Indirect Utility Maximization under Risk:

A Heterogeneous Panel Application

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Abstract

The curvature properties of the indirect utility function imply a set of refutable implications in the form of comparative static results and symmetric relations for the competitive firm operating under uncertainty. These hypotheses, first derived and empirically tested under output price uncertainty by Saha and Shumway (1998), are extended in this article to the more general case of both price and quantity uncertainty and result in an important theoretical finding. Using recently developed techniques for testing unit root and cointegration in heterogeneous panels, we develop a model of U.S. agricultural production based on the time series properties of a panel of state-level data and contrast test implications with those resulting from a traditional model that presumes stationarity in all variables. Although differing in specific outcomes, the empirical tests of the refutable hypotheses render the same conclusions for both models: we fail to reject most refutable hypotheses under output price and output quantity risk, symmetry conditions implied by a twice-continuously-differentiable indirect utility function are rejected, two restrictive risk preference hypotheses are also rejected, and, at individual observations, data are generally consistent with most (but not all) of the hypotheses implied by individual states acting as though they were expected utility-maximizing firms.

Key words: refutable implications, risk and uncertainty, panel unit root, panel cointegration

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Because of the long time periods between commitment of resources and generation of marketable output in production agriculture, a high level of uncertainty is associated with many production decisions. Because producers frequently have few options available to significantly alter input combinations after the decision is made to produce a commodity, opportunities to reduce the adverse consequences of risk are often limited in the short run. Consequently, economists concerned about decision making in production agriculture have had a long history of considering the impact of risk and uncertainty.

Building on the early work of Sandmo (1971) and Batra and Ullah (1974), who developed the theory of the competitive firm under output price uncertainty, agricultural economists have examined firm operations and developed testable firm models under various sources of risk. The pioneering work of Pope (1980) derived testable hypotheses expressed in symmetry and homogeneity results under constant absolute risk aversion and price uncertainty. His symmetry results proved simple enough for empirical application under certain classes of utility functions (Antonovitz and Roe 1986). Chavas and Pope (1985) extended Pope's work by examining price uncertainty within a general risk preference framework which facilitated empirical tests of firm behavior under the expected utility hypothesis. Paris (1988) analyzed the competitive entrepreneur under output and input price uncertainty in a long-run scenario. Dalal (1990) derived additional symmetry conditions for empirical application under price risk. Adrangi and Raffiee (1999) derived testable implications within a comparative statics framework for the competitive firm operating under output and input price uncertainty.

A number of studies have also provided empirical tests for behavioral hypotheses of the firm operating under risk. For example, Chavas and Holt (1990) developed an acreage supply response model consistent with expected utility maximization and empirically tested the symmetry restrictions using annual time-series data for U.S. corn and soybean acreage decisions. They found empirical evidence for the symmetry conditions and decreasing absolute risk aversion (DARA) on the part of the producer. Later they (Chavas and Holt 1996) tested the economic implications of producer behavior under price and production risk in U.S. corn and soybean acreage response decisions. The null hypothesis of CARA was rejected and evidence was again found to support DARA. Theoretical and functional form deficiencies in the Chavas-Holt analysis were addressed by Satyanarayan (1999), who extended previous works to the firm operating under domestic price and exchange rate uncertainty.

Park and Antonovitz (1992a, b) derived and empirically tested the reciprocity conditions linking optimal output and hedging decisions for the competitive firm that uses hedging to manage price uncertainty. They concluded that the symmetric results as well as constant absolute risk aversion (CARA) for their California feedlot could not be rejected. Dalal (1994) alleged a misspecification, criticized their conclusions, and developed a more general formulation using the envelope theorem and derivatives of the indirect expected utility function.

Saha and Shumway (1998) derived general refutable implications from the first-order and second-order curvature properties of the indirect utility function under output price uncertainty and empirically tested each postulate for a sample of Kansas wheat producers. They failed to reject any of the implications of expected utility maximization for their data set but rejected restrictive risk attitudes including both CARA and risk neutrality.

Several studies have recently investigated firm behavior under risk using pooled cross-sectional time-series data (e.g., Saha and Shumway 1998; Lien and Hardaker 2001; Kumbhakar 2002; Kumbhakar and Tveteras 2003; Roosen and Hennessy 2003). Using panel data has several benefits for empirical analysis. For example, it enlarges the sample size, enhances the power of statistical tests, and facilitates analysis of dynamic properties of relationships. However, a daunting challenge arising from both time series and panel data regressions is the possibility that variables involved in the regressions are nonstationary. Unless a linear combination of nonstationary variables is stationary, i.e., the variables are cointegrated, use of ordinary regression estimators may lead to spurious results (Phillips 1986; Engle and Granger 1987).

Traditional tests of unit roots and cointegration have low power against the alternate hypothesis of stationarity in small and moderate sized samples. Consequently, failure to reject the hypothesis of a unit root in the series or in the linear combination of variables may occur because of the low power of the tests as well as failure of the data to satisfy the necessary conditions. Whatever the cause, failure to find stationarity in each series or in a linear combination of the series gives the analyst pause when seeking to estimate long-run relationships in the data. Recent developments in time-series econometrics that combine time-series and cross-sectional information have provided important possibilities for surmounting this dilemma. Panel data increase the power of unit root and cointegration tests even though the length of the time series is unaffected. Consequently, confidence in time series test conclusions is increased by use of panel data.

Although pooled cross-sectional time-series data has been frequently used to examine firm behavior under risk, it appears that none has examined the time-series properties of the panel data. Consequently, reported results are subject to the possibility of the spurious regression problem. The current research seeks to at least partially fill this void by employing recent advances in the econometrics literature designed to test for panel unit roots (i.e. Im, Pesaran, and Shin 1997) and panel cointegration (i.e. Pedroni 1999).[1] These panel tests allow for both parametric and dynamic heterogeneity across groups and are considerably more powerful than conventional methods (Harris and Tzavalis 1999). Besides its unique application to firm behavior under risk, this investigation joins only a small number of other studies in reporting empirical applications of panel cointegration techniques to a heterogeneous panel with multiple regressors.[2]

With this background, the objectives of this article are to: (a) extend the previous theoretical work by careful derivation of refutable and testable implications of the indirect utility function under both output price and quantity risk, (b) demonstrate that one previously maintained hypothesis is not a necessary condition for the derived implications, (c) empirically test the derived implications as well as a set of hypotheses about the nature of risk aversion practiced by producers using a traditional model in which stationarity of the data is implicitly assumed and time is included as a proxy for technical change, (d) examine the time-series properties of variables involved in a system of input demand equations by employing recent developments in panel unit root and panel cointegration techniques, (e) develop a model for input demands consistent with the time series test results and with technical change proxied by public research expenditures, and (f) contrast important inferences from hypothesis test results from this model with those from the traditional model.

The plan of this article is as follows. The next section gives a brief overview of the behavioral theory implied by curvature properties of the indirect utility function and derives a set of testable hypotheses. The following section discusses our econometric model and introduces the panel testing methodologies employed in this article. Time series properties of our data based on panel unit root and cointegration tests are then reported along with empirical results of the refutable hypotheses from both models. Conclusions are presented in the last section.

Theoretical Model

Traditionally, the introduction of price uncertainty into the theory of the competitive firm has been approached within an expected utility framework. The seminal works of Arrow (1965) and Pratt (1964) defined preferences of expected utility-maximizing decision makers over final wealth. Despite their unambiguous reference to final wealth, much of the analysis of risk taking behavior of agricultural producers, beginning with Sandmo (1971), has used profit rather than wealth as the argument of utility (Meyer and Meyer 1998). Profit is the appropriate argument only if sources of wealth other than profit are nonrandom and held fixed. Since we do not wish to impose nonrandom constraints on other sources of wealth, we use wealth as the argument of utility in the following theoretical model. Therefore, the firm is assumed to maximize its expected utility of random wealth.

Following Feder (1977) and Saha and Shumway (1998), we assume that a competitive firm's random wealth $\tilde{W}$ can be structured as a nonrandom part $Z(\cdot)$, a random component $S(\cdot)$, and nonrandom initial (beginning of period) wealth endowment I:

(1) $$\tilde{W} = Z\left(\boldsymbol{x};\beta,\cdot\right) + S\left(\boldsymbol{x};\tilde{\varepsilon};\cdot\right) + \mathrm{I}$$

where $\boldsymbol{x}=(x_1, x_2,\ldots, x_n)'$ is an $n\times 1$ vector of decision variables, $\tilde{\varepsilon}$ is a random variable vector, β is a parameter vector, and $\cdot$ denotes the additional parameters concealed in $Z(\cdot)$ and $S(\cdot)$. The parameters, β, only enter the nonrandom part of wealth, $Z(\cdot)$, but not the random part $S(\cdot)$.

Although we later demonstrate that it is unnecessary for our refutable implications to hold under output price and output quantity risk, we initially maintain the standard expectation:

(2) $$\mathrm{E}\left[S\left(\boldsymbol{x};\tilde{\varepsilon},\cdot\right)\right]=0$$

where E denotes the expectation operator.

Conditional on twice-differentiable functions of Z and S, the expectation of random wealth defined by (1) and (2) can be written as:

(3) $$\bar{W}=\mathrm{E}\left(\tilde{W}\right)=Z\left(\boldsymbol{x};\beta,\cdot\right)+\mathrm{I}+\mathrm{E}\left[S\left(\boldsymbol{x};\tilde{\varepsilon};\cdot\right)\right]=Z\left(\boldsymbol{x};\beta,\cdot\right)+\mathrm{I}\,.$$

Refutable Implications of the Indirect Utility Function

For a competitive firm whose objective is to maximize the expected utility of random wealth specified by (1), the indirect utility function is defined by:

(4) $$V\left(\beta;\mathrm{I},\cdot\right)=max\left\{\mathrm{E}\left[U\left(Z\left(\boldsymbol{x};\beta,\cdot\right)+S\left(\boldsymbol{x};\tilde{\varepsilon};\cdot\right)+\mathrm{I}\right)\right]\right\},$$

where $U(\cdot)$ represents the von Neumann Morgenstern utility function, which is increasing in wealth, therefore is increasing in nonrandom part of wealth, $Z(\boldsymbol{x}; \beta, \cdot)$. Let $\boldsymbol{x}^*(\beta, \mathrm{I}, \cdot)$ denote the optimal input variables which are determined by (4). Under the assumptions of (1) and (2), the indirect utility function defined by (4) implies the following propositions (Saha and Shumway 1998):

Proposition 1: The indirect utility function defined by (1) has the following first-order curvature properties:

(i) Increasing in I,

(ii) Increasing (decreasing) in β if Z is increasing (decreasing) in β.

Proposition 2: The second-order curvature properties of the indirect utility function indicate:

(i) V quasiconvex in β and I if Z is convex in β,

(ii) V quasiconvex in β and I $\Leftrightarrow \Omega$ symmetric and positive semidefinite (SPSD), where $\Omega \equiv Z_{\beta\beta} + Z_{\beta\boldsymbol{x}}\left\{\boldsymbol{x}_{\beta}^{*} - \boldsymbol{x}_{\mathrm{I}}^{*} Z_{\beta}\right\}$.[3]

Corollary: Under risk neutrality or CARA, $\boldsymbol{x}_{\mathrm{I}}^{*}=0$, and Z convex in $\beta \Leftrightarrow Z_{\beta\beta} + Z_{\beta\boldsymbol{x}}\boldsymbol{x}_{\beta}^{*}$ is SPSD.

Obviously, $V(\beta;\, \mathrm{I}, \cdot)$ is increasing in I. Proposition 1(ii) indicates that the first-order curvature properties of the indirect utility function corresponding to β can be revealed by the first-order curvature characters of the nonrandom part of wealth $Z(\boldsymbol{x};\, \beta, \cdot)$. Proposition 2(i) implies the fundamental second-order curvature properties of the indirect utility function which can be explored by observing the properties of the second-order curvature of $Z(\boldsymbol{x};\, \beta, \cdot)$. By proposition 2(i), $V(\beta;\, \mathrm{I}, \cdot)$ is quasi-convex in β if Z is convex in β. This property implies and is implied by the testable postulates contained in proposition 2(ii). In proposition 2(ii), the symmetric and positive semi-definite (SPSD) matrix, Ω, which contains the comparative static and reciprocity results demonstrating the firm behaviors, includes the complete set of the refutable implications for the competitive firm under risk. Most importantly, propositions 1 and 2 do not rely on specific forms of $U(\cdot)$ that would otherwise impose an explicit risk preference (Love and Buccola 1991; Saha Shumway and Talpaz 1994). When combined with the empirically testable curvature properties of $Z(\boldsymbol{x};\, \beta, \cdot)$, they allow us to test the behavioral postulates without assuming a specific functional form for the indirect utility function.

These refutable propositions derived by Saha and Shumway (1998) have been empirically tested only under output price uncertainty. One important theoretical contribution of this article, the importance of which will be explained in the next section, is to demonstrate that the propositions hold even without assumption (2). From the proof in Saha and Shumway (1998), it is obvious that proposition 1 and proposition 2(ii) aren't conditioned on assumption (2), and all that is needed for them to hold is assumption (1). We refer readers to Saha and Shumway (1998) for the details. Before proving that proposition 2(i) holds without assumption (2), we claim the following result.

Claim. The firm's optimization problem defined in (4) is equivalent to a constrained optimization problem where $\boldsymbol{x}$ and $\bar{W}$ are jointly chosen. Defining $\mathbf{k}=\{\boldsymbol{x},\bar{W}\}$ and $\boldsymbol{\lambda}=\{\beta,\mathrm{I}\}$, then:

(5)
$$\begin{aligned} &V=\max_{x}\mathrm{E}U\left[Z\left(\boldsymbol{x};\beta,\cdot\right)+S\left(\boldsymbol{x};\tilde{\varepsilon};\cdot\right)+\mathrm{I}\right] \\ \Leftrightarrow\ &V=\max_{k}\left\{\mathrm{E}U\left[\bar{W}+S\left(\boldsymbol{x};\tilde{\varepsilon};\cdot\right)-\mathrm{E}\left(S\left(\boldsymbol{x};\tilde{\varepsilon};\cdot\right)\right)\right]\mid\bar{W}\leq Z\left(\boldsymbol{x};\beta,\cdot\right)+\mathrm{E}\left[S\left(\boldsymbol{x};\tilde{\varepsilon};\cdot\right)\right]+\mathrm{I}\right\}\end{aligned}.$$

Proof: First, we demonstrate that the constraint, $\bar{W}\leq Z(\boldsymbol{x};\beta,\cdot)+\mathrm{E}[S(\boldsymbol{x};\tilde{\varepsilon};\cdot)]+\mathrm{I}$, will be binding for all optimal values of $\bar{W}$ and $\boldsymbol{x}$. Suppose the constraint is not binding, then there must exist some parameter values $\mathbf{k}^0=\{\boldsymbol{x}^0,\ \bar{W}^0\}$ and $\boldsymbol{\lambda}^0=\{\beta^0,\ \mathrm{I}^0\}$ such that $\mathbf{k}^0=\{\boldsymbol{x}^0,\ \bar{W}^0\}$ and $\boldsymbol{\lambda}^0=\{\beta^0,\ \mathrm{I}^0\}$ maximize the indirect utility, given by (5), with the following condition

(6) $$\bar{W}^0<Z\left(\mathrm{x}^0;\beta^0,\cdot\right)+\mathrm{E}\left[S\left(x^0;\tilde{\varepsilon};\cdot\right)\right]+\mathrm{I}^0.$$

Therefore, there exists some $\bar{W}'>\bar{W}^0$ such that

(7) $$\bar{W}'=\mathrm{E}W'=Z(\boldsymbol{x}^0;\beta^0,\cdot)+\mathrm{I}^0+\mathrm{E}S(\boldsymbol{x}^0;\tilde{\varepsilon};\cdot),$$

which implies $\{\boldsymbol{x}^0,\ \bar{W}'\}$ is feasible.

Since the utility function is increasing in wealth, we have

(8) $$\mathrm{E}U(\bar{W}'+S(\boldsymbol{x}^0;\tilde{\varepsilon};\cdot)-\mathrm{E}[S(\boldsymbol{x}^0;\tilde{\varepsilon};\cdot)])>\mathrm{E}U(\bar{W}^0+S(\boldsymbol{x}^0;\tilde{\varepsilon};\cdot)-\mathrm{E}[S(\boldsymbol{x}^0;\tilde{\varepsilon};\cdot)]),$$

which contradicts the fact that $\mathbf{k}^0=\{\boldsymbol{x}^0,\ \bar{W}^0\}$ and $\boldsymbol{\lambda}^0=\{\beta^0,\ \mathrm{I}^0\}$ maximize the indirect utility. Thus, the constraint is binding for all optimal values of $\mathbf{k}$ and $\boldsymbol{\lambda}$, and the claim is proved by substituting the binding constraint $\bar{W}=\mathrm{E}W=Z(\boldsymbol{x};\beta,\cdot)+\mathrm{I}+\mathrm{E}S(\boldsymbol{x};\tilde{\varepsilon};\cdot)$ into (5).

With claim 1 proven, we can now prove that proposition 2(i) is implied by assumption (1). Let $H(k,\lambda) = \bar{W} - Z(\boldsymbol{x};\beta,\cdot) - \mathrm{E}S(\boldsymbol{x};\tilde{\varepsilon};\cdot) - \mathrm{I}$, which is non-positive. Then (5) is equivalent to the following expression:

(9) $$V(\mathbf{k},\cdot) = \max_{k}\left\{\mathrm{E}U\left[\bar{W} + S(\boldsymbol{x};\tilde{\varepsilon};\cdot) - \mathrm{E}\left(S(\boldsymbol{x};\tilde{\varepsilon};\cdot)\right)\right] \mid (\mathbf{k},\lambda) \le 0\right\}.$$

If $Z(\boldsymbol{x};\beta,\cdot)$ is convex in β, $Z_{\beta\beta} \ge 0$ and $-Z_{\beta\beta} \le 0$. The Hessian matrix of $H(\mathbf{k},\lambda)$ with respect to β and I is

(10) $$D = \begin{bmatrix} \dfrac{\partial^2 H}{\partial \beta^2} & \dfrac{\partial^2 H}{\partial \beta \partial I} \\ \dfrac{\partial^2 H}{\partial \mathrm{I} \partial \beta} & \dfrac{\partial^2 H}{\partial \mathrm{I}^2} \end{bmatrix} = \begin{bmatrix} -Z_{\beta\beta} & 0 \\ 0 & 0 \end{bmatrix}$$

Let λ', λ'' and $\bar{\lambda}$ be any feasible vectors such that $\bar{\lambda} = t\lambda' + (1-t)\lambda''$, $0 \le t \le 1$ and $\bar{k}$ denotes the optimal vector corresponding to $\bar{\lambda}$. Under the conditions $-Z_{\beta\beta} \le 0$ and $|D| = 0$, D is negative semi-definite, which implies $H(\mathbf{k},\lambda)$ is quasiconcave in $\lambda = (\beta, \mathrm{I})$. Therefore, the following inequality holds:

(11) $$\min\left\{H(\bar{\mathbf{k}},\lambda'), H(\bar{\mathbf{k}},\lambda'')\right\} \le H(\bar{\mathbf{k}},\bar{\lambda}) \le 0,$$

which is sufficient to ensure that either $H(\bar{\mathbf{k}},\lambda') \le 0$ or $H(\bar{\mathbf{k}},\bar{\lambda}) \le 0,$ or both. Therefore,

(12) $$V(\bar{\lambda},\cdot) \le \max\left\{V(\lambda',\cdot), V(\lambda'',\cdot)\right\}.$$

By definition, the inequality in (12) implies that $V(\cdot)$ is quasiconvex in $\boldsymbol{\lambda}$.

Testable Hypotheses

Consider a firm's production function that has the following general form:

(13) $$\tilde{\boldsymbol{Y}} = f(\boldsymbol{x}) + \varepsilon_Y,$$

and random price denoted by:

(14) $\tilde{\boldsymbol{P}} = \bar{\boldsymbol{P}} + \varepsilon_P,$

where $\tilde{\boldsymbol{Y}}$ is random output quantity; $f(\boldsymbol{x})$, a function of input vectors $\boldsymbol{x}$, is called the mean output function; $\tilde{\boldsymbol{P}}$ denotes random price; $\bar{\boldsymbol{P}}$ is the mean of price; ε_Y and ε_P are stochastic terms which represent random production shock and random price shock respectively; $E(\varepsilon_Y) = 0$ and $E(\varepsilon_P) = 0$. Letting $\mathbf{r} = \{r_1, \ldots, r_n\}'$ be the price vector of inputs, random wealth under output price and output quantity uncertainty will be:

(15) $\tilde{W} = \tilde{\boldsymbol{P}} \Box \boldsymbol{Y} - \mathbf{r} \Box \boldsymbol{x} + \mathrm{I} = \bar{\boldsymbol{P}} f(\boldsymbol{x}) + \bar{\boldsymbol{P}} \Box \varepsilon_Y + \varepsilon_P \Box f(\boldsymbol{x}) + \varepsilon_P \Box \varepsilon_Y - \mathbf{r} \Box \boldsymbol{x} + \mathrm{I}.$

In terms of the notation in the preceding section, $\mathbf{r}$ corresponds to β, the nonrandom part of wealth is:

(16) $Z(\boldsymbol{x}; \mathbf{r}, \Box) = \bar{\boldsymbol{P}} \Box f(\boldsymbol{x}) - \mathbf{r} \Box \boldsymbol{x},$

and the random component of wealth is:

(17) $S(\boldsymbol{x}; \tilde{\varepsilon}; \Box) = \bar{\boldsymbol{P}} \Box \varepsilon_Y + \varepsilon_P \Box f(\boldsymbol{x}) + \varepsilon_P \Box \varepsilon_Y$

Therefore, $\mathrm{E}\left[S(\boldsymbol{x}; \tilde{\varepsilon}; \Box)\right] = \mathrm{E}\left[\bar{\boldsymbol{P}} \Box \varepsilon_Y + \varepsilon_P \Box f(\boldsymbol{x}) + \varepsilon_P \Box \varepsilon_Y\right] = E(\varepsilon_P \Box \varepsilon_Y)$. Under the assumption of no correlation between output prices and quantities, $\mathrm{E}(\varepsilon_P \Box \varepsilon_Y) = 0$ and thus $\mathrm{E}\left[S(\boldsymbol{x}; \tilde{\varepsilon}; \Box)\right] = 0$, which is consistent with assumption (2).

For an individual firm operating in a competitive market $\mathrm{E}(\varepsilon_P \Box \varepsilon_Y) = 0$ because the firm's decisions cannot affect the general equilibrium of the market. However, much empirical analysis, including ours, uses data for aggregates of firms. Sometimes that is for convenience and other times it is necessary because essential firm-level data don't exist. Even though the decisions of individual price-taking firms can't affect the market equilibrium, the collective decisions of many firms can. Thus, since we have demonstrated that assumption (2) is unnecessary for any of the previous implications to hold, it is clear that we can make use of aggregate data, if necessary, to conduct empirical tests of both propositions.

With random wealth under output price and output quantity uncertainty defined as in equations (15), (16) and (17), the indirect utility function becomes:

$$(18)\qquad V(\mathbf{r};\mathrm{I},\cdot) = max\left\{\mathrm{E}\left[U\left(Z\left(\boldsymbol{x};\mathbf{r},\cdot\right)+S\left(\boldsymbol{x};\tilde{\varepsilon};\cdot\right)+\mathrm{I}\right)\right]\right\}.$$

By proposition 1(ii), the firm's indirect utility function, $V(\mathbf{r};\ \mathrm{I},\ \cdot)$, is decreasing in **r** since the firm's expected profit, i.e., a nonrandom portion of wealth, decreases in **r**. Applying the envelope theorem to (16), proposition 1(ii) can thus be translated to the following:

$$(19)\qquad V_{\mathbf{r}} \overset{S}{=} Z_{\mathbf{r}} = -\boldsymbol{x}^{*} < 0,$$

where $\overset{S}{=}$ denotes 'same sign as'. The result in (19) is the first-order curvature property of the indirect utility function. It indicates that, as input prices increase, the terminal wealth of the producer diminishes and leads to a decrease in the utility of final wealth. By again applying the envelope theorem, $Z_{\mathbf{rr}} = -\boldsymbol{x}_{\mathbf{r}}^{*}$ and $Z_{\mathbf{r}\boldsymbol{x}}$ is a negative identity matrix. Thus, we have:

$$(20)\qquad \begin{aligned}\Omega &\equiv Z_{\mathbf{rr}} + Z_{\mathbf{r}\boldsymbol{x}}\left\{\boldsymbol{x}_{\mathbf{r}}^{*} - \boldsymbol{x}_{\mathrm{I}}^{*}Z_{\boldsymbol{r}}\right\}\\ &= \boldsymbol{x}_{\mathrm{I}}^{*}Z_{\mathbf{r}} - 2\boldsymbol{x}_{\mathbf{r}}^{*}\\ &= -\left(\boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\mathbf{r}}^{*}\right)\end{aligned}$$

since $Z_{\mathbf{r}} = -\boldsymbol{x}^{*}$. Using this result, the second-order curvature result of proposition 2(ii) translates to:

$$(21a)\qquad V(\mathbf{r};\ \mathrm{I},\ \cdot)\text{ quasiconvex in }\mathbf{r}\text{ and I } \Leftrightarrow \Omega \equiv -\left(\boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\boldsymbol{r}}^{*}\right)\ \text{ is SPSD,}$$

which implies the following matrix is symmetric negative semidefinite:

$$(21b)\qquad \Psi = \boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\mathbf{r}}^{*}.$$

Specifically, when there are three input variables, (21b) can be rewritten as:

$$\text{(21c)}\quad \begin{bmatrix} 2\Box x^{*}_{1\mathbf{r}1} + x^{*}_{1I}\Box x^{*}_{1} & 2\Box x^{*}_{1\mathbf{r}2} + x^{*}_{1I}\Box x^{*}_{2} & 2\Box x^{*}_{1\mathbf{r}3} + x^{*}_{1I}\Box x^{*}_{3} \\ 2\Box x^{*}_{2\mathbf{r}1} + x^{*}_{2I}\Box x^{*}_{1} & 2\Box x^{*}_{2\mathbf{r}2} + x^{*}_{2I}\Box x^{*}_{2} & 2\Box x^{*}_{2\mathbf{r}3} + x^{*}_{2I}\Box x^{*}_{3} \\ 2\Box x^{*}_{3\mathbf{r}1} + x^{*}_{3I}\Box x^{*}_{1} & 2\Box x^{*}_{3\mathbf{r}2} + x^{*}_{3I}\Box x^{*}_{2} & 2\Box x^{*}_{3\mathbf{r}3} + x^{*}_{3I}\Box x^{*}_{3} \end{bmatrix}.$$

Equations (19) and (21a)-(21c) reveal that the propositions imply a set of testable hypotheses associated with the input responses of the firm operating under output price and output quantity uncertainty. Therefore, the propositions implied by the indirect utility function can be empirically tested by imposing parameter restrictions on a firm's demand equations.

Econometric Model and Empirical Methodology

Data

Because we lack essential data to conduct tests of these propositions for a broad cross-section of individual U.S. firms, the above methodology was applied to annual state-level data for the period, 1960-1999.[4] The major data source was the ERS annual agricultural output and input series for each of the contiguous 48 states for the period 1960-1999 (Ball 2002). This high-quality aggregate data set includes a comprehensive inventory of agricultural output and input prices and quantities compiled using theoretically and empirically sound procedures consistent with a gross output model of production (see Ball et al. 1999, for details). The data set includes three output groups (crops, livestock, and secondary outputs) and four input groups (materials, capital, labor, and land).

Initial stock of wealth, I, was proxied by equity, or "net worth", which measures farm business assets minus farm business debt. These data for each state were taken from the *Farm Balance Sheets* (USDA/ERS).

Deflated annual public research expenditures for each state for the period 1927-1995 were from Huffman (2002). These data served as proxies for technical innovation in the model based on the time series properties of the data. It has been showed that research expenditures can affect technology, or the nature of the production function, at least seven years later and sometimes as long as 30 years later (Chavas and Cox 1992; Pardey and Craig 1989). Akaike's Information Criterion (AIC) was used to select the optimal lag on public research expenditures.

Lagged output prices were used as proxies for expected output prices. Lagged equity was used as a proxy for initial (beginning period) wealth. To partially mitigate the effects of trending and autocorrelated data, expected output prices, equity, and current input prices were normalized by the price of land. To reduce heteroskedasticity and to permit estimation of identical non-intercept coefficients for all states in the panel data set, input quantities, normalized equity, and deflated research expenditures were scaled by the quantity of land.[5]

Econometric Model

Without maintaining any additional hypotheses about the input demand equations, we used a quadratic (second-order Taylor-series expansion) functional form to approximate the input demand framework. Input demand equations for materials/land, capital/land, and labor/land were each estimated as a fixed-effects panel data model:

(22) $$\boldsymbol{x}_{\mathrm{j}} + \mathbf{d}\alpha_{\mathrm{j}} + \mathbf{z}\phi_{\mathrm{j}} + 0.5\mathbf{z}\Gamma_{\mathrm{j}}\mathbf{z}' + \delta_{1\mathrm{j}}\mathrm{t} + 0.5\delta_{2\mathrm{j}}\mathrm{t}^2 + e_{\mathrm{j}}, \mathrm{j} = 1, 2, 3$$

where x_j is the quantity of the j^{th} input measured as input per unit of land; **d** is the vector of state dummy variables; the vector $\mathbf{z} = \{p_1, p_2, p_3, r_1, r_2, r_3, I\}$ contains lagged output prices p_i (for crops, livestock, and secondary outputs), current input prices r_j (for materials, capital, and labor), and lagged farm equity per unit of land I, each normalized by the price of land; t is the proxy for technological innovations and is represented by time = 1, . . ., 40 in the traditional model and by public research expenditures per unit of land in the time-series-based model; the error term is denoted by e_j: parameters to be estimated are the vectors α_j, ϕ_j, Γ_j, and the scalars δ_{1j}, δ_{2j}.

For each individual equation in the demand system specified by (22), fixed effects across cross-sectional observations were considered. So that all refutable implications under output price and output quantity risk contained in (19) and (21a)-(21c) could be tested, no restrictions were imposed on the estimated parameters across the equations.

Since stationarity of all variables is implicitly assumed when equation (22) is estimated without first examining their time-series properties, the results of the traditional model may be misleading. In the time-series-based model, we checked whether any of the variables contain unit roots, and if they do, whether a linear combination of the variables as represented in equation (22) also have a unit root (i.e., are not cointegrated). If they are cointegrated, a valid long-run relationship can be represented by equation (22). Variables are cointegrated if they are stationary after differencing and no unit root exists in the residuals (Engle and Granger, 1987). If all nonstationary variables in equation (22) are cointegrated, the equation represents a structural rather than a spurious relationship.

Unit Root Tests in Panel Data

The most common procedure used to test for a unit root in a data series is the augmented Dickey-Fuller (ADF) test. The null hypothesis of this test is nonstationarity. Given the small span of our time series (40 annual observations), conventional ADF tests conducted on each individual state series can have very low power and lead to seriously misguided conclusions. The preferred choice is to apply a panel unit root test.

Several procedures have been proposed to test for the null hypothesis of nonstationarity in panels. Quah (1992, 1994) developed a test for a unit root in panel data subject to homogeneous dynamics. Levin and Lin (1993) generalized this method to allow for fixed effects, individual deterministic trends, and heterogeneous serially correlated errors. However, the alternative hypothesis only allowed for the possibility of identical first-order autoregressive coefficients in all series. To allow for residual serial correlation and heterogeneous autoregressive coefficients across groups, Im, Pesaran, and Shin (1997) (hereafter IPS) proposed using an average of the ADF tests. Monte Carlo experiments showed that the IPS test outperforms Levin and Lin's test, especially having greater power and better small-sample properties (Im, Pesaran, and Shin 1997). Consequently, the IPS test is the panel unit root test we employ.

It consists of testing the null hypothesis H_0: $\rho_i = 0 \forall i$ (where i indicates a cross-sectional member) against the alternative hypothesis H_a: $\rho_i < 0$ for some or all i in the following equation:

(23) $$\Delta y_{it} = \alpha_i + \delta_i t + \rho_i y_{i,t-1} + \sum_{j=1}^{p_i} \varphi_{ij} \Delta y_{i,t-j} + \varepsilon_{it}, i = 1, 2, \ldots, N, t = 1, \ldots, T,$$

where y is a data series; t is time period; $\Delta y_{it} = y_{it} - y_{i,t-1}$; α and δ represent the idiosyncratic fixed effect and deterministic trend parameters to be estimated; ρ and φ are other parameters to be estimated; and ε is the error term. The IPS statistic is defined as the average of the ADF statistics for individual cross-sectional members. It is computed as:

(24) $$\bar{t}_{NT} = \frac{1}{N} \sum_{i=1}^{N} t_{iT} ,$$

where t_{iT} is the individual t-statistic for the ADF test of a unit root for an individual member in the panel. The resulting IPS statistic is:

(25) $$t_{IPS} = \frac{\sqrt{N}(\bar{t}_{NT} - E[t_T \mid \rho_i = 0])}{\sqrt{Var[t_T \mid \rho_i = 0]}} \Rightarrow \mathrm{N}(0,1) ,$$

where $E[t_T \mid \rho_i = 0]$ and $Var[t_T \mid \rho_i = 0]$ are the common mean and variance of t_{iT}, obtained by Monte Carlo simulation and tabulated in Im, Pesaran, and Shin (1997).

As noted by Pedroni (1997) and Kao, Chiang, and Chen (1999) regarding heterogeneous panels with multiple regressors, it is inappropriate to apply individual unit root tests to judge the stationarity of estimated residuals from linear combinations of nonstationary variables. Consequently we pool the time-series and cross-sectional data sets and use Pedroni's (1999) panel cointegration tests to test for the existence of a long-run relationship between the normalized input quantity x_j and the right hand-side variables in equations (22).

Consider the following time series panel regression:

(26) $$y_{it} = \alpha_i + X_{it}\beta_i + \delta_i t + e_{it}, \quad i = 1,...,N, \quad t = 1,...,T,$$

where y_{it} and X_{it} are the observable dependent and independent variables with dimensions $(N \times T) \times 1$ and $(N \times T) \times m$, respectively; m is the number of regressors; β are the regressor parameters to be estimated; e_{it} is a vector of disturbance terms. Pedroni (1999) proposed several statistics that can be classified into two categories. One category consists of within-dimension-based statistics (or panel statistics), in the spirit of Levin and Lin (1993). These statistics pool the residuals along the "within dimension" of the panel, i.e., numerator and denominator components of the test statistics are summed separately over the cross-sectional dimension. The second category consists of between-dimension-based statistics (or group mean statistics). Based on IPS (1997), these statistics obtain the ratio of numerator to denominator for each cross-sectional member prior to aggregating over the N dimension.

In both cases, the null hypothesis is the same, i.e., that the variables are not cointegrated for each cross-sectional member. The alternative hypothesis is different for the two test categories. The alternative for the first test category (panel statistics) is that the stationary autoregressive parameter is homogeneous. Maddala and Wu (1999) argue that this alternative is unreasonable, and that the second test category (group statistics) is more appropriate since the alternative hypothesis, which permits heterogeneous autoregressive parameters, is less restrictive.

Two statistics for the second category of tests are as follows:

(27) (Group ρ statistic) $$\tilde{Z}_{\hat{\rho}_{N,T-1}} = \sum_{i=1}^{N} (\sum_{t=1}^{T} \hat{e}_{i,t-1}^2)^{-1} \sum_{t=1}^{T} (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i)$$

(28) (Group t statistic) $$\tilde{Z}_{t_{NT}} = \sum_{i=1}^{N} (\hat{\sigma}_i^2 \sum_{t=1}^{T} \hat{e}_{i,t-1}^2)^{-1/2} \sum_{t=1}^{T} (\hat{e}_{i,t-1} \Delta \hat{e}_{i,t} - \hat{\lambda}_i)$$

where $\hat{\lambda}_i = \frac{1}{2}(\hat{\sigma}_i^2 - \hat{s}_i^2)$, and $\hat{\sigma}_i^2$ and $\hat{s}_i^2$ are individual long-run and contemporaneous variances, respectively, of the residuals $\hat{u}_{it}$ from the autoregression $\hat{u}_{it} = \hat{e}_{it} - \hat{\gamma}_i \hat{e}_{i,t-1}$.

Specifically,

(29) $$\hat{\lambda}_i = \frac{1}{T} \sum_{s=1}^{k_i} (1 - \frac{s}{k_i + 1}) \sum_{t=s+1}^{T} (\hat{u}_{it} \hat{u}_{i,t-s}) \text{, and}$$

(30) $$\hat{s}_i^2 = \frac{1}{T} \sum_{t=1}^{T} \hat{u}_{it}^2 .$$

Adjusted by appropriate constants obtained from the moments of the underlying Brownian motion functions, these statistics are distributed as standard normal when both *N* and *T* grow large. Large left tail values of these statistics imply rejection of the null hypothesis in favor of cointegration.

Empirical Results

Panel Unit Root and Cointegration Tests

As illustrated in figure 1, a structural change involving a break in volatility occurred in approximately 1981 for most of the states for all the normalized prices and normalized wealth. To mimic the effects of such a structural break, we split the data for normalized prices and wealth variables for all states into two groups at 1981. A linear regression of each variable on year was estimated for each time period, and standard deviations were computed. After dividing the normalized prices and equity in each time period by the respective standard deviation, the transformed data were used in the panel tests.

As also illustrated in figure 1, all cross-sectional members in the panel had almost the same time pattern for prices and equity variables. The implication is that the price series and equity tended to be driven by some common external disturbance. As recommended by IPS, the common time effects across states was purged by regressing each normalized price series and normalized equity on a set of time dummies and using these residuals in the unit root tests. This approach assumes that the disturbances for each member of the panel can be decomposed into common disturbances that are shared among all members of the panel and independent idiosyncratic disturbances that are specific to each member.

The results of the unit root tests proposed by IPS are shown for each variable in table 1. These tests allowed each panel member to have a different autoregressive coefficient and short run dynamics under the alternative hypothesis of trend stationarity. The tests were conducted using the econometric software package RATS version 6, routine PANCOINT. Following the suggestion of Newey and West (1994), the number of lags included in each test was determined by the Bartlett kernel with the bandwidth parameter, k_i , set equal to the integer of $4(T/100)^{2/9}$, i.e., k_i=3 in our application. The lag on research expenditures was determined by minimizing AIC for lags of 7-30 years. The optimal lag ranged from 17 to 30 years, depending on input demand equation. For convenience in subsequent analysis, an identical lag of 17 years was selected for all equations. This value was the optimal lag for the labor equation, and the distribution of AIC values was much flatter for the other equations than for the labor equation.

The unit root test statistics were distributed as N(0,1) under the null of a unit root with a one-tailed negative test statistic for the alternative hypothesis.

At the 5% significance level, a unit root was rejected only for the series x_3, r_3, and p_2. When the other (nonstationary) variables were tested for a unit root in first differences, the alternative hypothesis was stationarity without a trend since any time trend in levels was removed by differencing (Canning and Pedroni, 1999). The test statistic for 1^{st} differences was negative and significant at a 5% level in each variable except for x_1. The latter was significant at a 10% level. Although higher than our prespecified significance level, we accepted x_1 as a stationary series in first differences because it continued to exhibit nonstationarity at the 5% level even after 4^{th} differencing. Consequently, we conclude that x_3, r_3, and p_2 are stationary, i.e., integrated of order zero – I(0), and that all other variables are integrated of order one, I(1).

We next tested for cointegration among the nonstationary variables for each input demand equation. If the data are cointegrated for an input demand, equation (22) for that input can be estimated using the original (i.e., untransformed) data to capture the long-run relationships in the data. If the data are not cointegrated, first differences must be taken for all variables except x_3, r_3 and p_2 in order to capture the long-run relationships

In order to improve the power of the cointegration tests, we considered the trade-off between size and power of the tests (Haug, 1996). By pooling the data across states, the group mean statistics for panel cointegration tests in Pedroni (1999) could be applied. Some variables (i.e., all the normalized prices and equity) involved in the input demand equations (equation 22) tended to be cross-sectionally dependent, and the others did not. Therefore, in the panel cointegration testing procedure, we considered both the case including common time dummies (to capture effects that tend to cause individual state variables to move together over time) and the case without time dummies.

As suggested by Pedroni (1999), the adjustment terms for the panel cointegration tests were obtained by Monte Carlo simulation on the basis of 10,000 draws of 37 independent random walks (i.e., the number of regressors exclusive of dummy variables) of length T=10,000.[6] The results of the panel cointegration tests, presented in table 2, show that there is no evidence of cointegration among the variables for any of the demand equations. Consequently, the time-series-based input demand equations were estimated using differenced data for all variables except x_3, r_3, and p_2.

Econometric Model Estimates

For the purpose of comparison, two sets of input demand equations were estimated. They included (a) the traditional model in which all variables were implicitly assumed to be stationary and (b) the time-series-based model that accounted for non-rejected time series properties of the data investigated in last sub-section. In both models, each equation had the same regressors and no across-equation restrictions were imposed. Consequently, the SUR parameter estimates were identical to OLS estimates. The SUR estimation procedure was used to permit across-equation tests to be conducted, as required for proposition 2.

Before estimating the traditional model, we first tested for a 1st-order autoregressive (AR(1)) process in the error terms for each input demand equation defined in (22). Evidence of an AR(1) process was found in each equation with Durbin-Watson test statistics of 0.311, 0.317, and 0.674, respectively, for the materials, capital, and labor input demand equations. Subject to the assumption that the autoregressive coefficients (rho) within a demand equation were identical across states, estimates of rho for the three input demand equations were 0.971, 0.923, and 0.870, respectively. The data were transformed for 1st-order autocorrelation and used in a seemingly unrelated regression (SUR) estimation of the system of three input demand equations.[7] The traditional model estimates of the input demand equations are reported in table 3. The R^2 values for the three equations in (22) were 0.834, 0.542, and 0.791 respectively.

Parameter estimates for the time-series-based input demand equations are reported in table 4.[8] The R^2 values were considerably lower (0.153 and 0.204) for the materials and capital equations estimated by this model than by the traditional model. However, it should be recalled that the data used for the dependent variables were not the same. They were untransformed data in the traditional model and first differences in the time-series-based model. For the labor equation, the data used for the dependent variable was the same in both models and the R^2 value was higher (0.935) in the time-series-based model.

It is well known that failing to properly account for unit roots in time-series data often results in spurious conclusions being drawn about significant relationships. Our findings were consistent with that expectation. Far fewer estimated parameters were significant in our time-series-based model than in our traditional model. For example, 20, 46, and 51% of estimated parameters in the materials, capital, and labor demand equations, respectively, were significant at the 5% level of significance in the time-series-based model. These compared to 76, 58, and 73%, respectively, in the traditional model. Excluding dummy variables, the traditional model overestimated the number of significant relationships by 60-100%. In addition, of 35 common non-dummy coefficients in these two models, many changed signs – 11 in the materials demand equation, 20 in the capital demand equation, and 20 in the labor demand equation.

Hypothesis Test Results

Hypothesis tests of the propositions and corollary were conducted on the estimated parameters at the data means. These results, as well as a tabulation of predicted values consistent with the hypotheses at each observation, are presented in table 5 for both models. Proposition 1 was examined by testing whether each of the three predicted input demands in equation (22) was positive. These test results are listed as propositions 1.1-1.3 in table 5. The null hypothesis of a zero input demand level was rejected by both models in favor of positive predicted input demands at the data means for each input at a 5% significance level. In addition, nearly all the predicted input quantities were strictly positive at individual observations. For the traditional model, among 1,872 observations, only 11 predicted capital quantities and one predicted labor quantity violated first-order curvature properties. For the time-series-based model, a higher rejection rate were found – among 1,824 observations, 78 predicted capital quantities and 14 predicted labor quantities violated first-order curvature properties.

The second proposition that $\Omega \equiv -(\boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\mathbf{r}}^{*})$ is symmetric positive semidefinite was tested by the equivalent specification that $\Psi = \boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\mathbf{r}}^{*}$ is symmetric negative semidefinite. To test this proposition, three individual tests (tests 2.1-2.3 in table 5) were conducted for negative semidefiniteness and a joint test (test 3 in table 5) for symmetry. The tests for negative semidefiniteness involved tests that all the leading principal minors of Ψ alternative in signs, starting with a nonpositive first leading principal minor, i.e., the first diagonal element. None of the refutable behavioral hypotheses implied by second-order curvature properties of the indirect utility function was rejected at the data means by either model. In the traditional model, although both the second leading principal minor (test 2.2) and the determinant (test 2.3) of Ψ had unexpected signs at the data means, they were not significantly different from zero. Considerably more evidence of second-order curvature violations than of first-order curvature violations at individual observations than of first-order condition violations. Except for test 2.3 with the time-series-based model, individual violations didn't exceed 25% of the observations.

The test results for symmetry of Ψ are presented in test 3 in table 5. The three symmetric restrictions were rejected at the 5% significance level by the joint test conducted at data means in both models. Thus, the hypothesis implied by proposition 2 that Ω is symmetric positive semidefinite is statistically rejected at this data point. Whether rejection of symmetry constitutes a rejection of the hypothesis that the collection of firms in each state act as though they were a single expected utility-maximizing firm, or whether it simply implies that the indirect utility function is not twice continuously differentiable at the data means is ambiguous from these test results. Unfortunately, we are unable to resolve the ambiguity in this article.

Decision making consistent with constant absolute risk aversion or risk neutrality implies three restrictions on input demand responses. The result (test 4 in table 5) indicates that these restrictions were rejected by the joint test at the data means at the 5% significance level in both models.

Our results using state-level aggregates were similar in a number of respects to Saha and Shumway's (1998) findings about output price risk for Kansans wheat farmers. However, we found less support in the aggregate data than they found in the firm-level data for symmetry of the indirect utility function. Our conclusions about first-order curvature properties and the nature of producers' risk preference were the same as theirs. The extant literature has not reached a consensus regarding the nature of farmers' risk preferences (Goodwin and Mishra, 2002), but a few have found empirical support for the hypothesis of constant absolute risk aversion (CARA).

Among those are the work of Park and Antonovitz (1992a, 1992b) who failed to reject CARA for California feedlots.

Conclusions

This study has extended the Saha and Shumway (1998) model of a competitive firm operating under output price risk to a firm operating under both output price and output quantity risk. One important theoretical contribution to the previous literature is that the refutable propositions implied by the indirect utility function are shown to hold without one of the previously maintained hypotheses. Therefore, the only conditions required for the propositions to hold are: (a) random wealth can be structured as three parts – a nonrandom part of profit, a random part of profit, and nonrandom initial wealth, and (b) there exists an optimal input vector that maximizes the expected utility function. Both are common assumptions in the firm theory under uncertainty. Without requiring the previously imposed assumption that the expectation of the random part of profit is zero, the propositions can be empirically applied to varied market structures by permitting tests when there is a nonzero correlation between the error terms of random output price and random output quantity.

Moreover, a set of testable hypotheses associated with input responses under multiple sources of risk were derived from these propositions, and empirically tested for aggregates of firms operating under both output price and output quantity risk. This is the first study using an aggregate state-level panel data set to empirically test for utility-maximizing behavior by considering each aggregate as though it were an expected utility-maximizing firm. Aggregate agricultural production data for these states have previously been found to approximate nonparametric conditions for consistent behavior with this hypothesis.

To avoid the possibility of spurious estimation from statistical estimation using nonstationary data, we examined the time series properties of the data. The data were tested both for nonstationarity and cointegration using recent developments in time-series econometrics, i.e., Im, Pesaran, and Shin's panel unit root tests and Pedroni's panel cointegration tests. Most of the data series were found to be nonstationary but none of the demand equations exhibited evidence of cointegration among nonstationary variables. Two models were developed and used for comparison purposes to test the expected utility maximization hypotheses – a traditional model that implicitly assumed stationary data and a model based on nonrejected time series properties of the data.

In both models, parametric results showed that the behavioral postulates implied by the first-order curvature properties of the indirect utility function could not be rejected at the data means, and the data at nearly all individual observations were consistent with these properties. The second-order curvature properties were also not rejected at the data means, but a larger portion of the observations were inconsistent with the hypotheses. The symmetry property implied by a twice continuously differentiable indirect utility function was soundly rejected at the data means by both models. The empirical evidence from both models also failed to support *ad hoc* risk preference assumptions of either risk neutrality or constant absolute risk aversion.

Footnotes

[1] See Banerjee (1999), Baltagi *and* Kao (1999), and Phillips *and* Moon (1999) for surveys of the recent theoretical literature on panel unit root tests and panel cointegration tests.

[2] Exceptions are Bandiera *et al*. (2000), McCoskey and Kao (1999), and Sarantis and Stewart (2001).

[3] The following notation is used throughout this article: h_x denotes the partial derivative of $h(\cdot)$ with respect to x, h_{xy} represents the Hessian matrix whose ij^{th} element is $\partial^2 h / \partial x_i \partial y_j$, where $h(\cdot)$ is a real-value function of vectors x and y.

[4] The theory of the expected utility maximization applies to the individual, in this case the individual firm. Although tests of utility maximization have not been reported for state-level data, Lim and Shumway (1992) failed to reject the hypothesis that each of the states acted as though they were profit-maximizing firms. They used nonparametric testing procedures on annual data for the period 1956-1982, which overlaps with the first 23 years of our data period.

[5] Significant (5% level) groupwise heteroskadasticity was still found in the scaled data.

[6] Pedroni (1999) tabulated the adjustment terms for a maximum of seven regressors.

[7] Although evidence was found that significant heteroskedasticity still remained across states, we were unable to transform the data to remove cross-sectional heteroskedasticity because we had more cross-sectional units than time periods.

[8] An additional dummy variable was included in each input demand equation in the time-series-based model for the production year 1983 to pick up the effects of the PIK program.

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Table 1. Panel Unit Root Test Results

Variable[a]	Test Statistic[b]	Test Conclusion
Panel Unit Root Test for First Differences with Trend:		
x_1	0.803	Nonstationary
x_2	0.043	Nonstationary
x_3	-2.030***	Stationary
r_1	-0.491	Nonstationary
r_2	0.847	Nonstationary
r_3	-3.241***	Stationary
p_1	1.76896	Nonstationary
p_2	-2.131***	Stationary
p_3	-0.881	Nonstationary
w_0	-0.85731	Nonstationary
res[c]	0.628	Nonstationary
Panel Unit Root Test for First Differences without Trend:		
Δx_1	-1.371*	Stationary
Δx_2	-5.799***	Stationary
Δr_1	-6.622 ***	Stationary
Δr_2	-6.7845***	Stationary
Δp_1	-8.107 ***	Stationary
Δp_3	-7.755 ***	Stationary
Δw_0	-8.608 ***	Stationary
Δres	-8.922 ***	Stationary

[a] x_1, x_2, x_3, and res were tested without time dummies, and other variables were tested with time dummies.

[b] Based on Im, Pesaran, and Shin (1997):

* Reject the null of a unit root (nonstationarity) at the 10% level (lower-tail critical value = -1.282)

** Reject the null of a unit root at the 5% level (lower-tail critical value = -1.645)

*** Reject the null of a unit root at the 1% level (lower-tail critical value = -2.326)

[c] The variable res is public research expenditures. Other variables are defined in the text.

Table 2. Panel Cointegration Test Results

Test Statistic	Test With or Without Time Dummies	Demand Equation		
		x_1	x_2	x_3
Group ρ-Statistic	With	4.578	4.075	4.751
	Without	4.189	4.456	4.393
Group t-Statistic	With	-1.264	-5.621	-0.297
	Without	2.343	1.643	-1.321

Table 3. Parameter Estimates for the Input Demand Equations: Traditional model

Variable[a]	Material/Land Equation (x_1)		Capital/Land Equation (x_2)		Labor/Land Equation (x_3)	
	Estimated coefficient[b]	SE[c]	Estimated coefficient[b]	SE[c]	Estimated coefficient[b]	SE[c]
d1	0.218***	0.032	0.132***	0.014	0.359***	0.072
d2	0.091***	0.032	0.087***	0.014	0.239***	0.074
d3	0.035	0.031	0.028**	0.014	0.134*	0.072
d4	0.239***	0.030	0.132***	0.013	0.730***	0.067
d5	0.047	0.031	0.061***	0.014	0.162**	0.074
d6	0.170***	0.031	0.284***	0.014	1.068***	0.069
d7	0.739***	0.030	0.301***	0.013	0.722***	0.067
d8	0.112***	0.031	0.075***	0.014	0.413***	0.068
d9	0.235***	0.031	0.156***	0.014	0.435***	0.069
d10	0.114***	0.031	0.171***	0.014	0.362***	0.069
d11	0.070**	0.031	0.089***	0.014	0.266***	0.072
d12	0.092***	0.031	0.180***	0.014	0.310***	0.068
d13	0.138***	0.031	0.230***	0.014	0.454***	0.068
d14	0.075**	0.031	0.093***	0.014	0.230***	0.071
d15	0.091***	0.031	0.157***	0.014	0.435***	0.069
d16	0.086***	0.031	0.102***	0.014	0.278***	0.069
d17	0.125***	0.031	0.259***	0.014	1.070***	0.069
d18	0.309***	0.031	0.288***	0.013	0.755***	0.067
d19	0.146***	0.034	0.252***	0.015	0.730***	0.077
d20	0.200***	0.031	0.307***	0.014	0.786***	0.069
d21	0.178***	0.031	0.227***	0.014	0.567***	0.069
d22	0.115***	0.031	0.165***	0.014	0.465***	0.069
d23	0.131***	0.031	0.099***	0.014	0.273***	0.071
d24	-0.026	0.033	0.043***	0.015	0.159**	0.079
d25	0.191***	0.031	0.158***	0.014	0.516***	0.069
d26	0.018	0.033	0.076***	0.015	0.198***	0.077
d27	0.127***	0.031	0.107***	0.014	0.295***	0.070
d28	0.086***	0.031	0.202***	0.014	0.716***	0.070
d29	0.156***	0.031	0.529***	0.014	1.234***	0.067
d30	-0.011	0.033	0.039***	0.015	0.158**	0.079
d31	-0.041	0.037	0.033**	0.017	0.092	0.086
d32	0.184***	0.031	0.283***	0.014	0.757***	0.070
d33	0.145***	0.031	0.290***	0.014	0.650***	0.068

Table 3 (continued)

Variable[a]	Material/Land Equation (x_1)		Capital/Land Equation (x_2)		Labor/Land Equation (x_3)	
	Estimated coefficient[b]	SE[c]	Estimated coefficient[b]	SE[c]	Estimated coefficient[b]	SE[c]
d34	0.041	0.031	0.068***	0.014	0.237***	0.071
d35	0.125***	0.031	0.100***	0.014	0.369***	0.070
d36	0.221***	0.031	0.305***	0.014	1.000***	0.069
d37	0.097***	0.031	0.302***	0.014	1.012***	0.070
d38	0.158***	0.031	0.177***	0.014	0.518***	0.069
d39	0.033	0.031	0.079***	0.014	0.198***	0.074
d40	0.065**	0.031	0.122***	0.014	0.361***	0.071
d41	0.022	0.031	0.054***	0.014	0.165**	0.072
d42	0.015	0.032	0.056***	0.014	0.171**	0.075
d43	0.008	0.031	0.128***	0.014	0.347***	0.070
d44	0.110***	0.033	0.155***	0.015	0.493***	0.074
d45	0.121***	0.031	0.139***	0.014	0.469***	0.069
d46	0.249***	0.031	0.347***	0.014	0.993***	0.070
d47	0.0714**	0.031	0.135***	0.014	0.435***	0.071
d48	0.003	0.031	0.047***	0.014	0.157**	0.075
p_1	-0.048***	0.010	-0.006	0.004	0.032	0.024
p_2	0.0602***	0.012	0.017***	0.006	-0.064**	0.031
p_3	-0.034**	0.021	-0.019**	0.011	0.023	0.062
r_1	0.118***	0.044	0.002	0.022	0.321***	0.119
r_2	-0.046**	0.019	0.003	0.009	0.038	0.051
r_3	0.0002	0.023	-0.044***	0.012	-0.379***	0.072
I	0.003***	0.001	0.0003	0.000	0.002	0.002
p_1^2	0.015 **	0.007	-0.008**	0.003	-0.017	0.018
$p_1 p_2$	-0.005	0.011	0.014***	0.006	0.076**	0.029
$p_1 p_3$	-0.017	0.020	0.008	0.009	0.001	0.046
p_1r_1	0.033	0.039	0.004	0.016	-0.043	0.075
p_1r_2	-0.027	0.016	0.0002	0.007	-0.023	0.034
p_1r_3	0.021	0.025	-0.016	0.011	0.059	0.055
p_1I	-0.001	0.001	-0.003***	0.001	-0.016***	0.003
p_2^2	0.017	0.020	-0.022**	0.009	-0.197***	0.044
$p_2 p_3$	-0.008	0.023	0.017	0.010	0.182***	0.048
p_2r_1	-0.120**	0.048	-0.069***	0.020	-0.162**	0.094
p_2r_2	0.018	0.021	0.002	0.009	0.069	0.045

Table 3 (continued)

Variable[a]	Material/Land Equation (x_1)		Capital/Land Equation (x_2)		Labor/Land Equation (x_3)	
	Estimated coefficient[b]	SE[c]	Estimated coefficient[b]	SE[c]	Estimated coefficient[b]	SE[c]
p_2r_3	0.02806	0.038	0.019	0.017	-0.060	0.086
p_2I	0.0003	0.002	0.001*	0.001	0.009**	0.003
p_3^2	0.077	0.047	0.002	0.019	-0.122	0.087
p_3r_1	0.096	0.094	0.058	0.037	0.074	0.168
p_3r_2	-0.045	0.039	-0.016	0.017	-0.146*	0.080
p_3r_3	-0.014	0.058	0.002	0.027	0.239*	0.131
p_3I	0.0003	0.004	-0.006***	0.002	-0.016**	0.007
r_1^2	-0.337**	0.187	-0.192***	0.067	-0.515*	0.298
$r_1\ r_2$	0.059	0.053	0.023	0.021	0.079	0.103
$r_1\ r_3$	0.206*	0.115	0.138***	0.044	0.230	0.201
r_1I	0.008	0.006	0.015***	0.002	0.048**	0.009
r_2^2	-0.004	0.032	0.002**	0.014	0.053	0.065
r_2r_3	-0.040	0.041	-0.041**	0.017	-0.180**	0.080
r_2I	0.008***	0.003	-0.001	0.001	0.003	0.005
r_3^2	-0.052	0.067	0.004	0.029	0.185	0.139
r_3I	-0.010**	0.005	-0.001	0.002	-0.029***	0.008
I^2	0.0001	0.000	0.001***	0.0001	0.003***	0.0003
t	-0.004**	0.002	0.003***	0.001	-0.010***	0.004
t^2	0.0003***	0.00008	0.0002***	0.00003	0.0003**	0.0002
R-Square	0.834		0.542		0.791	

[a] Variable codes: p_1 is crop price, p_2 is livestock price, p_3 is secondary output price, r_1 is materials input price, r_2 is capital input price, r_3 is labor input price, I is farm equity, t is the time variable, d1-d48 are state dummy variables.

[b] Parameter estimates marked with *** are significant at the 1% level, ** at the 5% level, and * at the 10% level.

[c] SE is standard error.

Table 4. Parameter Estimates for the Input Demand Equations: Time-Series Model

Variable [a]	Material/Land (x_1)		Capital/Land (x_2)		Labor/Land (x_3)	
	Estimated Coefficient[b]	SE[c]	Estimated Coefficient[b]	SE[c]	Estimated Coefficient[b]	SE[c]
d35	0.051*	0.029	-0.051***	0.012	1.432***	0.098
d36	0.064**	0.027	-0.021*	0.011	5.949***	0.092
d37	-0.009	0.029	-0.027**	0.012	6.706***	0.099
d38	0.069**	0.027	-0.018*	0.011	3.110***	0.091
d39	-0.002	0.030	-0.074***	0.012	0.250**	0.101
d40	0.016	0.029	-0.043***	0.012	1.394***	0.099
d41	0.005*	0.029	-0.061***	0.011	-0.014	0.098
d42	0.002	0.030	-0.059***	0.012	0.228**	0.100
d43	0.002	0.028	-0.038***	0.011	1.614***	0.095
d44	0.049*	0.029	-0.034***	0.011	2.355***	0.097
d45	0.054**	0.027	-0.030***	0.011	2.141***	0.092
d46	0.055**	0.027	-0.036***	0.011	6.669***	0.091
d47	0.027	0.029	-0.050***	0.011	2.243***	0.097
d48	-0.009	0.029	-0.069***	0.012	-0.210**	0.099
d83	0.117***	0.039	0.022	0.016	0.294**	0.133
p_1	-0.052**	0.024	0.018*	0.010	0.069	0.083
p_2	-0.010	0.007	0.020***	0.003	0.428***	0.024
p_3	0.047**	0.027	-0.015	0.011	-0.174*	0.092
r_1	0.080**	0.036	-0.032**	0.014	-0.007	0.122
r_2	-0.093***	0.028	-0.006	0.011	-0.067	0.094
r_3	0.038**	0.017	0.007	0.007	-0.420***	0.059
I	0.002	0.012	-0.030***	0.005	-0.029	0.040
p_1^2	0.148*	0.042	0.020	0.017	-0.123	0.142
$p_1 p_2$	0.009	0.009	0.007*	0.004	0.023	0.032
$p_1 p_3$	-0.043	0.040	-0.0010	0.016	0.075	0.134
$p_1 r_1$	-0.083*	0.049	0.009	0.020	0.007	0.168
$p_1 r_2$	0.100**	0.039	-0.003	0.015	-0.007	0.132
$p_1 r_3$	-0.014	0.030	-0.027**	0.012	-0.035	0.102
$p_1 I$	-0.024	0.023	0.0006	0.009	-0.013	0.076
p_2^2	0.004	0.002	-0.002	0.0009	-0.041***	0.008
$p_2 p_3$	-0.017	0.012	0.001	0.005	0.061	0.041
$p_2 r_1$	-0.036**	0.018	0.005	0.007	0.087	0.062
$p_2 r_2$	0.032**	0.014	0.001	0.005	-0.044	0.046

Table 4 (continued)

Variable [a]	Material/Land (x_1)		Capital/Land (x_2)		Labor/Land (x_3)	
	Estimated Coefficient[b]	SE[c]	Estimated Coefficient[b]	SE[c]	Estimated Coefficient[b]	SE[c]
p_2r_3	-0.002	0.005	-0.003	0.002	-0.048***	0.018
d1	0.100***	0.028	-0.031***	0.011	1.477***	0.095
d2	0.053*	0.029	-0.044***	0.011	0.550***	0.098
d3	0.005	0.030	-0.057***	0.012	-0.049	0.100
d4	0.100***	0.026	-0.011	0.010	3.568***	0.088
d5	0.005	0.029	-0.068***	0.012	-0.030	0.100
d6	0.038	0.027	-0.028**	0.011	6.052***	0.093
d7	0.344***	0.026	-0.009	0.011	4.036***	0.090
d8	0.043	0.027	-0.018*	0.011	1.818***	0.090
d9	0.113***	0.027	-0.019*	0.011	2.225***	0.092
d10	0.007	0.028	-0.032***	0.011	1.811***	0.094
d11	0.026	0.029	-0.055***	0.012	0.706***	0.099
d12	0.002	0.027	-0.026**	0.011	1.560***	0.091
d13	0.026	0.027	-0.023**	0.011	2.625***	0.091
d14	0.010	0.029	-0.059***	0.011	0.564***	0.098
d15	0.035	0.028	-0.021*	0.011	2.350***	0.093
d16	0.027	0.028	-0.024**	0.011	1.467***	0.094
d17	0.017	0.027	-0.030***	0.011	6.616***	0.093
d18	0.125***	0.026	-0.008	0.011	4.286***	0.090
d19	0.033	0.029	-0.033***	0.012	4.226***	0.099
d20	0.048*	0.027	-0.031***	0.011	4.828***	0.092
d21	0.041	0.027	-0.032***	0.011	3.343***	0.093
d22	0.024	0.027	-0.025**	0.011	2.613***	0.092
d23	0.073**	0.029	-0.038***	0.011	1.202***	0.097
d24	-0.023	0.031	-0.073***	0.012	-0.212**	0.105
d25	0.100***	0.027	-0.024**	0.011	2.912***	0.093
d26	-0.012	0.031	-0.072***	0.012	0.109	0.105
d27	0.031	0.029	-0.048***	0.011	1.121***	0.097
d28	0.014	0.027	-0.033***	0.011	3.863***	0.093
d29	-0.006	0.026	0.026**	0.010	7.193***	0.089
d30	-0.027	0.031	-0.074***	0.012	-0.252**	0.104
d31	-0.006	0.033	-0.063***	0.013	-0.205*	0.112
d32	0.058**	0.028	-0.032***	0.011	5.006***	0.096

Table 4 (continued)

Variable [a]	Material/Land (x_1)		Capital/Land (x_2)		Labor/Land (x_3)	
	Estimated Coefficient[b]	SE[c]	Estimated Coefficient[b]	SE[c]	Estimated Coefficient[b]	SE[c]
d33	0.023	0.027	-0.026**	0.011	3.910***	0.092
d34	0.011	0.029	-0.061***	0.011	0.551***	0.097
p_2I	0.014*	0.008	-0.003	0.003	-0.054**	0.026
p_3^2	0.012	0.049	-0.028	0.019	0.126	0.165
p_3r_1	0.026	0.062	-0.004	0.025	-0.055	0.210
p_3r_2	-0.038	0.044	0.009	0.017	0.056	0.149
p_3r_3	0.028	0.038	-0.005	0.015	-0.089	0.128
p_3I	0.019	0.022	-0.001	0.009	-0.133*	0.075
r_1^2	-0.099	0.041	0.043	0.016	-0.285	0.137
$r_1\ r_2$	0.015	0.037	-0.011	0.015	0.116	0.126
$r_1\ r_3$	0.078	0.057	0.006	0.023	-0.166	0.193
r_1I	-0.007	0.041	0.004	0.016	-0.015	0.140
r_2^2	-0.029	0.035	0.013	0.014	-0.159	0.120
r_2r_3	-0.063	0.042	-0.007	0.017	0.138	0.143
r_2I	-0.012	0.027	-0.007	0.011	-0.088	0.092
r_3^2	-0.004	0.012	0.007	0.005	0.320***	0.042
r_3I	-0.035	0.022	0.023***	0.009	0.111	0.075
I^2	-0.029	0.011	-0.023***	0.004	0.168**	0.036
res	-0.003**	0.001	-0.001**	0.0005	-0.032***	0.004
res^2	0.00003	0.0001	-0.0001***	0.00003	-0.002***	0.0002
R-square	0.153		0.204		0.935	

[a] materials input price, r_2 is capital input price, r_3 is labor input price, I is farm equity, t is the time variable, d1-d48 are state dummy variables, and d83 is the 1983 dummy variable.

[b] Parameter estimates marked with *** are significant at the 1% level, ** at the 5% level, and * at the 10% level.

[c] SE is standard error.

Table 5. Expected Utility Maximization Hypothesis Test Results

Proposition	Null	Test type [a]	Traditional Model			Time Series Model		
			Test at Data Means		Rejections among 1,872 Observations	Test at Data Means		Rejections among 1,824 Observations
			Statistic	P-value		Statistic	P-value	
1. V is decreasing in **r**								
1.1 V is decreasing in r_1, $\hat{x}_1 > 0$	$\hat{x}_1 = 0$	AN	98.706	0.000	0	8.486	0.000	0
1.2 V is decreasing in r_2, $\hat{x}_2 > 0$	$\hat{x}_2 = 0$	AN	9.963	0.000	11	3.253	0.001	78
1.3 V is decreasing in r_3, $\hat{x}_3 > 0$	$\hat{x}_3 = 0$	AN	56.521	0.000	1	228.681	0.000	14
2. $\Psi = \boldsymbol{x}_I^* \boldsymbol{x}^* + 2\boldsymbol{x}_{\mathbf{r}}^*$ is negative semidefinite								
2.1 1st leading principal minor: $2x^*_{1r_1} + x^*_{1I} \cdot x^*_1 \le 0$	= zero	AN	-2.284	0.022	387	-4.739	0.000	1
2.2 2nd leading principal minor of $\Psi \ge 0$	= zero	AN	-1.736	0.083	460	3.258	0.001	232
2.3 Determinant of $\Psi \le 0$	= zero	AN	0.772	0.440	450	-2.173	0.030	840
3. Symmetry of Ψ [b]		W	71.770	0.000	--	14.471	0.002	--
4. CARA or RN [c] $x^*_{1I} = x^*_{2I} = x^*_{3I} = 0$	= zero	W	99.116	0.000	--	9.755	0.021	--

[a] AN is asymptotic normal test, and W is Wald chi-squared test.

[b] Test of symmetry involves jointly testing H_0: $2\cdot x^*_{1\mathbf{r}_2} + x^*_{1I}\cdot x^*_2 = 2\cdot x^*_{2\mathbf{r}_1} + x^*_{2I}\cdot x^*_1$,

$2\cdot x^*_{1\mathbf{r}_3} + x^*_{1I}\cdot x^*_3 = 2\cdot x^*_{3\mathbf{r}_1} + x^*_{3I}\cdot x^*_1$ and $2\cdot x^*_{2\mathbf{r}_3} + x^*_{2I}\cdot x^*_3 = 2\cdot x^*_{3\mathbf{r}_2} + x^*_{3I}\cdot x^*_2$.

[c] CARA is constant absolute risk aversion, and RN is risk neutrality

Figure 1. Plots of Prices and Equity