# Evidence on the Relationship between Risk and Incentives

Luis H.B. Braido

October 26, 2016

**Abstract**

Classic moral hazard theory predicts that exogenous risks discourage pay-for-performance compensations. Empirical works have assessed this risk-incentive relation through contracts undertaken by different agents. This is not ideal because the optimal compensation plan also depends on the agent's risk aversion. I access data on farmers managing multiple plots to compare compensation plans designed for the same agent. Contrary to the classic prediction, I find a positive (rather than negative) correlation between output volatility and pay for performance. After modeling the production function to control for endogenous input use, I find no statistically significant risk-incentive relation.

Keywords: Risk, incentives, principal, agent, tenancy, data.

JEL Classification: C52, D82, O12, Q15.

*I am thankful for comments from Marcelo Fernandes, Daniel Ferreira, Helena Perrone, and seminar participants at the University of Illinois at Urbana-Champaign, the Econometric Society World Conference (Montreal), and the 28th SBE Meeting (Salvador). Financial support from CNPq is gratefully acknowledged.

†FGV/EPGE, Praia de Botafogo 190, s.1100, Rio de Janeiro, RJ 22253-900, Brazil; lbraido@fgv.br.

## 1 Introduction

Payments based on performance are used in many economic activities to induce agents to make proper decisions about noncontractible actions. Since performance measures are usually affected by external risks, this practice creates incentives at the cost of imposing undesired risks on the agents. Since a risk-averse agent requires a higher average payment to take risks, one should expect to observe a negative relation between the intensity of exogenous risks and the adoption of contracts with high pay-for-performance sensitivity (i.e., high incentive power).

This intuitive idea holds in environments in which the principal is restricted to use linear contracts based on individual performance. When nonlinear schedules are considered, the inverse relation between risk and incentives depends on strong assumptions about preferences and shocks (see for instance Holmstrom and Milgrom, 1987). The sign of this relationship is undetermined in general models of moral hazard in teams, when payments based on relative performance are allowed. The same applies for dynamic settings and for environments with multi-task efforts or multidimensional asymmetric information.

Despite this theoretical controversy, the risk-incentive tradeoff motivates a large body of empirical works (see literature review in Section 2). This is partially justified by the fact that sophisticated mechanisms are not often used in practice, possibly because they are difficult to implement. In many cases, lack of intertemporal commitment limits the use of dynamic schemes. Mechanisms that are nonlinear functions of the performance measure or that are based on relative performance may induce manipulation.[1]

A major difficulty in the empirical analysis is that each agent is usually associated to a single contract. Contracts associated with different risk environments are usually undertaken by different agents, with possibly different degrees of risk aversion. This raises a concern about the possibility that less risk-averse agents—who are willing to accept compensations schemes with high pay-for-performance sensitivity—are matched with riskier projects. This paper uses a well-known data set on tenancy contracts, collected by the International Crops Research Institute for Semi-Arid Tropics (ICRISAT) in India, which contains a significant fraction of households that simultaneously manage multiple plots under different land con-

[1] In agriculture, for instance, where output is the usual performance measure, farmers could exploit nonlinearities by buying and selling output in the market or by switching output across nearby farms.

tracts. This feature of data allows one to study different contracts designed for the same agent, avoiding concerns about preference heterogeneity.

There are three general cropping regimes in the data, namely: ownership, in which the farm is managed by its owner; fixed rent, in which the tenant pays an upfront fee for using the land, bears all input costs, and retains the entire revenue; and sharecropping, in which the landlord supplies the land, the tenant bears most input costs, and they share the final output.[2] The pay-for-performance sensitivity is maximal in lands managed under ownership and fixed rent, as the farmer retains 100% of the final output. This paper tests whether households managing multiple plots adopt the sharecropping contract in the riskier lands, as predicted by the risk-sharing argument.

The empirical strategy proposes an econometric model to measure risk. I follow the general practice in this literature and use the risk of the contract's payoff.[3] Lafontaine and Bhattacharyya (1995) and Allen and Lueck (1999) identify the exogenous risk under the assumption that production is composed of two independent and additive parts, one endogenous and another exogenous. In agriculture, however, the final output is typically determined by the interaction of endogenous input choices and exogenous climatic shocks. Since detailed information on cropping activities is available, I use a stochastic Cobb-Douglas production function to model the interaction between the endogenous and exogenous variables affecting the final output.

Once these different plot-specific measures of risk are constructed (from the estimated residuals of the production function), a heteroskedasticity test is adapted to assess how risk differs across plots under different contracts. Household fixed effects are used to compare the risk-incentive relationship in the plots cropped by the same agent. They account for different risk aversion as well as other agent-specific features, such as different risk exposure derived from their financial and land-use portfolios. The results do not support the risk-sharing prediction.

The remainder of the paper is organized in the following manner. The next

[2] Share contracts are linear and depend only on the performance of each plot. In many cases, the landlord shares the cost of some inputs and provides supervision. Payments under both sharecropping and fixed rent are sometimes defined in terms of crop quantities instead of values.

[3] In addition to the works on executive compensation, franchising, and land tenancy summarized in Section 2, there is also an extensive literature using payoff risk to assess the asymmetric information problem in different insurance markets. I refer the reader to Chiappori and Salanié (1994) for an illustration on auto-insurance and to Cardon and Hendel (2001) and Braido and Dueire (2015) for evidence on health insurance.

section presents a brief review of the related empirical literature. Section 3 describes the data; Section 4 introduces the econometric setup; and Section 5 presents the results. A brief conclusion appears in Section 6.

## 2 Related Literature

Data on executive compensation, franchising, and land tenancy are commonly used in empirical papers about the incentive design of contracts. Lambert and Larker (1987); Garen (1994); Aggarwal and Samwick (1999); Jin (2002), and Dee, Lulseged, and Nowlin (2005) use data on executive compensation and find evidence supporting the existence of a trade-off between risk and incentives. The literature on franchising finds distinct signals for the risk-incentive relationship. For instance, Lafontaine (1992) show that the royalty rate paid by the franchisee does not increase with the risk of discontinuation but the fraction of franchised outlets does. Moreover, Lafontaine and Bhattacharyya (1995) show that risk sharing is not necessary to explain the evidence on franchising contracts.[4]

This debate is also active in the tenancy literature. In a pioneering work, Rao (1971) argues that share contracts in India are extensive for products (such as rice) and areas (such as the northern regions) where risk and entrepreneurial profit are low. Fixed-rent contracts are common in situations of high risk and significant scope for decision making (e.g., tobacco farms). This does not support the risk-sharing argument. In another important reference, Allen and Lueck (1992) study tenancy contracts from Nebraska and South Dakota in the U.S. and report that sharecropping contracts are more likely to be used in lands where the costs of dividing the output is low. They find that sharecropping contracts are associated with crops such as corn (high volatility) and wheat (low volatility), which suggests that there is no clear relation between risk and incentive power. Similarly, Allen and Lueck (1999) use four different land-leasing surveys (from Nebraska, South Dakota, British Columbia, and Louisiana) to test the relationship between risk and incentive power. They have data on the form of the tenancy contract (fixed rent or sharecropping) and the fraction of crop retained by the sharecropping tenant. Exogenous risk is measured by the variability of crop yield across plots of a certain region. Using a logit model, they show that risk does not have a negative impact on the probability of a crop being leased under fixed rent. Tobit regressions also indicate that share

[4] For additional references on executive compensation and franchising, see Prendergast (2002).

rates are not decreasing in risk.[5]

These papers do not control for potential heterogeneity in agents' preferences. It could be the case that executives, franchisees, and tenants under high-power schemes were exactly those with higher risk tolerance. In this case, the risk-incentive trade-off and the endogenous matching between projects and agents would act in opposite directions, compromising the causal interpretation of the results previously mentioned.

Ackerberg and Botticini (2002) attempt to address this issue by using geographical-based instruments to model the first-stage matching equation. They assume that variables such as the local distribution of land types affects the matching between tenants and farms but not the risk of each particular farm.[6] Their results support risk sharing as an important determinant of sharecropping in early Renaissance Tuscany.

In a similar vein, Pandey (2004) explores regional differences in the use of high-yelding variety (HYV)—as opposite to traditional crops—as an instrumental variable. Adoption of HYV crops depends on the type of soil and access to irrigation. It is argued that the productivity gains of HYV crops vary across regions and, for some of them, this technology could not be adopted at all. The results suggest that output risk reduces pay-for-performance sensitivity in the four villages of India considered in this study.

The data set used here allows me to directly control for preference heterogeneity by comparing the different contracts of each agent. Differently from Ackerberg and Botticini (2002) and Pandey (2004), and consistently with the other papers on sharecropping, my findings do not support the existence of a negative correlation between risk and incentives.

## 3 Data

The data set is part of the village level studies (VLS) conducted by the International Crops Research Institute for Semi-Arid Tropics (ICRISAT), from 1975 to 1984, in eight different villages in India. The villages were selected to represent major agroclimatic zones. Initially, six villages were sampled in two different states:

[5] See Allen and Lueck (2003) and Braido (2006) for further references on the tenancy literature.

[6] They explicitly assume that the local distribution of land types causes no productive externality (such as resistance to infestations). Moreover, this strategy implicitly assumes restrictions on migration such that the distribution of risk aversion is similar across all regions.

Aurepalle 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, ten households were randomly chosen in each of the following categories: large, medium, and small farmers, as well as landless workers. Households that emigrated from the villages were randomly replaced by another household in the same category. Resident investigators belonging to the same linguistic group as the villagers collected information on farming activities in each of the plots cultivated by the households. These investigators had rural backgrounds and their work was supervised by an economist from the ICRISAT.

Households typically cultivate multiple plots during each season of the year. Although the household is the primary sampling unit in the ICRISAT research, the schedule used here (the PS files) is organized at the plot level. Each observation refers to one of the plots cultivated by a household during a particular year and season. The panel is not balanced since farmers crop different plots over time (i.e., plots are not always observed through many periods). Moreover, there are plots that produce no output in some periods. These are likely to be plots under rotation or temporarily abandoned and, therefore, are not included in the study.

The sample comprises a total of 10,704 productive plots distributed across 275 different households between 1975 and 1984. Table 1 describes the variables available for analysis. Notice that there are many products and byproducts being produced in each plot, but one type of culture is usually predominant (this culture is defined as being the main crop and identified by the first letter in the cropping-pattern code). Cereals, oil seeds, pulses, and fiber crops are the most common crops. Moreover, the plots are mainly cultivated during the two seasons from June to February (i.e., the monsoon and post-monsoon seasons).

**[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 pumpsets and tractors) were recorded for each plot and season of the year. For home produced inputs and owned bullocks and machinery, the values were computed by multiplying the actual quantities used in each plot by village-specific prices and rents. Similarly, the database contains the actual value paid for hired labor, but 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 in each plot. Finally, the value of the main product and byproducts were recorded at the prevailing village prices at the time of harvest.[7] Table 2 presents the summary statistics for the quantitative variables.

**[Table 2]**

Table 3 compares the coefficient of variation of the per acre output value across lands managed under ownership, sharecropping, and fixed rent. It shows that, at least before controlling for the agents' characteristics, risk does not seem to be correlated with the land-contract format. The coefficient of variation is similar across lands under the three contract forms. Owner-operated lands present higher quality, and their productivity mean and standard deviation are proportionally higher.

**[Table 3]**

### 3.1 Describing Households under Multiple Contracts

A key characteristic of the database is the presence of households cropping multiple plots under different contracts. They are present in all the eight villages, but these households are mostly concentrated in the villages of Shirapur, Kalman, Kanzara, Boriya, and Rampura. The distribution of these plots across the years, seasons, and crops are similar to the full-sample pattern. There are households cropping lands under different contracts over time as well as households cropping lands under different contracts during the same period.

**Tenants with Different Contracts over Time** There are 6,862 plot-level observations from households who have managed other plots under a contract with different incentive power over the periods. Among the 10,704 plots sampled, one has: 3,706 plots managed by households who only had lands under ownership over the periods (pure owner); 136 plots managed by households who only had lands under sharecropping over the periods (pure sharecropper); 4,313 plots managed by households who own and sharecrop different plots over the periods (mixed owner-sharecropper); 942 plots managed by households with plots under ownership and

[7] For additional details, see Singh, Binswanger, and Jodha (1985).

fixed rent over the periods (mixed owner-renter); 7 plots managed by households with plots under sharecropping and fixed rent over the periods (mixed sharecropper-renter); and 1,600 plots managed by households with lands under ownership, sharecropping, and fixed rent over the periods (mixed owner-renter-sharecropper).[8]

**Tenants with Different Contracts in a Same Period** There are also 3,539 plot-level observations from households who have managed other plots under a contract with different incentive power in the same period (year and season). Among the 10,704 productive plots sampled, one has: 6,876 plots managed by households who only had lands under ownership during that particular period (pure owner); 252 plots managed by households who only had lands under sharecropping during that particular period (pure sharecropper); 37 plots managed by households who only had lands under fixed rent during that particular period (pure renter); 2,833 plots managed by households who own and sharecrop different plots during that particular period (mixed owner-sharecropper); 456 plots managed by households with plots under ownership and fixed rent during that particular period (mixed owner-renter); 5 plots managed by managed by households with plots under sharecropping and fixed rent during that particular period (mixed sharecropper-renter); and 245 plots managed by households with lands under ownership, sharecropping, and fixed rent during that particular period (mixed owner-renter-sharecropper).

## 4 Econometric Methodology

Changes in market prices and shocks in production are two important types of risk faced by the households. Prices are exogenous under the assumption that markets are competitive. However, final production could be affected by households' endogenous actions, which must be taken into account when measuring the exogenous risk.

As usual in the literature of agricultural economics, production is modeled here through a stochastic Cobb-Douglas function with constant return to scale. An observation $i$ refers to a plot managed by some household in a certain year and

[8] There is no plot managed by a farmer who only had lands under fixed rent over the years (pure renter).

season. For each $i$, we assume:

$$Y_i = A_i K_i^{\alpha_k} L_i^{\alpha_l} T_i^{(1-\alpha_k-\alpha_l)} \exp(u_i), \tag{4.1}$$

where $Y_i$ is the amount (quantity) of output produced; $K_i$vand $L_i$ represent the amount of nonlabor and labor input used; $T_i$ is the cropped area; $A_i$ is a technological factor that accounts for the cropping regime, observable characteristics of the land and the household, as well as specific effects associated with each village, year, season, and crop grown; $\alpha_k$ and $\alpha_l$ are positive parameters; and $\varepsilon_i$ is an unobserved random term that accounts for possible hidden actions and unpredictable climatic shocks, infestations, rainfalls, and monsoon arrivals.[9]

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 (4.1) in monetary units as follows:

$$y_i = \left(\frac{A_i p_i}{r_i^{\alpha_k} w_i^{\alpha_l}}\right) k_i^{\alpha_k} l_i^{\alpha_l} T_i^{(1-\alpha_k-\alpha_l)} \exp(u_i), \tag{4.2}$$

where $p_i$ represents the recorded price of the 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:

$$\ln\left(\frac{y_i}{T_i}\right) = \ln(a_i) + \alpha_k \ln\left(\frac{k_i}{T_i}\right) + \alpha_l \ln\left(\frac{l_i}{T_i}\right) + u_i, \tag{4.3}$$

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

[9] There is a literature discussing whether the cropping regime affects productivity. Sharecropping farmers could potentially exert less managerial effort as they earn only a fraction of the marginal production and bear the entire marginal cost. We refer the reader to Shaban (1987) and Braido (2008) for different views on this topic. Our empirical strategy does not depend on that as we allow the productivity factor $A_i$ to vary across plots under different regimes.

## 4.1 Measuring Exogenous Risks

The input choices ($k_i$ and $l_i$) are endogenous and the error term $u_i$ captures the exogenous shocks in production. In an environment without externality, the Pareto efficient input allocation should solve the following problem:

$$\max_{k_i,l_i} E\left(a_i T_i^{(1-\alpha_k-\alpha_l)} k_i^{\alpha_k} l_i^{\alpha_l} \exp\left(u_i\right) - k_i - l_i\right), \ \forall i. \tag{4.4}$$

The optimal amounts of nonlabor and labor inputs are given by:

$$k_i^* = T_i \left(\alpha_k^{(1-\alpha_l)} \alpha_l^{\alpha_l} a_i\right)^{\frac{1}{1-\alpha_k-\alpha_l}}, \tag{4.5}$$

$$l_i^* = T_i \left(\alpha_l^{(1-\alpha_k)} \alpha_k^{\alpha_k} a_i\right)^{\frac{1}{1-\alpha_k-\alpha_l}}. \tag{4.6}$$

**TFP Approach** One can then use the Pareto optimal inputs (4.5)-(4.6) to rewrite equation (4.2) as:

$$y_i = T_i \left[(\alpha_k)^{\alpha_k} (\alpha_l)^{\alpha_l} a_i\right]^{\frac{1}{1-\alpha_k-\alpha_l}} \exp\left(u_i\right). \tag{4.7}$$

The log-linear version of (4.7) is then given by:

$$\ln\left(\frac{y_i}{T_i}\right) = \gamma_0 + \gamma_1 \ln a_i + u_i, \tag{4.8}$$

where $\gamma_0 = \alpha_k \ln(\alpha_k) + \alpha_l \ln(\alpha_l)$ and $\gamma_1 = \frac{1}{1-\alpha_k-\alpha_l}$. In a first approach, I measure $u_i$ by predicting the error term after an OLS regression of (4.8), where a large number independent variables are used to proxy the variations in the technological factor $a_i$. The control variables used in this regression are: dummies for the cropping regime, the log of the land value, and fixed effects for the village, irrigation, soil category, and for the interaction among the farmer id, the year, and the cropping season.

**Labor Input Approach** In spite of the large number of fixed effects used in the first approach, one should fear that land quality is still poorly measured by the observed variables. I therefore pursue the following alternative strategy to measure $u_i$. Notice from (4.6) that:

$$a_i = \frac{\left(\frac{l_i^*}{T_i}\right)^{(1-\alpha_k-\alpha_l)}}{\alpha_l^{(1-\alpha_k)} \alpha_k^{\alpha_k}}. \tag{4.9}$$

Therefore, equation (4.7) can also be written as:

$$y_i = \frac{1}{\alpha_l} l_i^* \exp(u_i). \tag{4.10}$$

The log-linear version of (4.10) is:

$$\ln(y_i) - \ln(l_i^*) = \ln\left(\frac{1}{\alpha_l}\right) + u_i. \tag{4.11}$$

Since detailed data on labor supply is available, one can also measure $u_i$ from the residuals of an OLS regression of $\ln(y_i) - \ln(l_i^*)$ on a constant term. Our estimate for the constant is 1.392 with a standand deviation of .020. This implies an estimate for $\alpha_l$ equals 0.25.

**Nonlabor Input Approach** By a symmetric argument, one can also use the nonlabor inputs to measure $u_i$. Take equations (4.5) and (4.7) and write

$$\ln(y_i) - \ln(k_i^*) = \ln\left(\frac{1}{\alpha_k}\right) + u_i. \tag{4.12}$$

This equation can also be estimated by OLS and used to project $u_i$. Our estimate for the constant is .915 with a standand deviation of .024. This implies an estimate for $\alpha_k$ equals 0.40.

## 4.2 Testing the Incentive-Risk Relation

The variability of error term $u_i$ accounts for exogenous shocks such as climatic changes, infestations, and blights. Three different regression procedures are used to measure it. Given that, I use the heteroskedasticity test (see Glesjer, 1969) to assess whether the variance of $u_i$ differs across plots managed by a given farmer under different contracts.

Formally, consider the following class of models:

$$u_i^2 = g(d_i\beta + z_i\varphi + v_i), \tag{4.13}$$

where $g(\cdot)$ is a continuous and increasing function; $d_i$ is a vector with the relevant contract dummies; $z_i$ is a vector with household dummies to control for the household's risk aversion; $\beta$ and $\varphi$ are parameter vectors; and $\upsilon_i$ is an error term.

For the commonly used linear and quadratic specifications of the function $g(\cdot)$, the heteroskedasticity model becomes (respectively):

$$u_i^2 = d_i\beta + z_i\varphi + \upsilon_i, \tag{4.14}$$

and

$$| u_i | = d_i\beta + z_i\varphi + \upsilon_i. \tag{4.15}$$

In both cases, the vector $\beta$ indicates whether the variability of $u_i$ differs across lands under different contracts.[10]

# 5 Empirical Results

As mentioned before, I used three alternative approaches to measure risk. Since the results are qualitatively identical, I present here the results for the labor input approach. Table 4 presents the results. The linear and quadratic specifications of the models are estimated three times: (i) without fixed effects; (ii) with household fixed effects; and (iii) with fixed effects per household and period (season of each year). Overall, risk is statistically equal across lands under fixed rent and sharecropping and slightly higher in owner-operated lands. This does not support the risk-sharing argument.

**[Table 4]**

I then present two different exercises to test the robustness of these results.

## 5.1 Subsample of Leased Plots

It is interesting to investigate the validity of the risk-sharing prediction in a restricted subsample containing only leased plots. If owners and tenants accessed the same technology, these results should not differ from those based on the entire sample. In this case, restricting attention to the subsample of leased plots would only reduce efficiency of the estimates. However, if owners and tenants accessed different technologies, then the first-step regression and the risk measure could be

[10] Note that linear regressions do not compute causal relationships, but only conditional correlations. Here, in particular, the exogenous term $u_i^2$ appears in the left-hand side of equation (4.13), while the endogenous contract dummies appear in its right-hand side.

modified when one restricts attention to the subsample of leased plots. Checking this possibility is the main motivation behind the exercise performed here.

This subsample contains 1,796 leased plots, cropped by 134 different households. Around 88.7% of these plots are sharecropped and 11.3% of them are leased under fixed rent. Moreover, there are 479 plots being cropped by households who manage multiple plots under sharecropping and fixed rent during the years of data collection (allowing one to introduce household fixed effects). Finally, there are also 126 plots cropped by tenants that manage multiple plots under sharecropping and fixed rent during the same period (allowing one to introduce household-per-period fixed effects).

The procedure based on the Glesjer's heteroskedasticity test is replicated for this subsample. I use the three approaches discussed before to measure of risk. For each of them, I run six different specifications of the Glesjer's test. Table 5 presents the results for the case where the labor input approach is used to measure risk. The results are qualitatively the same when the other two approaches are used. They confirm that the exogenous error term is homoscedastic across plots under sharecropping and fixed rent.

[**Tables 5**]

### 5.2 Results Per Type of Crop

Allen and Lueck (1992) argue that the costs of dividing the output affect the design of land-leasing contracts. Since these costs vary across cropping varieties, it is worth investigating whether the risk-sharing prediction is valid for some isolated crops.

Our testing procedure is then performed for subsamples of plots cultivating each of the five most common crops—namely, cereals; oilseeds; pulses; fiber crops; and vegetables and spices. We use the labor-input approach to perform a total of 30 regressions relatively to 6 different specifications of the Glesjer's test for 5 crop categories. Among them, there are only three isolated regressions (for different crops) in which either the ownership dummy or the fixed-rent dummy were statistically negative at the 5% level. Overall, the risk-sharing prediction is systematically rejected.

## 6 Concluding Remarks

This paper tests a classic prediction of the moral hazard theory: the negative correlation between the contract's incentive power and its underlying risk, for each given agent. The empirical literature on contract theory relies on contracts from different agents to test this prediction. Ackerberg and Botticini (2002) point out for potential endogeneity bias inherent to this strategy. Here, the risk-sharing prediction is assessed by means of a database on tenancy contracts that contains households cropping multiple plots under different contracts. This feature allows us to compare the risk of different plots cropped by the same agent under different contracts. The findings do not support the existence of a negative risk-incentive relationship.

The theoretical implication tested in this paper holds under the assumption that the agents consume the final payment and do not access external financial instruments (exclusive contracts). Townsend (1994) and Chiappori et al. (2014) show that household consumption is smoother than agricultural production in the ICRISAT villages. Townsend and Mueller (1998) also find evidence suggesting that Indian farmers access different sources of credit and use them to smooth consumption. Credit and other consumption smooth aggreements are possibly behind the empirical failure of the classic risk-incentive negative relation.

## References


[1] **Ackerberg, Daniel A. and Maristella Botticini** "Endogenous Matching and the Empirical Determinants of Contract Form." *Journal of Political Economy*, June 2002, 110 (3), 564-591.

[2] **Allen, Douglas and Dean Lueck** "Contract Choice in Modern Agriculture: Cash Rent versus Cropshare." *Journal of Law and Economics*, October 1992, 35 (2), 397-426.

[3] **Allen, Douglas and Dean Lueck** "Transaction Costs and the Design of Cropshare Contracts." *RAND Journal of Economics*, Spring 1993, 24 (1), 78-100.

[4] **Allen, Douglas W. and Dean Lueck** "The Role of Risk in Contract Choice." *Journal of Law, Economics, and Organization*, October 1999, 15 (3), 704-736.

[5] **Allen, Douglas W. and Dean Lueck** "The Nature of the Farm: Contracts, Risk and Organization in Agriculture." MIT Press, Cambridge, MA, 2003.

[6] **Aggarwal, Rajesh K. and Andrew A. Samwick** "The Other Side of the Trade-Off: The Impact of Risk on Executive Compensation." *Journal of Political Economy*, February 1999, 107 (1), 65-105.

[7] **Braido, Luis H.B.** "Insurance and Incentives in Sharecropping." In *Competitive Failures in Insurance Markets*, P.A. Chiappori and C. Gollier (eds.), MIT Press, Cambridge, MA, 2006.

[8] **Braido, Luis H.B.** "Evidence on the Incentive Properties of Share Contracts." *Journal of Law and Economics*, May 2008, 51 (2), 327-349.

[9] **Braido, Luis H.B. and Genaro L. Dueire** "Morbidity Risk and Health-Insurance Coverage." *FGV working paper*, March 2015.

[10] **Cardon, James H. and Igal Hendel** "Asymmetric Information in Health Insurance: Evidence from the National Medical Expenditure Survey. " *RAND Journal of Economics*, Autumn 2001, 32 (3), 408-427.

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

[12] **Chiappori, Pierre-André, Krislert Samphantharak, Sam Schulhofer-Wohl, and Robert M. Townsend** "Heterogeneity and Risk Sharing in Village Economies." *Quantitative Economics*, March 2014, 5 (1), 1-27.

[13] **Dee, Carol Callaway, Ayalew Lulseged, and Tanya S. Nowlin** "Executive Compensation and Risk: The Case of Internet Firms." *Journal of Corporate Finance*, December 2005, 12 (1), 80-96.

[14] **Garen, John E.** "Executive Compensation and Principal-Agent Theory." *Journal of Political Economy*, December 1994, 102 (6), 1175-1199.

[15] **Glesjer, H.** "A New Test for Heteroscedasticity." *Journal of the American Statistical Association*, March 1969, 64 (325), 316-323.

[16] **Holmstrom, Bengt and Paul Milgrom** "Aggregation and Linearity in the Provision of Intertemporal Incentives." *Econometrica*, March 1987, 55 (2), 303-328.

[17] **Jin, Li** "CEO Compensation, Diversification, and Incentives." *Journal of Financial Economics*, October 2002, 66 (1), 29-63.

[18] **Lafontaine, Francine** "Agency Theory and Franchising: Some Empirical Results." *RAND Journal of Economics*, Summer 1992, 23 (2), 263-283.

[19] **Lafontaine, Francine and Sugato Bhattacharyya** "The Role of Risk in Franchising." *Journal of Corporate Finance*, October 1995, 2 (1-2), 39-74.

[20] **Lambert, Richard and David Larker** "An Analysis of the Use of Accounting and Market Measures of Performance in Executive Compensation Contracts." *Journal of Accounting Research*, Supplement 1987, 25 (Studies on Stewardship Uses of Accounting Information), 85-125.

[21] **Pandey, Priyanka** "Effects of Technology on Incentive Design of Share Contracts." *American Economic Review*, September 2004, 94 (4), 1152-1168.

[22] **Prendergast, Canice** "The Tenuous Trade-off between Risk and Incentives." *Journal of Political Economy*, October 2002, 110 (5), 1071-1102.

[23] **Rao, C.H. Hamunantha** "Uncertainty, Entrepreneurship, and Sharecropping in India." *Journal of Political Economy*, May-June 1971, 79 (3), 578-595.

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

[25] **Singh, R.P., H.P. Binswanger and N.S. Jodha** "Manual of Instructions for Economic Investigators in ICRISAT's Village Level Studies." Technical Report, International Crops Research Institute for Semi-Arid Tropics, May 1985.

[26] **Townsend, Robert M.** "Risk and Insurance in Village India." *Econometrica*, May 1994, 62 (3), 539-591.

[27] **Townsend, Robert M. and Rolf A.E. Mueller** "Mechanism Design and Village Economies: From Credit to Tenancy to Cropping Groups." *Review of Economic Dynamics*, January 1998, 1 (1), 119-172.

**Table 1. Data Description**

| Variable | Description |
|---|---|
| Output | Value of main output and byproducts, measured in Indian rupees |
| Ownership Dummy | 1 if plot is owned (83.2%); 0 otherwise |
| Fixed-Rent Dummy | 1 if plot is rented on a fix-rent basis (1.9%); 0 otherwise |
| Area Cropped | Actual area cropped, measured in acres |
| Nonlabor Input | Value of seeds, fertilizers, pesticides, 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, etc., obtained from a village specialist |
| Irrigation Dummy | 1 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; 0.5% problem soil (saline, etc.); 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; 0.4% garden crops; 14% pulses; 0.8% 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; 0.2% perennial crops |
| Household | Village-specific numerical code that identifies the household |

*Note:* Data 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 during each season of the year.

**Table 2. Summary Statistics**

| Variable | Mean | Min. | Max. | St. Dev. | Sample Size |
|---|---|---|---|---|---|
| Per Acre Output | 754.1 | 0.68 | 24,964 | 1,106 | 10,704 |
| Per Acre Nonlabor Input | 318 | 0 | 16,478.8 | 507.2 | 10,704 |
| Per Acre Labor Input | 150 | 0.29 | 3,064 | 181.6 | 10,704 |
| Per Acre Land Value | 34 | 0 | 160 | 24.6 | 10,704 |

*Note:* Data from the ICRISAT’s Village Level Studies.

**Table 3. Summary Statistics by Land Contract**

| | Per Acre Output | | | |
|---|---|---|---|---|
| | **Coefficient of Variation (σ/μ)** | **Standard Deviation (σ)** | **Mean (μ)** | **Sample Size** |
| **Ownership** | 1.45 | 1,166.5 | 804.5 | 8,908 |
| **Fixed Rent** | 1.23 | 722.4 | 587.0 | 203 |
| **Sharecropping** | 1.37 | 678.0 | 493.5 | 1,593 |

*Note:* Data from the ICRISAT's Village Level Studies.

**Table 4. Heteroscedasticity Test**

*Ordinary Least Square*

| | No Fixed Effect | | Household Fixed Effects | | Household-Period Fixed Effects | |
|---|---|---|---|---|---|---|
| | $(\hat{u}_{it})^2$ | $\lvert\hat{u}_{it}\rvert$ | $(\hat{u}_{it})^2$ | $\lvert\hat{u}_{t}\rvert$ | $(\hat{u}_{it})^2$ | $\lvert\hat{u}_{it}\rvert$ |
| **Ownership Dummy** | 0.050 | 0.022 | **0.080*** | **0.039*** | 0.079 | 0.038 |
| Robust Std. Err. | (0.039) | (0.019) | (0.043) | (0.022) | (0.051) | (0.027) |
| **Fixed-Rent Dummy** | 0.104 | 0.036 | -0.120 | -0.048 | -0.137 | -0.058 |
| Robust Std. Err. | (0.144) | (0.064) | (0.132) | (0.042) | (0.152) | (0.049) |
| **Constant** | **0.535***** | 0.547*** | Yes | Yes | Yes | Yes |
| *Sample Size* | *10,704* | *10,704* | *10,704* | *10,704* | *10,704* | *10,704* |

*Note:* The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The cluster method is used to compute robust t-statistics and standard errors in order to account for the fact that households, rather than plots, are the primary sampling unit. Household fixed effects refer to 275 dummy variables generated from codes identifying the household (constant over different periods). Similarly, 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).

**Table 5. Heteroscedasticity Test – Subsample of Leased Plots**

*Ordinary Least Square*

| | **No Fixed Effect** | | **Household Fixed Effects** | | **Household-Period Fixed Effects** | |
|---|---|---|---|---|---|---|
| | $(\hat{u}_{it})^2$ | $\lvert \hat{u}_{it} \rvert$ | $(\hat{u}_{it})^2$ | $\lvert \hat{u}_{t} \rvert$ | $(\hat{u}_{it})^2$ | $\lvert \hat{u}_{it} \rvert$ |
| **Fixed-Rent Dummy** | 0.089 | 0.023 | -0.083 | -0.001 | -0.167 | -0.007 |
| Robust Std. Err. | (0.135) | (0.060) | (0.203) | (0.068) | (0.265) | (0.103) |
| **Constant** | **0.534*** ** | **0.552*** ** | Yes | Yes | Yes | Yes |
| *Sample Size* | *1,796* | *1,796* | *1,796* | *1,796* | *1,796* | *1,796* |

*Note:* The asterisks ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively. The cluster method is used to compute robust t-statistics and standard errors in order to account for the fact that households, rather than plots, are the primary sampling unit. Household fixed effects refer to 134 dummy variables generated from codes identifying the household (constant over different periods). Similarly, household-period fixed effects refer to 663 dummy variables generated through the iteration of codes identifying the household and the period (year and season).