal of Development Economics* 68:35–64.
- Grossman, Sanford J., and Oliver D. Hart. 1983. An Analysis of the Principal-Agent Problem. *Econometrica* 51:7–45.
- Hodges, Dorothy J. 1969. A Note on Estimation of Cobb-Douglas and CES Production Function Models. *Econometrica* 37:721–25.
- Holmström, Bengt R. 1979. Moral Hazard and Observability. *Bell Journal of Economics* 10:74–91.
- Jacoby, Hanan G., Guo Li, and Scott Rozelle. 2002. Hazards of Expropriation: Tenure Insecurity and Investment in Rural China. *American Economic Review* 92:1420–47.
- Jacoby, Hanan G., and Ghazala Mansuri. 2002. Incomplete Contracts and Investment: A Study of Land Tenancy in Pakistan. Unpublished manuscript. World Bank, Washington, D.C.
- Jodha, N. S. 1981. Agricultural Tenancy: Fresh Evidence from Dryland Areas in India. *Economic and Political Weekly* 16(52):A118–A128.
- Jodha, N. S., M. Asokan, and J. C. Ryan. 1977. Village Study Methodology and Resource Endowment of the Selected Villages in ICRISAT's Village Level Studies. Economics Program Occasional Paper No. 16. International Crops Research Institute for Semi-Arid Tropics, Hyderabad.
- Johnson, D. Gale. 1950. Resource Allocation under Share Contracts. *Journal of Political Economy* 58:111–23.
- Laffont, Jean-Jacques, and Mohamed S. Matoussi. 1995. Moral Hazard, Financial Constraints and Sharecropping in El Oulja. *Review of Economic Studies* 62:381–99.
- Mas-Colell, Andreu, Michael D. Whinston, and Jerry R. Green. 1995. *Microeconomic Theory*. New York: Oxford University Press.
- Mundlak, Yair. 1996. Production Function Estimation: Reviving the Primal. *Econometrica* 64:431–38.
- Radner, Roy. 1981. Monitoring Cooperative Agreements in a Repeated Principal-Agent Relationship. *Econometrica* 49:1127–48.
- . 1985. Repeated Principal-Agent Games with Discounting. *Econometrica* 53:1173–98.
- Rao, C. H. Hanumantha. 1971. Uncertainty, Entrepreneurship, and Sharecropping in India. *Journal of Political Economy* 79:578–95.
- Rubinstein, Abreu, and Menahem E. Yaari. 1983. Repeated Insurance Contracts and Moral Hazard. *Journal of Economic Theory* 30:74–97.
- Shaban, Radwan A. 1987. Testing between Competing Models of Sharecropping. *Journal of Political Economy* 95:893–920.
- Singh, R. P., H. P. Binswanger, and N. S. Jodha. 1985. Manual of Instructions for Economic Investigators in ICRISAT's Village Level Studies. Technical Report. International Crops Research Institute for Semi-Arid Tropics, Hyderabad.
- Stiglitz, Joseph E. 1974. Incentives and Risk Sharing in Sharecropping. *Review of Economic Studies* 41:219–55.

- Walker, Thomas S., and James G. Ryan. 1990. *Village and Household Economies in India's Semi-arid Tropics*. Baltimore: Johns Hopkins University Press.
- Zellner, Arnold, Jan Kmenta, and Jacques H. Drèze. 1966. Specification and Estimation of Cobb-Douglas Production Function Models. *Econometrica* 34:784–95.