The Role of Risk in Contract Choice

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Structuring contracts to share risk in light of incentive problems is the central premise of contract theory, yet the risk-sharing implications have rarely been thoroughly tested using micro-level contract data. In this article we test the major implications of a principal-agent model of contracts using detailed data on more than 4000 individual contracts from modern North American agriculture. On a case-by-case basis, our evidence fails to support the standard principal-agent model with risk aversion as an explanation of contract choice in modern North American farming. At the same time, we find some support for models that assume risk-neutral contracting parties and stress multiple margins for moral hazard and enforcement costs.

1. Introduction

The theory of contracts is an important development in modern economics, having matured from casual intuition to a rigorous framework in roughly two decades. Empirical work on contracts is still catching up, however, and key theoretical implications remain largely untested. One of the more important empirical gaps pertains to the role risk plays in determining the choice and structure of contracts. That contracts are often structured to allocate risk is a time-honored assumption of contract theory, yet rarely have its implications been rigorously tested using micro-level data. In this article we test the major risk implications of the standard principal-agent model of contracts using detailed data on more than 4000 individual contracts from modern North American agriculture.

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Economists' long-standing interest in contracts, and their particular fascination with agricultural share contracts, can be traced to Adam Smith's criticism of sharecropping in *The Wealth of Nations*. Smith, along with John Stuart Mill and Alfred Marshall, noted the farmer's moral hazard inherent in share contracts. This appraisal of share contracts went unchallenged until Johnson's (1950) study of Midwestern farming signaled the beginning of efforts to explain contract choice. Modern contract theory subsequently emerged with a focus on sharecropping that postulated a trade-off between risk and moral hazard incentives (Cheung, 1969; Stiglitz, 1974). The risk-sharing foundation remains more or less intact today and has been used to explain various contractual arrangements including executive compensation (Garen, 1994), franchising (Martin, 1988), insurance (Townsend, 1994), leasing (Leland, 1978), partnerships (Gaynor and Gertler, 1995), as well as sharecropping.[1]

For economists studying agriculture, in both developed and undeveloped economies, the principal-agent framework with risk aversion was adopted quickly and still retains its primacy. Indeed, Stiglitz (1987:321) writes: "the sharecropping model has served as the basic paradigm for a wider class of relationships known as principal-agent relationships," and Sappington (1991:46) notes, "The classic example of the principal-agent relationship has a landlord overseeing the activities of a tenant farmer." In an important study, Otsuka et al. (1992:2012) claim that risk aversion "provides the most consistent explanation for the existence of a share contract." Relying on the standard risk-sharing framework, they further state (1992:1987): "As in typical agency models, the most obvious factor to be accounted for in considering the optimum contract choice is the presence of uncertainty coupled with the risk aversion of the contracting parties." The dominance of this approach in modeling the behavior of farmers is not limited to those studying developing countries or economic history (e.g., Otsuka et al., 1992; Townsend, 1994). It is routine among agricultural economists studying farm behavior—including acreage and crop choice studies as well as contract studies—to assume that farmers are more risk averse than landowners and stress the role of risk in determining behavior (e.g., Chavas and Holt, 1990; Pope and Just, 1991).

Despite the prominence of the principal-agent paradigm, the empirical evidence to support its implications is scarce.[2] In agriculture there has been little empirical work at the contract level and nearly all of this has been in developing economies or medieval Europe (Otsuka et al., 1992). In one of the few studies to confront risk sharing and contract choice, Rao (1971) found that crops with high yield and profit variability were *less* likely to be sharecropped, directly

1. Milgrom and Roberts (1992:207) summarize: "efficient contracts balance the costs of risk bearing against the incentive gains that result."

2. Not only is the evidence scare, but what there is is mixed. Prendergast (1999:21) states: "there is some evidence that contracts are designed to optimally trade off risk against incentives. However, the evidence is hardly overwhelming, with some studies showing the effect of noise on piece rates while others show little." Allen and Lueck (1995) summarize related literature with similar findings to Prendergast.

refuting the anecdotal evidence originally provided by Cheung (1969). At the same time, studies by Rao and others (e.g., Higgs, 1973) tend to use rather small samples of highly aggregated data, making clear inferences difficult. In fact, most empirical land contracting studies have examined the effects of contract choice on input use rather than estimate the factors that determine contract choice (Otsuka et al., 1992). Empirical contract studies (e.g., Crocker and Masten, 1988; Joskow, 1987) outside of agriculture have successfully focused on incentives such as enforcement costs, moral hazard, and specific assets, and routinely have ignored risk allocation issues.[3] And even though there have been studies of agricultural contracts that ignore differences in attitudes toward risk (e.g., Alston and Higgs, 1982; Alston et al., 1984; Eswaran and Kotwal, 1985; Laffont and Matoussi, 1995; Allen and Lueck, 1992b, 1993), the risk framework is still the standard.

Our article begins by summarizing the main predictions from the principal-agent literature on share contracting and shows how these predictions can be empirically implemented. Next, we test some of the major risk implications of this literature against our contract data. In general, we find almost no support for predictions motivated by risk sharing. The strength of our study lies in our ability to match the risk-based principal-agent model of contracts to a set of data on individual farmland contracts, and then to link this contract data to credible measures of exogenous risk by using data on crop yield variability. We finish the study by contrasting the risk-based predictions with those derived from pure incentive-based contracting models of risk-neutral parties. Because the contracts we examine have features common to contracts elsewhere, our findings have implications beyond agriculture and should be of broad interest.

2. The Principal-Agent Framework with Risk Aversion

The standard model of agricultural contracts is a principal-agent model with several routine assumptions: the principal is a risk-neutral landowner and the agent is a risk-averse farmer; the effort of the farmer is not observable; the landowner is unable to shirk and the land cannot be exploited by the farmer; and finally, farm production is variable, depending on both the effort of the farmer and random forces.

2.1 The Basic Structure and Implications

Under these assumptions the standard model takes on the following specific form. For a plot of land, crop production is $q = (e + \theta)$, where e is the unobservable effort of the farmer, and θ is a random variable with mean 0 and variance σ^2.[4] The agent's (farmer's) utility is typically a linear mean-variance function of income from the rented land and includes a coefficient

3. Shelanski and Klein (1995) review the large and expanding literature.

4. This production function is routine in principal-agent analyses applied to agriculture (e.g., Otsuka et al., 1992; Laffont and Matoussi, 1995) and to business (e.g., Kawasaki and McMillan, 1987; Garen, 1994).

of absolute risk aversion.[5] The farmer's problem is to maximize his expected utility by choosing his optimal effort level given the terms of the land contract. Because farmer effort is unobservable and because there is uncertainty in farm production, there is moral hazard in any contract for which the farmer receives less than 100% of the crop. The principal (landowner) maximizes expected profits by choosing the optimal contract parameters, usually some combination of a share of the output and a fixed payment. The landowner makes his choice given the agent's behavior; that is, subject to the farmer's incentive compatibility and individual rationality constraints.

The equilibrium contract that solves this model trades off the incentive effects of greater output shares to the agent against the risk aversion of the agent. If, for instance, the farmer were risk neutral, then the optimal contract would be a fixed rent contract in which the farmer was the complete residual claimant of the output. Farmer effort would be first-best since there would be no moral hazard. Thus, by incorporating risk-averse preferences into the model, a rationale for share contracts emerges. This is because a risk-averse farmer prefers a contract in which he is not compensated solely on the basis of variable output, as in a fixed rent contract. The greater the risk aversion of the farmer the more likely a contract will share output. Similarly, as the random component of nature becomes larger (larger σ^2), the more likely it is that a contract will have a sharing component. Principal-agent models with this structure generate a number of predictions.[6] Below we list the more important predictions we are able to test with our contract data.

- *P1a: As output variability (σ^2) increases it is more likely that a share contract will be chosen over a cash rent contract.*
- *P1b: As output variability (σ^2) increases the farmer's share of output will decrease.*
- *P2: Share contracts will not be chosen unless farmers are risk averse.*
- *P3a: Under declining absolute risk aversion, as farmer wealth increases it is more likely that cash rent contract will be chosen over a cropshare contract.*
- *P3b: Under declining absolute risk aversion, as farmer wealth increases, the farmers' share of output will increase.*

2.2 Implementing the Predictions

In a standard principal-agent model the farmer's utility depends on the level and variance of income derived from the land contract. The farmer's income, in turn, depends on the price of the crop (P) times the crop quantity (Y). In principle, the variance in income (PY) will influence the choice of contract, yet

5. The linear mean-variance utility function is routinely used, especially in agriculture (e.g., Chavas and Holt, 1990; Pope and Just, 1991; Gaynor and Gertler, 1995).

6. There are numerous sources for these predictions (e.g., Cheung, 1969; Stiglitz, 1974; Leland, 1978; Kawasaki and McMillan, 1987; Hirshleifer and Riley, 1992) but they are most conveniently summarized in Otsuka et al. (1992).

the above predictions ignore income variability and focus exclusively on output (crop yield) variability. We are able to ignore price and income variability in the tests we perform because of the way we develop our contract data sample.[7] In our tests of predictions 1a and 1b we use contract data in which all farmers grow the same crop. Moreover, all of these crops are sold in world markets in which individual farmers are price takers. This means that there is no variance in price across farmers and that income variance is equivalent to yield variance.[8]

Even when the test conditions are so controlled that price variability can be ignored there arise other issues for the appropriate measure of yield variability. Testing Predictions 1a and 1b requires data on the variance in the random input, σ^2. We measure this "exogenous variability" by using data on crop yields.[9] Still, successfully conducting these tests has potential problems because production (crop yield) variability has two sources: 1) exogenous variability that cannot be influenced by the contracting parties (variability of θ or σ^2); and 2) endogenous variability that is influenced by the actions of any contracting party (variability of e). The impediment to performing tests of risk sharing lies in the difficulty of finding a reasonable empirical counterpart for σ^2 at the contract level, one that is not contaminated with endogenous variability.[10] Finding such measures in studies of franchising and other areas has proved difficult (Lafontaine and Battacharyya, 1995b), so most have relied on proxies which often seem reasonable but are not often clearly linked to the underlying theoretical model and may be highly endogenous to the firm's behavior.[11]

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7. Even when data on prices is relevant it is not clear that historical price variability data is a relevant measure of a farmer's forward-looking price variability because of continual changes in market conditions. Historical measures of yield variability are more reliable because they are mostly determined by long-term natural forces such as weather and pest populations.

8. If P and Y are independent then $\text{var}(PY) = \sigma_P^2\sigma_Y^2 + \sigma_P^2\mu_P^2 + \sigma_Y^2\mu_Y^2$, which implies that data on the mean and variance of output prices would be needed to test the standard principal-agent model. Even when price is constant, $\text{var}(PY) = P^2\sigma_Y^2$, and including price data is still required. If price has no variability across the observations because of price-taking markets, then two possibilities emerge: (1) If price is literally constant then $\text{var}(PY) = k\sigma_Y^2$, where k is a scale parameter and incorporating price data in a regression would simply rescale the estimated coefficients on yield variability; (2) If price is random, but the same for all observations, then the regression constant incorporates the price data.

9. The possibility of a negative correlation between yield and price might suggest that sharing output could actually mitigate risk. However, because all of the farmers in our sample operate in competitive world markets, this is highly unlikely. Indeed, calculations of price-yield correlations at the state or province level indicate that statistically significant negative relationships are unusual (see the Data Appendix, Table A.3). More important, because our tests exploit regional and county (or parish) yield variability, even negative statewide price-yield correlations are not relevant.

10. Alternatively, one could, in principle, test the model with data on individual risk preferences. Ordinarily such data would seem to be impossible to obtain, although some (e.g., Gaynor and Gertler, 1995) have used self-reported risk preference measures.

11. For instance, a recent study of executive compensation contracts by Garen (1994) notes the "endogeneity problem" and thus uses industry-wide research and development (R&D) expenditures as a measure of the exogenous variability, claiming that "settings in which R&D is important should display a greater variance in returns in investment opportunities." Kawasaki and McMillan (1987) and Lafontaine (1992) use proxy variables that are endogenous to firm behavior as well.

In order to completely purge endogenous variability in farm production, a true measure of variability in the random input would require daily time-series data on a composite variable *for each crop* that included all natural factors from rainfall and temperature to sunlight and insect populations. Such a composite variable would be a proxy for θ and would require measures of the quantities of these natural parameters. More important, it would also require measures of the *timing* of these parameters. Such data are simply not available on a crop-by-crop basis. Timing is of particular importance for weather variables such as rainfall.[12] Simple measures of rainfall would not, for example, provide information about hailstorms or rain coming in the middle of a harvest. It is entirely possible, for instance, that a late August rainfall in South Dakota can severely harm a swathed wheat crop ready to be combined and simultaneously aid a standing crop of corn or sunflowers to be harvested later.

In lieu of this measurement problem, we use data on crop yield variability for the region in which a plot of farmland is located, to approximate this ideal measure of exogenous variability when there are large numbers of farmers in a relatively homogeneous region. To illustrate, define a "region" as an area where n farmers produce the same crop and face the same exogenous forces of nature and use the same technology each year. For any individual farmer i producing crop j, the output or yield (per acre) for period t will be

$$Y_{ijt} = e_{ijt} + \theta_{jt} \text{ for } i = 1, \ldots, n;\ j = 1, \ldots, k;\ \text{ and } t = 1, \ldots, T; \tag{1}$$

where θ_{jt} is distributed with mean 0 and intertemporal variance σ_j^2, as in the theoretical model. The random input θ_{jt} varies across time and crops but not across farms within a region. Aggregating across n farmers, average per-period regional yield for crop j is $\bar{Y}_{jt} = \left(\sum_{i=1}^{n} Y_{ijt}\right)/n$, which simplifies to

$$\bar{Y}_{jt} = \left[\sum_{i=1}^{n} \frac{e_{ijt}}{n}\right] + \theta_{jt}. \tag{2}$$

The first term on the right-hand side of Equation (2) approaches a time-independent constant as n gets "large," so the variance of average regional yield for crop j becomes[13]

$$\text{var}(\bar{Y}_{jt}) = \text{var}(\theta_{jt}) = \sigma_j^2. \tag{3}$$

The counties and parishes in our dataset closely approximate the conditions described by the model in Equations (1)–(3). First, each county or parish has several hundred or more farmers using nearly identical technology. In particular, the mean number of farms per county or parish is 456 for Louisiana, 650 for Nebraska, and 551 for South Dakota. Second, the regions for which data are

12. Rosenzweig and Binswanger (1993), confirming many studies, find that the timing of monsoons is an important variable in explaining crop yields in India, but that rainfall amounts are not good explanatory variables.

13. This requires that the total output of the region be bounded. This model assumes the covariance between effort e and natural parameters θ is zero, which is consistent with the standard production technology assumed in the principal-agent literature.

available are reasonably homogeneous areas where "idiosyncratic risks" are not important.[14] As a result, for the crops and regions we examine, variability in average regional yields (measured as the standard deviation or coefficient of variation) is a solid, but not perfect, measure of the variability in the random input (θ).

To implement this approach we collected 10 to 15 years of time-series data on the variability in crop yields for 13 different crops for the region of each observed contract (see Data Appendix). Crop yield is calculated as total crop output in a region divided by total acres of the crop in the region. By doing this we measure exogenous variability for each contract choice observation in our dataset. We calculate yield variability, which approximates exogenous variability (σ^2), two ways: 1) $STD(\bar{Y}_t)$ is the standard deviation of yield over time; and 2) $CV(\bar{Y}_t)$ is the coefficient of variation of yield over time. For the Nebraska–South Dakota contract data we calculate these measures at the county level and for larger, homogeneous regions that include several counties. For Louisiana we use only parish (county) yield data and for British Columbia we use only yield data from rather large geographic regions. Table 1 reports their means (and standard errors) for each crop.[15] The calculations and sources for these data are explained in the Data Appendix.

3. Empirical Analysis of Agricultural Contract Data

To test the model we must couple the data on exogenous variability with micro-level data on individual farm contracts. We begin this section by describing our contract data and examining some preliminary findings. We then examine the extent to which the risk parameters (derived above) explain contract features by examining contract-level data. We also examine related risk predictions based on the wealth, institutions, and the extent of future's markets.

3.1 Farm-Level Contract Data

Four surveys provide the contract data: the 1986 Nebraska and South Dakota Leasing Survey, the 1992 British Columbia Farmland Ownership and Leasing Survey, the 1979 British Columbia Farming Lease Survey, and the 1992 Louisiana Farmland Ownership and Leasing Survey. Each survey gathered data on farmland contracts and other organizational features of agriculture in the respective regions. Table 2 defines the contract variables as well as the variables

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14. For other types of agriculture heterogeneous regions may generate enough idiosyncratic risk that performing this test may not be possible. Lafontaine and Battacharyya (1995b) suggest that such heterogeneity plagues franchising studies of risk sharing. On the other hand, if regions were *perfectly* homogeneous one might expect relative performance contracts for farm production. Such contracts are *never* observed in our dataset but are found in chicken production where (homogeneous) technology and inputs are provided by a single supplier to many growers (Knoeber, 1989).

15. Table 1 cannot be completed for British Columbia because its regions tend to encompass the entire provincial production for the crops we examine. Also, our measures of crop yield variability are not consistent between British Columbia and the other three states because of data limitations. In particular, British Columbia yield data is not available for smaller, countylike areas.

Table 1. Variable Means for Crop Yield Data

Nebraska–South Dakota Crop Samples

Yield variable	Dryland corn	Irrigated corn	Dryland soybeans	Irrigated soybeans	Dryland sorghum	Irrigated sorghum	Barley	Oats	Wheat
REGIONAL CV	0.24	0.09	0.18	0.10	0.19	0.09	0.24	0.24	0.22
	(0.04)	(0.04)	(0.02)	(0.02)	(0.04)	(0.01)	(0.03)	(0.06)	(0.07)
COUNTY CV	0.26	0.12	0.20	0.11	0.20	0.11	0.29	0.24	0.21
	(0.05)	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.06)	(0.06)	(0.07)
REGIONAL STD	17.61	11.79	5.19	3.93	11.15	8.37	9.05	10.86	6.47
	(4.54)	(5.08)	(0.46)	(0.67)	(0.88)	(1.15)	(0.76)	(2.49)	(1.58)
COUNTY STD	19.33	14.88	5.71	4.54	12.98	9.79	10.88	10.99	6.35
	(4.58)	(4.35)	(0.84)	(0.79)	(1.79)	(1.67)	(1.92)	(2.37)	(1.42)
REGIONAL MEAN	73.29	127.31	29.40	40.51	62.53	90.71	38.87	45.98	31.11
	(12.65)	(6.01)	(1.99)	(1.44)	(13.13)	(4.92)	(4.52)	(4.77)	(4.51)
COUNTY MEAN	74.29	125.56	29.44	40.51	67.27	90.06	37.80	46.73	31.07
	(12.08)	(8.61)	(2.92)	(2.39)	(10.58)	(5.61)	(4.73)	(6.72)	(5.06)

Louisiana Crop Samples

Yield variable	Cotton	Corn	Rice	Sorghum (milo)	Soybeans	Sugarcane	Wheat
PARISH CV	0.19	0.34	0.15	(0.33)	0.24	0.18	0.23
	(0.05)	(0.13)	(0.04)	(0.11)	(0.08)	(0.04)	(0.04)
PARISH STD	136.70	26.19	6.09	14.71	5.85	5.11	7.77
	(31.23)	(9.95)	(1.52)	(2.99)	(0.92)	(0.97)	(1.40)
PARISH MEAN	697.74	77.76	40.42	45.46	25.85	29.00	33.27
	(82.48)	(12.14)	(4.47)	(6.03)	(5.01)	(1.46)	(1.89)

Standard errors are in parentheses.

Table 2. Definition of variables

Dependent variables		
CONTRACT	=	1 if contract was a cropshare contract; = 0 if cash rent.
SHARE	=	Fraction of crop owned by the farmer in a share agreement.
Independent variables		
ACRES	=	Number of acres covered by contract.
AGE	=	Farmer's age in years (a categorical variable for Nebraska and South Dakota).
BUILDINGS	=	Total value in $1000s of all owned buildings multiplied by the equity in the farm.
CORN, OATS,...	=	1 if (corn, oats,...) was the major crop on the contracted land.
EQUIPMENT	=	Total value in $1000s of all owned equipment multiplied by the equity in the farm.
FAMILY	=	1 if the farmer and the landowner were related.
FARM INCOME	=	1 if less than 30% of total income came from farming, 2 if 30%–49%, 3 if 50%–80%, 4 if > 80%.
FUTURES MARKET	=	1 if there is an organized futures market for the crop (barley, canola, cotton, corn, oats, rice, soybeans, sugar, wheat).
FULLTIME	=	1 if the operator is a full-time farmer.
INSTITUTION	=	1 if the landowner is an institution (available only for Nebraska and South Dakota farmer samples).
IRRIGATION	=	Percent of land under irrigation.
LAND	=	Total value in $1000s of all owned land multiplied by the equity in the farm.
WEALTH	=	Total value of all owned buildings, equipment, and land multiplied by the equity in the farm.
Exogenous variables		
COUNTY CV	=	Coefficient of variation for crop yield in a county or parish.
REGIONAL CV	=	Coefficient of variation for crop yield in a region.
STATE CV	=	Coefficient of variation for crop yield in a state or province.
COUNTY MEAN	=	Mean crop yield in a county or parish.
REGIONAL MEAN	=	Mean crop yield in a region.
COUNTY STD	=	Standard deviation of crop yield in a county or parish.
REGIONAL STD	=	Standard deviation of crop yield in a region.

used to measure exogenous variability. The Data Appendix describes the data sources, shows summary statistics (Table A.1), explains calculations, and shows that these samples are unlikely to be systematically biased (see Table A.2).

3.2 Preliminary Findings: Crop Yield Variability and Contract Type

The most famous risk implications (Prediction 1a) is that, given risk-averse farmers, share contracts are more likely to be chosen in settings where uncertainty is high. A simple and preliminary way to confront this prediction is to examine the relationship between the yield variability of particular crops and the prevalence of share contracts for those crops. Table 3 presents the statewide coefficient of variation (CV) in yield for the major crops in British Columbia, Louisiana, Nebraska, and South Dakota. The coefficient of variation is used instead of standard deviation for two reasons. First, the coefficient of variation has no units and many of the crops we examine are measured in different units. For example, hay is measured in tons while wheat is measured in bushels. Sec-

Table 3. Yield Variability and Contract Choice

Crop (dataset)	Crop yield coefficient of variation	Fraction cropshare contracts		Fraction acres cropshared		
				Leased		All
South Dakota, 1975–1991						
Corn (irrigated)*	0.023	0.58				
Corn (dryland)*	0.140	0.64				
Soybeans	0.143	0.72				
Oats	0.191	0.59				
Sorghum	0.195	0.59				
Barley	0.238	0.53				
Wheat	0.247	0.61				
Nebraska, 1975–1991						
Alfalfa (irrigated)	0.035	0.51				
Sorghum (irrigated)	0.081	0.71				
Soybeans (irrigated)	0.085	0.67				
Corn (irrigated)	0.112	0.69				
Wheat	0.114	0.86				
Barley	0.139	0.91				
Sorghum (dryland)	0.145	0.83				
Oats	0.155	0.80				
Soybeans (dryland)	0.168	0.76				
Corn (dryland)	0.235	0.74				
Louisiana, 1975–1991						
Milo (sorghum)	0.057	0.76		0.77		0.56
Sugarcane	0.099	0.78		0.81		0.70
Soybeans	0.121	0.75		0.76		0.58
Hay	0.121	0.67		0.94		0.29
Cotton	0.197	0.53		0.52		0.30
Wheat	0.207	0.76		0.78		0.59
Rice	0.278	0.68		0.76		0.61
Corn	0.293	0.62		0.41		0.37
British Columbia, 1980–1991		**1979**	**1992**	**1979**	**1992**	**1992****
Alfalfa	0.126	0.10	0.15	0.05	0.01	0.004
Hay	0.149	0.34	0.23	0.37	0.13	0.03
Wheat	0.175	0.83	0.79	0.75	0.68	0.38
Apples	0.184	0.66	0.66	0.75	0.77	0.16
Oats	0.212	0.50	0.43	0.40	0.38	0.05
Barley	0.216	0.41	0.58	0.42	0.85	0.17
Canola (rapeseed)	0.250	0.59	0.25	0.37	0.05	0.00
Corn	0.270	0.03	0.20	0.65	0.36	0.04

*1984–1991 only.
**Data not available from 1979 survey.

ond, using the coefficient of variation controls for differences in means even for those crops that are measured in the same units. This is important when comparing dryland and irrigated crops, where irrigation, as expected, always increases mean yield.

Using this measure, a greater CV indicates a more variable crop and thus is predicted to be a crop that is more often governed by share contracts rather than cash leases. For each state or province the crop CVs are listed in ascending order, from top to bottom. Table 3, however, shows there is no clear relationship between the use of share contracts and crops with inherently high CVs. In particular, Table 3 shows the statewide and provincewide CVs and the prevalence of share contracts as a fraction of all contracts, as a fraction of leased acreage, and as a fraction of all farmland. Simple inspection of the data shows no obvious positive correlation and does not support Prediction 1a.[16] Consider, for example, the case of sugarcane in Louisiana. Sugarcane has one of the most stable crop yields of any crop in our dataset (CV = 0.099), yet sugarcane land is overwhelmingly cropshared (78% of all leases and 81% of all leased acres). By Prediction 1a sugarcane is expected to be a crop that should be cash rented relatively more often than other crops.

3.3 The Effect of Risk on Contract Choice

Although the aggregate data in Table 3 does not support the risk model, these inferences are limited because of the level of data aggregation. A more explicit test of the relationship between risk and contract choice requires regression analysis using data on individual contracts. Examining the extent of share contracts for a single crop across regions where natural parameters such as weather and pests directly influence the yield variability of the crop can do this. By selecting a sample of land contracts for which crops are the same we can examine how natural variability affects contract choice.[17] Natural variability for a homogeneous locale is measured using both CV and STD for two sizes of geographic regions. REGIONAL CV and REGIONAL STD measure the coefficient of variation and standard deviation, respectively, for each crop for regions within the states. Similarly, COUNTY CV and COUNTY STD measure risk at the county or parish (for Louisiana) level.

We combine the Nebraska and South Dakota samples because they are contiguous states from south to north and because the contract data for both comes from the same 1986 survey. In both states the eastern reaches are comprised of better soils, more precipitation, and a more predictable climate compared to

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16. The following OLS estimate—using pooled data from Table 2—confirms the intuition gained from simply inspecting Table 3:

$$\begin{aligned}\text{CROPSHARE} = {} & \underset{(3.82)}{(0.43)^*}\text{CONSTANT} - \underset{(0.17)}{(0.08)^*}CV + \underset{(0.24)}{(0.02)^*}BC79 + \underset{(3.13)}{(0.28)^*}LA \\ & + \underset{(2.08)}{(0.19)^*}SD + \underset{(3.64)}{(0.33)^*}NE\end{aligned}$$

where absolute t-statistics are in parentheses, the adjusted $R^2 = 0.42$, and the overall F-value = 4.97. CROPSHARE is the fraction of cropshare contracts, while the other independent variables are state-provincial dummies for four of the five samples. Higgs (1973) conducts a similar exercise using aggregate data from 11 southern states for 1910. Considering only two crops (corn and cotton) he finds a positive effect on CV but notes the U.S. Census data mix sharecroppers (unskilled laborers without capital) and share farmers who provide their own capital.

17. Where the data allow it, we separate irrigated from dryland farming even for the same crops because irrigation uses different technology and reduces the yield variance.

their western counterparts. It is worth noting that the far eastern portions of these two states border Iowa and are effectively part of the Corn Belt, while the far western portions border Wyoming and are effectively part of the High Plains. The general consequence is that crops in the western counties tend to have lower and more variable yields compared to eastern counties.[18] Louisiana exhibits a similar variability, although it runs mainly from south to north instead. South Louisiana tends to have a more stable, subtropical climate that makes crop yields higher and less variable than those grown in the north. British Columbia, which is larger than all three states combined, exhibits greater heterogeneity than do any of these three states. In many cases the heterogeneity is so strong that crops are strictly limited to certain regions.[19]

The variation in crop yield CVs (and STDs) across these jurisdictions is substantial.[20] For example, in Nebraska the minimum COUNTY CV for corn is 0.21, the maximum COUNTY CV is 0.75, and the mean COUNTY CV is 0.28. For South Dakota, the same measures are 0.10, 0.40, and 0.23, respectively. In Louisiana, the measures are 0.14, 0.76, and 0.30, respectively. Table A.4 in the Data Appendix shows these statistics for other crops and for COUNTY STD. This variability in natural conditions within the jurisdictions we study allows us to conduct tests of the risk model under favorable conditions.

3.3.1 The Choice of Contract: Cropshare versus Cash Rent. To test Prediction 1a with crop-specific contract data we use the following empirical specification, where for any contract i and crop j the complete model is

$$\hat{c}_{ij} = \sigma_j^2 \Delta_j + X_j \Pi_j + \varepsilon_{ij} \qquad i = 1, \ldots, n_j; \quad j = 1, \ldots, 14; \text{ and} \tag{4}$$

$$c_{ij} = \begin{cases} 1 \text{ if } \hat{c}_{ij} > 0 \\ 0 \text{ if } \hat{c}_{ij} \leq 0, \end{cases} \tag{5}$$

where $\hat{c}_{ij}$ is an unobserved contract response variable; c_{ij} is the observed dichotomous choice of farmland contracts for crop j, which is equal to 1 for cropshare contracts and equal to 0 for cash rent contracts; n_j is the number of contracts for a crop-specific sample; σ_j^2 is the crop-specific variability of the random input for a given plot of land (as measured by CV or STD); Δ_j is the corresponding coefficient for crop j; X_j is a row vector of control variables including the constant; Π_j is a column vector of unknown coefficients; and ε_{ij} is a crop-specific error term. The control variables, which include measures of plot size, family relationships, and farmer and land characteristics, are similar but not identical across the datasets (see the Data Appendix).

18. The two states are not clones though. Nebraska has a greater fraction of land similar to the Corn Belt and South Dakota has more land similar to the High Plains. Also, climate and soil tend to improve as one travels from north to south.

19. Unfortunately, data limitations in calculating yield variability prevent us from estimating these effects in British Columbia using the specification below.

20. Again, because these farmers all face the same market prices, there is no variation in prices across our sample of contracts.

We use a logit model to generate maximum likelihood estimates of the model given by Equations (4) and (5) for 14 crop-specific contract samples ($j = 15$), 9 in the Midwest and 5 in Louisiana. Table 4 presents the logit coefficient estimates from 46 separate estimated equations for the Midwestern (36 equations) and Louisiana (10 equations) data for the two exogenous variability measures at both the county and regional level. Each entry in Table 4 is an estimated CV or STD coefficient, that is, an estimate of Δ_j, and its associated t-statistic, derived from a *separate* estimated equation.[21] For example, the entry in the upper left cell (-12.59) is the estimated coefficient for REGIONAL CV from the equation using a sample of dryland corn contracts ($n_j = 539$) in Nebraska and South Dakota. The remaining entries in the first column use the same contract sample but replace REGIONAL CV with the other three measures of σ^2. The remaining columns represent the same exercise using contract samples for other crops. For Nebraska and South Dakota we estimate these equations with nine crop samples using four measures of σ_j^2 (REGIONAL CV, REGIONAL STD, COUNTY CV, and COUNTY STD). This produces 36 coefficient estimates presented in the top half of Table 4. For Louisiana the number of estimated equations and coefficient estimates for Δ_j is 10 because we have data on only five crops and because the state of Louisiana collects data only for parishes, eliminating the use of REGIONAL CV and REGIONAL STD.[22] Prediction 1a implies a *positive* coefficient for σ_j^2—the more variable is the yield for crop j in a region, the more likely it will be shared—that is, the model implies $\Delta_j > 0$ for all j crops.

Overall, the estimates fail to support the risk model. The estimates consistently show that increases in exogenous crop yield variability do not increase the probability of cropsharing. In 46 estimated equations there is not a single statistically significant and positive coefficient estimate of Δ_j. In fact, more than one-half of the coefficient estimates are negative. Moreover, 11 of these negative estimates are statistically significant, showing that increases in exogenous risk actually reduce the probability of share contracting. We also estimate Equations (4) and (5) without control variables (using only CV or STD), and with a smaller set of control variables than used in Table 4. Neither of these alternative specifications change the findings reported in Table 4, although the specification reported in Table 4 consistently gave better estimates.

3.3.2 The Choice of Contract: The Farmer's Crop Share. In this section we test Prediction 1b, which implies that higher variability crops result in a lower share

21. We also use MEAN as a control variable when STD is used to approximate σ_{ij}^2.

22. The size of some Louisiana crop samples (mostly sorghum and wheat) were further restricted because we were not able to identify the parish for some farmers. Regional yield statistics are not available in British Columbia, so this test could not be performed. The samples (n_j) were generally smaller for COUNTY CV and STD, compared to REGIONAL CV and REGIONAL STD, because the states do not calculate yields for counties when total output is below a threshold; therefore COUNTY CV and COUNTY STD were not always available, even when REGIONAL CV and REGIONAL STD were available.

Table 4. Estimates of CV and STD Coefficients from 46 Logit Regressions of Contract Choice

Dependent variable = 1 if cropshare contract; 0 if cash rent contract.

Nebraska and South Dakota Crop Samples

Exogenous variability	Dryland corn	Irrigated corn	Dryland soybeans	Irrigated soybeans	Dryland sorghum	Irrigated sorghum	Barley	Oats	Wheat
Regional measures									
REGIONAL CV	−12.59	−1.50	−31.62	12.08	−1.46	9.83	−1.51	−6.80	−2.49
	(−2.62)*	(−3.24)*	(−2.79)*	(1.61)	(−0.26)	(0.68)	(−0.21)	(−2.09)*	(−1.55)
REGIONAL STD	−0.16	−0.02	−0.24	0.30	−0.10	0.18	−0.85	−0.12	−0.03
	(−2.22)*	(−0.78)	(−0.48)	(1.58)	(−0.47)	(0.95)	(−2.24)*	(−1.69)*	(−0.36)
Observations (n_j)	539	1378	479	524	341	276	234	540	1250
County measures									
COUNTY CV	−1.95	−5.33	−6.99	1.90	2.57	1.13	−0.52	−8.40	−1.94
	(−0.54)	(−1.88)*	(−0.94)	(0.27)	(0.30)	(0.12)	(−0.11)	(−2.45)*	(−1.19)
COUNTY STD	0.01	−0.04	−0.09	0.07	0.17	0.03	−0.16	−0.19	0.01
	(0.15)	(−1.91)*	(−0.93)	(0.39)	(0.99)	(0.23)	(−0.97)	(−2.35)*	(0.15)
Observations (n_j)	521	1257	477	522	321	269	226	540	1248

Louisiana Crop Samples

Exogenous variability	Corn	Soybeans	Cotton	Rice	Sugarcane
Parish measures					
COUNTY CV	−11.98	−43.00	14.16	5.21	9.75
	(−1.26)	(−0.83)	(1.63)	(0.56)	(0.73)
COUNTY STD	−0.98	0.42	0.01	−0.34	−0.01
	(−1.32)	(1.29)	(0.51)	(−1.03)	(−0.02)
Observations (n_j)	18	92	61	79	52

t-statistics in parentheses.
*Significant at the 5% level for a one-tailed test.
Control variables include ACRES, AGE, FAMILY, IRRIGATION (see appendix).

to the farmer. For this exercise we use the farmer's contracted share of output as our dependent variable. Because this variable ranges from zero to one (cash contract), the model for each share contract i for crop j is

$$\begin{aligned} \alpha_{ij} &= \sigma_{ij}^2\gamma_j + Z_{ij}\xi_j + \mu_j \quad && \text{if } \alpha_{ij} < 1; \quad \text{and} \\ \alpha_{ij} &= 1 && \text{otherwise}, i = 1, \ldots, n_j; \;\; j = 1, \ldots, 14; \end{aligned} \tag{6}$$

where α_{ij} is the farmer's share of the crop for the ith contract governing the jth crop; σ_j^2 is the crop-specific variability of the random input for a given plot of land (again measured by CV or STD); γ_j is the corresponding crop-specific coefficient; Z_{ij} is a row vector of explanatory variables including the constant; ξ_j is a column vector of unknown coefficients; and μ_{ij} is a crop-specific error term. The control variables are nearly identical to those used in the estimation of Equations (4) and (5) and are explained in the Data Appendix.

We use a right-censored tobit model to generate maximum likelihood estimates of the model given by Equation (6) for the same 15 crop-specific samples of contracts used for the logit estimates above.[23] Table 5 presents the tobit coefficient estimates of γ_j from 46 estimated equations, 36 using Midwestern crop samples and 10 using Louisiana crop samples. Like Table 4, each entry in Table 5 is an estimated CV or STD coefficient, that is, an estimate of γ_j, derived from a separate estimated equation. Accordingly, the entry in the upper left cell (21.96) is the estimated tobit coefficient for REGIONAL CV from Equation (6) using a sample of contracts for dryland corn ($n_j = 539$) in Nebraska and South Dakota. The rest of the table is organized like Table 4. Prediction 1b implies a *negative coefficient* for the CV and STD variables; that is, $\gamma_j < 0$ for all j crops.

Of the 46 coefficient estimates, 28 are not statistically different from zero, thus failing to support the risk thesis. More than half (30) of the estimated coefficients actually have a *positive* coefficient, and 14 of these are statistically significant. Only four estimates are negative and significant. We also estimated the 46 equations without control variables, using only the CV or STD variables, and with a smaller set of control variables than used in Table 5. None of these alternative specifications change the findings reported in Table 5.

3.4 Wealth, Risk, and Contract Choice

It is often assumed that as wealth increases individuals become less risk averse in absolute terms. The assumption of declining absolute risk aversion (DARA) for farmers is so routine among agricultural economists that Pope and Just (1991:743) note that: "Decreasing absolute risk aversion has emerged as a 'stylized' fact or belief." In the standard principal-agent model, DARA implies

23. We also estimate these share equations excluding all cash contracts (share = 100%) from the sample. For this exercise we use Heckman's two-step estimation method in order to control for the contract choice selection problem. These estimates are similar to the tobit estimates using all contracts, generally finding little support for the risk-sharing predictions. Of the 46 coefficient estimates, only six are negative and statistically significant at the 10% level. They are available from the authors upon request.

Table 5. Estimates of CV and STD Coefficients from 46 Tobit Regressions of Output Shares in Crop Share Contracts

Dependent variable = SHARE

Nebraska and South Dakota Crop Samples

Exogenous variability	Dryland corn	Irrigated corn	Dryland soybeans	Irrigated soybeans	Dryland sorghum	Irrigated sorghum	Barley	Oats	Wheat
Regional measures									
REGIONAL CV	21.96	−57.75	84.81	−82.64	23.65	−32.46	64.70	53.96	19.90
	(1.14)	(−3.69)*	(2.01)*	(−1.24)	(0.63)	(−0.36)	(1.89)*	(4.33)*	(2.88)*
REGIONAL STD	0.10	−0.40	−3.53	−2.25	0.52	−0.29	4.77	1.16	−0.38
	(0.39)	(−3.27)*	(−2.19)*	(−1.25)	(0.32)	(−0.24)	(3.20)*	(4.12)*	(−1.09)
Observations (n_j)	539	1378	479	524	341	276	234	540	1250
County measures									
COUNTY CV	−5.31	−15.03	33.75	−7.30	7.32	44.64	16.56	68.21	22.53
	(−0.32)	(−0.88)	(1.57)	(−0.11)	(0.41)	(0.68)	(0.88)	(5.26)*	(3.20)*
COUNTY STD	−0.32	−.12	−0.90	−0.02	−0.96	0.78	0.43	1.51	0.20
	(−1.49)	(−0.89)	(−1.13)	(−0.01)	(−2.62)*	(0.99)	(0.69)	(4.89)*	(0.57)
Observations (n_j)	521	1257	477	522	321	269	226	540	1248

Louisiana Crop Samples

Exogenous variability	Corn	Cotton	Rice	Soybeans	Sugarcane
Parish measures					
COUNTY CV	5.30	2.11	7.81	6.51	12.70
	(0.80)	(0.85)	(2.73)*	(4.73)*	(3.99)*
COUNTY STD	0.17	0.37E-02	0.12	0.34	0.27
	(1.02)	(0.79)	(2.20)*	(3.73)*	(1.57)
Observations (n_j)	18	61	79	92	52

t-statistics in parentheses.
*Significant at the 5% level in a one-tailed test.
Control variables include ACRES, AGE, FAMILY, IRRIGATION (see appendix).

wealthy farmers should cash rent more often than poor farmers (Prediction 3a). This follows, because as wealth increases, the amount of exogenous risk the farmer is willing to bear should rise. A corollary to this prediction is that the share the farmer receives should also rise with his wealth (Prediction 3b). Larger output shares mean that the farmer is bearing more of the exogenous variability.

Only the 1992 surveys for British Columbia and Louisiana have adequate information on farmer wealth levels to conduct appropriate tests. These surveys have information on the value of all owned land, buildings, and equipment, and the amount of equity the farmer has in the farm. The values of total assets in these samples ranges from zero to more than three million dollars. Although these data do not perfectly measure wealth, they are close approximations because farmers in the regions we examine tend to derive most of their income from farm activities. In our Louisiana sample 93% of the farmers are full-time operators and in our British Columbia sample 75% are full-time farmers (see Table A.1). Furthermore, because farmers generate wealth from many parcels of land (owned and leased) over their careers, each of these variables measure wealth that is exogenous to the farmland contracts we examine.

Table 6 reports two sets of estimates for both British Columbia and Louisiana. These equations use a sample of all contracts (and all crops) for British Columbia and Louisiana. The control variables include crop dummies and the variables that measure various characteristics of farmers, land, and landowners (see the Data Appendix). The crop dummies control for variance in income across crops and allows us to focus on these alternative risk predictions. The upper panel shows logit parameter estimates of contract choice and the lower panel shows tobit parameter estimates of the farmer's contracted share of output. For both logit and tobit estimation we use either i) the aggregate level of wealth (WEALTH), or ii) the component parts (BUILDINGS, EQUIPMENT, and LAND) of total wealth. Under DARA the coefficient signs for WEALTH and other variables measuring wealth should be *negative* for the logit estimates, but *positive* for the tobit estimates.

Overall, as Table 6 shows, the estimates give only limited support of the predictions based on DARA.[24] The logit estimates of the WEALTH coefficient are not significantly different from zero for both British Columbia and Louisiana, failing to support DARA. When the wealth measure is broken into its component parts, the estimates become less consistent. For British Columbia, none of the estimates are significantly different from zero, and the signs are not the same. For Louisiana, all coefficient estimates are significant, but the results are mixed with negative effects for BUILDINGS and LAND and a positive effect for EQUIPMENT.

The estimates from the tobit share equations in the lower panel of Table 6 give similarly mixed results. Like the logit estimates, the tobit estimates of the

24. We recognize, of course, that we are jointly testing the hypothesis of DARA and optimal risk allocation from the standard principal-agent model.

Table 6. Estimated Coefficients for Futures Markets, Institutions, and Wealth

Logit estimation of contract choice: dependent variable = 1 if share contract; = 0 if cash rent.				
Independent variables	British Columbia		Louisiana	
WEALTH	9.2E-05	–	−4.0E-04	–
	(0.15)		(−0.93)	
BUILDINGS	–	−2.1E-07	–	−3.4E-06
		(−0.14)		(−1.91)*
EQUIPMENT	–	−5.4E-07	–	3.13E-06
		(−0.18)		(3.28)*
LAND	–	3.8E-08	–	−1.6E-06
		(0.07)		(−2.96)*
FUTURES MARKET	0.98	1.00	1.11	1.54
	(1.94)*	(1.86)*	(2.10)*	(2.71)*
INSTITUTION	−1.04	−0.96	0.07	−0.48
	(−1.48)	(−1.32)	(0.14)	(−0.86)
Model χ^2 (df)	20.56(9)	20.62(9)	24.62(9)	55.55(11)
Correct Predictions	70%	70%	69%	72%
Observations	176	176	355	355
Tobit estimation of output share: dependent variable = SHARE.				
WEALTH	0.28E-04	–	0.27E-03	–
	(0.82)		(1.31)	
BUILDINGS	–	0.14E-06	–	−0.78E-07
		(1.46)		(−0.09)
EQUIPMENT	–	−0.28E-06	–	−0.78E-06
		(−0.16)		(−1.94)*
LAND	–	0.54E-07	–	0.41E-06
		(0.17)		(1.83)*
FUTURES MARKET	−0.38	−0.36	0.19	−1.77
	(−1.36)	(−1.17)	(0.80)	(−5.96)*
INSTITUTION	0.55	0.41	0.31	0.34
	(1.52)	(1.10)	(1.16)	(1.15)
Log Likelihood	−351.37	−350.35	−1204.75	−2377.03
Observations	176	176	355	355

t-statistics are in parentheses.
*Significant at the 5% level in a one-tailed test.
Control variables include ACRES, AGE, FARM INCOME, FULLTIME (see appendix).

WEALTH coefficient are not significantly different from zero for both British Columbia and Louisiana, failing to support DARA. When WEALTH is broken into its three components the results remain unfavorable to DARA. Of the six estimated coefficients, only one is positive and statistically significant, while four are insignificantly different from zero.

3.5 Further Tests: Futures Markets, Large Landowners, and Off-Farm Income

The risk predictions examined thus far have all been drawn from the principal-agent literature model. There are, however, additional predictions consistent with risk sharing that can be tested with our data, using the variables FUTURES MARKET, INSTITUTION, and FARM INCOME. The tests that we perform using these variables are scattered across many estimated equations and are sometimes, but not always presented in the tables connected with the previous tests. In this section we discuss this final set of risk tests.

3.5.1 Futures Markets. First, consider tests using FUTURES MARKET. Because futures markets are an alternative method of allocating risk, when they are present the farmer is ceteris paribus less likely to choose a share contract (e.g., Stiglitz, 1974). The dummy variable FUTURES MARKET equals one when a crop is traded in an organized futures market. By this risk hypothesis FUTURES MARKET should be negatively correlated with share contracts. Table 6 includes logit estimates of contract choice as well as tobit estimates of the farmer's output share. The predicted coefficient estimate for FUTURES MARKET is *negative* for the logit equations, but is *positive* for the tobit equations. The top panel of the table shows that none of the four logit estimates support this version of risk sharing. All four estimates are positive and statistically significant, indicating that crops with futures markets are more likely to be cropshared. The tobit estimates in the bottom panel in Table 6 also show no support for this hypothesis. Three estimated coefficients are negative (one is statistically significant) and the only positive estimate is not statistically significant.[25]

3.5.2 Institutions. Next, consider the variable INSTITUTION, used to isolate the effects of landowner wealth on contract choice. INSTITUTION identifies large, wealthy landowners (e.g., banks, Indian tribes, municipalities), thus isolating the cases when, by all traditional measures, the landowner should be less risk averse than the farmer. These landowners should be more likely than smaller landowners to share contract with farmers. Risk sharing thus predicts *positive* INSTITUTION coefficients for the logit estimation of contract choice and *negative* INSTITUTION coefficients for the tobit estimation of the farmer's cropshare. The coefficient estimates for INSTITUTION are reported in Table 6, along with the wealth and futures market variables, and offer no support for the risk prediction. In the logit estimates in the upper panel, only one estimated coefficient is positive, but it is not statistically significant. In the tobit estimates in the lower panel, all estimated coefficients are positive (rather than negative) but not statistically significant.

Other estimates of INSTITUTION coefficients further undermine support for this risk prediction. INSTITUTION was included (but not reported in Table 4) in the crop-specific logit estimation of Equations (4) and (5). For each crop sample we estimated four equations, corresponding to the four different measures of exogenous variability. For Louisiana, we estimate these equations for only three crops (soybeans, rice, sugarcane), resulting in just six estimated coefficients. We find that four of the six are insignificantly different from zero, but that both

25. It is possible that futures markets may have arisen for those crops that have highly variable yields, although this seems highly unlikely. Simple inspection of our data shows that futures markets are found for nearly all widely traded and storable crops.

rice coefficients are positive.[26] In order to estimate these equations for the Nebraska–South Dakota data we use a smaller sample for which the variable INSTITUTION was available (see Data Appendix). Because there were no institutional landowners for sorghum (dryland and irrigated), we estimate the crop-specific contract choice equations for only seven crops. This produces a total of 28 estimated coefficients (7 crops times 4 risk measures). *None* of the estimated coefficients are significantly different from zero, indicating the INSTITUTION does not affect contract choice as predicted by the risk-sharing model.

Similarly, INSTITUTION was included (but not reported in Table 5) in the crop-specific tobit estimates of Equation (6). For Louisiana, we estimate these equations for the same three crops resulting in six estimated coefficients. We find that *none* of the coefficient estimates are significantly different from zero. Again, for the Nebraska–South Dakota data, we use a smaller sample to estimate the crop-specific output share equations, resulting in a total of 28 estimated coefficients. *None* of these coefficient estimates are significantly different from zero.

3.5.3 Sources of Farmer Income. Finally, we use FARM INCOME to test the related hypothesis that farmers with little or no outside or "off-farm" sources of income will be more likely to share contract in order to share risk with the landowner. FARM INCOME measures the amount of a farmer's income derived from farming in four categories, ranging from a small to high fraction. In the risk framework, the estimated FARM INCOME coefficients are expected to be *positive* for logit estimates of contract choice and *negative* for tobit estimates of the farmer's share. FARM INCOME was included in the crop-specific logit estimation of Equations (4) and (5) and in the crop-specific tobit estimation of Equation (6).[27] For Louisiana, we estimate these equations for four crops (cotton, rice, soybeans, sugarcane) resulting in 16 (8 logit and 8 tobit) estimated coefficients.

First, consider the logit estimates of Equations (4) and (5). For Louisiana, we find that all eight estimated coefficients are negative, rather than positive, and six of these are statistically significant. *None* are positive and significant. Conducting the same exercise for the Nebraska–South Dakota data results in 28 estimated coefficients. All estimated coefficients for FARM INCOME are negative and nine are statistically significant. Contrary to the risk-sharing prediction, *none* of the estimated coefficients are positive and significantly different from zero.

FARM INCOME was also included in the crop-specific tobit equations used to estimate the coefficients for CV and STD in Table 5. For Louisiana, we estimate these equations for the same four crops resulting in eight estimated coefficients. Again, we find that *none* of the coefficient estimates are negative

26. This is hardly surprising, however, since Table 3 shows that rice land is nearly always cropshared.

27. Again, these estimates were not reported in Tables 4 and 5.

and statistically significant; in fact, four are positive and statistically significant. For the Nebraska–South Dakota data we obtain 28 estimated coefficients and find that *all* are positive and 19 statistically significant. Overall, like the estimates of coefficients for FUTURES MARKET and INSTITUTION, the estimates for FARM INCOME do not support risk sharing.

4. Risk Neutrality and Share Contracting

The evidence presented in Tables 3–6 fail to support the standard principal-agent approach, which has dominated the study of agricultural contracts (Otsuka et al., 1992). In particular, the predictions based on changing risk parameters are consistently refuted.[28] In this section we consider how risk-neutral models that focus exclusively on incentive trade-offs can explain agricultural share contracts and some of our empirical findings.

4.1 Risk-Neutral Approaches to Share Contracts

In the traditional principal-agent model, risk aversion is a *necessary condition* for share contracting because the only behavioral margin is the farmer's (unobservable) effort, providing the well-known trade-off between farmer shirking and risk avoidance. Risk aversion need not be required to explain share contracting, however, as long as other behavioral margins besides farmer effort are considered. Indeed, even with risk-neutral parties and contrary to Prediction 2, share contracts can be optimal when there are additional incentive problems, such as double-sided moral hazard (Eswaran and Kotwal, 1985; Bhattacharyya and Lafontaine, 1995), multi-task agency (Holmstrom and Milgrom, 1991; Slade, 1996; Allen and Lueck, 1998), and measurement costs (Allen and Lueck, 1992b, 1993).

For farming, there is good reason to believe that the single margin moral hazard model is an unrealistic model of farmer and landowner incentives. Land, like farmer effort, is also a variable input that allows for landowner moral hazard. Landowners, for instance, may not properly maintain fences or irrigation equipment. At the same time, farmers can damage the land because lease contracts for land do not, and cannot, specify all the characteristics of the land.[29] In addition, there are often significant costs of measuring and dividing the shared output and input costs. The ability of farmers to misreport crops can often be a crucial parameter in designing efficient contracts (Allen and Lueck, 1992b, 1993).

In risk-neutral models of share contracting the trade-offs are distinct from the risk versus moral hazard trade-off. First, share contracts distribute the deadweight losses from moral hazard over many margins. Second, share contracts create incentives for overuse and underreporting for those assets (inputs and/or

28. We also note that the data strongly refute the prediction that share contracts will normally be accompanied by a cash payment [(Equation 4)]. Of our 1166 land rent contracts from the 1992 surveys, only 63 (5.5%) are share-cash combination contracts.

29. While reputations and repeated contracting can prevent serious contracting failures such as using the land for nonfarm activities (Allen and Lueck, 1992a), the large role of nature prevents a complete solution, especially for small, daily tasks.

output) that are shared. As a result, share contracts may be chosen when the costs of dividing and measuring shared assets are low and the margins for moral hazard are large and many. On the other hand, fixed payment contracts may emerge when measurement costs are high and moral hazard margins are small and few.

Under risk neutrality, optimal contract parameters and contract choice comparative statics depend on knowledge of the production process and contracts. For example, Allen and Lueck (1992b) provide evidence, using 1986 data, that the choice between Midwestern cash rent and pure cropshare contracts is best modeled by restricting contract parameters so that only a trade-off between soil exploitation and crop underreporting by the farmer exist. In this setting, the advantage of the share contract is that it mitigates a farmer's incentive to exploit inputs supplied by the landowner. Share contracts help to maintain moisture in the soil by curbing certain tilling techniques that increase current output at the expense of long-run soil viability. The downside of the share contract is that it affects all input margins, not just those being exploited, and it creates an incentive to underreport the (shared) crop. A similar set of incentives is present when cropshare contracts also share input costs (e.g., fertilizer and seed) between farmer and landowner. When the possibility of input theft is high and inputs are hard to measure, sharing input costs such as fertilizer and seed is less common (Allen and Lueck, 1993).

4.2 Another Look at the Risk Evidence

The most important principal-agent prediction (Prediction 1a)—*as output variability increases, share cropping should be more common*—was not supported by the data from Louisiana, Nebraska, and South Dakota in Tables 3–6. A plausible risk-neutral approach, however, implies the *opposite* relationship of Prediction 1a. Under risk neutrality, avoiding exogenous variability through sharing offers no benefits. At the same time, as output becomes more variable, the opportunities for the farmer to underreport (steal) the crop increase (Holmstrom and Milgrom, 1991; Allen and Lueck, 1992b). Greater exogenous yield variability allows the farmer to hide his actions behind Mother Nature. Increases in output variability increase the cost of share contracts, so we would expect a decrease in the use of cropshare contracts, or a *negative* coefficient on CV and STD. This prediction is generally supported by our data, both at the aggregate level (Table 3) and at the contract level (Table 4).

Table 3 shows that land contracts for low-variability crops are often dominated by the sharing arrangement. In Louisiana this is especially true for sugarcane, which has one of the lowest CVs (0.099) in our sample, yet is predominantly shared (80% of all leased acres). In the Midwest share contracting for corn is important (60%–70% of contracts) even though it has a relatively low CV (roughly 0.100). At the contract level, Table 4 shows that 27 of 48 estimated coefficients are negative and 11 of these are statistically significant at the 5% level, generating much more support than the standard principal-agent model.[30]

30. Crop underreporting, however, is only part of the risk-neutral transaction cost story. Row crops like corn, soybeans, and sorghum tend to be shared because of soil exploitation problems

4.3 The Distribution of Contracts Across Assets

In agricultural applications, the principal-agent framework has focused on the land lease contract. Yet land is only one of many important farm inputs governed by contracts. Many other assets besides land—buildings, equipment, skilled and unskilled labor—are important and contracts routinely govern their use. A risk-sharing rationale for land sharing should also imply share contracts for other important assets like buildings and equipment. Data from British Columbia and Louisiana, however, offer no indication that other assets are treated like land. Table 7 shows the distribution of sole ownership, shared ownership, and leasing for buildings, equipment, and land. Sole ownership is by far the dominant regime for buildings and equipment, but not for land. Buildings are not often leased apart from land, and in these cases they are *never* leased on a cropshare basis. Equipment leasing, too, is *never* based on output shares and is far less common than for land leasing. When farmers lease equipment they usually pay a daily rate or a rate based on hours of engine use, measured with gauges in tractors and combines.

Table 7. Ownership and Leasing of Agricultural Assets

	British Columbia			Louisiana		
Asset	Owned	Leased		Owned	Leased	
Equipment						
Tractors	99%	1%		96%	4%	
Harvesting equipment	99	1		96	4	
Cultivator	100	0		97	3	
Trucks	99	1		98	2	
Sprayer	100	0		98	2	
Buildings						
House	99%	1%		92	8%	
Shop	97	3		78	22	
Barn	99	1		85	15	
Storage	98	2		78	22	
Land		Cash rent	Crop share		Cash rent	Crop share
Crops	76%	15%	9%	30%	22%	48%
Grass	74	20	6	71	21	8
Pasture	70	30	0	74	23	3
Fruit	81	7	12	83	17	0

Sources: 1992 Louisiana Farmland Leasing and Ownership Survey
1992 British Columbia Farmland Leasing and Ownership Survey

(Allen and Lueck, 1992b). Soil exploitation problems also increase with increased variance in the random input, so these crops are predicted to have lower farmer shares when output variability increases. Grain crops, on the other hand, do not experience as severe a soil exploitation threat as row crops, and therefore the farmer's share rises with output variability to counter underreporting.

The paucity of equipment leasing is consistent with a risk-neutral (pure incentive) framework and inconsistent with risk sharing. Equipment use is difficult to monitor and leasing reduces the incentive for optimal maintenance. Even though leased equipment is measured in time, it is virtually impossible to determine how a farmer has treated the machine during the lease period (e.g., overheating engines, damaging the transmission). Another important reason for the dominance of equipment ownership vis-à-vis leasing is that the random forces of nature make it important for farmers to have equipment available on the spur of the moment. Ownership guarantees the temporal availability of equipment, whereas contracts with uncertain delivery dates would leave a farmer susceptible to "exploitation" by the equipment owner.

The ownership and leasing of farmland can be examined in a similar fashion. Table 7 also shows the distribution of land ownership and lease contract type for various farmland uses in British Columbia and Louisiana. The extent of ownership varies across land uses, as does the choice of lease contract. It is worth noting, for example, that it is extremely rare (0% of the farmland in British Columbia and just 3% in Louisiana) for pasture to be leased on a share basis. Measurement costs are likely to be crucial here. It is difficult to measure and divide output when that "product" is the weight gain of a livestock herd; cash rent is an enforceable lease contract and land ownership can create long-term incentives to husband the land.

4.4 A Risk Preference Reversal in North American Farming?

The standard principal-agent approach routinely assumes landowners are risk neutral and farmers are risk averse. If the landowner were more risk averse than the farmer, however, the model predicts cash rent contracts.[31] Could our empirical findings in Table 4 be explained by simply reversing the risk preferences of some farmers and landowners? There are many reasons to think the answer is no. Preference reversal does not explain the coefficient estimates on the FUTURES MARKET or INSTITUTION variables. Nor is preference reversal consistent with the wealth effects examined in Table 6. Moreover, two additional sets of facts grind against this explanation of our findings. First, farmers and landowners in North America have remarkably similar demographic characteristics, so it is not obvious how to evaluate risk preferences. Second, farmers simultaneously hold more than one type of contract and play both sides of the farmland lease market.

Table 8 points out a number of characteristics of farmers and landowners that are common across all of our datasets. Table 8 shows that 60% of the landowners are or were at one time farmers. Furthermore, Table 8 shows that renters are often landowners, and in some cases (6%) rent out land simultaneously, as

31. As Lafontaine (1992) notes, risk preference assumptions are also crucial in franchising models. In the typical view—the franchisee is risk averse but the franchisor is risk neutral—risk sharing implies that greater exogenous variability will result in more fixed payment contracts (hired managers). If, as some have argued, risk preferences are reversed (Martin, 1988), the contract choice prediction is reversed.

well as hold both share and cash rent contracts. The similar socioeconomic background and demographic features of farmers and landowners along with the coexistence of owning and leasing are inconsistent with a model that posits dichotomous preferences and risk sharing.

5. Conclusion

We have used detailed data on individual contracts in modern North American agriculture—where cropshare contracts remain an important part of farming—to test some well-known predictions derived from principal-agent models that include risk-averse preferences. On a case-by-case basis, using many different empirical specifications, our evidence consistently fails to support the predictions of the traditional risk models. Collectively our tests provide robust evidence that forces besides risk sharing are more important in shaping agricultural land contracts. At the same time, we find some support for models that assume risk-neutral contracting parties and stress multiple margins for moral hazard and enforcement costs, thus supporting longtime critics of risk aversion such as Goldberg (1990).

Although we are able to conduct empirical tests for agricultural contracts, risk-sharing implications are notoriously difficult to test, which limits their value to empirical economists. At the same time, risk-sharing models distract economists from other important forces shaping contracts. Theorists, too, have been changing their approach in recent years. Transaction cost theorists such as Coase (1937) and Williamson (1979), who shunned models relying on risk-averse agents, have now been joined by contract theorists who assume risk-neutral agents and focus on incentive trade-offs (e.g., Eswaran and Kotwal, 1985; McAfee and McMillan, 1987; Holmstrom and Milgrom, 1991, 1994; McAfee and Schwartz, 1994; Battacharyya and Lafontaine, 1995; Laffont and Matoussi, 1995). Our findings suggest that the recent theoretical advances are warranted and that it is time to move beyond contract theories based on risk sharing.

Data Appendix

Nebraska and South Dakota Contract Data

Data for the landowner-farmer cropshare contracts come from the 1986 Nebraska and South Dakota Leasing Survey conducted by Professors Bruce Johnson (University of Nebraska) and Larry Jansen (South Dakota State University). A summary of the study and the survey procedures is available (Johnson et al., 1988). Each observation represents a single farmer or landowner for the 1986 crop season. The data are organized so that observations are individual contracts. There are 2101 observations for Nebraska and 1331 for South Dakota. Because the variables FARM INCOME and INSTITUTION are available only for contracts in which the farmer supplied the data, we also use a smaller sample with 1261 contracts for those equations using FARM INCOME and INSTITUTION as independent variables. This sample is only used in the tests reported in Section 3.2.

Table 8. Characteristics of Farmers and Landowners

Variable	British Columbia 1979	British Columbia 1992	Louisiana	Nebraska/South Dakota
Average age				
Landowners	52.8	57.0	63.9	≈50
Farmers	40.9	47.2	46.5	≈40
Average Years of education				
Landowners	8.3	—	—	—
Farmers	11.0	—	—	—
Average acres of owned land				
Landowners	—	499.5	748.5	661.2
Farmers	—	439.4	122.7	435.5
Farmers with no leased land	—	147.4	418.4	
Farmers with only share leases	—	412.1	116.8	—
Farmers with only cash leases	—	241.3	185.4	—
Percent of women				
Landowners	—	—	—	34
Farmers	—	—	—	6
Percent of landowners with farming experience	60	69.5	57.2	—
Percent of farmers that rent and own land	—	93	57	—
Percent of farmers that rent and rent out land	—	6	6	6
Percent of farmers using both share and cash leases	—	10	24	23

1979 British Columbia Contract Data

Data for the 1979 British Columbia landowner-farmer contracts come from the British Columbia Ministry of Agriculture Lease Survey. This survey was conducted by the Farm Management group in the Vernon, B.C., office of the ministry. The survey was done by telephone and included farmers from throughout the province; however, farmers in the Okanagan Region were oversampled. The number of usable responses was 378. This survey asked fewer questions and thus has fewer variables.

1992 British Columbia Contract Data

Data for the landowner-farmer cropshare contracts come from the 1992 British Columbia Farmland Ownership and Leasing Survey (Burnaby, B.C.: Simon Fraser University, 1993), which we conducted in January 1993. The survey was sent to a random sample of 3000 British Columbia farm operators. The number of usable responses was 460. The data are organized so that observations are individual contracts.

Louisiana Contract Data

Data for the landowner-farmer cropshare contracts come from the 1992 Louisiana Farmland Ownership and Leasing Survey (Baton Rouge, LA: Louisiana State University, 1993), which we conducted in January 1993. The survey was sent to a random sample (chosen by the parish USDA county agents) of 5000 Louisiana farm operators. The number of usable responses was 530. The data are organized so that observations are individual contracts. The survey questionnaire was the same as the one used for the 1992 British Columbia survey. Al Ortego, USDA Extension Economist at Louisiana State University, and Howard Joynt, British Columbia Ministry of Agriculture, both provided help in designing the 1992 survey and collecting related data. The summary statistics for all data sets are reported in Table A.1.

Contract Data Compared to State and Provincial Averages

For selected variables we compared our sample means to those taken from statewide census data from the *1987 Census of Agriculture*. The comparisons are shown in Table A.2. In many cases the means are nearly identical; in all cases they are within one standard deviation of each other. Data is unavailable to make the same comparison for the British Columbia data, but we are able to compare the two British Columbia samples. We conclude that our samples do not exhibit any systematic bias for agriculture in British Columbia, Louisiana, Nebraska, or South Dakota.

Crop Yield Variability Data

Data on yield variability comes from state and provincial agricultural statistical offices. We collected a time series (1975–1991) of per acre yields for each crop at the county and parish level for Louisiana, Nebraska, and South Dakota. The precise number of years varied across crops because of data availability. The most common unit of measure is bushels and tons, although these vary by crop

Table A.1. Summary Statistics for Leased Farmland

Variable name	Louisiana 1992			British Columbia 1992			British Columbia 1979			South Dakota and Nebraska 1986		
	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.	Mean	SD	Obs.
CONTRACT	0.67	0.47	934	0.29	0.46	232	0.39	0.49	626	0.71	0.46	3432
SHARE	77.4	6.8	607	75.07	11.1	68	73	11.4	235	59.2	9.9	2424
ACRES	2989	369	916	281.8	100	232	111.3	1204	634	445.8	980.9	3432
AGE	47	13	917	47.6	11.4	231	40.9	12.5	573	4.2*	1.68	3432
BUILDINGS	71,970	71,964	900	139,650	147,309	231	NA	NA	NA	NA	NA	NA
EQUIPMENT	142,907	162,513	857	79,334	91,408	229	NA	NA	NA	NA	NA	NA
FAMILY	NA	NA	NA	NA	NA	NA	NA	NA	NA	0.44	0.50	3432
FARM INCOME	3.06	1.17	922	2.6	1.2	226	NA	NA	NA	1.90	1.30	3432
FULLTIME	0.93	0.26	929	0.75	0.44	232	NA	NA	NA	NA	NA	NA
FUTURES	0.78	0.41	934	0.18	0.39	232	0.12	0.33	637	0.75	0.43	3432
INSTITUTION**	NA	NA	NA	NA	NA	NA	NA	NA	NA	0.90	0.29	1261
IRRIGATION	26.2	42.01	891	35	46	221	0.54	0.49	626	0.36	0.48	3432
LAND	173,022	442,614	934	153,770	326,906	232	NA	NA	NA	NA	NA	NA
WEALTH***	243,530	298,190	412	288,100	305,800	190	NA	NA	NA	NA	NA	NA

*For the South Dakota and Nebraska data AGE was a categorical variable. The mean is approximately 50 years.
**INSTITUTION: this variable is only available for the data obtained from farmers.
***The decline in sample size for the WEALTH variable is a result of the low response rate to the equity question in the 1992 surveys of Louisiana and British Columbia.

Table A.2. Comparison of Contract Data with State/Province Averages

British Columbia: Farm size in acres

	1979 survey		1992 survey	
Crop	Mean	SD	Mean	SD
Barley	725	841	1631	2857
Oats	1212	1110	1704	3309
Wheat	783	431	1887	3434
Corn	117	75	184	166
Apples	21.8	34	20	38

Louisiana

	1987 census	1992 survey	
Owned land in acres	Mean	Mean	SD
Statewide	293	321	511
Milo	278	152	410
Wheat	137	229	197
Rice	183	241	252
Soy	220	248	395
Cotton	307	303	439
Cane	396	703	803
Value of equipment	$38,323	$142,907	$162,513
Value of land and buildings	$268,630	$249,564	$447,780

Nebraska and South Dakota: Farm size in acres

	1987 census	1987 survey	
	Mean	Mean	SD
Nebraska	749	565	2041
South Dakota	1214	589	1322

and jurisdiction. For Nebraska and South Dakota, the same data was collected for "regions," which are from 5 to 10 counties, and their compositions are drawn from the respective state Department of Agriculture crop reporting systems. Regional data was unavailable for Louisiana crops. For British Columbia, yield data are only available for each of the eight "census agricultural regions," most of which are larger and more heterogeneous than the American states used in the study. As a result, these regions are of little use for the risk tests that we used for the U.S. data. Table A.4 shows the distribution of yield variability (measured both by coefficient of variation and by standard deviation) for some of the major widespread crops in the four jurisdictions.

Control Variables Used in Various Equations

Throughout the paper we reported coefficient estimates only for those variables explicitly cited in the theoretical predictions. All parameter estimates are available from the authors upon request. In Table 4 the control variables are not reported. Where we use standard deviation in crop yield instead of coefficient of variation we use mean yield as a control variable in the equations. For all

Table A.3. Price-Yield Correlations for Various Crops at the State or Province Level

Crop	British Columbia	Louisiana	Nebraska	South Dakota
Alfalfa	NA	NA	0.220	NA
Apples	−0.009	NA	NA	NA
Barley	0.025	NA	0.060	−0.588*
Corn (irrigated)	NA	NA	−0.449	−0.578
Corn (dryland)	NA	NA	−0.411	−0.665
Corn (all)	NA	−0.239	NA	NA
Cotton	NA	−0.288	NA	NA
Hay	NA	0.267	NA	NA
Oats	0.133	NA	−0.709*	−0.727*
Rapeseed (canola)	0.568	NA	NA	NA
Sorghum (irrigated)	NA	NA	−0.470	NA
Sorghum (dryland)	NA	NA	−0.576*	NA
Sorghum (all)	NA	−0.026	NA	−0.407
Sugarcane	NA	−0.026	NA	NA
Soybeans (irrigated)	NA	NA	−0.172	NA
Soybeans (dryland)	NA	NA	−0.414	NA
Soybeans (all)	NA	0.135	NA	−0.404
Rice	0.275	−0.652*	NA	NA
Wheat	NA	0.208	−0.235	−0.278

*Significant at the 0.05 level.

Sources: Nebraska Agricultural Statistics Service, U.S. Department of Agriculture, report prepared for Dean Lueck. "Historic Estimates, Principal Crops, South Dakota" (no other information on this available). South Dakota Agricultural Statistics Services, U.S. Department of Agriculture. "Agricultural Statistics & Prices for Louisiana 1985–1991," Hector Zapata & David Frank, Louisiana Agricultural Statistics Services. "Agricultural Statistics & Prices for Louisiana 1986–1992," Hector Zapata, Louisiana Agricultural Statistics Services. British Columbia Ministry of Agriculture, internal statistics, 1994.

regressions, the control variables included the total acres farmed (ACRES), whether or not a family member is the other party in the contract (FAMILY), and the age of the farmer (AGE). The variable IRRIGATION in also included in the barley, oats, and wheat samples. For the Midwestern data, crops that were used in the rotation were also included. We use these dummies because these data only identify the most dominant crop for a plot of land. The results are very robust with respect to whether these variables are included or not. For the Midwestern data, the sum of the observations exceeds the total number of contracts in the dataset because some farmers grow more than one crop on a single plot of rented land. For the tests in Section 3.5 we used FARM INCOME and INSTITUTION. For the Louisiana data, the number of observations (8) was too small to estimate equations for sorghum and wheat.

In Table 5 the control variables—ACRES, AGE, FAMILY, IRRIGATION (for the barley, oats and wheat samples)—are not reported. Where we use standard

Table A.4. Distribution of Crop Yield Variability Within States and Provinces

	SD	Coefficient ov variation	SD	Coefficient of variation
	Louisiana		British Columbia	
	Corn (bushels/acre)		Apples(1000 tons/acre)	
Minimum	6.05	0.14	89.33	0.02
Maximum	50.38	0.76	9494.32	0.56
Mean	23.46	0.3	2658.12	0.27
SD	9.21	0.12	3568.52	0.20
Observations	33	33	6	6
	Wheat (bushels/acre)			
Minimum	3.3	0.1		
Maximum	11.82	0.35		
Mean	7.37	0.22		
SD	2.12	0.07		
Observations	37	37		
	Rice (tons/acre)			
Minimum	2.44	0.06		
Maximum	20.73	0.39		
Mean	7.07	0.16		
SD	4.2	0.08		
Observations	29	29		
	Nebraska		South Dakota	
	Corn (bushels/acre)		Corn (bushels/acre)	
Minimum	9.83	0.21	6.16	0.10
Maximum	28.08	0.75	19.41	0.40
Mean	17.53	0.28	13.14	0.23
SD	4.43	0.06	3.20	0.07
Observations	89	89	38	38
	Wheat (bushels/acre)		Wheat (bushels/acre)	
Minimum	3.03	0.09	4.33	0.14
Maximum	11.39	0.44	10.15	0.38
Mean	5.71	0.17	7.15	0.28
SD	1.53	0.05	1.32	0.06
Observations	89	89	65	65
	Oats (bushels/acre)		Oats (tons/acre)	
Minimum	4.99	0.1	4.81	0.17
Maximum	12.55	0.29	18.18	0.42
Mean	9.31	0.2	12.13	0.29
SD	1.65	0.03	2.49	0.06
Observations	88	88	66	66

Data for corn, oats, and wheat excludes irrigated acreage.
Observations are counties for Nebraska and South Dakota, parishes for Louisiana, and provincial regions for British Columbia.

deviation in crop yield instead of coefficient of variation we use mean yield as a control variable in the equations. For Louisiana there is not enough data to estimate the equations for sorghum and wheat. For the tests in Section 3.5 we used FARM INCOME and INSTITUTION.

In Table 6 the control variables included ACRES, AGE, FARM INCOME, FULLTIME, INSTITUTION, and IRRIGATION, as well as individual crop dummies. We also used only those observations for which the WEALTH variable was positive.

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