RISK, INDUCED INNOVATION, AND PRODUCTIVITY CONVERGENCE IN U.S. AGRICULTURE

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Abstract

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This dissertation empirically analyzes the refutable implications of output price and quantity risk, price-induced innovation, and factor productivity convergence. The dissertation is organized following the manuscript format approved by the school and university, with separate self-contained chapters devoted to each of the three empirical questions.

Refutable implications based on the curvature properties of the indirect utility function for the competitive firm operating under uncertainty are extended to the case of both price and quantity uncertainty. Using unit roots and cointegration tests for heterogeneous panels, a model of U.S. agricultural production is developed based on the time series properties of a panel of state-level data. Most refutable hypotheses under output price and output quantity risk are not rejected, but symmetry conditions implied by a twice-continuously-differentiable indirect utility function are rejected. Ad-hoc risk preference assumptions of either risk neutrality or constant absolute risk aversion are also rejected. The same test conclusions are obtained from a traditional model that presumes stationarity in all variables.

The hypothesis of induced innovation is tested for U.S. agriculture using a high-quality state-level panel data set and three disparate testing techniques – time series, econometric, and nonparametric. The conclusion of little support for the hypothesis is robust across testing techniques. However, each test maintains the hypothesis that the relative marginal cost of developing and implementing technologies that save one input is the same as for any other input. Lacking data on development and implementation costs of input-saving technologies, nonparametric procedures are used to estimate relative differences required for technological change to be consistent with the induced innovation hypothesis. For consistency with the hypothesis, the marginal cost of developing and implementing land- and capital-saving technology must have been greater than for material-saving technology.

Considering dynamic effects of health and inter-state and inter-industry knowledge spillovers, total factor productivity (TFP) convergence in U.S. agriculture is examined using recently developed procedures for panel data and a growth accounting model. Strong evidence is found to support the hypothesis that the TFP converges to a steady-state. Health care access in rural areas and research spillovers from other states and from nonagricultural sectors are found to have significant impacts on the productivity growth rate both in the short-run and long-run. These results suggest richer opportunities for policymakers to enhance productivity growth.

Dedication

This dissertation is dedicated to my parents Chihua Liu
and Guichun Wu, and to my wife Xin Wang,
and to my son Matt, with whom I am bonded
not only by love but by our blood.

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CHAPTER 1

INTRODUCTION

This dissertation is composed of an introductory chapter and three empirical chapters – Testing Expected Utility Maximization under Price and Quantity Risk with a Heterogeneous Panel, Induced Innovation in U.S. Agriculture, and Productivity Convergence in U.S. Agriculture. Three common threads run through these sections: (a) they focus on important issues in U.S. agricultural production, (b) they use high quality state-level panel data sets, and (c) they explicitly test and account for the time series properties of the data.

In chapter two, "Testing Expected Utility Maximization under Price and Quantity Risk with a Heterogeneous Panel," the refutable hypotheses implied by the behavioral properties of a firm operating under both output price and output quantities uncertainty are tested. Issues related to firm behavior under uncertainty are often of great concern to researchers since a high level of uncertainty is associated with production decisions. This is particularly important in agricultural production where the commitment of resources and generation of marketable product often takes a long period of time. During this time interval, producers have few opportunities to alter production decision to reduce the adverse consequences of uncertainty.

Economists have conducted research on the firm model under risk for over three decades beginning with the pathbreaking work of Sandmo (1971). However, the literature that develops empirically refutable comparative static results for competitive firms operating under risk is much more modest. Further, empirical tests of refutable hypotheses of the firm model under risk have been limited to price risk as the only source of uncertainty, and little attention has been given to the time series properties of the data.

This chapter extends the Saha and Shumway (1998) model of a competitive firm operating under output price uncertainty to a firm operating under both price and output quantity uncertainty. The refutable implications implied by the indirect utility function are demonstrated to hold without one of the previously maintained hypotheses, i.e., that the expectation of the random part of profit is zero. As a result, the propositions can be empirically applied to a wide range of market structures by permitting tests when there is a nonzero correlation between the error terms of random output price and random output quantity. To avoid the possibility of misleading results due to time series properties of data, the panel testing procedures of Im, Pesaran, and Shin (1997) and Pedroni (1999) are used to test for stationarity and cointegration. This is the first study using an aggregate state-level panel data set to empirically test for utility-maximizing behavior and the first to apply panel cointegration techniques to firm behavior under risk.

These propositions are found to be consistent with a set of testable hypotheses which can be empirically tested by systematically imposing and relaxing restrictions on the input responses of aggregates of firms operating under both output price and output quantity uncertainty. These hypotheses were tested using two models -- – a traditional model that implicitly assumed stationary data and a model based on nonrejected time series properties of the data.

Parametric findings from this study show 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. However, the symmetry property implied by a twice continuously differentiable indirect utility function was soundly rejected at the data means. The empirical evidence also failed to support ad hoc risk preference assumptions of either risk neutrality or constant absolute risk aversion. The same test conclusions were obtained from both the model specified to be consistent with the nonrejected time-series hypotheses and from thetraditional model that presumes stationarity in all variables.

In chapter three, "Induced Innovation in U.S. Agriculture: Time-series, Econometric, and Nonparametric Tests," the hypothesis of price-induced innovation is tested. U.S. agricultural productivity has experienced rapid growth for many decades. The average annual rate of total factor productivity growth was two percent for the period 1960-1993 (Ball et al., 1997). This productivity growth has been achieved through development and implementation of output-augmenting and input-saving technologies and through economic decisions that substituted relatively cheap inputs for relatively expensive ones. Therefore, the nature of technical change is an important subject for empirical examination.

The theory of price-induced innovation has been particularly important in focusing attention of economists on technological innovation. This theory asserts that changes in relative prices of factors are expected to induce development and implementation of new technology to save the relatively more expensive factors. Although first proposed by Hicks in 1932, this theory has been empirically examined only during the last four decades. Most analytical tools that have been used to test the hypothesis can be broadly grouped into three methodological classes: econometric, time series, and nonparametric methods. No stylized fact on induced innovation in the U.S. agriculture currently exists. It should be cautioned that all the tests conducted to date have only tested the demand side of the hypothesis. The marginal cost of developing and implementing technologies that save 1 percent of an input has implicitly been assumed to be the same for each input (i.e., neutral innovation possibilities).

This chapter reports comprehensive demand-side tests of the IIH for U.S. agriculture using a state-level panel data set, Estimates of relative differences in the marginal cost of developing and implementing input-saving technology required for consistency with the hypothesis are also developed and reported. The time-series procedure used in our time-series method follows the testing logic developed by Thirtle et al. (1998), Oniki (2000), and Thirtle et al. (2002). One extension in this chapter is that the method was applied to a state-level panel data set using panel time-series techniques. The econometric testing approach follows the recent work of Armanville and Funk (2003). Their procedure is extended by formalizing the relationship between productivity changes and research and extension investments rather than treating productivity changes as a function only of time. The nonparametric approach is based on Chavas et al. (1997). The final calculation of relative differences in the marginal cost of developing and implementing input-saving technology for various inputs required for consistency with the hypothesis is based on an extension of the Chavas et al. (1997) procedure.

The test conclusions were robust to testing procedure. Little support for the IIH was found in the U.S. agricultural sector by any of these state-of-the-art tests using high-quality state-level panel data and the comprehensive, disparate testing procedures. Lacking data on the development and implementation costs of various input-saving technologies, nonparametric procedures were used to estimate the relative differences that would have been required for technological change to be consistent with the IIH. For consistency with the hypothesis, the marginal cost of developing and implementing land-saving technology must have generally been greater than for capital-saving technology, which in turn must have been greater than for material-saving technology. The marginal cost of developing and implementing labor-saving technology was less clear, but the preponderance of evidence suggested it must have been between that for land- and materials-saving technologies, but the conclusion was dependent on the type of innovation investment.

Chapter four, "Productivity Convergence in U.S. Agriculture: New Cointegration Panel Data Results," tests three total factor productivity convergence hypotheses and examines the importance of various policy instruments in explaining the rate of productivity growth in U.S. agriculture. It is the first paper to examine the impact of health care access as well as inter-state and inter-industry private research spillovers on agricultural productivity growth. It has been widely noted that agricultural productivity varies greatly among U.S. states. This variability has important public policy ramifications not only in the movement toward steady-state rates of growth but also on the efficient allocation of limited resources to achieve sustainable productivity growth.

Based on the existing agricultural growth models, states can expect to increase productivity growth by increasing public investments in knowledge creation, capacity to absorb public research spillovers, and agricultural worker education. However, there remain several deficiencies in the extant literature. First, health as a major influence on the accumulation of human capital has been ignored in the agricultural growth literature. Second, failure to consider private innovation spillovers could result in biased estimates of the impact of other drivers of productivity growth. Consequently, a systematic analysis of the impact of these major variables on productivity growth performance warrants explicit empirical testing. In addition, the estimation methods previously used to examine agricultural productivity growth and productivity convergence have important weaknesses that could produce inconsistent and misleading results. To address this inconsistency, this chapter applies the pooled mean group estimator (PMGE) developed by Pesaran et al. (1999), which presumes weak homogeneity by constraining the long-run slope coefficients to be identical across groups but allowing the short-run coefficients and error variances to vary across groups.

Three types of convergence hypotheses are examined in thischapter: cross-sectional tests for σ-convergence (examines whether the dispersion of TFP among countries or regions diminishes over time) and absolute β-convergence (tests whether agriculture in the 48 contiguous U.S. states converge to the same steady-state) and a pooled cross-section, time-series test for conditional β-convergence (tests whether each state converges to a steady-state when technologies, preferences and/or institutions differ). Strong evidence in favor of both absolute and conditional β-convergence was found, but no support for σ-convergencewas found. These findings conclude that the gap in agricultural TFP among the 48 states tends to narrow over time. That is, states with lower initial TFP levels grow more rapidly than states with higher initial TFP levels.

Two error correction models, with and without considering the short-run dynamic effects of exogenous shocks, were developed and employed to test conditional β-convergence and to examine the impacts of policy variables. Besides the positive impact of public research and extension investments and externality of public research, evidence was also found that public investment and incentives for private investment in rural health care access and privately funded research spillovers can also strengthen agricultural productivity growth as well as the steady-state TFP level. Therefore, even with similar public research and development investments and education levels, a state can directly improve its agricultural productivity by improving rural health care access and/or by increasing the absorptive capability of inter-industry and/or inter-state knowledge spillovers. Consequently, this study identifies a richer set of potential policies for raising long-run TFP levels and for accelerating the pace of reaching them.

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CHAPTER 2

TESTING EXPECTED UTILITY MAXIMIZATION UNDER PRICE AND QUANTITY RISK WITH A HETEROGENEOUS PANEL[1]

Introduction

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, 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

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[1] The data used in the analysis are available on request from the advisory committee chair, Richard Shumway (shumway@wsu.edu).

several 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. Saha and Shumway (1998) derived general refutable implications from the first-order and second-order curvature properties of the indirect utility function under price uncertainty.

Several studies have 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). 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 have been used to examine firm behavior under risk, it appears that none of the studies 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 important advances in the econometrics literature designed to test for panel unit roots (Im, Pesaran, and Shin 1997) and panel cointegration (Pedroni 1999). 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) demonstrate that one previously maintained hypothesis in the risk literature is not a necessary condition for the refutable and testable implications of the indirect utility function, (b) empirically test with U.S. state-level agricultural production data the derived implications as well as a set of hypotheses about the nature of risk aversion practiced by producers facing both price and quantity risk, (c) examine the time-series properties of variables included in the model using panel unit root and cointegration techniques, and (d) contrast important test conclusions from a model that is consistent with the time series test results with those from a traditional model in which stationarity of the data is implicitly assumed.

Theoretical Model

Traditionally, the introduction of price uncertainty into the theory of the competitive firm has been approached within an expected utility framework.[3] 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

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[2] It joins work by Chakrabarti (2003), Bandiera et al. (2000), Sarantis and Stewart (2001), and McCoskey and Kao (1999).

[3] Examples are Abdukadri, Langemeier, and Featherstone (2006), Key, Roberts, and O'Donoghue (2006), Ozanne (1998), Saha and Shumway (1998), Saha at al. (1994), Love and Buccola (1991), Chavas and Holt (1990), and Myers (1989).

nonrandom constraints on other sources of wealth, we use wealth as the argument of utility in the following theoretical and empirical models. 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 a nonrandom initial (beginning of period) wealth endowment I:

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

where $\boldsymbol{x}$ is a 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 $S(\cdot)$. A different set of parameters can be included in the random part $S(\cdot)$, but that is ignored since it is not the focus of this paper. Although we later demonstrate that the following assumption is unnecessary for our refutable implications to hold under output price and output quantity risk, we initially maintain the standard assumption:

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

where E denotes the expectation operator. This condition is commonly maintained in the risk literature and specifies the central moment of the distribution of the stochastic wealth component.[4]

Conditional on twice-differentiable functions of *Z* and *S*, the expectation of random wealth defined by (2.1) and (2.2) can be written as:

$$\text{(2.3)} \quad \bar{W} = \mathrm{E}\left(\tilde{W}\right) = Z\left(\boldsymbol{x};\beta,\cdot\right) + \mathrm{I} + \mathrm{E}\left[S\left(\boldsymbol{x};\tilde{\varepsilon};\cdot\right)\right] = Z\left(\boldsymbol{x};\beta,\cdot\right) + \mathrm{I}\,.$$

Refutable Implications of the Indirect Utility Function

For a competitive firm whose objective is to maximize the expected utility of random wealth specified by (2.1), the indirect utility function is defined by:

$$\text{(2.4)} \quad V\left(\beta;\mathrm{I},\cdot\right) = max\left\{\mathrm{E}\left[U\left(Z\left(\boldsymbol{x};\beta,\cdot\right) + S\left(\boldsymbol{x};\tilde{\varepsilon};\cdot\right) + \mathrm{I}\right)\right]\right\},$$

where *U*(·) represents the von Neumann Morgenstern utility function, which is increasing in the 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 (2.4). Under the assumptions of (2.1) and (2.2), this indirect utility function implies the following propositions (Saha and Shumway 1998):

Proposition 1: The indirect utility function defined by (2.4) has 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 this indirect utility function

[4] With a single source of risk, this assumption defines the distribution properties on the first-order moment of risk. For example, under output price risk, let $\tilde{P} = \bar{P} + \varepsilon_p$ denote random output price with mean $\bar{P}$ and random variable ε_p. The random component of wealth is defined by $S(\varepsilon_p) = \varepsilon_p \cdot Y$, where Y is output quantity. Then, assumption (2.2) is equivalent to $E(\varepsilon_p) = 0$ which is a commonly maintained hypothesis in the economics literature. However, under the scenario of both output price and output quantity risk, assumption (2.2) imposes a strict condition on the nature of the market and on empirical properties of the data when testing hypotheses derived from expected utility maximization. We will relax this assumption and demonstrate its importance for testing under both price and quantity risk in a later section.

indicate:

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

(ii) V quasiconvex in β and I $\Leftrightarrow$ Ω symmetric and positive semidefinite,

where $\Omega \equiv Z_{\beta\beta} + Z_{\beta x}\left\{\boldsymbol{x}_{\beta}^{*} - \boldsymbol{x}_{\mathrm{I}}^{*} Z_{\beta}\right\}$.[5]

Corollary: Under risk neutrality or under constant absolute risk aversion (CARA), $\boldsymbol{x}_{\mathrm{I}}^{*} = 0$, and Z convex in $\beta \Leftrightarrow Z_{\beta\beta} + Z_{\beta x}\boldsymbol{x}_{\beta}^{*}$ is symmetric and positive semi-definite.

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 that the fundamental second-order curvature properties of the indirect utility function can be revealed by the second-order curvature properties 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 matrix, Ω, contains the refutable comparative static and reciprocity results for the competitive firm under risk. 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).

Assumption (2) Unnecessary

These refutable propositions derived by Saha and Shumway (1998) have been empirically tested only under output price uncertainty. One theoretical contribution of

[5] 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. Transpose notation for vectors and matrices is not used.

this article, the importance of which will be explained in the next section, is to demonstrate that the propositions hold even without assumption (2.2). From the proof in Saha and Shumway (1998), it is obvious that proposition 1 and proposition 2(ii) aren't conditioned on assumption (2.2), and all that is needed for them to hold is assumption (2.1). We refer readers to Saha and Shumway (1998) for the details. Before proving that proposition 2(i) holds without assumption (2.2), we claim the following result.

Claim. The firm's optimization problem defined in (2.4) 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:

$$(2.5)\quad \begin{aligned} &V = \max_x \mathrm{E}U\left[Z(\boldsymbol{x};\beta,\cdot) + S(\boldsymbol{x};\tilde{\varepsilon};\cdot) + \mathrm{I}\right] \\ \Leftrightarrow\ &V = \max_k \left\{\mathrm{E}U\left[\bar{W} + S(\boldsymbol{x};\tilde{\varepsilon};\cdot) - \mathrm{E}\left(S(\boldsymbol{x};\tilde{\varepsilon};\cdot)\right)\right] \mid \bar{W} \le Z(\boldsymbol{x};\beta,\cdot) + \mathrm{E}\left[S(\boldsymbol{x};\tilde{\varepsilon};\cdot)\right] + \mathrm{I}\right\} \end{aligned}.$$

Proof: First, we demonstrate that the constraint, $\bar{W} \le Z(\boldsymbol{x};\beta,\cdot) + \mathrm{E}[S(\boldsymbol{x};\tilde{\varepsilon};\cdot)] + \mathrm{I}$, 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 expected utility, given by (2.5), with the following condition

$$(2.6)\quad \bar{W}^0 < Z\left(\mathrm{x}^0;\beta^0,\cdot\right) + \mathrm{E}\left[S\left(x^0;\tilde{\varepsilon};\cdot\right)\right] + \mathrm{I}^0.$$

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

$$(2.7)\quad \bar{W}' = \mathrm{E}W' = Z(\boldsymbol{x}^0;\beta^0,\cdot) + \mathrm{I}^0 + \mathrm{E}S(\boldsymbol{x}^0;\tilde{\varepsilon};\cdot),$$

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

Since the utility function is increasing in wealth, we have

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

which contradicts the fact that $\mathbf{k}^0 = \{\boldsymbol{x}^0,\ \overline{W}^0\}$ and $\boldsymbol{\lambda}^0 = \{\beta^0,\ \mathrm{I}^0\}$ maximize expected utility. Thus, the constraint is binding for all optimal values of **k and** $\boldsymbol{\lambda}$, and the claim is proved by substituting the binding constraint $\overline{W} = \mathrm{E}W = Z(\boldsymbol{x};\beta,\cdot) + \mathrm{I} + \mathrm{E}[S(\boldsymbol{x};\tilde{\varepsilon};\cdot)]$ into (2.5).

With claim 1 proven, we can now prove that proposition 2(i) is implied by assumption (2.1). Let $H(\mathbf{k},\boldsymbol{\lambda}) = \overline{W} - Z(\boldsymbol{x};\beta,\cdot) - \mathrm{E}[S(\boldsymbol{x};\tilde{\varepsilon};\cdot)] - \mathrm{I}$, which is non-positive. Then (2.5) is equivalent to the following expression:

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

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 $H(\mathbf{k},\boldsymbol{\lambda})$ with respect to β and I is

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

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

(2.11) $\quad \min\left\{H(\overline{\mathbf{k}},\boldsymbol{\lambda}'), H(\overline{\mathbf{k}},\boldsymbol{\lambda}'')\right\} \le H(\overline{\mathbf{k}},\overline{\boldsymbol{\lambda}}) \le 0,$

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

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

By definition, the inequality in (2.12) implies that $V\left(\cdot\right)$ is quasiconvex in $\boldsymbol{\lambda}$.

Testable Hypotheses

Consider a firm's set of nonjoint production functions that have the following general form:

(2.13) $\tilde{\boldsymbol{Y}} = \bar{\boldsymbol{Y}}\boldsymbol{(x)} + \boldsymbol{\varepsilon}_Y$,

and random prices denoted by:

(2.14) $\tilde{\boldsymbol{P}} = \bar{\boldsymbol{P}} + \boldsymbol{\varepsilon}_P$,

where $\tilde{\boldsymbol{Y}}$ is the random output quantity vector; $\bar{\boldsymbol{Y}}$ is the mean vector of outputs; $\tilde{\boldsymbol{P}}$ is the random price vector; $\bar{\boldsymbol{P}}$ is the mean vector of prices; $\boldsymbol{\varepsilon}_Y$ and $\boldsymbol{\varepsilon}_P$ are stochastic terms which represent random production shock and random price shock respectively; $E\left(\boldsymbol{\varepsilon}_Y\right)=0$ and $E\left(\boldsymbol{\varepsilon}_P\right)=0$.[6] Letting **r** be the price vector of inputs, random wealth under output price and output quantity uncertainty will be:

(2.15) $\tilde{W} = \tilde{\boldsymbol{P}}\tilde{\boldsymbol{Y}}\boldsymbol{(x)} - \mathbf{r}\boldsymbol{x} + \mathrm{I} = \bar{\boldsymbol{P}}\bar{\boldsymbol{Y}}\boldsymbol{(x)} + \bar{\boldsymbol{P}}\boldsymbol{\varepsilon}_Y + \boldsymbol{\varepsilon}_P\bar{\boldsymbol{Y}}\boldsymbol{(x)} + \boldsymbol{\varepsilon}_P\boldsymbol{\varepsilon}_Y - \mathbf{r}\boldsymbol{x} + \mathrm{I}.$

In terms of the notation in the preceding section, **r** corresponds to β, the nonrandom part of wealth is:

(2.16) $Z\left(\boldsymbol{x};\mathbf{r},\cdot\right) = \bar{\boldsymbol{P}}\bar{\boldsymbol{Y}} - \mathbf{r}\boldsymbol{x}$,

and the random component of wealth is:

---

[6] This specification provides the convenient, but not necessary, result that the expected values of the stochastic terms are zero.

(2.17) $S\left(\boldsymbol{x};\tilde{\boldsymbol{\varepsilon}};\cdot\right)=\overline{\boldsymbol{P}}\boldsymbol{\varepsilon}_{Y}+\boldsymbol{\varepsilon}_{P}\overline{\boldsymbol{Y}}+\boldsymbol{\varepsilon}_{P}\boldsymbol{\varepsilon}_{Y}$

Therefore, $\mathrm{E}\left[S\left(\boldsymbol{x};\tilde{\boldsymbol{\varepsilon}};\cdot\right)\right]=\mathrm{E}\left[\overline{\boldsymbol{P}}\boldsymbol{\varepsilon}_{Y}+\boldsymbol{\varepsilon}_{P}\overline{\boldsymbol{Y}}+\boldsymbol{\varepsilon}_{P}\boldsymbol{\varepsilon}_{Y}\right]=E\left(\boldsymbol{\varepsilon}_{P}\boldsymbol{\varepsilon}_{Y}\right)$. Under the assumption of no correlation between output prices and quantities, $\mathrm{E}\left(\boldsymbol{\varepsilon}_{P}\boldsymbol{\varepsilon}_{Y}\right)=0$, and thus $\mathrm{E}\left[S\left(\boldsymbol{x};\tilde{\boldsymbol{\varepsilon}};\cdot\right)\right]=0$, which is consistent with assumption (2.2).

For an individual firm operating in a competitive market, $\mathrm{E}\left(\boldsymbol{\varepsilon}_{P}\boldsymbol{\varepsilon}_{Y}\right)=0$ because the firm's decisions cannot affect the market equilibrium. However, much empirical analysis, including ours, uses data for aggregates of firms. Sometimes that is for convenience, sometimes it is necessary because essential firm-level data don't exist, and other times it facilities generation of aggregate policy inferences. Even though the decisions of individual price-taking firms can't affect the market equilibrium, the decisions of firms with market power as well as the collective decisions of many price-taking firms can. Thus, since we have demonstrated that assumption (2.2) is unnecessary for any of the previous implications to hold, it is clear that we can make use of aggregate data or imperfectly competitive firm data, where $\mathrm{E}\left(\boldsymbol{\varepsilon}_{P}\boldsymbol{\varepsilon}_{Y}\right)\neq 0$, to conduct empirical tests of both propositions.[7]

With random wealth under output price and output quantity uncertainty defined as in equations (2.15), (2.16) and (2.17), the indirect utility function becomes:

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

By proposition 1(ii), the firm's indirect utility function, $V(\mathbf{r};\mathrm{I},\cdot)$, is decreasing in **r** since

[7] Because they implicitly treated assumption (2.2) as a necessary condition, Saha and Shumway (1998) did not demonstrate that their propositions and corollary were applicable for testing the expected utility maximization hypothesis under all types of risk, market structure, and aggregation level.

the firm's expected profit, i.e., a nonrandom portion of wealth, decreases in **r** and the marginal utility of money is assumed to be positive. Applying the envelope theorem to (2.18), proposition 1(ii) can thus be translated to the following:

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

where $\overset{s}{=}$ denotes 'same sign as', and $\boldsymbol{x}$ is now the vector of input quantities summed across outputs. The result in (2.19) is the first-order curvature property of the indirect utility function and is a consequence of the fact that in (2.18) only Z is a function of **r**. It indicates that, as input prices increase, the terminal wealth of the producer diminishes and leads to a decrease in the expected utility of final wealth. Furthermore, $Z_{\mathbf{rr}} = -\boldsymbol{x}_{\mathbf{r}}^{*}$, and $Z_{\mathbf{r}\boldsymbol{x}}$ is a negative identity matrix. Thus, we have the Hessian matrix of V in terms of both **r** and I:

$$\begin{aligned} \Omega &\equiv Z_{\mathbf{rr}} + Z_{\mathbf{r}\boldsymbol{x}}\left\{\boldsymbol{x}_{\mathbf{r}}^{*} - \boldsymbol{x}_{\mathrm{I}}^{*} Z_{\mathbf{r}}\right\} \\ &= \boldsymbol{x}_{\mathrm{I}}^{*} Z_{\mathbf{r}} - 2\boldsymbol{x}_{\mathbf{r}}^{*} \\ &= -\left(\boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\mathbf{r}}^{*}\right) \end{aligned} \tag{2.20}$$

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

(2.21a) $V(\mathbf{r};\cdot)$ quasiconvex in **r** and I $\Leftrightarrow \Omega \equiv -\left(\boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\mathbf{r}}^{*}\right)$ is symmetric and positive semi-definite,

which implies the following matrix is symmetric negative semidefinite:

(2.21b) $\Psi = \boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\mathbf{r}}^{*}.$

Specifically, when there are three input variables, (2.21b) can be rewritten as:

$$(2.21c)\quad \begin{bmatrix} 2\boldsymbol{x}^*_{1\mathbf{r}1} + \boldsymbol{x}^*_{1\mathrm{I}}\boldsymbol{x}^*_1 & 2\boldsymbol{x}^*_{1\mathbf{r}2} + \boldsymbol{x}^*_{1\mathrm{I}}\boldsymbol{x}^*_2 & 2\boldsymbol{x}^*_{1\mathbf{r}3} + \boldsymbol{x}^*_{1\mathrm{I}}\boldsymbol{x}^*_3 \\ 2\boldsymbol{x}^*_{2\mathbf{r}1} + \boldsymbol{x}^*_{2\mathrm{I}}\boldsymbol{x}^*_1 & 2\boldsymbol{x}^*_{2\mathbf{r}2} + \boldsymbol{x}^*_{2\mathrm{I}}\boldsymbol{x}^*_2 & 2\boldsymbol{x}^*_{2\mathbf{r}3} + \boldsymbol{x}^*_{2\mathrm{I}}\boldsymbol{x}^*_3 \\ 2\boldsymbol{x}^*_{3\mathbf{r}1} + \boldsymbol{x}^*_{3\mathrm{I}}\boldsymbol{x}^*_1 & 2\boldsymbol{x}^*_{3\mathbf{r}2} + \boldsymbol{x}^*_{3\mathrm{I}}\boldsymbol{x}^*_2 & 2\boldsymbol{x}^*_{3\mathbf{r}3} + \boldsymbol{x}^*_{3\mathrm{I}}\boldsymbol{x}^*_3 \end{bmatrix}.$$

Equations (2.19) and (2.21a)-(2.21c) 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

Having completed the first (theoretical) objective, we now turn to the three empirical objectives. Using U.S. state-level agricultural production data, we empirically test the two propositions and the corollary, examine the time-series properties of variables included in the model, and contrast important test conclusions from a model that is consistent with the time series test results with those from a traditional model in which stationarity of the data is implicitly assumed.

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 which was estimated as a fixed-effects panel data model:

$$(2.22)\quad \boldsymbol{x}_{\mathrm{j}} = \mathbf{z}\boldsymbol{\phi}_{\mathrm{j}} + 0.5\mathbf{z}\boldsymbol{\Gamma}_{\mathrm{j}}\mathbf{z}' + \delta_{1\mathrm{j}}\mathrm{t} + 0.5\delta_{2\mathrm{j}}\mathrm{t}^2 + \mathbf{d}\boldsymbol{\alpha}_{\mathrm{j}} + e_{\mathrm{j}},\ \mathrm{j} = 1, 2, ..., m$$

where $\boldsymbol{x}_j$ is the quantity of the j^{th} input; the vector **z** contains three expected output prices p_i, three current input prices r_j, and initial (beginning period) wealth I; **d** is the vector of state dummy variables for the 48 contiguous U.S. states that are included to capture impacts of unique state-specific policies and agricultural resources on input demands; t is the proxy for technological innovations and is represented by time = 1, . . ., 40 and its square in the traditional model and by public research expenditures per unit of land and its square in the time-series-based model; the error term is denoted by e_j: parameters to be estimated are the vectors $\boldsymbol{\alpha}_j$, $\boldsymbol{\phi}_j$, $\boldsymbol{\Gamma}_j$, and the scalars δ_{1j}, δ_{2j}.

For each equation in the demand system specified by (2.22), fixed effects across cross-sectional observations were considered. So that all refutable implications under output price and output quantity risk contained in (2.19) and (2.21a)-(2.21c) could be tested, no restrictions were imposed on the estimated parameters across the equations.

Since stationarity of all variables is implicitly assumed when (2.22) 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 (2.22) also have a unit root (i.e., are not cointegrated). If they are cointegrated, a valid long-run relationship can be represented by (2.22). 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 (2.22) 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) 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, including having greater power and better small-sample properties (IPS). Consequently, the IPS test is the panel unit root test we employ.

The IPS consists of testing the null hypothesis H_0: $\rho_i = 0$ for all 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:

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

where y is a data series; the subscript t is time period; the subscript i is cross-sectional unit; T is the total number of time periods; N is the total number of cross-sectional units;

$\Delta y_{it} = y_{it} - y_{i,t-1}$; 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:

$$(2.24) \quad \bar{t}_{NT} = \frac{1}{N}\sum_{i=1}^{N} t_{iT} \ ,$$

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:

$$(2.25) \quad t_{IPS} = \frac{\sqrt{N}(\bar{t}_{NT} - E[t_T \mid \rho_i = 0])}{\sqrt{Var[t_T \mid \rho_i = 0]}} \Rightarrow \mathrm{N}(0,1)\,,$$

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 IPS (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 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 (2.22).

Consider the following time series panel regression:

$$(2.26) \quad y_{it} = \alpha_i + \delta_i t + \sum_{m=1}^{M}(\beta_{mi} X_{mit}) + e_{it}, \quad i = 1,...,N, \quad t = 1,...,T,$$

where y_{it} and X_{mit} are the observable dependent and independent variables respectively; the variable t is year; M is the number of regressors; estimated parameters include α_i a group-specific intercept, δ_i a group-specific coefficient on time variable t; and β_{mi} a regressor parameter; e_{it} is the disturbance term, and subscripts t, i, N, and T are as previously defined. 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.[8] Adjusted by appropriate constants obtained from the moments of the underlying Brownian motion functions, all panel statistics and group mean statistics are distributed as standard normal when both N and T grow large. Under the alternative hypothesis, all the statistics diverge to negative infinity except the panel-v statistic which diverges to positive infinity. Therefore, each is a one-sided test for which a large positive value for the panel-v statistic or large negative values for the other statistics result in rejection of the null hypothesis of

[8] 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 panel statistics category is that the stationary autoregressive parameters are homogeneous; the alternative for the group mean statistics allows them to be heterogeneous.

no cointegrated relation among the variables.[9]

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.[10] 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 (see Ball, Hallahan, and Nehring 2004). 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 and quality-adjusted input flows (see Ball et al. 1999, for details). Output prices account for both market price and government payments. 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 (2005). These data served as proxies for technical innovation in

[9] The group-ρ statistic is slightly undersized and empirically the most conservative in small panels. The panel-v tends to have the best power relative to the others when the panel is fairly large. The other statistics lie between these two extremes and have little comparative advantage in terms of testing power, either in small or large panels. In our case the N dimension exceeds the T dimension, which may cause all the statistics to become overly conservative (Pedroni 2004).

[10] The theory of 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.

the model based on the time series properties of the data.

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 quality-adjusted index of land quantity.[11]

Empirical Results

Panel Unit Root and Cointegration Tests

Although no formal statistical test was conducted for structural breaks, a visual inspection of the data was conducted in each state. As illustrated in figure 2.1 for two prices and equity in five states, 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.

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

The results of the IPS unit root tests are shown for each variable in table 2.1. 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.[12] 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.

It has been shown that public research investment 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). 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. These lag lengths are similar to those found by Liu and Shumway (2006) (11 years), Thirtle at al. (2002) (23 years), Makki at al. (1999) (20 years). 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.

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%

[12] This routine is available from the Estima website, http://www.estima.com.

significance level, a unit root was not rejected for the series x_2, r_1, r_3, r_1r_3, and res^2. When the nonstationary variables were tested for a unit root in first differences, the alternative hypothesis was stationarity without a trend since any linear time trend in levels was removed by differencing (Canning and Pedroni, 1999). The test statistic for 1st differences was negative and significant at a 5% level in each variable. Consequently, we conclude that x_2, r_1, r_3, r_1r_3, and res^2 are stationary in first differences, i.e., integrated of order 1 – I(1), and that all other variables are integrated of order zero, I(0).

We next tested for cointegration among the nonstationary variables for each input demand equation. If the data are cointegrated for an input demand, equation (2.22) 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 I(1) variables, x_2, r_1, r_3, r_1r_3, and res^2, in order to capture the long-run relationships.

The results of the panel cointegration tests are presented in table 2.2. Seven cointegration tests were conducted for each demand equation. For the materials (x_1) and labor (x_3) demand equations, the hypothesis of no cointegration was rejected at the 5% significance level by six and five of the seven test statistics, respectively. For the capital (x_2) equation, six of the statistics failed to reject the hypothesis of no cointegration. Thus, it is concluded that cointegration exists for both the x_1 and x_3 demand equations but not for the x_2 equation. Consequently, the time-series-based input demand equations x_1 and x_3 were estimated using original data for all variables, and x_2 was estimated using differenced data for I(2) variables, x_2, r_1, r_3, r_1r_3, and res^2, and original data for other variables.

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 (2.22). 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.[13] The R^2 values for the three equations of the traditional model in (2.22) were 0.834, 0.542, and 0.791

[13] 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.

respectively. The R^2 value was considerably lower (0.229) for the capital equation estimated by the time-series-based model than by the traditional model.[14] 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 capital equation in the time-series-based model. Lower R^2 is not unusual for regressions with differenced data, which tend to amplify the impact of noise in the data. For the materials and labor equations, the data used for the dependent variables were the same in both models, and the R^2 values were higher (0.865 and 0.902) in the time-series-based model.

The estimation results are reported in Table 2.3 and 2.4 respectively for traditional model and time-series 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. For example, approximately 66, 46, and 77% 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 42% in the capital demand equation compared to the time-series-based model but underestimated the number of significant relationship by 13% and 15% for the materials and labor demand equations compared to the time-series-based model. In addition, of 35 common non-dummy coefficients in these two models, a few changed signs – two in the materials demand

[14] 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.

equation and six in the capital 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 2.5 for both models. Proposition 1 (first-order curvature) was examined by testing whether each of the three predicted input demands in equation (2.22) was positive. These test results are listed as propositions 1.1-1.3 in Table 2.5. 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 were not consistent with proposition 1. For the time-series-based model, none of the predicted materials and labor quantities violated the proposition, but more violations were found in the predicted capital quantities.

The second proposition, that $\boldsymbol{\Omega} \equiv -(\boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\mathrm{r}}^{*})$ is symmetric positive semidefinite, was tested by the equivalent specification that $\boldsymbol{\Psi} = \boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\mathrm{r}}^{*}$ is symmetric negative semidefinite. To test this proposition, three individual tests (tests 2.1-2.3 in Table 2.5) were conducted for negative semidefiniteness (second-order curvature) and a joint test (test 3 in Table 2.5) for symmetry. The tests for negative semidefiniteness involved tests that all the leading principal minors of $\boldsymbol{\Psi}$ 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. Although both the second leading principal minor (test 2.2) in the traditional model and the determinant (test 2.3) of Ψ in both models had unexpected signs at the data means, they were not significantly different from zero. Considerably fewer individual violations of second-order curvature were found in the time-series-based model than in traditional model. Our test conclusions with regard to first-order and second-order curvature of the indirect utility function under both output quantity and output price risk were the same as Saha and Shumway's (1998) conclusions for Kansas wheat producers considering only output price risk.

The test results for symmetry of Ω are presented in test 3 in Table 2.5. The three symmetric restrictions were rejected at the 5% significance level by the joint test conducted at the data means using both models. Thus, the hypothesis implied by proposition 2 that Ω is symmetric positive semidefinite is rejected. This conclusion differs from Saha and Shumway (1998).

To determine if this difference was due to our use of aggregate data, we repeated our tests based on output quantity and output price risk using the Saha-Shumway data set and obtained the same test conclusions (See Table 2.6 for details). Thus, we infer that the difference in results is more likely due to our consideration of both price and quantity risk than to aggregation of the data. However, rejection of symmetry under both price and quantity risk and non-rejection under price risk does not imply that the production function is known with certainty and little consideration of output quantity risk is needed in expected utility models. Considerable firm-level quantity risk is evident in agricultural production although it may not be captured as clearly at the aggregate level as is price risk (Pope 1982, Coyle 1992). Further, quantity risk has been found to result in unexpected consequences such as causing supply to backbend (Love and Buccola 1991).

The rejection of test 3 warrants further comment. Our hypothesis tests were derived from the joint hypothesis that expected utility is maximized and that the utility function includes both random and nonrandom components, both of which are twice continuously differentiable. In principle, first- and second-order curvature conditions can be derived without the assumption of twice continuous differentiability, but the symmetry condition is a direct consequence of that property. Consequently, rejection of hypotheses 1 or 2 would have constituted very significant blows to the hypothesis of expected utility maximization under output price and output quantity risk. Rejection of hypothesis 3, on the other hand, could be simply due to one of the components of expected utility not being twice continuously differentiable. 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 tests results.

We should also note that, as in all statistical tests, there are other possible explanations for rejection (non-rejection) of a hypothesis other than a false (true) hypothesis. Both Type I and Type II errors are possible and may be due, for example, to measurement error,[15] aggregation error, incorrect functional form, incorrect specification of the stochastic nature of variables, inadequate price variability,[16] or other specification errors.

Our final test was to determine whether the state-level manifestations of firm decision making were consistent with either of two specific and *ad hoc* risk preference structures – constant absolute risk aversion or risk neutrality. Within the framework of our model, these two risk preference structures are observationally equivalent and imply the joint hypothesis of three restrictions on input demand responses. The result (test 4 in Table 2.5) indicates that these restrictions were rejected at the 5% significance level in both models by the joint test at the data means, a finding which was also consistent with Saha and Shumway (1998). Regarding the nature of farmers' risk preferences, the extant literature has not reached a clear consensus (Goodwin and Mishra, 2002). While a few articles have found empirical support for the hypothesis of constant absolute risk aversion,[17] most studies have not.[18] Consequently, our rejection of this specific risk preference structure is also consistent with the bulk of existing literature.

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[15] See Lusk, et al.(2002) for an example of the frailties of measurement error in causing violation of dual relationships implied by economic theory.

[16] The importance of sufficient price variability in recovering dual relationships has long been known. See, for example, Quiggin and Bui-Lan (1984).

[17] For example, Park and Antonovitz (1992a, 1992b) found empirical support for the hypothesis of constant absolute risk aversion (CARA) for California feedlots. Ozanne (1998) found that the presumed CARA parameter was significant for aggregate U.S. agriculture. Abdulkadri, Langemeier, and Featherstone (2003) found that the hypothesis of CARA was not rejected for Kansas irrigated corn farmers.

[18] For example, Dalal (1994) criticized Park and Antonovitz' (1992 b) conclusion supporting CARA and argued that their results contradicted rather than confirmed the existence of CARA. Chavas and Holt (1990, 1996) rejected the null hypothesis of CARA and supported DARA for U.S. aggregate corn and soybean producers. Abdulkadri, Langemeier, and Featherstone (2003) rejected the hypothesis of CARA for Kansas dryland wheat and dairy farmers.

Summary and Conclusions

This study 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 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 needed for the propositions to hold are that: (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 theory of the firm under uncertainty. Without requiring the previously maintained hypotheses that the expectation of the random part of profit is zero, the propositions can be empirically applied to various market structures by permitting tests when there is a nonzero correlation between the error terms of random output price and random output quantity.

A set of testable hypotheses associated with input responses under multiple sources of risk were obtained from these propositions and empirically tested for aggregates of firms operating under both output price and output quantity risk. This is the first known study using an aggregate state-level panel data set to empirically test for utility-maximizing behavior under uncertainty. Each state aggregate was examined as though it were an individual firm maximizing its expected utility. The ability to use aggregate data for such purposes is particularly important when policy-relevant implications are needed, and aggregate agricultural production data for these states had previously been found to approximate nonparametric conditions for consistency with profit-maximizing behavior. The parametric results of these tests failed to reject the behavioral postulates implied by the first-order and second-order curvature properties of the indirect utility function at the data means. Consistent with prior literature, the data were also consistent with the first-order curvature properties at nearly all individual observations. However, the symmetry property implied by twice continuous differentiability of the indirect utility function was soundly rejected. Consistent with a large part of prior literature, the empirical evidence also failed to support *ad hoc* risk preference assumptions of either risk neutrality or constant absolute risk aversion.

To avoid the possibility of spurious estimation from statistical estimation using nonstationary data, the time series properties of the data were examined. The data were tested both for nonstationarity and cointegration using procedures designed for panel data, i.e., Im, Pesaran, and Shin's (1997) panel unit root tests and Pedroni's (1999) panel cointegration tests. Several data series were found to be nonstationary, and the null hypothesis of no cointegration was rejected for the materials and labor equations but not for capital demand.

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. Although failure to account for the time series properties of data frequently results in spurious estimation, our test conclusions were robust to the time series properties of data.

For the purpose of guiding further research, it is important to place our findings in context of the extant literature on expected utility maximization and time series testing. Two qualifying points are warranted:

(a) Although our two models generated exactly the same test conclusions, robustness of important test conclusions to the time series properties of data is not particularly common. Evidence of spurious estimation with serious consequences is often found when the time series properties are ignored. Consequently, until robustness to time series properties of the data is found across a wide spectrum of economic research problems, careful testing of the time series properties continues to be warranted both for empirical analysis and hypothesis testing.

(b) Auxiliary tests revealed that our rejection of the symmetry property of the indirect utility function was more likely due to considering both price and quantity risk than to aggregating data to the state level. Nevertheless, because there is so much empirical evidence of large output quantity risk in the production of many agricultural commodities, it would be a mistake to ignore quantity risk in future specifications of expected utility models for agriculture. Also, an insufficient number of empirical tests have been conducted to develop a stylized fact suggesting that the expected utility maximization hypothesis is inconsistent with empirical evidence. Our rejection of the joint hypothesis that included expected utility maximization could have been due to measurement error, incorrect functional form, non-twice differentiability, or any number of other reasons besides non-maximization of expected utility.

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Table 2.1. Panel Unit Root Test Results

Variable [a]	Test Statistic [b]	Test Conclusion
Panel Unit Root Test for Levels with Trend:		
Materials/land (x_1)	-2.095	Stationary
Capital/land (x_2)	-1.134	Nonstationary
Labor/land (x_3)	-7.321	Stationary
Normalized materials price (r_1)	-0.630	Nonstationary
Normalized capital price (r_2)	-5.691	stationary
Normalized labor price (r_3)	0.996	Nonstationary
Normalized expected crop price (p_1)	-6.527	Stationary
Normalized expected livestock price (p_2)	-7.244	Stationary
Normalized expected secondary output price (p_3)	-4.087	Stationary
Normalized equity (w_0)	-12.286	Stationary
Square of normalized expected crop price (p_1^2)	-11.031	Stationary
Cross product of p_1 and p_2 (p_1p_2)	-11.917	Stationary
Cross product of p_1 and p_2 (p_1p_3)	-8.552	Stationary
Cross product of p_1 and r_1 (p_1r_1)	-5.338	Stationary
Cross product of p_1 and r_2 (p_1r_2)	-10.621	Stationary
Cross product of p_1 and r_3 (p_1r_3)	-5.487	Stationary
Cross product of p_1 and w_0 (p_1w_0)	-16.067	Stationary
Square of normalized expected livestock price (p_2^2)	-14.359	Stationary
Cross product of p_2 and p_3 (p_2p_3)	-10.238	Stationary
Cross product of p_2 and r_1 (p_2r_1)	-8.868	Stationary
Cross product of p_2 and r_2 (p_2r_2)	-12.958	Stationary
Cross product of p_2 and r_3 (p_2r_3)	-6.929	Stationary
Cross product of p_2 and w_0 (p_2w_0)	-17.109	Stationary
Square of normalized expected secondary output price (p_3^2)	-7.723	Stationary
Cross product of p_3 and r_1 (p_3r_1)	-4.106	Stationary
Cross product of p_3 and r_2 (p_3r_2)	-8.589	Stationary
Cross product of p_3 and r_3 (p_3r_3)	-4.031	Stationary
Cross product of p_3 and w_0 (p_3w_0)	-13.996	Stationary
Square of normalized materials price (r_1^2)	-1.683	Stationary
Cross product of r_1 and r_2 (r_1r_2)	-5.888	Stationary
Cross product of r_1 and r_3 (r_1r_3)	-1.279	Nonstationary
Cross product of r_1 and w_0 (r_1w_0)	-10.311	Stationary
Square of normalized capital price (r_2^2)	-9.634	Stationary
Cross product of r_2 and r_3 (r_2r_3)	-4.774	Stationary

Table 2.1. (continued)

Variable[a]	Test Statistic[b]	Test Conclusion
Cross product of r_2 and w_0 (r_2w_0)	-15.069	Stationary
Square of normalized capita; price (r_3^2)	-2.396	Stationary
Cross product of r_3 and w_0 (r_3w_0)	-10.311	Stationary
Square of normalized equity (w_0^2)	-18.556	Stationary
Public research expenditures/land (res)	-3.799	Stationary
Square of public research expenditures/land (res^2)	-0.688	Nonstationary
Panel Unit Root Test for First Differences without Trend:		
Δ Capital/land (Δx_2)	-5.160	Stationary
Δ Normalized materials price (Δr_1)	-34.874	Stationary
Δ Normalized capital price (Δr_3)	-34.011	Stationary
Δ Cross product of r_1 and r_3 (Δr_1r_3)	-42.471	Stationary
Δ Square of public research expenditures/land (Δres^2)	-43.640	Stationary

[a] All variables were tested without time dummies.

[b] Critical 1-tailed test values for rejecting unit root (Im, Pesaran, and Shin 1997): 10% level -1.282, 5% level -1.645, 1% level -2.326.

Table 2.2. Panel Cointegration Test Results

Test Statistic [a]	Demand Equation [b]		
	Materials/land (x_1)	Capital/land (x_2)	Labor/land (x_3)
Panel v-statistic	5.567***	-3.137	0.378
Panel ρ-statistic	-2.429***	1.942	-2.297**
Panel t-statistic (nonparametric)	-9.439***	-1.778**	-8.946***
Panel t-statistic (parametric)	-8.353***	0.096	-6.354***
Group ρ-Statistic	-0.376	3.418	-0.165
Group t-statistic (nonparametric)	-9.552***	-1.562*	-8.458***
Group t-statistic (parametric)	-8.819***	0.653	-5.563***

[a] Critical 1-tailed test values for rejecting the hypothesis of no cointegration via the panel v-statistic are 1.282 at the 10% level *, 1.645 at the 5% level **, and 2.326 at the 1% level ***. Critical values for the other statistics are the negatives of these values (Pedroni 1999).
[b] When testing for cointegration, a time trend was included.

Table 2.3. 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 2.3 (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 2.3 (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	0.028	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] An asterisk indicates the parameter is significant at the 5% level.

[c] SE is standard error.

Table 2.4. Parameter Estimates for the Input Demand Equations: Time-series 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	2.586*	0.194	0.045*	0.018	2.161*	0.148
d2	1.204*	0.192	0.013	0.018	1.306*	0.146
d3	0.036	0.176	0.069*	0.016	1.300*	0.134
d4	2.810*	0.154	0.018	0.015	4.141*	0.117
d5	0.716*	0.170	0.033*	0.016	1.116*	0.129
d6	2.359*	0.191	-0.001	0.018	7.029*	0.145
d7	8.325*	0.186	0.040*	0.018	4.920*	0.141
d8	0.968*	0.169	0.035*	0.016	2.761*	0.129
d9	2.981*	0.191	0.056*	0.018	2.983*	0.145
d10	2.480*	0.180	0.013	0.017	2.131*	0.137
d11	1.217*	0.186	0.022	0.018	1.237*	0.142
d12	1.809*	0.177	-0.002	0.017	1.837*	0.135
d13	2.329*	0.180	0.000	0.017	2.812*	0.137
d14	1.513*	0.185	0.026	0.018	1.300*	0.141
d15	1.738*	0.182	0.039*	0.017	2.724*	0.139
d16	0.057	0.185	0.101*	0.017	2.835*	0.141
d17	2.243*	0.185	-0.012	0.018	6.674*	0.141
d18	3.725*	0.192	0.016	0.018	4.680*	0.146
d19	2.893*	0.168	0.069*	0.016	5.196*	0.128
d20	3.242*	0.181	0.013	0.017	5.341*	0.137
d21	3.283*	0.185	0.040*	0.018	3.858*	0.141
d22	2.151*	0.183	0.005	0.017	2.683*	0.139
d23	1.232*	0.194	0.085*	0.018	2.023*	0.148
d24	0.095	0.176	0.021	0.017	0.663*	0.134
d25	2.275*	0.182	0.039*	0.017	3.450*	0.139
d26	0.646*	0.201	0.025	0.019	0.756*	0.153
d27	2.431*	0.181	0.037*	0.017	1.831*	0.137
d28	1.283*	0.172	0.044*	0.016	4.762*	0.131
d29	2.387*	0.194	0.045*	0.018	7.746*	0.148
d30	0.254	0.158	0.025	0.015	0.799*	0.120
d31	-0.668*	0.160	0.059*	0.015	1.115*	0.122
d32	2.743*	0.187	0.071*	0.017	6.254*	0.142
d33	2.532*	0.182	-0.014	0.017	4.053*	0.139
d34	1.038*	0.180	0.032	0.017	1.396*	0.137

Table 2.4 (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]
d35	2.160*	0.193	0.048*	0.018	2.274*	0.147
d36	3.962*	0.185	0.017	0.018	6.311*	0.141
d37	0.952*	0.190	0.044*	0.018	7.769*	0.144
d38	1.776*	0.186	0.054*	0.018	3.694*	0.142
d39	1.382*	0.188	-0.010	0.018	0.797*	0.143
d40	1.201*	0.216	0.042*	0.020	1.642*	0.165
d41	0.636*	0.179	0.032	0.017	0.861*	0.136
d42	0.113	0.179	0.032	0.017	1.253*	0.136
d43	0.229	0.201	0.062*	0.019	1.935*	0.153
d44	1.831*	0.173	0.037*	0.016	3.032*	0.132
d45	1.047*	0.179	0.037*	0.017	3.082*	0.136
d46	4.612*	0.176	0.048*	0.017	7.076*	0.134
d47	1.021*	0.212	0.044*	0.020	2.770*	0.161
d48	0.448*	0.173	0.036*	0.017	0.972*	0.132
d83	0.194	0.134	-0.080*	0.013	-0.026	0.102
p_1	0.194	0.134	-0.080*	0.013	-0.026*	0.102
p_2	-0.009	0.120	-0.048*	0.011	-0.386	0.092
p_3	0.021	0.153	0.058*	0.015	0.093*	0.116
r_1	0.206	0.148	-0.035*	0.013	0.280	0.113
r_2	-0.090*	0.097	-0.041	0.009	-0.103*	0.074
r_3	-0.211	0.105	0.006*	0.010	0.425*	0.080
I	0.045*	0.088	-0.018*	0.007	-0.302	0.067
p_1^2	-0.174	0.075	0.014*	0.007	-0.016	0.057
$p_1 p_2$	0.021	0.058	0.012	0.006	0.085*	0.044
$p_1 p_3$	-0.028	0.055	-0.006	0.005	-0.153	0.042
$p_1 r_1$	0.021	0.041	0.001	0.004	0.012*	0.031
$p_1 r_2$	0.040	0.029	-0.004	0.003	0.069	0.022
$p_1 r_3$	0.015*	0.030	-0.001	0.003	-0.013	0.023
$p_1 I$	-0.086	0.036	0.002*	0.003	-0.038*	0.028
p_2^2	-0.045*	0.030	0.006	0.003	0.094	0.023
$p_2 p_3$	0.219*	0.090	0.005	0.009	-0.087*	0.069
$p_2 r_1$	-0.207	0.062	0.009*	0.006	0.215*	0.047
$p_2 r_2$	0.006	0.038	-0.007	0.004	-0.061	0.029

Table 2.4 (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	0.031	0.038	0.000	0.003	0.025	0.029
p_2I	0.024	0.033	-0.010*	0.003	-0.012	0.025
p_3^2	0.371*	0.068	-0.006	0.007	-0.095	0.052
p_3r_1	-0.073	0.041	-0.001	0.004	-0.084*	0.031
p_3r_2	-0.091*	0.044	0.005	0.004	0.088*	0.033
p_3r_3	-0.003	0.032	-0.004	0.003	-0.042	0.024
p_3I	-0.122*	0.032	0.001	0.003	-0.158*	0.024
r_1^2	-0.099*	0.043	0.008	0.004	0.052	0.033
$r_1 r_2$	0.077*	0.038	0.001	0.004	-0.055	0.029
$r_1 r_3$	0.061*	0.027	0.003	0.002	0.013	0.021
r_1I	0.071*	0.024	0.000	0.002	0.090*	0.018
r_2^2	-0.019	0.040	0.001	0.004	-0.023	0.030
r_2r_3	-0.001	0.030	-0.001	0.003	-0.025	0.023
r_2I	0.008	0.021	-0.003	0.002	-0.084*	0.016
r_3^2	-0.063	0.034	0.003	0.003	0.072*	0.026
r_3I	0.032	0.019	0.004*	0.001	0.048*	0.015
I^2	0.071*	0.020	-0.002	0.002	0.058*	0.015
res	0.086*	0.004	-0.002*	0.0002	-0.053*	0.003
res^2	-0.0007*	0.0001	0.00001	0.00001	0.0003*	0.0001
R-Square	0.865		0.229		0.902	

[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] An asterisk indicates the parameter is significant at the 5% level.
[c] SE is standard error.

Table 2.5. Expected Utility Maximization Hypothesis Test Results

Proposition	Null	Test type [a]	Traditional Model: Test at Data Means: Statistic	Traditional Model: Test at Data Means: P-value	Traditional Model: Rejections among 1,872 Observations	Time Series Model: Test at Data Means: Statistic	Time Series Model: Test at Data Means: P-value	Time Series Model: Rejections among 1,824 Observations
1. V is decreasing in input prices (**r**)								
1.1 V is decreasing in materials price (r_1), $\hat{x}_1 > 0$	$\hat{x}_1 = 0$	AN	98.706	0.000	0	7.836	0.000	0
1.2 V is decreasing in capital price (r_2), $\hat{x}_2 > 0$	$\hat{x}_2 = 0$	AN	9.963	0.000	11	3.297	0.001	144
1.3 V is decreasing in labor price (r_3), $\hat{x}_3 > 0$	$\hat{x}_3 = 0$	AN	56.521	0.000	1	252.559	0.000	0
2. $\boldsymbol{\Psi} = \boldsymbol{x}_{\mathrm{I}}^{*}\boldsymbol{x}^{*} + 2\boldsymbol{x}_{\mathbf{r}}^{*}$ is negative semidefinite								
2.1 1st leading principal minor: $2x_{1r_1}^{*} + x_{1I}^{*}x_1^{*} \le 0$	= zero	AN	-2.284	0.022	387	-2.620	0.001	0
2.2 2nd leading principal minor of $\boldsymbol{\Psi} \ge 0$	= zero	AN	-1.736	0.083	460	2.230	0.026	15
2.3 Determinant of $\boldsymbol{\Psi} \le 0$	= zero	AN	0.772	0.440	450	1.958	0.051	10
3. Symmetry of $\boldsymbol{\Psi}$ [b]		W	71.770	0.000	--	45.243	0.000	--
4. CARA or RN [c] $x_{1I}^{*} = x_{2I}^{*} = x_{3I}^{*} = 0$	= zero	W	99.116	0.000	--	67.843	0.000	--

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

[b] Test of symmetry involves jointly testing

H_0: $2x_{1r_2}^{*} + x_{1I}^{*}x_2^{*} = 2x_{2r_1}^{*} + x_{2I}^{*}x_1^{*}$, $2x_{1r_3}^{*} + x_{1I}^{*}x_3^{*} = 2x_{3r_1}^{*} + x_{3I}^{*}x_1^{*}$, and $2x_{2r_3}^{*} + x_{2I}^{*}x_3^{*} = 2x_{3r_2}^{*} + x_{3I}^{*}x_2^{*}$.

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

Table 2.6. Expected Utility Maximization Hypothesis Test Results: Saha and Shumway (1998)'s Data

Proposition	Null	Test type [a]	Test at Data Means		Rejections among 1,872 Observations
			Statistic	P-value	
1. V is decreasing in input prices (**r**)					
1.1 V is decreasing in materials price (r_1), $\hat{x}_1 > 0$	$\hat{x}_1 = 0$ [b]	AN	22.255	0.000	0
1.2 V is decreasing in capital price (r_2), $\hat{x}_2 > 0$	$\hat{x}_2 = 0$ [b]	AN	17.563	0.000	0
2.1 1^{st} leading principal minor: $2x^*_{1r_1} + x^*_{1I}x^*_1 \le 0$	= zero	AN	0.544	0.587	0
2.2 Determinant of $\Psi \ge 0$	= zero	AN	1.899	0.058	0
3. Symmetry of Ψ [c]		W	6.820	0.009	--
4. CARA or RN [c] $x^*_{1I} = x^*_{2I} = 0$	= zero	W	8.142	0.017	--

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

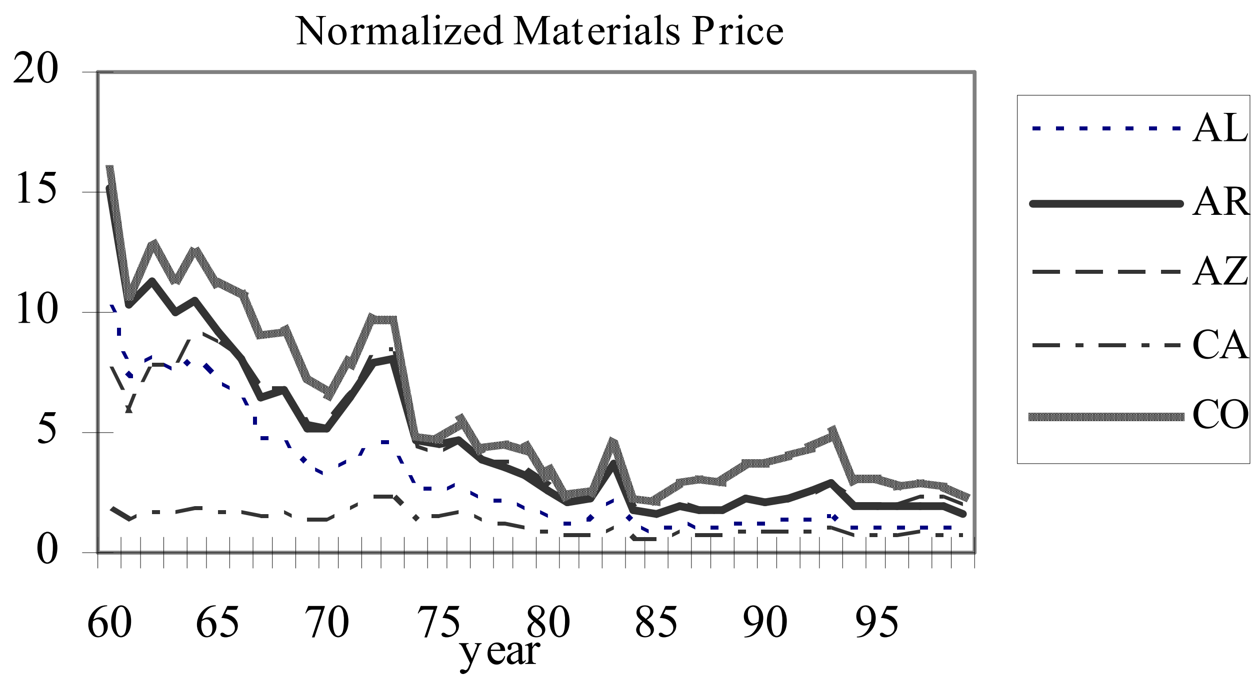
[b] Codes: x_1 and x_2 are capital input and material input respectively.

[c] Test of symmetry involves jointly testing

H_0: $2x^*_{1r_2} + x^*_{1I}x^*_2 = 2x^*_{2r_1} + x^*_{2I}x^*_1$, and $2x^*_{1\mathbf{r}_2} + x^*_{1I}x^*_2 = 2x^*_{\mathbf{2r}_1} + x^*_{2I}x^*_1$,

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

Figure 2.1. Plots of Prices and Equity



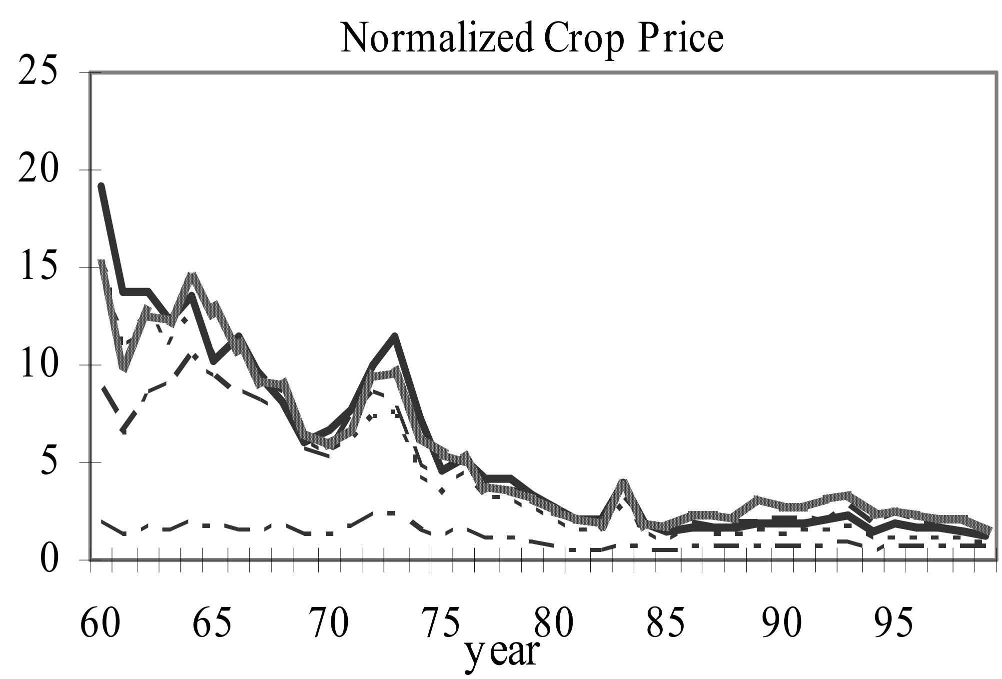
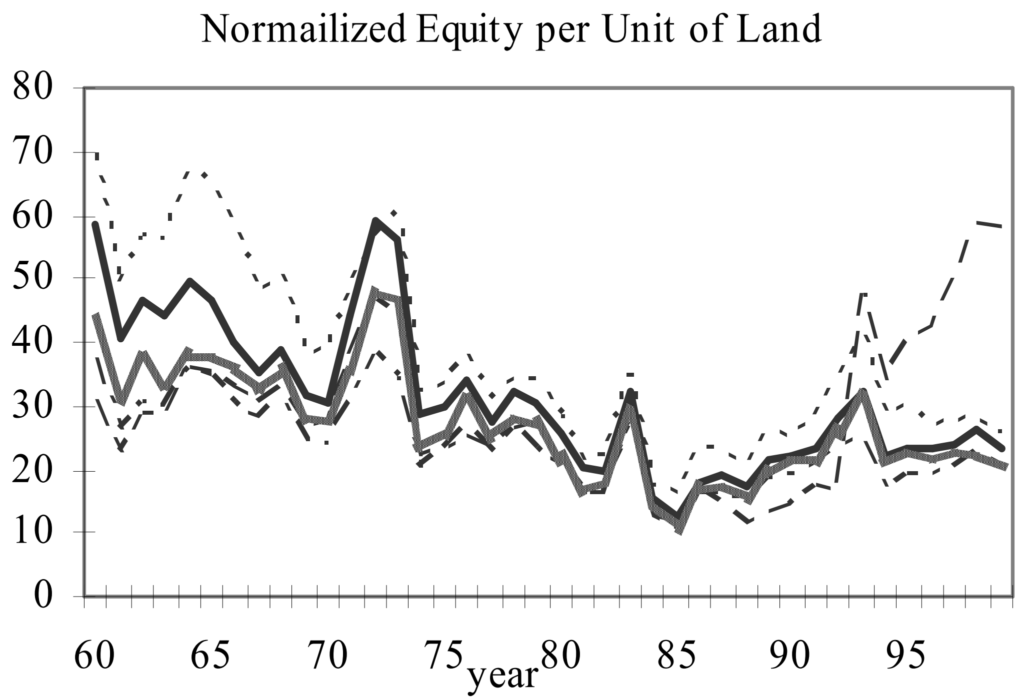


Figure 2.1. (Continued)



CHAPTER 3

INDUCED INNOVATION IN U.S. AGRICULTURE: TIME-SERIES, ECONOMETRIC, AND NONPARAMETRIC TESTS [19]

Introduction

Productivity in nearly all industries and throughout most of the world has experienced rapid growth for many decades. This is particularly true of U.S. agriculture. Measured as the ratio of total outputs to total inputs, the average annual rate of total factor productivity growth was two percent for the period 1960-1993 (Ball *et al*., 1997) and three percent for the period 1980-1999 (Huffman and Evenson, 2003). This productivity growth has been achieved through development and implementation of output-augmenting and input-saving technologies and through economic decisions that substituted relatively cheap inputs for relatively expensive ones. It clearly is a result of choices and decisions made both by researchers (and others involved in innovation discovery, development, outreach, and technology transfer) and by producers and others who choose technologies to implement from among currently available technologies.

The processes by which output-augmenting and input-saving technologies are developed are varied and diffuse. They include both fortuitous (or accidental) discoveries

[19] The data used in the analysis are available on request from the advisory committee chair, Richard Shumway (shumway@wsu.edu).

and planned (organized) research and development activities. Their implementation also includes both fortuitous and planned elements.

The theory of price-induced innovation has been particularly important in focusing attention of economists on technological innovation. This theory asserts that changes in relative prices of factors are expected to induce development and implementation of new technology to save the relatively more expensive factors. For example, relatively expensive labor in U.S. agriculture has induced labor-saving technology which encourages the migration of farm workers to the non-agricultural sector (Kako, 1978).

Although first proposed by Hicks in 1932, this theory has been empirically examined only during the last four decades. Based on the microeconomic foundations of induced innovation theory proposed by Ahmad (1966),[20] Hayami and Ruttan (1970) conducted the first formal test of the induced innovation hypothesis (IIH) and concluded that the evolution of relative factor demand "represents a process of dynamic factor substitutions accompanying changes in the production function induced by changes in relative factor prices" (p. 1135). Since that time it has been tested in a wide variety of countries and industries using various analytical tools and data.

Using a four-factor econometric model, Binswanger (1974a) extended the Hayami- Ruttan methodology to the measurement of technical change bias with many factors of production. He incorporated a linear time trend variable in a translog cost

[20] Ahmad (1966) developed the microeconomic foundations for this theory by proposing the concept of an innovation possibility curve (IPC). The IPC is the envelope of all isoquants of potential production processes which firms might develop given the research and development budget.

function to measure the bias of factor usage. He found support for the IIH in U.S. agriculture for labor and fertilizer, but not for machinery. Modifications of Binswanger's econometric approach were used by Antle (1984), Hayami and Ruttan (1985), Thirtle (1985), Kawagoe *et al*. (1986), and Huffman and Evenson (1989). All of these couched their tests within a static framework and concluded that their findings were consistent with the IIH for U.S. agriculture. Under the assumption that firms use lagged prices to form expectations, Antle (1986) found support for the IIH but concluded that it depended on the specification of expectations.

Based on the overall consistency of all these test results, a stylized fact had developed by the early 1990s that technical change in U.S. agriculture was generally consistent with the induced innovation theory. The hypothesis faced its first serious challenge in this industry by the work of Olmstead and Rhode (1993). Their historical analysis of important technological developments as well as a subsequent econometric test (Olmstead and Rhode, 1998) both failed to support the IIH in U.S. agriculture. They provided strong evidence that "the lessons of the induced innovation literature need to be reconsidered" (Olmstead and Rhode, 1993, p.116).

Despite repeated testing, a stylized fact has not re-emerged from the empirical tests of the last 15 years. Using a broader and superior array of testing procedures and data, empirical evidence has rejected the hypothesis for U.S. agriculture as often as it has rendered support. Thus, current evidence relative to the hypothesis is highly ambiguous.

Most analytical tools that have been used to test the IIH can be broadly grouped into three methodological classes: econometric, time series, and nonparametric methods.[21] Econometric models have been used most frequently. While most have built on the modeling approach of Binswanger, important variants include tests using a dynamic econometric model (Lin, 1998) and input demand equations jointly estimated with the innovation possibility frontier (Armanville and Funk, 2003). Lin rejected the IIH for U.S. agriculture, and Armanville and Funk found that support was sensitive to the specification of the innovation possibility frontier. Several have tested the hypothesis using time series procedures. Lambert and Shonkwiler (1995) and Thirtle *et al*. (2002) concluded their evidence confirmed the IIH in this industry, while Machado (1995), Tiffin and Dawson (1995), and Liu and Shumway (2006) failed to find clear evidence supporting the hypothesis. The most recently developed and least-used procedures for testing the IIH have involved nonparametric economic models. Chavas *et al.* (1997) found evidence supporting the IIH for actively traded inputs but not for land and farm labor in the U.S.

Because the IIH has such strong theoretical and intuitive underpinnings, many regard the recent failures to consistently support the hypothesis as data or methodological inadequacies. However, it should be cautioned that all the tests conducted to date have only tested the demand side of the hypothesis. Although both Binswanger (1974a) and Olmstead and Rhode (1993) acknowledged the demand-side nature of the hypothesis tests, most others who have tested the IIH have generally been silent about this important

[21] These three categories are not all inclusive. For example, they don't capture the notable work of Olmstead and Rhode (1993).

limitation (Coxhead, 1997, is an exception).[22] All tests of the hypothesis have implicitly maintained the hypothesis that the marginal cost of developing and implementing technologies that save one input is the same as the marginal cost of saving an equal percent of any other input. Since it is highly unlikely that innovation possibilities are this neutral, it is possible that the IIH is in fact a valid explanation and yet producers augment cheaper factors because the marginal costs of developing and implementing input-saving technologies for the relatively expensive inputs are greater than for the relatively cheap ones. That is, technical change may not bias toward saving a particular input even when it tends to be relatively expensive.

Unfortunately, data on the development and implementation costs of various input-saving technologies are lacking. In this paper, we approach this problem indirectly by asking how different the marginal cost of developing and implementing input-saving technology for one input must be from that for another input for the observed evidence to be consistent with the IIH.

The objectives of this paper are to (a) conduct comprehensive demand-side tests of the IIH for U.S. agriculture using a rich state-level panel data set, and (b) if the hypothesis is not unambiguously supported, estimate relative differences in the marginal cost of developing and implementing input-saving technology required for consistency with the hypothesis. The hypothesis is tested using three state-of-the-art testing procedures. They include time-series, econometric, and nonparametric tests. The high-

[22] Binswanger (1974a, pp. 975) wrote, "But despite that price rise, technical change was machinery-using, not saving. Had innovation possibilities been neutral, this could not occur." Olmstead and Rhode (1993, pp. 110) wrote, "…the evolving structure of American agriculture cannot be explained simply in terns of the relative supplies and prices of a few factors.…The induced innovation hypothesis puts too many eggs in the demand-side basket."

quality, 40-year panel data set permits tests to be conducted that have higher power than those previously used. Consequently, this is the most comprehensive and theoretically complete analysis of the IIH to be conducted in any country for any industry using a single high-quality data set.

The remainder of this paper is organized as follows. The three testing methods and the procedure for estimating differences in marginal cost of developing and implementing input-saving technologies required for consistency with the hypothesis is given in section II. It is followed by the data description in section III. The test results and marginal cost calculations are reported in section IV. The last section summaries our main findings and concludes.

Methodology

In this section we sequentially describe the three disparate procedures we use to test the IIH. We also develop the logic used to estimate relative marginal costs for augmenting factors under the restriction that the IIH was valid for U.S. agriculture over the period 1960-1999.

Time-series Approach

The procedure used in our time-series method follows the testing logic developed by Thirtle *et al.* (1998), Oniki (2000), and Thirtle *et al.* (2002).[23] Thirtle *et al.* (2002) argue that five requirements must be satisfied for the IIH to be supported via time-series properties: (a) the affected series must have time-series properties allowing for

[23] Using time-series data for South Africa, Japan, and the United States respectively, these studies found evidence supporting the IIH in agriculture in each of these countries.

cointegration, (b) cointegration must exist among the series, (c) the correlation between factor price ratios and the factor quantity ratios must be negative, (d) causality must run from factor prices to factor quantity ratios, and (e) the change in factor quantity ratios cannot be fully explained by factor substitution. Although this method is appealing both because of its logic and its rigor, it has only been applied using standard time-series procedures to one aggregate country-level data set. Application of the method to state-level panel data using panel time-series techniques will provide a more robust test for the IIH.

We maintain one of the common assumptions in the induced innovation literature, i.e., that the production technology can be approximated by a two-level CES functional form (e.g., de Janvry *et al.*, 1989; Frisvold, 1991; Thirtle *et al.*, 2002). Letting A, M, L, K represent the quantities of land, materials, labor, and capital, respectively, and explicitly incorporating efficiency augmenting variables of research and extension investments and farm size, the logarithms of the first-order conditions of profit maximization can be expressed as: [24]

$$(3.1)\ \ln(R_i) = \alpha_{0i} + \alpha_{1i}\ln(P_i) + \alpha_{2i}\ln(R_{pri}) + \alpha_{3i}\ln(R_{pub}) + \alpha_{4i}\ln(Ext) + \alpha_{5i}\ln(Size), \quad i = A/M, L/K,$$

where R_i and P_i, are the factor quantity ratio and factor price ratio respectively; R_{pri} is private research investment, R_{pub} is public research investment, Ext is public extension investment, $Size$ is average farm size; α are parameters. In this model, the land-material ratio and the labor-capital ratio are explained by the own-price ratio and four efficiency

[24] For the derivations and detailed discussion, see de Janvry *et al.* (1989).

augmenting variables.[25] This specifiction provides a straightforward approach for directly testing the IIH. Hereafter, we refer to equation (3.1) as the time-series model.

We begin our analysis by testing the time-series properties of the panel data. In small or moderate sized samples, failure to reject unit roots or cointegration may often be due to the low power of traditional time-series tests. The current research employs recent developments in time-series econometrics designed for panel unit roots (Hadri, 2000) and panel cointegration tests (Pedroni, 1999). These tests allow for both parametric and dynamic heterogeneity across groups and are considerably more powerful than conventional methods (Harris and Tzavalis, 1999).

If a cointegrated relationship exists among nonstationary variables in the input demand equations, the short-run and long-run relationships of the variables are estimated by an error correction model (ECM) in the second step of the analysis. Our ECM is based on a re-parameterization of an autoregressive distributed lag model (ARDL) of the input demand equations defined in (3.1). The pooled mean group estimation procedure (PMGE) developed by Pesaran *et al.* (1999) is used for this purpose.[26] The structure of the ARDL model is given as:

$$(3.2)\quad \Delta \ln(R_{iht}) = \mu_i + \lambda_i(\ln(R_{iht-1}) - \theta_i' x_{iht}) + \beta_i' Z_i + \varepsilon_{iht},\ i = A/M \text{ and } L/K,$$

[25] The efficiency parameter or factor productivity is frequently treated as a function of research and development expenditures in economic growth model (e.g., Griffith, *et al*., 2004; Hu, Gary and Qian, 2005; Luintel and Khan, 2004). Following de Janvry *et al*. (1989), we also include farm size to account for transaction costs.

[26] The PMGE uses the Newton-Raphson algorithm to estimate the ECM by maximizing the log-likelihood function. The main benefit of the PMGE procedure is that it only constrains the long-run coefficients to be identical for the cross-sectional units but allows the short-run coefficients and error variances to vary across groups. This weak homogeneity assumption is preferable to the traditional procedures such as fixed effects, instrumental variables, and generalized method of moments which presume strong homogeneity across groups (Pesaran *et al*., 1999).

where $x_{iht} = (\ln(P_{iht}), \ln(R_{pri,ht}), \ln(R_{pub,ht}), \ln(Ext_{ht}), \ln(Size_{ht}))'$; Z_i is a vector of the lagged terms of $\ln(R_{iht})$ and x_{iht} where the optimal lags are selected based on the Akaike Information Criterion (AIC); h identifies the state; t is time; Δ is the differencing operator; θ is a vector of long-run parameters accounting for the long-run equilibrium relationship between factor quantity ratio and the explanatory variables; λ is the corresponding error correction coefficient; [27] μ and β are vectors of parameters; ε is a disturbance term

Since all the variables are in logarithms, the absolute value of long-run coefficients are estimates of long-run elasticities of substitution, and the short-run elasticities of substitution are estimated by the associated absolute value of short-run parameters. The short-run elasticities of substitution are curvature measures along the isoquant, while the long-run elasticities are curvature measures along the innovation possibility curve. Induced innovation requires the estimated long-run elasticities of substitution to be significantly greater than the estimated short-run elasticities (Oniki, 2000).

The next step of the analysis is to examine whether the factor price ratio Granger causes factor-saving technical bias. We use the mixed fixed and random coefficients estimation algorithm initially developed by Hsiao *et al.* (1989) and extended to the

[27] The error correction coefficient measures the speed of adjustment for the system to move back to long-run equilibrium. Specifically, a zero value for the error correction coefficient means no long-run relationship, a value between -1 and 0 indicates partial adjustment, a value of -1 implies full adjustment, a value smaller than -1 indicates the model overadjusts in the current period, and a positive value implies the system moves away from equilibrium in the long-run.

dynamic panel model by Nair-Reichert and Weinhold (2001).[28]

Based on the estimation of the ECM, the short-run and long-run elasticities are computed and used to decompose the factor ratio changes into those induced by price changes and those accounted for by factor substitution (Thirtle *et al.*, 2002).

Econometric Approach

The econometric model also relies on the same two-level CES production technology and builds upon the work of Funk (2002) and Armanville and Funk (2003). In contrast to other empirical literature that implicitly assumes a specific form for the efficiency augmenting variables, Armanville and Funk (2003) explicitly included the innovation possibilities frontier (IPF) which specifies the feasible technical change set as a constraint to the profit maximization problem. This frontier captures the innovative decisions that researchers and producers can make to achieve a higher rate of factor-augmenting technical change for one input by accepting a lower rate of augmentation for other inputs.

The first-order conditions of this maximization problem imply that the profit maximizer will choose the set of factor augmentations such that the slope of the IPF equals the market relative shares measured in efficiency units (Funk, 2002; Armanville and Funk, 2003). Armanville and Funk argued that it is the market relative shares (in efficiency units) rather than the relative prices *per se* that play the essential role in determining direction of technical change. They developed two tests of the IIH – a

[28] This procedure is followed since it results in least bias among the estimators (Nair-Reichert and Weinhold, 2001). In the mixed fixed and random coefficients model, the coefficient on the lagged dependent variable is specific to the group, and the coefficients on the exogenous explanatory variables are taken as randomly distributed.

“weak” test that innovative decisions move in the same direction predicted by the IIH, and a “strong” test that innovation decisions satisfy the first-order conditions for profit-maximizing choice of innovations.

In our empirical application, we extend Armanville and Funk’s (2003) procedure by formalizing the relationship between productivity changes and research and extension investments rather than treating productivity changes as a function only of time. We estimate the following relative demand equations:

$$\text{(3.3)}\quad \ln(R_{iht}) = \tau_{1i} + \tau_{2i}\ln(P_{iht}) - (\tau_{2i}+1)\left(\gamma_i F_{iht} + 2\delta_{1i}\sum_{s=1}^{t}\ln(R_{pri,hs}) + 2\delta_{2i}\sum_{s=1}^{t}\ln(R_{pub,hs}) + 2\delta_{3i}\sum_{s=1}^{t}\ln(Ext_{hs})\right)$$

where $F_{iht} = P_{iht}R_{iht}$; τ, γ, δ are parameters.

By estimating equation (3.3), all the parameters concealed in the production function and the IPF can be recovered. With this specification, a strong test of the IIH is equivalent to testing the null hypothesis that $\gamma_i = 1$ for i = A/M, L/K. The null was tested by the equivalent hypothesis that the sum of the coefficients on the price ratio and F_{iht}, i = A/M, L/K, equals negative one. The null hypothesis for the weak test is dependent on the magnitude of the elasticity of substitution. If the elasticity of substitution between A and M (for i = A/M) or between L and K (for i = L/K) is less (greater) than 1, the hypothesis is that $\gamma_i > 0$ ($\gamma_i < 0$). Testing this hypothesis is equivalent to testing whether the ratio of the coefficient on F_{iht} and the negative of (1 plus the coefficient on the price ratio) is significantly positive (negative) when the elasticity of substitution is less (greater) than 1. This model not only provides a simple specification for joint estimates of the production function and IPF but an empirically tractable approach for directly conducting strong and weak tests of the IIH. Additional details of the econometric estimation equations and hypothesis tests are in Appendix 3.A.

Nonparametric Approach

The nonparametric testing procedure follows Chavas *et al*. (1997) who extended earlier work by Afriat (1972) and Varian (1984) to both account for technical change and examine evidence relative to induced innovation. A main benefit of this method is that it allows production technology changes to be examined without requiring any parametric representation of the production or profit function. Assuming (a) profit maximizing behavior, (b) a closed, convex, and monotonic technology set, and (c) factor augmentation, we define actual netputs at observation *t* by an $m \times 1$ vector $X_t = (X_{1,t}, ..., X_{m,t})'$ with associated price vector $P_t = (P_{1,t}, ..., P_{m,t})'$. In our case, the netput vector is 5x1: $X_t = (Y_t,\ \text{-}X_{A,t},\ \text{-}X_{M,t},\ \text{-}X_{L,t},\ \text{-}X_{K,t})$. The feasible netput choices satisfy $X_t \in F$, where *F* is the feasible technology set.

Allowing for technical change, the technology-constant "effective" netput vector at observation *t* is denoted $x_t = (x_{1,t}, ..., x_{5,t})'$, which is a function of actual netput levels and their augmentations, $B_{i,t}$:

(3.4) $x_{i,t} = g(X_{i,t}, B_{i,t}), \quad i = Y, A, M, L, K, \ \ t \in T$.

We follow Chavas *et al.* (1997) in treating $g(X, \cdot)$ as a reversible function, specifying augmentation following the translating hypothesis, i.e., $X_i = x_i + B_i$,[29] and in specifying

[29] Another simple augmentation specification sometimes maintained in analysis of technical change relies on the scaling hypothesis: $x_i = X_i B_i$. One computational complication of this specification for our purposes is that it renders the weak axiom of profit maximization (WAPM) nonlinear in *B*.

three augmentation restrictions needed to implement nonparametric testing of the IIH.

The first augmentation restriction is that the relationship between innovation investments and input augmentation is presumed to take the following form:[30]

$$(3.5) \qquad B_{i,t} = \alpha_{i,t} + \sum_{j=0}^{r} \left\{ [\beta_{i,j} + (p_{i,t-j} - 1)\gamma_{i,j}] R_{t-j} \right\}, \; i = A, M, L, K, \;\; t \in T,$$

where r is a vector of the maximum number of lags on innovation investments, j is the lag number, $p_{i,t-j}$ is the price of the i^{th} input relative to a Tornqvist index of all input prices at time t-j (so it equals 1 if the i^{th} input price moves in proportion to the index of all input prices), the $k \times 1$ vector $R_{t-j} = (R_{pri,t-j}, R_{pub,t-j}, Ext_{t-j})'$, $\alpha_{i,t}$ is a scalar that measures the impact of exogenous shocks on augmentation in the absence of innovation investments, $\beta_{i,j}$ is a $1 \times k$ parameter vector measuring the marginal effect of R_{t-j} on $B_{i,t}$ for constant relative prices (i.e., $p_{i,t-j} = 1$);[31] the 1xk parameter vector $\gamma_{i,j}$ measures the interaction effect of $p_{i,t-j}$ and R_{t-j} on $B_{i,t}$. We set the maximum number of lags at 28 for public research, 21 for private research, and 10 for extension and allowed the $\beta_{i,j}$'s and $\gamma_{i,j}$'s to be nonzero for $3 < j < 28$ for public research, $2 < j < 21$ for private research, and $3 < j < 10$ for extension. The IIH is corroborated by $\gamma_{i,j} > 0$ for some j with no $\gamma_{i,j} < 0$ and constitutes the critical test via this nonparametric method.

The second restriction smooths output augmentation variables to maintain the hypothesis of nonregressive technical change subject to random weather effects that can

[30] Since we use an aggregate index for outputs, the following specification, which allows for both exogenous shocks and investment-induced augmentation, applies to output augmentation: $B_{y,t} = \alpha_{y,t} + \sum_{j=0}^{r} \beta_{y,t} R_{t-j}$, $t \in T$.

[31] The β's also contain information on the marginal cost of augmenting inputs, a topic which is discussed in the next section.

alter productivity in individual years.

The third restriction maintains the hypothesis that the marginal effect of innovation activities on augmentation indices is nonnegative.

To test the IIH, we determine the minimum weighted values of α, β, and γ required to be consistent with the weak axiom of profit maximization (WAPM) under the three augmentation restrictions. Following Chavas *et al*. (1997), we solve the following quadratic programming problem:

$$
(3.6)\qquad \min_{B,\alpha,\beta,\gamma} \left[\sum_{i\in N} \left\{ \sum_{t\in T} w_1 \alpha_{i,t}^2 + \sum_j (w_2 \beta_{i,j}^2 + w_3 \gamma_{i,j}^2) \right\} : \begin{array}{l} (X_{i,t} - B_{i,t}) \geq 0, i = Y; \\ (X_{i,t} - B_{i,t}) \leq 0,\ i = A, M, L, K;\ \ t \in T; \\ \text{WAPM; the three augmentation restrictions} \end{array} \right]
$$

where w_1, w_2, w_3 are positive weights.[32] Equation (3.6) minimizes the weighted sum of squared parameters measuring varied sources of impact on technical change over time. The intuition is to make the augmentation indices "as close to the data as possible" by searching for the smallest absolute values for the α's, β's, and γ's that satisfy WAPM (Chavas *et al.,* 1997). Thus, with observed data on actual netputs and associated prices, we seek to reveal the nature of technical change. Additional details of the nonparametric test are in the Appendix 3.B.

For economy of computation, we conducted the nonparametric tests for only nine states. A broad cross-section of major agricultural states was selected. They represent all regions of the U.S. and include Florida, North Carolina, and New York in the east, Texas,

[32] Following Chavas *et al.* (1997), we use unit weights on all three parameters. That is, each of the terms in equation (3.5) is treated as being equally important to the augmentation indices.

Iowa, Kansas, and Michigan in the center, and California and Washington in the west.

The Missing Link: Marginal Cost of Developing and Implementing Input-Saving Technology

As have all other tests of the IIH, our three testing procedures focus exclusively on the demand for innovation. Each test implicitly maintains the hypothesis that the marginal cost of developing and implementing technologies that save one input is the same as the marginal cost of saving an equal percent of any other input. Although, as early as 1974, Binswanger recognized this limitation in his comments about neutral innovation possibilities, it appears that none of the empirical tests of the IIH have attempted to surmount it. Unfortunately, data on the development and implementation costs of various input-saving technologies are generally lacking, so it is not possible to conduct explicit tests of the induced innovation accounting for differences in these costs. Consequently, it is possible that the IIH is correct and yet we may observe producers augmenting cheap factors because the marginal costs of developing and implementing input-saving technologies for the relatively expensive inputs are greater than for the relatively inexpensive ones. That is, technical change may not bias toward saving a particular input even when the input is relatively expensive, even when the elasticity of substitution is less than 1.

In the absence of data to conduct an explicit test of the IIH accounting for both demand and supply incentives, we approach this dilemma by asking what the minimum differences in marginal costs of developing and implementing input-saving technologies for the various inputs would have to be for revealed consistency with the IIH. We implement these computations by a modification of the nonparametric model.

In equation (3.5), the parameter $\beta_{i,j}$ was interpreted as the marginal impact of innovation investments in lagged period j on the current input augmentation index given constant relative input prices. That is, this parameter can be viewed as the marginal effect of a unit investment in an innovation activity on the productivity of the input given constant relative input prices. Thus, the inverse of $\beta_{i,j}$ could be interpreted as the marginal cost in the lagged period j of a 1% change in current productivity of the input given constant relative input prices. Consequently their ratios would be measures of the implied relative marginal costs for augmenting associated inputs under revealed consistency with the IIH.

Making use of the marginal cost information embodied in the inverse of the β's, we compute minimum differences in the marginal costs of developing and implementing input-saving technology by including one additional restriction in the optimization problem in equation (3.6). This restriction assures that actual observations are consistent with the IIH:

(3.7) $\gamma_{i,j} \geq \varepsilon, \forall i \in N, \forall j \in r_i$,

where ε is an arbitrarily small positive number, 0.0000001. The weights (w_1, w_2, w_3) and all other implementation conditions in (3.6) remain the same. To create summary marginal cost measures for each input, the implied marginal cost for the i^{th} input at each lag j, i.e., the inverse of $\beta_{i,j}$, is discounted to the current period (j = 0) using a discount rate of 0.03,[33] and they are summed across j for each innovation investment type.

The optimization problem (3.6) and (3.7) provides a simple framework for investigating relative differences in the marginal costs of technology development and implementation that must have existed over our data period for the IIH to have been the sole motivation for input-saving technologies in the U.S. farm sector.

Data

Panel data on input quantities and prices for the 48 contiguous states for the period 1960-1999 come from Ball *et al*. (2004). This high-quality aggregate data set includes a comprehensive price and quantity inventory for three categories of agricultural outputs (crops, livestock, and secondary outputs) and four categories of inputs (capital, land, labor, and materials) compiled using theoretically and empirically sound procedures which preserve the economic integrity of national and state production accounts and are consistent with a gross output model of production.

Deflated annual agricultural public research investment data for the period 1927-1995 were compiled for each state by Huffman (2005). Agricultural extension investments for the U.S. for the period 1951-1996 are from Huffman, Ahearn, and Yee (2005). They are total cooperative extension investments in current dollars divided by the price index for agricultural research.

The number of private patents is used as a proxy for private research investments. The data come from Johnson's (2005) inventory of patents by state and by industry as the

[33] This rate is a little higher than the average real discount rate of 0.023 calculated by subtracting inflation rate from the 1-year treasury bond rate for the years 1962-1999.

primary user of the patent for the period 1883-1996. The panel data set was prepared by multiplying the percent of patents granted by state each year by the number of patents granted in the U.S. for use in agriculture. Johnson's patent classification since 1976 follows the international protocol, and the Yale Technology Concordance (Johnson and Evenson, 1997) was used to calculate industries of manufacture and sectors of use. Prior to 1976, the Wellesley Technology Concordance (Johnson, 1999) was followed to classify patents.

Average farm size for each state was measured as the average gross value of farm assets per farm. It was computed for each year as the total gross value of farm assets reported for the state divided by the number of farms. Farm assets data for the years 1960-1999 were taken from the *Farm Balance Sheets* (USDA/ERS, 1960-2003). Data on the number of farms for the same years were taken from *Farms, Land in Farms, & Livestock Operations* (and its predecessor publication) (USDA/NASS, 1960-2005) and compiled by Strickland (2005).

In order to fully utilize the 40 years of state-level input and output price and quantity data, it was necessary to have state-level data on research and extension investments for many years prior to 1960. As noted above, they (or reasonable proxies) were available for at least 28 prior years for research investments and for 9 years for extension investments. However, state-level data on the input prices that created incentive to develop input-saving technologies prior to 1960 were not available. Consequently, we created state-level input price proxies for the period 1932-1959 using Ball's (Ball *et al.*, 1997; Ball, 2006) U.S.-level input price data that was developed using the same procedures as the state-level data for the period 1948-1999 and Thirtle *et al.*'s (2002) U.S. input price data for earlier years. Details of the construction of state-level input price proxies this data set are provided in Appendix 3.C.

Empirical Results

The empirical results from each estimation procedure are presented sequentially in this section. They are followed by estimates of the minimum differences in marginal costs of developing and implementing saving-technology for the various inputs to be consistent with the IIH.

Time-Series Test Results

The Hadri stationarity test results for all variables are reported in Table 3.1.[34] Accounting for heteroskedastic errors across units and associated P-values for all series imply that stationarity was rejected at a 0.05 significance level for each series in levels. Five variables (Ln($R_{A/M}$), Ln($P_{A/M}$), Ln($P_{L/K}$), Ln(R_{pri}), Ln(R_{pub})) were found to be stationary in first differences, i.e., they followed I(1) processes, at the 0.05 level. Three series, Ln($R_{L/K}$), Ln(*Ext*), Ln(*Size*), were found to be I(2) processes at the 0.05 level. Again, A is land, M is materials, L is labor, K is capital, P_i is price of the i^{th} input, R_{pri} is private research investments, R_{pub} is public research investments, *Ext* is extension investments, *Size* is average farm size.

Because investments in research and extension may not induce technological change for several years, Akaike's information criterion (AIC) was used to determine

[34] The tests were conducted using the econometric software package, STATA, Version 9.0, Routine HADRILM.

optimal lags on extension, public and private research investments for both the time-series and econometric testing procedures. The optimal lag on public research investments was chosen from lags of 7-30 years. The optimal lag on private research investments was chosen from lags between 3 years and the optimal lag on public research investments. Because of the more limited data series, the optimal lag on extension investments was chosen from lags between 3 years and 9 years. The lag on public research investments that minimized the AIC was 28 years for the land-material ratio equation and 16 years for the labor-capital ratio equation. In both factor ratios, a lag of 13 years on private research investments minimized the AIC. The optimal lag on extension investments was 3 for the land-material equations and 4 for the labor-capital equations. For convenience in subsequent analysis, identical lags were selected for both factor ratio equations. A lag of 16 years was selected for public research investments and 3 years for extension investments. These lags were selected because the distributions of AIC values were much steeper at these values for the respective equation than were the distributions for the optimal lag in the other equation.

Based on the integration order of the time series, we analyzed the long-run relationship between the factor ratios and associated explanatory variables in equations (3.1) and (3.2) for the time-series model. If the data are cointegrated for a factor ratio equation, the factor ratio can be formulated using the original (i.e., undifferenced) data for I(1) series and first differences for I(2) series to capture the long-run relationships in the data for both time-series and econometric models. If the data are not cointegrated, the IIH is rejected by the time-series testing approach.

The results of the cointegration analysis are reported in the last four rows of Table 3.1. The seven test statistics recommended by Pedroni (1999) are reported for each cointegration test. [35] Five of the seven test statistics for the land-material equation in the time-series model resulted in rejection of the hypothesis of no cointegration at the 0.05 significance level and another at a 0.10 significance level. For the labor-capital equation in the time-series model, all statistics but one supported rejection of the hypothesis of no cointegration at the 0.01 significance level. Thus, based on the preponderance of test evidence, it is concluded that cointegration, and consequently a long run relationship, exists for both the land-material and the labor-capital time-series equations, which is consistent with the IIH.

Having concluded that a cointegration relationship exists among the variables in both equations of the time-series model, we next estimated the error correction model (ECM) for each factor ratio. Based on the stationarity test results, the dynamic form of the ECM was specified by using first differences for each of the I(2) variables, Ln($R_{L/K}$), Ln(*Ext*) and Ln(*Size*), and original data for the others.

Using the Hausman test, the hypothesis of long-run homogeneity was not rejected at a 0.05 significance level for each variable in each equation. Thus, it was concluded that the pooled mean group estimator (PMGE) was the appropriate method for estimating the ECM. The lag orders for dependent and independent variables were chosen by minimizing the AIC subject to a maximum lag length of 3. In this application, an ARDL(3,3,3,3,3,3) was determined by this process for each factor ratio equation.

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[35] The tests were conducted using the econometric software package, RATS, Version 6.01, and Routine PANCOINT.

The Pesaran PMGE parameter estimates of the ECM are reported in Table 3.2.[36] Consistent with the IIH, the own-price parameter is negative both in the short-run and the long-run for each factor ratio equation. The error correction term, λ_i, is negative and significant in each equation which indicates that the system adjusts toward equilibrium. However, in the labor-capital equation, the estimated value is -1.3109, which implies that the error correction over-adjusts towards the long-run equilibrium. As a result, the short-run direct elasticity of substitution between labor and capital (0.049) is larger than the long-run elasticity (0.037).[37] The failure of the long-run elasticity (along the IPF) to exceed the short-run elasticity (along the isoquant) is a crucial inconsistency with the IIH (Oniki, 2000). Based on requirement (d), it **necessitates rejection of the IIH for labor and capital inputs by time series procedures**. Additional testing with time-series procedures will be restricted to the land and materials inputs.

The estimated value of the error correction term in the land-material equation is -0.1373, which implies that, when the system is not in the equilibrium, there is a 13.73% correction towards the long-run equilibrium in the current period. Thus, the long-run elasticity of substitution (0.0409) is larger than the short-run elasticity (0.0056), which is also consistent with the IIH.

Two of the innovation variables (public and private research investments) have significantly negative long-run effects on the land-material ratio. The significantly negative coefficients on these two innovation variables imply that increased research

[36] The estimates were computed using a GAUSS program by Pesaran, Shin, and Smith

[37] The direct elasticity of substitution is measured as the absolute value of the own-price parameter. In the state-specific analyses, all states exhibited larger short-run than long-run elasticities of substitution for labor and capital.

investments lead to land-saving technical bias. The farm size parameter was negative and significant. A 10% increase in farm size would decrease the land-material ratio by 10.62%, thus increasing the bias towards land-saving technical change. These results imply that research investments and larger farms increase the bias towards land-saving technical change. Also, except for extension investments, all of the long-run coefficients in the state-specific estimates (not reported here) were significant and had the same signs as in the panel estimates. Research investments and larger farms increase the bias toward land-saving technical change in the short-run, but extension investments increase the short-run bias toward material-saving technical change.

The final time-series test of the IIH was conducted to determine whether causality ran from the factor price ratio and innovation variables to the factor quantity ratio for land and materials. We estimated a dynamic model in which the land-material ratio was modeled as a function of its lags, other explanatory variables, and their lags. We selected a lag length of two for all the variables. The lagged terms of the dependent variable were included to proxy omitted variables (Nair-Reichert and Weinhold, 2001). The Nair-Reichert and Weinhold mixed-fixed-and-random-coefficients estimates are reported in Table 3.3.[38] Insignificance of the coefficients on the two terms representing lagged own-price ratios result in rejection of the hypothesis that causality runs from the factor price ratio to the factor quantity ratio as required for consistency with the IIH. The hypothesis that research and extension activities Granger-cause the change in factor quantity ratio was also rejected. Thus, the **testing results for causal relationships in the land-**

[38] The tests were conducted using a GAUSS program by Nair-Reichert and Weinhold.

material equation fail to support the IIH. Despite other evidence supporting the IIH in land and materials inputs, this violation **necessitates rejection of the IIH in all four inputs using this robust, panel time-series testing procedure**.

Econometric Model Results

Before estimating the econometric model, we first tested for AR(1) and heteroskedasticity in each equation's residuals.[39] Finding evidence of both autocorrelation and heteroskedasticity in the residuals of the land-material and labor-capital equations specified in equation (3.3), we estimated both equations using a heteroskedasticity- and autocorrelation-consistent covariance matrix estimator (HACCME).[40] HACCME computes the coefficients using a least-squares approach. The parameter estimates and test statistics are reported in Table 3.4.

The estimated coefficient associated with the factor price ratio had the expected sign in both equations. The estimates of partial elasticities of substitution (i.e., the negative of the coefficients on the price ratios) are both less than 1 (0.6167 and 0.1422 respectively). Therefore, the weak test of the IIH is that $\gamma_i > 0$ for i = A/M, L/C, which is tested by determining whether the alternate hypothesis that $\gamma_i = 0$ is rejected by a one-sided test at the 0.05 level. The test results for the weak and strong hypotheses are reported in the last two rows of Table 3.4. The weak hypothesis was rejected (i.e., the tested null hypothesis was not rejected) for both equations. In addition, the strong

[39] We first attempted to specify the econometric model to be consistent with the non-rejected time-series properties of the variables. Unfortunately, the use of differenced data as required for some of the variables resulted in serious multicollinearity.
[40] The Durbin-Watson and Breusch-Pagan test statistics were 0.134 and 47.814, respectively, in the land-materials equation and 0.171 and 20.835 respectively, in the labor-capital equation.

hypothesis that $\gamma_i = 1$, i= A/M, L/C, was soundly rejected for both equations. We failed to find support for the strong hypothesis in either equation. Thus, **our econometric test results provide no support for either test of the IIH for either pair of inputs**.

Generalized Model Results

To determine whether test conclusions were sensitive to the restrictive CES functional form, all time-series and econometric model tests were repeated using a generalization of the two-stage CES. The generalization included three additional explanatory variables – two more price ratios and output level, all in logarithms. Thus, each equation included three price ratios ($P_{A/M}$, $P_{L/K}$, and $P_{A/L}$), output level, and the four efficiency variables (R_{pri}, R_{pub}, *Ext, Size*). This generalization was treated only as an approximation to an unknown but more general functional form. **The time-series model conclusions were qualitatively unaffected by the functional form generalization. In the econometric model, the land-material ratio equation was found to be consistent with the weak version of the IIH, but the strong hypothesis conclusions were unaffected by the generalization.**

Nonparametric Test Results

The nonparametric findings regarding the validity of the IIH are reported in Table 3.5 for each input and each of nine states. To provide nonparametric support for the IIH, we required that $\gamma_{i,j} > 0$ for some *j* with no $\gamma_{i,j} < 0$. With four inputs, three innovation investments, and nine states, there were 108 individual tests of the hypothesis. Of these tests, 79 rejected the hypothesis and 29 supported the hypothesis. The only input that received support by a majority of the tests was materials. Land received the least support, followed in succession by labor and capital. Frequent rejections of the hypothesis in the less actively traded inputs (land, labor, and capital) were consistent with the findings of Chavas *et al*. (1997). In no state did a majority of the tests support the hypothesis, and in one state all tests rejected the hypothesis. For each of the innovation investment types, approximately ¼ of the tests supported the hypothesis and ¾ rejected the hypothesis.

Thus, **the nonparametric test results were consistent with both the time series and econometric model test results**. Findings from all three approaches imply that relative input prices failed to play a major role in guiding development and implementation of new technologies for U.S. agriculture that saved relatively expensive inputs. Our conclusion that the IIH is not supported in U.S. agriculture is consistent with the findings of Liu and Shumway (2006), Olmstead and Rhode (1993, 1998), Machado (1995), and Tiffin and Dawson (1995). However, it is counter to the conclusions of Hayami and Ruttan (1970, 1985), Binswanger (1978), Antle (1984), Thirtle (1985), Kawagoe *et al*. (1986), Huffman and Evenson (1989), Lambert and Shonkwiler (1995), and Thirtle *et al.* (2002).

Marginal Cost of Developing and Implementing Input-Saving Technologies

Having failed to find support for the IIH relying exclusively on the demand for innovation and lacking essential data to distinguish differences in innovation supply, we calculated relative differences in the marginal costs of developing and implementing saving technologies for the various inputs to be consistent with the hypothesis. The qualitative pairwise results of these nonparametric computations are reported for the nine representative states in Table 3.6.

For differences in marginal costs of technology development and implementation to render the data consistent with the IIH, it is clear that the marginal cost of land- and capital-saving technologies must have been greater than the marginal cost of material-saving technologies in nearly all states. This finding was robust across the various types of input-saving innovation investment. If these marginal cost differences actually existed, then the higher cost of developing and implementing land- or capital-saving technologies could have induced profit-maximizing technical change that was biased toward augmenting materials rather than land or capital even when land and capital were the relatively more expensive inputs.

For consistency with the IIH, the marginal cost of developing and implementing land-saving technology must have been greater than for labor-saving technology in most states for all types of innovation investment. The marginal cost of land-saving technology must also have been greater than for capital-saving technology in all states for research investments and in a majority of states for extension investments. This same observation also applies in nearly all states for labor vs. material-saving technologies. However, the order ranking of required marginal cost differences for labor and capital was less clear. For private research investments, 2/3 of the states required higher marginal costs for labor-saving technologies than for capital-saving technologies. Nearly the reverse was found for extension investments, and neither dominated for public research investments.

Conclusions

The hypothesis of induced innovation (IIH) is that technology is developed and implemented in ways that facilitate replacement of relatively scarce and expensive production factors by abundant and cheap factors. Over nearly four decades, this hypothesis has been empirically tested in many ways, using a wide variety of data and test periods for many industries in many countries. U.S. agriculture has been the most tested of all industries. During the first two decades of testing, a stylized fact emerged that supported the IIH in U.S. agriculture as well as in many other industries and countries. However, while most early tests indicated support for the hypothesis, recent tests with a wider variety of testing methods and data have resulted in nearly even support for and refutation of the hypothesis. Thus, no stylized fact on induced innovation in this industry currently exists.

Possible reasons for the recent conflicting test results are inadequate data, the low power of traditional testing methods, and inflexibility of specification. Also, all prior literature has tested the hypothesis only from the innovation demand side. The marginal cost of developing and implementing technologies that save 1 percent of an input has implicitly been assumed to be the same for each input (i.e., neutral innovation possibilities). In this paper, we sought to overcome each of these limitations by using a high-quality, 40-year, state-level, panel data set for U.S. agriculture rather than time series data. We also employed testing procedures that are both more powerful and more comprehensive than those previously used to formally test the IIH. The test procedures included time series, econometric, and nonparametric methods.

Our empirical finding was robust to test procedures and to functional specification. The demand-side of the IIH was found to be inadequate to explain input-saving technologies developed and implemented in U.S. agriculture between 1960 and 1999. The hypothesis was soundly rejected by all test procedures. This finding cautions against the efficacy of policies based on the premise that price signals alone induce efficient technical change. Although research and extension investments were found to have positive impacts on development and implementation of factor-saving inputs, they were not motivated exclusively by relative prices. If the marginal cost of developing and implementing input-saving technology is the same for all inputs, the IIH must be emphatically rejected for U.S. agriculture by this, the most rigorous and comprehensive set of empirical tests ever conducted with a single, high-quality data set.

However, differences in the marginal cost of developing and implementing input-saving technology have not been taken into account in any formal test of the IIH. Differences in the relative costs of creating technology to save an equal percent of each input could cause violations of the demand-side tests even when innovation is induced by relative price changes.

Unfortunately, data do not exist to test whether differences in marginal costs explained the lack of support for the hypothesis. As an alternative, we developed and applied a nonparametric procedure to determine differences in the marginal cost of developing and implementing input-saving technology for four inputs required for consistency with the IIH. To be consistent with the hypothesis, we estimated that, in most states, the marginal cost of developing and implementing technology that would save 1 percent of an input must have been greater for land and capital than for materials, greater for land than for capital (for research investments), greater for land than for labor (for private research investments), and greater for labor than for materials (for research investments). We found little evidence to argue that marginal costs for labor-saving and capital-saving innovations must have differed for consistency with the hypothesis. Likewise, there was little evidence that marginal costs of extension investments had to differ between land and capital-saving innovations or between labor and materials-saving innovations for consistency with the hypothesis.

There are several obvious limitations of our study. Because we used a nonparametric procedure to compute differences in required marginal costs of developing and implementing input-saving technologies, we were unable to develop confidence intervals around our estimates. Because we lacked data on actual costs of development and implementation of augmenting technologies, we were also unable to test whether the IIH was supported or refuted when both supply and demand sides were taken into account.

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Table 3.1. Stationarity and Cointegration Test Results

	Stationary Test Results					
	Levels		1st Differences		2nd Differences	
Data Series [a]	Statistic [b]	P-value	Statistic [b]	P-value	Statistic [b]	P-value
Ln(A/M)	64.045	0.000	-2.294	0.960		
Ln(L/K)	101.568	0.000	6.006	0.000	-7.130	1.000
Ln(P_A/P_M)	78.049	0.000	-3.776	1.000		
Ln(P_L/P_K)	51.773	0.000	-3.735	1.000		
Ln(R_{pri})	211.161	0.000	-2.451	0.993		
Ln(R_{pub})	79.132	0.000	-2.529	0.994		
Ln(Ext)	81.702	0.000	2.324	0.010	-7.168	1.000
Ln($Size$)	125.088	0.000	35.034	0.000	-6.645	1.000

	Cointegration Test Results [c]			
Test Statistic [b]	Land-Materials		Labor-Capital	
	Panel	Group	Panel	Group
v-statistic	1.005		1.130	
ρ-statistic	-1.484	3.447	-12.797*	-6.241*
t-statistic (nonparametric)	-3.341*	-5.007*	-36.561*	-39.311*
t-statistic (parametric)	-1.792*	-3.244*	-24.079*	-24.722*

[a] Codes: Ln is logarithm, A is land, M is materials, L is labor, K is capital, P_i is price of input i, R_{pri} is private research investments, R_{pub} is public research investments, Ext is extension investments, $Size$ is average farm size.
[b] A time trend was included when testing for stationarity in levels and in testing for cointegration.
[c] Critical 1-tailed test values for rejecting the hypothesis of no cointegration is 1.645 for the panel v-statistics and -1.645 for the other statistics at the 0.05 significance level (Pedroni 1999). Significant cointegration test coefficients are identified by an asterisk.

Table 3.2. Estimated Error Correction Model [a]

Variable [b]	Land-Materials Coefficient	Land-Materials Standard Error	Labor-Capital Coefficient	Labor-Capital Standard Error
Long-run effects:				
Ln(*own-price ratio*)$_t$	-0.0409*	0.0187	-0.0374*	0.0054
ΔLn(*Size*)$_t$	-1.0624*	0.1277	-0.0312	0.0227
Ln(R_{pri})$_t$	-0.2846*	0.0308	0.0330*	0.0064
Ln(R_{pub})$_t$	-0.1694*	0.0255	0.0380*	0.0043
ΔLn(*Ext*)$_t$	0.0982	0.0927	-0.0181	0.0164
Error correction coefficient	-0.1373*	0.0170	-1.3109*	0.0541
Short-run effects:				
Ln(*own-price ratio*)$_t$	-0.0056*	0.0007	-0.0490*	0.0020
ΔLn(*Size*)$_t$	-0.1459*	0.0181	-0.0409*	0.0017
Ln(R_{pri})$_t$	-0.0391*	0.0049	0.0432*	0.0018
Ln(R_{pub})$_t$	-0.0233*	0.0029	0.0409*	0.0017
ΔLn(*Ext*)$_t$	0.0135*	0.0017	-0.0238*	0.0010
ΔLn(*own-quantity ratio*)$_{t-1}$ [c]	-0.0725*	0.0292	0.1327*	0.0362
ΔLn(*own-quantity ratio*)$_{t-2}$ [c]	-0.0312	0.0170	0.0509*	0.0220
ΔLn(*own-price ratio*)$_t$	0.0023	0.0076	-0.1533*	0.0227
ΔLn(*own-price ratio*)$_{t-1}$	0.0006	0.0045	0.0067	0.0123
ΔLn(*own-price ratio*)$_{t-2}$	-0.0076	0.0048	-0.0052	0.0085
Δ^2Ln(*Size*)$_t$	0.1124*	0.0327	0.1831*	0.0354
Δ^2Ln(*Size*)$_{t-1}$	-0.0250	0.0354	0.0936*	0.0329
Δ^2Ln(*Size*)$_{t-2}$	0.0977*	0.0219	-0.0215	0.0346
ΔLn(R_{pri})$_t$	0.0041	0.0076	-0.0311*	0.0122
ΔLn(R_{pri})$_{t-1}$	0.0146	0.0081	-0.0328*	0.0095
ΔLn(R_{pri})$_{t-2}$	0.0196*	0.0064	0.0105	0.0090
ΔLn(R_{pub})$_t$	-0.0116	0.0071	0.0111	0.0245
ΔLn(R_{pub})$_{t-1}$	0.0286*	0.0122	0.0005	0.0116
ΔLn(R_{pub})$_{t-2}$	-0.0019	0.0071	-0.0013	0.0170
Δ^2Ln(*Ext*)$_t$	-0.0779*	0.0226	0.1194*	0.0352
Δ^2Ln(*Ext*)$_{t-1}$	-0.0623*	0.0182	0.0158	0.0298
Δ^2Ln(*Ext*)$_{t-2}$	-0.0150	0.0198	-0.0340*	0.0157
Constant	0.3999*	0.0644	-0.9315*	0.0379
$\overline{R}^2$	0.430		0.710	

[a] The critical t-values for these 2-tailed tests are 1.96 at the 0.05 significance level. Significant coefficients are identified by an asterisk. $\overline{R}^2$ is an average of state-specific R-square values.
[b] Ln(R_{pri})$_t$, Ln(R_{prub})$_t$ and Ln(*Ext*)$_t$ are lagged 13 years for private research, 16 years for public research, and three years for extension investments. These optimal lags were selected by minimizing the AIC.
[c] These variables are twice differenced and the dependent variable is first differenced in the labor-capital equation.

Table 3.3. Causality Test for the Land-Materials Ratio [a]

Variable	Estimated Coefficient	Standard Error
Constant	-1.2587*	0.5861
$\mathrm{Ln}(R_{A/M})_{t\text{-}1}$	0.2110	0.4395
$\mathrm{Ln}(R_{A/M})_{t\text{-}2}$	0.1493	0.4418
$\mathrm{Ln}(P_{A/M})_{t\text{-}1}$	-0.0038	0.1335
$\mathrm{Ln}(P_{A/M})_{t\text{-}2}$	-0.0116	0.1351
$\mathrm{Ln}(R_{pri})_{t\text{-}1}$	0.0160	0.2137
$\mathrm{Ln}(R_{pri})_{t\text{-}2}$	-0.0284	0.2162
$\mathrm{Ln}(R_{pub})_{t\text{-}1}$	0.0566	0.1757
$\mathrm{Ln}(R_{pub})_{\mathrm{t}\text{-}2}$	0.0534	0.1753
$\mathrm{Ln}(Ext)_{t\text{-}1}$	-0.4072	0.9361
$\mathrm{Ln}(Ext)_{t\text{-}2}$	0.1539	0.9789
$\mathrm{Ln}(Size)_{t\text{-}1}$	-0.0133	0.1243
$\mathrm{Ln}(Size)_{t\text{-}2}$	-0.0086	0.1237

[a] The critical t value is 1.96 at the 0.05 significance level. Significant coefficients are identified by an asterisk.

Table 3.4: Estimated Econometric Model [a]

Land-Materials Equation			Labor-Capital Equation		
Variable	Coefficient	Standard Error	Variable	Coefficient	Standard Error
Constant	-1.4467*	0.0900	Constant	0.8118*	0.0332
$\mathrm{Ln}(P_{A/M})$	-0.6167*	0.0446	$\mathrm{Ln}(P_{L/K})$	-0.1422*	0.0405
F_1	0.00013*	0.000031	F_2	0.0227*	0.0021
$\sum_{s=1}^{t} \ln(R_{pri,s})$	-0.0045*	0.0007	$\sum_{s=1}^{t} \ln(R_{pri,s})$	0.00025	0.00039
$\sum_{s=1}^{t} \ln(R_{pub,s})$	0.0042	0.0027	$\sum_{s=1}^{t} \ln(R_{pub,s})$	0.0034*	0.0012
$\sum_{s=1}^{t} \ln(Ext_s)$	-0.0031	0.0027	$\sum_{s=1}^{t} \ln(Ext_s)$	-0.0047*	0.0013
$\overline{R}^2$ [b]	0.488		$\overline{R}^2$	0.357	
Hypothesis	Tested Null	Wald Statistic	Hypothesis	Tested Null	Wald Statistic
Weak Test, $\gamma_{A/M} > 0$	$\gamma_{A/M} \leq 0$	3.677	Weak Test, $\gamma_{L/K} > 0$	$\gamma_{L/K} \leq 0$	-9.664
Strong Test, $\gamma_{A/M} = 1$	$\gamma_{A/M} = 1$	73.838*	Strong Test, $\gamma_{L/K} = 1$	$\gamma_{L/K} = 1$	473.041*

[a] Critical values at the 0.05 significance level are 1.96 for the 2-tail t-ratios and 3.84 for the 1-tail Wald chi-square statistics. Significant coefficients are identified by an asterisk.
[b] $\overline{R}^2$ is an average of state-specific adjusted R-square values.

Table 3.5. Nonparametric Tests of the Induced Innovation Hypothesis, Selected States [a]

	Land			Materials			Labor			Capital		
	R_{pri}	R_{pub}	*Ext*	R_{pri}	R_{pub}	*Ext*	R_{pri}	R_{pub}	*Ext*	R_{pri}	R_{pub}	*Ext*
CA	R	R	A	R	A	A	R	R	R	R	R	R
FL	R	R	R	A	A	A	R	R	R	A	R	R
IA	R	R	R	R	R	A	R	R	R	R	A	R
KS	R	R	R	A	A	A	R	R	R	R	A	R
MI	R	R	R	R	R	A	R	R	A	R	R	R
NC	R	R	R	A	A	A	A	R	R	R	A	R
NY	R	R	R	R	R	R	R	R	R	R	R	R
TX	R	R	R	A	A	A	R	R	R	R	R	R
WA	R	R	R	A	A	A	A	R	R	A	R	A

[a] Codes: R_{pri} is private research investments, R_{pub} is public research investments, *Ext* is extension investments. A means accept the IIH, R means rejected the IIH.

Table 3.6. Nonparametric Estimates of Relative Marginal Cost of Developing and Implementing Input-Saving Technology Required for Consistency with the Induced Innovation Hypothesis [a]

Input Pair	Marginal Cost Relationship	Input-Saving Innovation Investments		
		R_{pri}	R_{pub}	*Ext*
Land vs. materials	$MC_A > MC_M$	CA, FL, IA, KS, MI, NC, NY, TX, WA	CA, FL, IA, KS, MI, NC, NY, TX, WA	CA, FL, IA, KS, MI, NC, NY, TX, WA
Labor vs. capital	$MC_L > MC_K$	CA, FL, KS, NY, TX, WA	CA, FL, KS, TX, WA	CA, KS, WA
	$MC_L = MC_K$			FL
	$MC_L < MC_K$	IA, MI, NC	IA, MI, NC, NY	IA, MI, NC, NY, TX
Land vs. capital	$MC_A > MC_K$	CA, FL, IA, KS, MI, NC, NY, TX, WA	CA, FL, IA, KS, MI, NC, NY, TX, WA	CA, KS, NC, NY, WA
	$MC_A = MC_K$			FL, IA, MI,TX
Labor vs. materials	$MC_L > MC_M$	CA, FL, IA, KS, NC, NY, TX, WA	CA, FL, IA, KS, NC, TX, WA	CA, FL, IA, KS, WA
	$MC_L < MC_M$	MI	MC, NY	MI, NC, NY, TX
Land vs. labor	$MC_A > MC_L$	CA, IA, KS, MI, NC, NY, TX, WA	IA, MI, NC, NY, WA	IA, MI, NC, NY, TX, WA
	$MC_A = MC_L$	FL	FL	FL, KS
	$MC_A < MC_L$		CA, KS, TX	CA
Capital vs. materials	$MC_K > MC_M$	CA, FL, IA, KS, NC, TX, WA	CA, FL, IA, KS, MI, NC, NY, TX, WA	CA, FL, IS, KS, MI, NC, TX, WA
	$MC_K < MC_M$	MI, NY		NY

[a] Codes: R_{pri} is private research investments, R_{pub} is public research investments, *Ext* is extension investments. MC_i represents marginal cost of developing and implementing input-saving technologies for input i.

Appendix 3.A: Structure of the Econometric Model

Let A, M, L, K represent the quantities of land, materials, labor, and capital, respectively, E_A, E_M, E_L, and E_K represent their factor augmentations. Suppose output (Y) is produced with a land input index, $X_A(E_A A, E_F M)$, and a labor input index, $X_L(E_L L, E_K K)$, according to a two-level production technology:

(A1) $Y_t = F_t[X_{A,t}(E_{A,t}A_t, E_{M,t}M_t), X_{L,t}(E_{L,t}L_t, E_{K,t}K_t)]$,

where $F_t(\cdot)$ is assumed to vary across time t.

We assume the production technology can be approximated by a two-level CES functional form (e.g., de Janvry *et al.*, 1989; Frisvold, 1991; Thirtle *et al.*, 2002):

(A2) $Y_t = [\gamma X_{A,t}^{-\rho} + (1-\gamma)X_{L,t}^{-\rho}]^{-1/\rho}$,

(A3) $X_{A,t} = [\alpha(E_{A,t}A_t)^{-\rho_1} + (1-\alpha)(E_{M,t}M_t)^{-\rho_1}]^{-1/\rho_1}$,

(A4) $X_{L,t} = [\beta(E_{L,t}L_t)^{-\rho_2} + (1-\beta)(E_{K,t}K_t)^{-\rho_2}]^{-1/\rho_2}$,

where $\alpha, \beta, \gamma, \rho, \rho_1, \rho_2$ are parameters and $\rho, \rho_1, \rho_2 > -1$.

The logarithms of the first-order conditions of profit maximization can be rearranged to give:

(A5) $\ln(A_t / M_t) = [1/(1+\rho_1)]\ln[\alpha/(1-\alpha)] - [1/(1+\rho_1)]\ln(P_{A,t}/P_{M,t}) - [\rho_1/(1+\rho_1)]\ln(E_{A/M,t})$

(A6) $\ln(L_t / K_t) = [1/(1+\rho_2)]\ln[\beta/(1-\beta)] - [1/(1+\rho_2)]\ln(P_{L,t}/P_{K,t}) - [\rho_2/(1+\rho_2)]\ln(E_{L/K,t})$

where P_A P_M, P_L, and P_K are the prices of land, materials, labor, and capital, respectively; $E_{A/M,t} = E_{A,t}/E_{M,t}$, and $E_{L/K} = E_{L,t}/E_{K,t}$.

Following Armanville and Funk (2003) and using notation (E_i) to represent the efficiency variables (factor augmentations), we define the IPF as the following set of instantaneous rates of factor augmentation ($(\hat{E}_{A,t},\ \hat{E}_{M,t}),(\hat{E}_{L,t},\hat{E}_{K,t})$) that producers can choose: [41]

(A7) $\{(\hat{E}_{A,t},\ \hat{E}_{M,t}),\ (\hat{E}_{L,t},\ \hat{E}_{K,t}\ ) : \hat{E}_{M,t} \le \phi_1(\hat{E}_{A,t}); \hat{E}_{K,t} \le \phi_2(\hat{E}_{L,t})\}$,

where the circumflexes (^) denote relative rates of change, i.e., $\hat{E}_{i,t} = (E_{i,t} - E_{i,t-1}) / E_{i,t-1}$; $\phi_1(\cdot)$ and $\phi_2(\cdot)$ are the first-level innovation possibility frontiers which are assumed to be differentiable, decreasing, strictly concave, and ellipses centered at (-1,-1), [42] i.e.,

(A8) $\phi_1(\cdot):\ (\hat{E}_{A,t}+1)^2+n_{1,t}^2(\hat{E}_{M,t}+1)^2 = m_{1,t}^2$,

(A9) $\phi_2(\cdot):\ (\hat{E}_{L,t}+1)^2+n_{2,t}^2(\hat{E}_{K,t}+1)^2 = m_{2,t}^2$,

where *n* is a slope parameter and *m* is a level parameter. The parameters *n* and *m* measure the augmentation trade-off rate between factors. The slopes of $\phi_1(\cdot)$ and $\phi_2(\cdot)$ with respect to E_A, and E_L, respectively, at given $(\hat{E}_{A,t},\ \hat{E}_{M,t})$ and $(\hat{E}_{L,t}, \hat{E}_{K,t})$ are:

(A10) $-\phi_{1,t}' = -dE_{M,t} \big/ dE_{A,t} = (\hat{E}_{A,t}+1)/[n_{1,t}^2(\hat{E}_{M,t}+1)]$,

(A11) $-\phi_{2,t}' = -dE_{K,t} \big/ dE_{L,t} = (\hat{E}_{L,t}+1)/[n_{2,t}^2(\hat{E}_{K,t}+1)]$.

Generally, innovations can be viewed as activities that reallocate resources among factor augmentations for the purpose of profit maximization. The hypothesis of induced innovation is that a firm chooses a feasible set of factor augmentations on the IPF to

[41] When the producers simultaneously choose all four factors to maximize profit, the IPF should be defined as the following set: $\{(\hat{E}_{A,t}, \hat{E}_{M,t}, \hat{E}_{L,t}, \hat{E}_{K,t}\ ) \mid \hat{E}_{A,t} \le \phi(\hat{E}_{M,t}, \hat{E}_{L,t}, \hat{E}_{K,t})\}$. However, this four-dimensional innovation possibility frontier proves to be intractable for empirical application. By maintaining weak separability between (*A, M*) and (*K, L*), the two-level production technology facilitates empirical testing of the IIH.

[42] The assumption that the IPF is centered at (-1, -1) is imposed to assure that the slope of the IPF at the axis points is finite and nonzero (Armanville and Funk, 2003).

maximize profit given the amount of employed factors (Funk, 2002; Armanville and Funk, 2003). Letting π denote profit, the firms' innovative decisions are made as follows:

(A12) $$\underset{\hat{E}_{A,t},\hat{E}_{M,t},\hat{E}_{L,t},\hat{E}_{K,t}}{\text{Max}} \{\hat{\pi}_t : \hat{E}_{M,t} \le \phi_1(\hat{E}_{A,t}); \hat{E}_{K,t} \le \phi_2(\hat{E}_{L,t})\},$$

given M_t, A_t, K_t, L_t and technology as defined in equation (A1). Since the constraint is always binding at the optimum, the first-order conditions of the maximization problem with respect to factor augmentations are:

(A13a) $$\partial\hat{\pi}_t \big/ \partial\hat{E}_{A,t} = (\partial\hat{F}_t \big/ \partial X_{A,t})[\partial X_{A,t} / \partial(\hat{E}_{A,t}A_t)]A + \lambda_1\phi_1' = 0$$

(A13b) $$\partial\hat{\pi}_t \big/ \partial\hat{E}_{M,t} = (\partial\hat{F}_t \big/ \partial X_{M,t})[\partial X_{M,t} / \partial(\hat{E}_{M,t}M_t)]M_t - \lambda_1 = 0$$

(A13c) $$\partial\hat{\pi}_t \big/ \partial\hat{E}_{L,t} = (\partial\hat{F}_t \big/ \partial X_{L,t})[\partial X_{L,t} / \partial(\hat{E}_{L,t}L_t)]L + \lambda_2\phi_2' = 0$$

(A13d) $$\partial\hat{\pi}_t \big/ \partial\hat{E}_{K,t} = (\partial\hat{F}_t \big/ \partial X_{K,t})[\partial X_{K,t} / \partial(\hat{E}_{K,t}K_t)]K_t - \lambda_2 = 0$$

Since the factor's marginal productivity is equal to its normalized price at instantaneous equilibrium, (A13a-d) yield:

(A14a) $$-\phi_{1,t}' = (P_{A,t}A_t)/(P_{M,t}M_t) = \Phi_{1,t},$$

(A14b) $$-\phi_{2,t}' = (P_{L,t}L_t)/(P_{K,t}K_t) = \Phi_{2,t}.$$

Equations (A14a-b) specify the first-order curvature properties of the IPF required to satisfy the hypothesis of induced innovation. In this specification, the profit maximizer will choose the set of factor augmentations such that the slope of the IPF equals the relative input shares.

As demonstrated by Funk (2002), the hypothesis of induced innovation can be derived from a microeconomic model with fully rational firms. Suppose firms can make profits with an innovation chosen from their perceived IPF until this innovation is imitated by other firms. With the aggregate technology defined in (A2), the IPF defined in (A7), and profit-maximizing choice of innovations in a continuous-time setting,[43] the slopes of the IPF are:[44]

(A15) $-\phi'_{1,t} = [\alpha/(1-\alpha)]^{\sigma_1}[(P_{A,t}/E_{A,t})/(P_{M,t}/E_{M,t})]^{1-\sigma_1}$,

(A16) $-\phi'_{2,t} = [\beta/(1-\beta)]^{\sigma_2}[(P_{L,t}/E_{L,t})/(P_{K,t}/E_{K,t})]^{1-\sigma_2}$,

where $\sigma_1 = 1/(1+\rho_1)$ is the elasticity of substitution between land (*A*) and materials (*M*), and $\sigma_2 = 1/(1+\rho_2)$ is the elasticity of substitution between labor (*L*) and capital (*K*). Equations (A15-16) imply that, when the elasticity of substitution is greater (less) than one, an increase in efficiency-adjusted relative prices induces much (little) substitution between the factors given any technology. Thus, we get the surprising result that, after the substitution, it is more profitable to augment the intensively-used factor even if it is relative cheaper when the elasticity of substitution is greater than one (Armanville and Funk, 2003). If the elasticity of substitution is less than one, we get the well-known result that it is more profitable to augment the relatively more expensive factor.

Consequently, one test for the IIH in this framework is to determine whether the bias of technical change is positively (negatively) correlated with relative prices in efficiency units (i.e., relative input shares) when the elasticity of substitution is greater (less) than one. For example, if the elasticity of substitution is less than one, the null hypothesis for testing the IIH in land (*A*) and materials (*M*) can be expressed as:

[43] In this case, the length of the period between innovation and imitation tends to zero.
[44] See Funk (2002) for details and discussion of the derivation.

H$_0$: $corr(\hat{E}_{A,t} - \hat{E}_{M,t}, (P_{A,t} / E_{A,t})/(P_{M,t} / E_{M,t})) > 0$ or H$_0$: $corr(\hat{E}_{A,t} - \hat{E}_{M,t}, \Phi_{1,t}) > 0$

where *corr* denotes the correlation operator. Failure to reject the null hypothesis implies that the direction of producers' innovative decisions are guided by efficiency-adjusted relative prices as predicted by the IIH. Armanville and Funk (2003) labeled this directional test as a "weak" test of the IIH.

A "strong" test would determine whether quantitative innovation choices correspond to those predicted by the hypothesis, i.e., whether innovative behavior fully satisfies equations (A14a-b). Following Armanville and Funk (2003), a strong test can be developed from (A14a-b) by determining whether γ_1 and γ_2 equal 1 in the following specification of the slopes of the first-level innovation possibility frontiers:

(A17) $-\phi'_{1,t} = \Phi_{1,t}^{\gamma_1}$

(A18) $-\phi'_{2,t} = \Phi_{2,t}^{\gamma_2}$

That is, for the IIH to be strongly supported, the elasticity of the slopes of $\phi_1(\cdot)$ and $\phi_2(\cdot)$ with respect to relative input shares must be 1.

From equations (A10-11) and (A17-18), we derive the following relationships: [45]

(A19) $E_{A,t} / E_{M,t} = (E_{A,0} / E_{M,0}) \prod_{s=1}^{t} n_{1,s}^2 \Phi_{1,s}^{\gamma_1}$

(A20) $E_{L,t} / E_{K,t} = (E_{L,0} / E_{K,0}) \prod_{s=1}^{t} n_{2,s}^2 \Phi_{2,s}^{\gamma_2}$

Intuitively, the relative factor productivities at time *t* depend on past values of the slope

[45] Combining equation (B10-11) and (B17-18) and noting that $\hat{E}_{i,t} + 1 = E_{i,t} / E_{i,t-1}$ ($i = M, A, K, L$) gives: $(E_{A,t} / E_{A,t-1})/(E_{M,t} / E_{M,t-1}) = n_{1,t}^2 \Phi_{1,t}^{\gamma_1}$ and $(E_{L,t} / E_{L,t-1})/(E_{K,t} / E_{K,t-1}) = n_{2,t}^2 \Phi_{2,t}^{\gamma_2}$, $\forall t$. By substituting backward until $t = 1$, we obtain equation (B19-20).

parameter n_i, past values of the relative input shares, and the relative productivities at the starting period.

By substituting (A19-20) into (A5) and (A6), respectively, we obtain:

$$\text{(A21)}\quad \ln\frac{A_t}{M_t}=\frac{1}{1+\rho_1}\ln\frac{\alpha}{1-\alpha}-\frac{1}{1+\rho_1}\ln\frac{P_{A,t}}{P_{M,t}}-\frac{\rho_1}{1+\rho_1}\left(\gamma_1\sum_{s=1}^{t}\ln\Phi_{1,s}+2\sum_{s=1}^{t}\ln n_{1,s}+\ln\frac{E_{A,0}}{E_{M,0}}\right)$$

$$\text{(A22)}\quad \ln\frac{L_t}{K_t}=\frac{1}{1+\rho_2}\ln\frac{\beta}{1-\beta}-\frac{1}{1+\rho_2}\ln\frac{P_{L,t}}{P_{K,t}}-\frac{\rho_2}{1+\rho_2}\left(\gamma_2\sum_{s=1}^{t}\ln\Phi_{2,s}+2\sum_{s=1}^{t}\ln n_{2,s}+\ln\frac{E_{L,0}}{E_{K,0}}\right)$$

Since data are available for factor prices and the relative input shares (Φ_1 and Φ_2), the relative demand equations (A21-22) can be estimated if slope parameters n_1 and n_2 are specified. Instead of following Armanville and Funk (2003) in making the n's a function only of time, we treat them as functions of innovation investments, including public research R_{pub}, private research R_{pri}, and extension Ext:

$$\text{(A23)}\quad \ln(n_{j,t})=\delta_{j,1}\ln(R_{pri,t})+\delta_{j,2}\ln(R_{pub,t})+\delta_{j,3}\ln(Ext_t)\ \ (j=1,2),$$

where δ_{ji} (j = 1, 2; i = 1, 2, 3) is a constant.

Assuming that innovation investments are allocated evenly for factor augmentation at the starting period, i.e., $E_{A,0}/E_{M,0}=1$ and $E_{L,0}/E_{K,0}=1$, rewriting equations (A21-22) gives equation (3.3) in the paper.

Appendix 3.B: Additional Detail of Nonparametric Approach

Under the translating hypothesis, i.e., $X_i = x_i + B_i$, the weak axiom of profit maximization (WAPM) is equivalently written as:

$$\text{(B1)}\quad P_t'x_t \ge P_t'x_s,\ \forall s,t\in T\text{, or}$$

(B2) $P_t'(X_t - B_t) \geq P_t'(X_s - B_s),\ \forall s,t \in T$,

where x_t, x_s, X_t, and X_s are effective and actual netput vectors at observations *t* and *s*, and B_t and B_s are the augmentation vectors at the respective observations. If the data satisfy the WAPM, there exists a closed, convex, and negative monotonic production possibilities set that rationalizes the data in *T*, and there exists a profit-maximizing output supply and input demand solution. The WAPM specified in equation (B2) also allows us to recover the technology in the presence of technical change given the data observations. If $B_{i,t} > B_{i,s}$ for an input, technical change between *s* and *t* is *i*th-input saving. In another words, to achieve the same level of effective input at time *t* as in time *s* requires a smaller quantity of the *i*th-input. If $B_{i,t} > B_{i,s}$ for outputs, technical change between *s* and *t* is output augmenting. For the same actual level of all inputs, more output is produced at time *t* than in time *s*.

We follow Chavas *et al*. (1997) in specifying three augmentation restrictions needed to conduct nonparametric testing of the IIH. The first restriction specified in equation (3.5) in the text, treats the technology indices as functions of a constant term and a weighted sum of a finite lag of past innovation investments. The idea for this model specification is that R&D investments can generate technical progress, and the process of technical change takes time. Also the Hicksian IIH emphasizes the crucial role of relative price changes in determining the direction of research investments towards augmenting particular factors, which suggests that the marginal impact of R&D depends on relative prices. Thus, it provides an approach to directly investigate the Hicksian IIH.

The second restriction – smoothing restriction on the output augmentation variables has the following expression:

(B3) $B_{y,t} \geq (\sum_{j=1}^{c} B_{y,t-j})/c$

This restriction requires output augmentation to be at least as large as a moving average of previous values, so augmentation is not permitted to trend downward over time. The moving average allows for weather to dampen output augmentation in individual years. Following Chavas *et al.* (1997), we used a 5-year moving average.

The third restriction assumes nonnegativity of the marginal effect of innovation activities on augmentation indices:

(B4) $\partial B_{i,t} / \partial R_{t-j} = \beta_{i,j} + (P_{i,t-j} - 1)\gamma_{i,j} \geq 0,\ i = A, M, L, K,\ \ j = 1, \cdots, r_i$, and

(B5) $\partial B_{y,t} / \partial R_{t-j} = \beta_{y,j} \geq 0,\ \ j = 1, \cdots, r_y$.

In the last step, these parameters are estimated by solving a quadratic programming problem. The intuition is to make the augmentation indices and the impact of exogenous shifters "as close to the data as possible" while satisfying the WAPM. Based on the estimates of these parameters, the induced innovation hypothesis and the nature of technical change in U.S. agriculture are examined.

Appendix 3.C: Construction of Input Price Proxies for the Period 1932-1959

Using prices for machinery and fertilizer from the Thirtle *et al* (2002) data set to represent prices of capital and materials, respectively, we indexed both Ball's (2006) and Thirtle *et al*.'s U.S.-level data sets to Ball's (2004) state-level series in the following way: First, we computed averages of Ball's and Thirtle *et al*.'s U.S. prices for each input category for the first five years in the Ball series, 1948-1952. Second, we merged Thirtle *et al*.'s prices for each input category into Ball's U.S. series by multiplying Thirtle *et al*.'s U.S. prices series for 1932-1947 by the ratio of Ball's and Thirtle *et al*'s U.S. average prices for 1948-1952 and denote it the Ball-TST data set. Third, we computed averages of each state-level price series and of Ball's U.S. prices for the first five years of the state-level series, 1960-1964. Lastly, we spliced the Ball-TST U.S. prices with the state-level series by multiplying the Ball-TST data for 1932-1959 by the ratio of the state average to the U.S. average price in 1960-1964 for each state and input.

CHAPTER 4

PRODUCTIVITY CONVERGENCE IN US AGRICULTURE: NEW COINTEGRATION PANEL DATA RESULTS

Introduction

"Given limited resources, productivity growth is the only way to sustain and increase standards of living." (Acs *et al*., 1999, p. 367) Yet, agricultural productivity varies greatly among countries and regions (Kawagoe, Hayami, and Ruttan, 1988; Prasada Rao, 1993; Gutierrez, 2000). Even in the U.S., although every state has exhibited a positive growth rate in agricultural productivity for many decades, considerable variability of total factor productivity (TFP) growth has occurred among them. For example, during the period 1960-1999, the average annual TFP growth rate ranged from 0.73% for Oklahoma to 2.59% for Michigan (Ball *et al*., 2004). The existing variability of productivity among states has important public policy ramifications. For example, does TFP tend to converge or diverge for states in the U.S.? In order to improve TFP for those states with lower productivity growth rates, how should limited resources be allocated among the important drivers of productivity growth? How do investments in health, education, research, and extension affect productivity growth both in the short-run and in the long-run? A systematic analysis of the impact of these major variables on productivity growth performance is central to answering these questions.

Many reasons have been proposed to explain agricultural productivity growth. They include agricultural research and development (R&D) (e.g., Huffman and Evenson, 1992; Alston *et. al*., 1998; McCunn and Huffman, 2000), human capital (e.g., Huffman and Evenson, 1992; Makki, *et al*., 1999; McCunn and Huffman, 2000; Yee *et al*., 2002; Yee *et al.*, 2004), and farm size (e.g. Berry and Cline, 1979; Carter, 1984; Smith *et al*., 1984; Weersink and Tauer, 1991; Barrett, 1996; Thirtle *et al*., 2004). A stylized fact has emerged from both theoretical and empirical work that public agricultural research, public extension, and education have significantly positive impacts on productivity growth. As to the impact of farm size, a positive relationship with agricultural productivity has generally been found in developed countries (e.g., Smith *et al*., 1984; Weersink and Tauer, 1991; Thirtle *et al*., 2004) and a negative relationship in developing countries (Berry and Cline, 1979; Carter, 1984; and Barrett, 1996).

Despite the considerable amount of research that has focused on agricultural productivity, there remain several deficiencies in the *extant* literature. These include the narrow definition of human capital, failure to consider private innovation spillovers, and use of inadequate estimation methods.

For example, while human capital has been argued to be a central driver of productivity growth, nearly all previous literature on agricultural productivity growth has relied exclusively on schooling as a proxy for aggregate human capital. Although health has been recognized as a major influence on the accumulation of human capital (Barro, 1998), its role in agricultural productivity growth has been ignored. By increasing productivity of human resources, improved health can be expected to accelerate accumulations of both human and physical capital and thus advance sectoral productivity and standard of living (Bhargava *et al*., 2001).

The impact of geographic and sectoral spillovers of private innovation on agricultural productivity growth has not been explored. Because innovation is at least partly a public good, productivity growth is conditional not only on an entity's own innovation efforts but also on the innovation efforts of others (Coe and Helpman, 1995; Fung, 2005).[46] While the spillover effects of public agricultural research on agricultural productivity growth has received attention (e.g. Huffman and Evenson, 1992; McCunn and Huffman, 2000; Yee *et al.*, 2002), spillovers from privately funded innovations have not. Failure to consider these spillovers could result in biased estimates of the impact of other drivers of productivity growth.

In addition, the estimation methods previously used to examine agricultural productivity growth and productivity convergence have important weaknesses that could produce inconsistent and misleading results. Although panel data, with their important advantages over cross-sectional or time-series data, have been used to examine agricultural productivity and productivity convergence hypotheses, the estimation procedures utilized have not accounted for heterogeneity across groups. Since the strong assumption of homogenous slope coefficients across groups is frequently rejected (Pesaran *et al*., 1999), imposing this constraint on dynamic panel data growth models can produce inconsistent and misleading estimates.

The objectives of this paper are to surmount these past weaknesses by testing three productivity convergence hypotheses and by examining the impacts of major drivers of productivity growth in U.S. agriculture. We pursue these objectives in ways

[46] See for example Griliches (1992) for surveys of the literature on knowledge spillovers.

that achieve greater reliability in the estimation and thus advance the literature in two ways. First, the paper measures the impact of health capital (proxied by access to health care in rural areas) and private R&D spillovers (both inter-state and inter-industry) on agricultural productivity growth in each of the contiguous 48 states. Second, improved panel estimation procedures are employed that permit reliable examination of the dynamic effects of policy variables on productivity growth.[47]

The paper is organized as follows. The next section gives a brief overview of the theoretical concepts of productivity growth and introduces the panel testing and estimation techniques. The data are described in the subsequent section. That is followed by the empirical results which include the time series properties of the data, tests of three convergence hypotheses in U.S. agricultural productivity, and findings about the importance of various determinants in explaining productivity growth. The last section summaries our main findings and concludes.

Method of Analysis

Two primary concepts have been used to measure convergence of productivity growth across countries or regions. The first notion, called σ-convergence, considers whether the dispersion of TFP among countries or regions diminishes over time. The second, β-convergence, considers whether a steady-state TFP level exists for each geographic unit, i.e., whether the correlation between a state's initial TFP level and its

[47] In addition to human capital and R&D spillovers, this paper also examines the impact on agricultural productivity growth of average farm size and other policy variables, including investments within the state on public and private R&D and public extension.

subsequent growth in TFP is negative. Although β-convergence is a necessary condition for σ-convergence, it is not a sufficient condition because β-convergence doesn't necessarily indicate declining cross-sectional variance in TFP (or σ-convergence) (Quah, 1993; Sala-i-Marin, 1996); Bernard and Jones, 1996a).

Theoretical Model

To test for σ-convergence, we use the movements of variance across states to measure dispersion in TFP growth. Following Sala-i-Martin (1996), the basic model is defined as follows:

(4.1) $\text{var}_t(\ln \text{G}) = \alpha_1 + \alpha_2 t + \varepsilon_t$

where G is TFP, $\text{var}_t(\ln \text{G})$ is across-states variance of the logarithm of TFP in period t, α are parameters, and ε is a zero-mean random disturbance term. A significantly negative coefficient associated with the time variable *t*, i.e., $\alpha_2 < 0$, implies σ-convergence.

In the economic growth literature, two different tests of β-convergence have been developed. The first is known as absolute β-convergence. It is implemented in this study to examine whether agriculture in the 48 contiguous U.S. states converge to the same steady-state TFP level in the long-run regardless of the state's initial conditions. A presumption of this type of convergence is that the only difference among the states is their initial TFP, which can be eliminated over time if all states are homogeneous in technologies, preferences and institutions (Sala-i-Martin, 1996; Gutierrez, 2000; Funk, 2005).

The second, conditional β-convergence, tests whether each state converges to a steady-state TFP level when technologies, preferences and/or institutions differ. The intuition is that TFP is driven by conditional variables (state-specific factors) that are at least partially under the control of local public and private decision makers and thus influence the growth endogenously. Because technologies, preferences, and institutions do differ across states, absolute β-convergence does not imply conditional β-convergence. Nor do tests of absolute β-convergence facilitate examination of the impact of productivity drivers that could lead to differences in state-specific steady-state TFPs. Consequently, a systematic analysis of the impact of major drivers of productivity growth require empirical testing of conditional β-convergence whether or not absolute β-convergence is rejected.

Following Fung (2005), we test absolute β-convergence based on the following model:

(4.2) $$g_i^A = \ln \tilde{G}_i - \ln G_i^0 = \beta_1 + \beta_2 \ln G_i^0 + \varepsilon_i^A ,$$

where g_i^A denotes TFP growth in state i between the initial and final periods; G_i^0 and $\tilde{G}_i$ are state i's TFP in the initial and final periods, respectively; and β are parameters. Testing for absolute β-convergence is equivalent to testing whether the growth rate of TFP is negatively related to the productivity level in the initial period. A significant negative coefficient associated with G_i^0 , i.e., $\beta_2 < 0$, implies absolute β-convergence. If this hypothesis is not rejected, we conclude that all states converge to a common steady-state when technologies, preferences, and institutions are homogeneous. To reduce random noise, we define t = 1 to $t = s$ as the initial time period, and $t = T - s + 1$ to $t = T$ as the final period. T is total length of both time periods.

Thus, $G_i^0 = \sum_{t=1}^{s} G_{it} / s$ and $\tilde{G}_i = \sum_{t=T-s+1}^{T} G_{it} / s$.

Testing conditional β-convergence is based on the following dynamic growth model:[48]

(4.3) $\ln G_{i,t} = \mu + \phi \ln G_{i,t-1} + \delta' X_{i,t} + \varepsilon_{i,t}$

where $G_{i,t}$ denotes state i's TFP at time t; X is a vector of the determinants of TFP and includes farmer average education level (*Edu*), average health care access level in rural areas (*Hs*), average farm size (*Fs*), public agricultural research investments (*Rpub*), private agricultural research investments (*Rpri*), public extension investments (*Ext*), public agricultural research spillovers (*PubSpill*), private agricultural research spillovers (*PriSpill*), and inter-sector private research spillovers (*InterSpill*); and μ, ϕ, and δ are parameters. Since research and extension investments can affect productivity growth several years later, we use Akaike's Information Criterion (AIC) to determine the optimal lag on the variables of public and private agricultural research investment and public agricultural extension, respectively.

By subtracting $\ln G_{i,t-1}$ from both sides of equation (4), we obtain the error correction model (ECM):

(4.4) $\Delta \ln G_{i,t} = \mu + \lambda [\ln G_{i,t-1} + (\delta' / \lambda) X_{i,t}] + \varepsilon_{i,t}$

[48] A dummy variable is also included in the estimation equation to account for the impact of the 1983 PIK program on TFP.

where Δ represents first difference, $\lambda = \phi$-1 which directly measures the speed of convergence toward a state-specific steady-state. A significantly negative estimate of λ implies conditional β-convergence.

Estimation and Testing Procedures

When testing for conditional β-convergence, we first examine the time series properties of each variable involved in the conditional growth model, equation (4.3). The low power of traditional tests for unit roots in small and moderate sized samples can lead to misleading results, but greater power can now be achieved using recent developments in panel unit root and cointegration test procedures (Hadri, 2000; Pedroni, 1999).

To test for stationarity, we apply the procedure developed by Hadri (2000) which tests the null hypothesis that all the individual series are stationary around a deterministic level or around a deterministic trend against the alternative of a unit root in panel data. Hadri's unit root statistic is a residual-based Lagrange multiplier (LM) statistic. It can be developed by considering the following regression:

(4.5) $\quad y_{it} = x'_{it}\beta + r_{it} + \varepsilon_{it}$

where ε_{it} is a stationary process, x_{it} is the deterministic component, r_{it} is the stochastic component defined as $r_{it} = r_{it-1} + u_{it}$, and u_{it} is independently and identically distributed with variance σ_u^2. Using backward substitution, equation (4.5) can be rewritten as:

(4.6) $\quad y_{it} = x'_{it}\beta + e_{it}$

where $e_{it} = \sum_{j=1}^{t} u_{ij} + \varepsilon_{it}$. From equation (4.6), the estimated variance of the error, denoted $\hat{\sigma}_e^2$, can be obtained as:

(4.7) $$\hat{\sigma}_e^2 = \frac{1}{NT}\sum_{i}^{N}\sum_{t=1}^{T}\hat{e}_{it}^2$$

where $\hat{e}_{it}$ is the estimated residual, T is the number of time periods, N is the number of cross-sectional units. Hadri (2000) computes the LM statistic as:

(4.8) $$LM = \frac{\frac{1}{N}\sum_{i=1}^{N}\frac{1}{T^2}\sum_{t=1}^{T}S_{it}^2}{\hat{\sigma}_e^2}$$

where $S_{it} = \sum_{j=1}^{t}\hat{e}_{ij}$ is the partial sum of the residuals. With large T and N and adjusted by appropriate constants obtained from the moments of the underlying Brownian motion functions, the LM is distributed as standard normal under the hull hypothesis of stationarity. A large positive value of this statistic implies rejection of the null hypothesis of stationarity in the panel.

The second time-series step is to test panel cointegration for linear combinations of non-stationary variables. We test the hypothesis of cointegration by employing Pedroni's (1999) cointegration tests, which allow coefficients (cointegration vectors) to vary across units, includes individual fixed effects and time trends, and is considerably more powerful than conventional methods (Harris and Tzavalis, 1999). Pedroni (1999) calculates seven test statistics that are asymptotically normally distributed under the null:

(4.9) $$\frac{Z_{N,T} - \mu\sqrt{N}}{\sqrt{V}} \overset{a}{\sim} N(0,1)$$

where $Z_{N,T}$ is the statistic, and μ and V are the adjustment terms obtained from the moments of the underlying Brownian motion functions.[49]

Estimation issues have gained much attention in panel data growth models because heterogeneity in the intercepts or in slope coefficients can produce inconsistent estimates of convergence speed (Lee *et al*., 1997). This inconsistency can't be eliminated asymptotically (Lee *et al*., 1997). To address this inconsistency problem, some alternative estimators have been proposed recently in the econometrics literature. They include the pooled mean group estimator (PMGE), dynamic ordinary least squares (DOLS), and fully modified ordinary least squares estimator (FMOLS). In this paper, we apply the pooled mean group estimator (PMGE) developed by Pesaran *et al*. (1999), which presumes weak homogeneity by constraining the long-run slope coefficients to be identical across groups but allowing the short-run coefficients and error variances to vary across groups. The reason to expect the long-run relationship among variables to be similar across all states is that they have access to similar financial markets and technology influences (Pesaran *et al*, 1999).

Data and Variables

The indexes of TFP for each of the contiguous 48 states for the period 1960-1999 were computed by Ball *et al*. (2004) as the ratio of output to an index of land, capital,

[49] The critical values of these test statistics are tabulated in Pedroni (1999, Table 2) for up to seven explanatory variables. Because we use nine explanatory variables, the adjustment terms for the panel cointegration tests were obtained as suggested by Pedroni (1999) by Monte Carlo simulation on the basis of 10,000 draws of nine independent random walks (i.e., the number of regressors) of length T=10,000. Under the alternative hypothesis, all the statistics diverge to negative infinity (one to positive infinity). Therefore, each is a one-sided test for which a large positive value for the "panel v statistic" or a large negative value for the other tests results in rejection of the null hypothesis of no cointegrated relation among the variables.

labor, and materials inputs. The comprehensive inventory of agricultural output and input quantities was compiled using theoretically and empirically sound procedures consistent with a gross output model of production and quality-adjusted input flows (see Ball *et al*. 2004 for details).

Deflated annual agricultural public research investment data for the period 1927-1995 for each state were compiled by Huffman (2005). Agricultural extension investments for the U.S. for the period 1951-1996 were from Huffman, Ahearn, and Yee (2005). They are total cooperative extension investments in current dollars deflated by the price index for agricultural research.

Average farm size for each state was measured as the average gross value of farm assets for each state. This measure of farm size is preferred since it captures not only the gross value of product but also the productive capacity of a farm.[50] It was computed for each year as the total gross value of farm assets reported for the state divided by the number of farms. Farm asset data for the years 1960-1999 were taken from the *Farm Balance Sheets* (USDA/ERS). Farm numbers for the same years were taken from *Farms, Land in Farms, & Livestock Operations* (and its predecessor publication) (USDA/NASS, various issues) and compiled by Strickland (2005).

Farmers' education level was approximated by the weighted average of weekly working hours across various education levels and types of employment for each state. We constructed this index using demographically cross-classified weekly working hours

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[50] There are various other ways to measure farm size, e.g., acreage or gross value of sales or product. Although these traditional ways are easy to quantify, acreage does not account for differences in the productive capacity of the land input (Yee and Ahearn, 2005), and gross value of sales is an output measure rather than an input capacity measure.

data where weekly hours of work were classified by gender, age, education and employment types (including hired and self-employed workers). The data of weekly working hours, gender, age, education index, and employment types by employment category were from Ball (2005).

Without data on the health status of farm workers, we used a proxy of health care access (*Hs*) measured by the total numbers of Medical Doctors (MDs) per 10,000 population in rural counties of each state. County-level data on the numbers of MDs and population for the years 1960, 1970, 1975, 1980-1983, 1985, 1986, 1988-1990, 1992-2004 were from the Bureau of Health Professions/National Center for Health Workforce Analysis. Rural counties in each state were identified using Urban Influence Codes developed by USDA/ERS which divide counties into metropolitan counties and non-metropolitan (rural) counties. A cubic interpolation algorithm was used to approximate missing values. This interpolation technique is generally more accurate than other methods such as linear interpolation (Maeland, 1988). In this technique, all of the knots (known observations) are required to define all the polynomials that make up the entire curve rather than only using the neighboring knots to define piecewise interpolated curves as in the linear interpolation and double parabolic interpolation methods. Thus, using this technique allows us to fully use the information incorporated in the available observations.

Agricultural private research investments and inter-state and inter-industry knowledge spillovers for each state were proxied by the number of state-level patents. The data were from Johnson's (2005) inventory of patents by state and by industry as the primary user of the patent for the period 1883-1996. Before 1976, the patents were classified using the Wellesley Technology Concordance (Johnson, 1999). Since 1976, Johnson's patent classification follows the international protocol. The Yale Technology Concordance (Johnson and Evenson, 1997) was used to calculate industries of manufacture and sectors of use. The panel data set on agricultural private research was prepared by multiplying the percent of patents granted by state each year by the number of patents granted for use in the agricultural sector.

The spillovers of private agricultural research in state *i* were computed by subtracting the number of patents granted in the state from the total number of patents granted in all states in the associated ERS region. The states were grouped into 10 ERS regions (McCunn and Huffman, 2000): Northeast, Lake States, Corn Belt, Northern Plains, Appalachia, Southeast, Delta States, Southern Plains, Mountain States, and Pacific States.

The inter-industry spillovers of private agricultural research were computed by subtracting the number of patents granted in agriculture as the industry of manufacture from the number of patents granted for use in agriculture by state for each year.

The spillovers of public agricultural research in state *i* were computed by subtracting the state's public research investments from the sum of the public research investments for all states in the associated ERS region.

Empirical Results

In this section we present the results of the three convergence hypothesis tests and draw inferences about the primary productivity drivers for the contiguous 48 states. We start by testing for σ-convergence and absolute β-convergence. We then examine the time series properties of the variables included in the conditional TFP growth model, as well as their implications for estimation techniques. The time series properties are followed by estimates of the conditional TFP growth model and further investigation of the role of policies on productivity growth.

The results for the σ-convergence test are presented in Table 4.1. This hypothesis (that the dispersion of TFP across states diminishes over time) is rejected since the coefficient on the time variable *t* is positive rather than significantly negative. This finding is consistent with McCunn and Huffman (2000) and Gutierrez (2000). A common explanation for rejection of this hypothesis is that σ-convergence is sensitive to temporary shocks. In the agricultural sector, these could include fluctuation of demands, disease, or weather conditions (McCunn and Huffman, 2000; Gutierrez, 2000).

Before testing for absolute β-convergence (that all states converge to the same steady-state TFP level), we allowed for different time lags between the beginning and final time periods to reduce effects of random noise. We chose three cases with starting periods, $t = 1,\ldots,s$, with s set at 3, 5, and 10 respectively. The results are reported in Table 4.2. The estimated coefficient associated with initial TFP ($\ln(G_i^0)$) is significantly negative at a 5% significance level for all three cases. These findings strongly support the hypothesis that agricultural TFP converges toward a common steady-state level for the 48 contiguous U.S. states when technologies, preferences, and institutions are homogeneous. This finding is in line with the partial productivity results of Gutierrez (2000) who found that agricultural labor productivity converged to a common steady-state for all U.S. states during the period 1970-1992.

We next proceed to answer the primary questions proposed in this paper by testing the hypothesis of conditional β-convergence and by examining the impacts of crucial policies on productivity growth. To do so validly requires time series properties of the data to be tested and, depending on findings, testing for condition β-convergence by estimating an error correction model.

We first test for stationarity in each time series involved in the conditional productivity growth model defined in equation (4.3). The Hadri panel stationarity test statistics are reported in Table 4.3. They show that the null hypothesis of stationarity is clearly rejected in levels for all of the series. When stationarity is tested in differenced data, six of the series are stationary at a 5% significance level in 1st differences and four are stationary in 2nd differences. Consequently, we conclude that ln(*G*), ln(*Edu*), ln(*Hs*), ln(*Rpub*), ln(*InterSpill*), and ln(*RpubSpill*) are integrated of order 1, I(1), and ln(*Rpri*), ln(*Ext*), ln(*Fs*), and ln(*RpriSpill*) are integrated of order two, I(2). Intuitively, existence of a unit root or rejection of stationarity in the TFP variable indicates persistence of shocks, which provides further evidence for absence of σ-convergence in U.S. agriculture.

Before conducting the cointegration test, potential test implications and determination of optimal lag lengths of the innovation investments need to be clarified since investments in innovation may not affect technology, or the nature of the production function, for at least seven years and perhaps as long as 30 years (Chavas and Cox, 1992; Pardey and Craig, 1989). Akaike's information criterion (AIC) was used to determine optimal lags on extension, public and private research investments. The optimal lag on public research investments was chosen from lags of 7-30 years. The optimal lag on private research investments was chosen from lags of 3-23 years.[51] Because of the more limited length of the data series, the optimal lag on extension investments was chosen from lags of 3-9 years. The AIC was minimized at a lag length of 25 years for public research investments, 15 for private research investments, and 7 for extension investments. To be consistent with that of public research investments, the optimal lag for public research spillovers was set to be 25. For the private research spillovers, including inter-state spillovers and inter-industry spillovers, the optimal lags were set to be identical to the private research investments, i.e., 15 years.

Table 4.4 reports the results of the cointegration analysis. Strong evidence was found to support cointegration. Six of the seven statistics support rejection of the hypothesis of no cointegration at a 0.05 significance level. Existence of cointegration implies presence of a long-run relationship between TFP and its determinants.

Having found a cointegration relationship among the series, we next estimated the error correction representation, equation (4.4), of the conditional growth model. To capture the long-run relationships in the data, the conditional growth model can be formulated using 1st differenced data for I(2) variables and original data for I(1) variables when a cointegration relationship is found among nonstationary variables. Thus, the

[51] Applying a nonparametric approach, Chavas and Cox (1992) found that the effects of private research on U.S. agricultural production increased slowly in the first 7 years, increased rapidly in the next 8 years, and decreased with no effects beyond 23 years.

dynamic model specified in (4.4) was modified by replacing ln(*Rpri*), ln(*Ext*), ln(*RpriSpill*), and ln(*Fs*) with the first differences of these four variables.

In addition to equation (4.4) (hereafter ECM I), another error correction model (hereafter ECM II) was estimated to capture the dynamic effects of exogenous shocks by including the 2nd differenced terms on $X_{i,t}$.[52]

The Pesaran PMG estimates are reported in table 5.[53] The error correction coefficient (λ) (i.e., the coefficient on the variable $\ln(G_{i,t-1})$) was negative and significant in both models at a 5% significance level. A significantly negative error correction coefficient indicates that, even with shocks to the system, each state adjusts toward a state-specific steady-state. This result is consistent with the hypothesis of conditional β-convergence.

The finding of productivity β-convergence in U.S. agriculture is consistent with previous literature. For example, Ball *et al*. (2004) found evidence for technology catch up in the contiguous 48 states which is consistent with TFP β-convergence. McCunn and Huffman (2000) found evidence of conditional β-convergence in 42 states for the period 1950-1982.

Results show that the convergence speed measured by λ is insensitive to the dynamic effects of exogenous shocks. In the ECM II model that considers dynamic short-run effects, the reported value of λ is -0.44 which is similar to that of the ECM I model (-0.41). This convergence coefficient measures the speed at which the system moves back to the steady-state growth path after an exogenous shock and the speed at which the

[52] For I(2) variables, 3rd differences were included.
[53] These estimates were computed using a GAUSS program distributed by Pesaran, Shin and Smith

productivity gap diminishes.[54] Our estimate of convergence speed is considerably higher than those estimated by McCunn and Huffman (2000) (2.8%) and Gutierrez (2000) (1.8%) for U.S. agriculture, perhaps due to our improved model specification.[55] They are closer to prior estimates in other countries than in the U.S. For example, Bernard and Jones (1996a) estimated a 21% convergence speed for OECD agriculture, and Martin and Mitra (2001) estimated a 10% convergence speed for agriculture in a wide range of countries.

Table 5 also provides a number of important insights about source of productivity growth. Of particular note is the significantly positive relationship between health care access in rural areas (proxied by the number of medical doctors per 10,000 population) and productivity growth in U.S. agriculture both in the short-run and long-run. Since increased health accelerates human capital accumulation and advances technical progress, states with higher health levels would be expected to grow faster at each particular point of time and to end up with a higher steady-state agricultural TFP growth rate. We find that expectation strongly supported by the relationship between health care access and productivity. The results from ECM I show that a 1% increase in health care access in rural areas would enhance the TFP growth rate by 24% in the short run and raise the steady-state TFP growth rate by 58%. ECM II also indicates significant and similarly

[54] Although the average convergence speed exceeds 40%, it exhibits high volatility across the 48 states. For example, the state-specific convergence speed (not report here) estimated from ECM II ranges from a low of 10% for Connecticut to a high of 105% for South Carolina. Intuitively, Connecticut is the state relatively closest to its steady-state while South Carolina is furthest away from its steady-state.

[55] Our study advances previous studies in three ways. First, our model accounts for data nonstationarity and cointegration relationships using more reliable test procedures. Second, the effects of the policy variables are assessed within a dynamic panel data framework. Third, we consider the impacts of health care access and inter-state and inter-industry innovation spillovers.

substantial response but with somewhat lower payoffs both in the short-run (17%) and long-run (38%).

Results from both models show that publicly funded research and extension also have significantly positive impacts on TFP growth rates both in the short-run and long-run.[56] Therefore, increased investments in public research by the states with lagging productivity will facilitate their narrowing the gap with the productivity leaders in the long-run. Further, significantly positive short-run and long-run coefficients on public research spillovers indicate that assimilating public knowledge spillovers from other states also augments a state's TFP growth rate. Therefore, productivity-lagging states are able to grow faster both by investing more in public research and extension and by receiving public innovation spillovers from other states in their region. As a result of both, their TFPs will tend to converge.

Because it takes into account short-run dynamic effects of exogenous shocks, the ECM II is the more realistic model and its results are particularly informative. In this model, all variables except farm size and public extension have a significant long-run impact on agricultural productivity. Intuitively, in the absence of short-run dynamic effects, farmers' education and private research investments might be adequately captured through farm inputs. Taken together, short-run dynamic effects amplify the residual effects of these variables beyond embodiment in farm inputs. ECM II estimates a significantly positive impact of private spillovers but a significantly negative impact of private research investments on TFP growth both in the long-run and in the short-run.

[56] However, the long-run impact of an increase in public extension investments is insignificant in the presence of dynamic impacts from exogenous shocks (ECM II).

However, the payoffs from the former are larger than the latter in both cases and show an overall positive residual impact of private research investments on short-run and long-run TFP growth.

Although a productivity-lagging state can grow more rapidly by efforts to capture the positive externality of both publicly and privately funded research in other states, it is unlikely they can catch up by relying solely on these public good effects. As the productivity-lagging states approach that of the leader, significant amounts of their own research investments aimed at genuine innovations are necessary for further growth. The absorptive capability of external research spillovers depends partly on own research efforts (Cameron, 2005; Funk, 2005).

Farm size, defined as gross value of farm's assets, plays a significant role in enhancing farm productivity growth only in the short-run. This result is consistent with the findings of Weersink and Taur (1991), Yee *et al*. (2004), and Thirtle *et al*. (2004).

The estimated impact on productivity growth of the one-year PIK program in 1983 was significantly negative.

Summary and Conclusions

In this paper we have tested three convergence hypotheses about total factor productivity in U.S. agriculture and examined the role of key dynamic drivers. It is the first paper to examine the impact of health care access, inter-state or inter-industry private research spillovers on agricultural productivity growth. It has also employed improved panel estimation procedures that permit examination of the dynamic effects of policy variables on productivity growth.

Cross-sectional tests were conducted for σ-convergence and absolute β-convergence. A pooled cross-section, time-series test was conducted for conditional β-convergence. We found strong evidence in favor of both absolute and conditional β-convergence but no support for σ-convergence. Finding evidence supporting absolute β-convergence results in the conclusion that the gap in agricultural TFP among the 48 states tends to narrow over time when technologies, preferences, and institutions are homogeneous. That is, states with lower initial TFP levels tend to grow more rapidly than states with higher initial TFP levels.

Two error correction models, with and without considering the short-run dynamic effects of exogenous shocks, were developed and employed to test conditional β-convergence and to examine the impacts of policy variables. In addition to failing to reject conditional β-convergence, the econometric results highlight several important drivers of productivity growth. Most important is the consistent finding of significantly positive short-run and long-run impacts of health care access in rural areas. While health has been identified as a theoretically important variable in measures of human capital, it has not previously been included in agricultural productivity growth models. Data limitations have prevented inclusion of any direct measures of actual health levels, but data on health care access were used as a proxy for health status in this model with highly informative results. Accounting for the short-run effects of exogenous shocks, our results imply that a 1% increase in rural health care access increases the long-run (steady-state) agricultural TFP growth rate by a remarkable 38%. Significant short-run effects indicate that states with higher rural health care access also catch up faster in agricultural TFP.

We also examined the roles played by R&D and associated spillovers in TFP growth. Public research and extension investments generally had a significant influence both on the short-run and steady-state TFP growth rate. This finding supports the expectation that an increase in public research investments will lead to an increase in TFP not only in the short-run but also in the long-run. Additionally, knowledge spillovers from agricultural public research investments, agricultural private research investments, and nonagricultural sectors' research efforts advance the TFP growth both in the short-run and long-run. As a result, an increase in assimilation of research efforts from other states and from other industries raises the ability for productivity lagging states to catch up with the leaders. Farmers' education levels are also quantitatively important as well as statistically significant in advancing the productivity growth rate. Farm size, however, has no significant impact on the long-run TFP growth rate. Its influence is limited to the short-run.

The finding of positive impacts of health care access and privately-funded knowledge spillovers from other states and from other sectors also call for more policy activism. Based on the existing agricultural growth literature, states could expect to increase productivity growth by increasing public investments in knowledge creation, capacity to absorb public research spillovers, and agricultural worker education, and by promoting greater investment and possibly a redesigned funding plan at the federal level. This study provides evidence that public investments and incentives for private investment in rural health care access and privately funded research spillovers can substantially strengthen agricultural productivity growth. Even with similar public research and development investments and education levels, a state can directly improve its agricultural productivity by improving rural health care access and/or by increasing the absorptive capability of inter-industry and/or inter-state privately funded knowledge spillovers. Therefore, this study identifies a richer set of potential policies for raising long-run TFP levels and for accelerating the pace of reaching them.

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Table 4.1. Test for σ convergence of TFP

Variable	Estimated Coefficients	Standard Error
Intercept	0.037*	0.001
t	0.00001	0.0001

[a] Critical t-value for the 1-tailed test is 1.684 at the 0.05 significance level. Significant coefficients are identified by an asterisk.

Table 4.2. Cross-section Tests for Absolute Convergence of TFP

	Estimated Coefficients	Standard Error [a]
s = 10	-0.204*	0.089
s = 5	-0.249*	0.099
s =3	-0.264*	0.100

[a] Critical t-value for these 1-tailed tests is 1.645 at the 0.05 significance level. Significant coefficients are identified by an asterisk.

Table 4.3. Hadri Panel Stationarity Tests

Variable [a]	Levels		1st Differences		2nd Differences	
	Statistic [b]	P-value	Statistic [b]	P-value	Statistic [b]	P-value
Ln(*TFP*)	35.558	0.000	-5.441	1.000		
Ln(*Edu*)	126.786	0.000	-5.583	1.000		
Ln(*Hs*)	57.701	0.000	-4.307	1.000		
Ln(*Rpri*)	249.752	0.000	16.362	0.000	-7.128	1.000
Ln(*Rpub*)	79.132	0.000	-2.529	0.994		
Ln(*Ext*)	81.702	0.000	2.324	0.010	-7.168	1.000
Ln(*Fs*)	125.088	0.000	35.034	0.000	-6.645	1.000
Ln(*RpubSpill*)	88.685	0.000	-1.595	0.945		
Ln(*RpriSpill*)	297.868	0.000	22.154	0.000	-6.865	1.000
Ln(*InterSpill*)	212.767	0.000	-1.817	0.965		

[a] Codes: Ln is logarithm, *Rpri* is private research investment, *Rpub* is public research investment, *Ext* is extension investment, Size is farm size, *RpriSpill* is private agricultural spillovers from other states, *RpubSpill* is public agricultural research spillovers from other states, *InterSpill* is spillovers from other industries to the agricultural sector, *Edu* is farmers' average education level, *Hs* is health care access level in rural areas.
[b] When testing for stationarity in levels, a time trend was included. For the differences, stationarity was tested without a time trend.

Table 4.4. Pedroni Panel Cointegration Tests

Test Statistic [a]	
Panel v-statistic	3.845*
Panel ρ-statistic	-6.666*
Panel t-statistic (nonparametric)	-11.584*
Panel t-statistic (parametric)	-6.348*
Group ρ-statistic	4.863
Group t-statistic (nonparametric)	-11.510*
Group t-statistic (parametric)	-5.271*

[a] Critical 1-tailed test values for rejecting the hypothesis of no cointegration via the panel-v statistic is 1.645 at the 5% level. Critical values for the other statistics are the negatives of these values (Pedroni 1999). Significant coefficients are identified by an asterisk.
[b] When testing for cointegration, a time trend was included.

Table 4.5. Pesaran PMG Estimates for Conditional Growth Model

Variable [a]	ECM I		ECM II	
	Coefficient	Standard Error [b]	Coefficient	Standard Error [b]
Long-run Coefficients				
ln(*Edu*)	0.0149	0.0211	0.0497*	0.0212
ln(*Hs*)	0.5751*	0.0278	0.3766*	0.0307
Δln(*Fs*)	0.0504	0.0440	0.0212	0.0521
ln(*Rpub*)	0.0338*	0.0142	0.0404*	0.0139
Δln(*Rpri*)	-0.0054	0.0087	-0.0486*	0.0196
Δln(*Ext*)	0.1275*	0.0339	0.0165	0.0296
ln(*PubSpill*)	0.1724*	0.0163	0.1280*	0.0184
Δln(*PriSpill*)	-0.0274	0.0181	0.0980*	0.0330
ln(*InterSpill*)	0.0079	0.0106	0.0544*	0.0114
ln($G_{i,t-1}$) [c]	-0.4122*	0.0401	-0.4444*	0.0378
Short-run Coefficients				
Δln(*Edu*)	0.0061*	0.0006	0.0221*	0.0019
Δln(*Hs*)	0.2368*	0.0230	0.1674*	0.0142
Δ^2ln(*Fs*)	0.0207*	0.0020	0.0094*	0.0008
Δln(*Rpub*)	0.0139*	0.0014	0.0180*	0.0015
Δ^2ln(*Rpri*)	-0.0022*	0.0002	-0.0216*	0.0018
Δ^2ln(*Ext*)	0.0525*	0.0051	0.0073*	0.0006
Δln(*PubSpill*)	0.0710*	0.0069	0.0569*	0.0048
Δ^2ln(*PriSpil*)	-0.0113*	0.0011	0.0435*	0.0037
Δln(*InterSpill*)	0.0032*	0.0003	0.0242*	0.0021
Δ^2ln(*Edu*)			-0.8915*	0.1050
Δ^2ln(*Hs*)			0.3932*	0.1218
Δ^3ln(*Fs*)			-0.0521*	0.0171
Δ^2ln(*Rpub*)			-0.0213	0.0175
Δ^3ln(*Rpri*)			0.0076*	0.0029
Δ^3ln(*Ext*)			0.0494*	0.0204
Δ^2ln(*PubSpill*)			-0.0564	0.0302
Δ^3ln(*PriSpil*)			-0.0322*	0.0069
Δ^2ln(*InterSpill*)			-0.0670*	0.0100
D83	-0.1034*	0.0144	-0.1094*	0.0164
Constant	-2.1398*	0.2111	-1.8819*	0.1594
$\bar{R}^2$	0.2989		0.3362	

[a] D83 is a dummy variable included to pick up the impacts of the PIK program in year 1983. $\bar{R}^2$ is an average of state-specific adjusted R-square values. ln(*Rpub*), ln(*Rpri*) and ln(*Ext*) are lagged 25 years for public research, 15 years for private research, and 7 years for extension investments. These optimal lags were selected by minimizing the AIC.

[b] The critical t-value is 1.96 for the 2-tailed tests and 1.645 for the 1-tailed tests at the 0.05 significance level. Significant coefficients are identified by an asterisk.

[c] This is the error correction coefficient.

APPENDIX A

COMPUTER PROGRAMS FOR CHAPTER 2

APPENDIX A

COMPUTER PROGRAMS FOR CHAPTER 2

I. Rats program for IPS panel unit root test:

```
calendar( panelobs=40 )
allocate 48//40
open data "e:\unitroot_refutable.xls"
data(for=xls,org=col) / x1 x2 x3 r1 r2 r3 p1 p2 p3 w0 res
set p11 = p1*p1
set p12 = p1*p2
set p13 = p1*p3
set p1r1 = p1*r1
set p1r2 = p1*r2
set p1r3 = p1*r3
set p1w0 = p1*w0
set p22 = p2*p2
set p23 = p2*p3
set p2r1 = p2*r1
set p2r2 = p2*r2
set p2r3 = p2*r3
set p2w0 = p2*w0
set p33 = p3*p3
set p3r1 = p3*r1
set p3r2 = p3*r2
set p3r3 = p3*r3
set p3w0 = p3*w0
set r11 = r1*r1
set r12 = r1*r2
set r13 = r1*r3
set r1w0 = r1*w0
set r22 = r2*r2
set r23 = r2*r3
set r2w0 = r2*w0
set r33 = r3*r3
set r3w0 = r3*w0
set w00 = w0*w0
set res2 = res*res
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# x1
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
```

```
# x2
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# x3
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r1
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r2
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r3
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p1
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p2
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p3
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# w0
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# res
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p11
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p12
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p13
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p1r1
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p1r2
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p1r3
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p1w0
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p22
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p2r1
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p2r2
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p2r3
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p2w0
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
```

```
# p33
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# p3w0
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r11
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r12
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r13
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r1w0
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r22
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r23
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r2w0
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r33
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# r3w0
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# w00
@pancoint( mlag=3,block=40,trend,notdum,nounweightd )
# res2
```

II. Rats program for computing AIC for different lag of public research

```
open data "e:\refutable.xls"
data(for=xls,org=col) /x1 r1 r11 r12 r13 r14 r1w0 r2 r22 r23 r24 r2w0 r3 r33 $
r34 r3w0 r4 r44 r4w0 p1 p11 p12 p13 p1r1 p1r2 p1r3 p1r4 p1w0 p2 p22 p23 $
p2r1 p2r2 p2r3 p2r4 p2w0 p3 p33 p3r1 p3r2 p3r3 p3r4 p3w0 w0 w00 res res2

*
cmom
# constant x1 r1 r11 r12 r13 r14 r1w0 r2 r22 r23 r24 r2w0 r3 r33 r34 r3w0 r4 r44 r4w0 $
p1 p11 p12 p13 p1r1 p1r2 p1r3 p1r4 p1w0 p2 p22 p23 p2r1 p2r2 p2r3 p2r4 p2w0 $
p3 p33 p3r1 p3r2 p3r3 p3r4 p3w0 w0 w00 res res2

report(action=define,hlabels=||'Akaike','Schwarz'||)
linreg(cmom,noprint) x1
  # constant r1 r11 r12 r13 r14 r1w0 r2 r22 r23 r24 r2w0 r3 r33 r34 r3w0 r4 r44 r4w0 $
   p1 p11 p12 p13 p1r1 p1r2 p1r3 p1r4 p1w0 p2 p22 p23 p2r1 p2r2 p2r3 p2r4 p2w0 p3 $
   p33 p3r1 p3r2 p3r3 p3r4 p3w0 w0 w00 res res2
```

```
   compute akaike =log(%rss/%nobs)+%nreg*2.0/%nobs
   compute schwarz =log(%rss/%nobs)+%nreg*log(%nobs)/%nobs
   report(row=new,atcol=1) akaike schwarz

report(action=format,picture='*.####')
report(action=show)
```

III. Rats Program for Pedroni's Cointegration Test

```
calendar( panelobs=39 )
allocate 48//39
open data "e:\cointegration_refutable.xls"
data(for=xls,org=col) / x1 x2 x3 r1 r2 r3 p1 p2 p3 w0 res
set r13 = r1*r3
set res2 = res*res
@pancoint( mlag=3,block=39,trend,notdum,nounweightd )
# x1 r1 r3 r13 res2

calendar( panelobs=39 )
allocate 48//39
open data "e:\cointegration_refutable.xls"
data(for=xls,org=col) / x1 x2 x3 r1 r2 r3 p1 p2 p3 w0 res
set r13 = r1*r3
set res2 = res*res
@pancoint( mlag=3,block=39,trend,notdum,nounweightd )
# x2 r1 r3 r13 res2
```

IV. Shazam program for test of refutable hypotheses:

(a) Time-series Model

```
*// all prices and equity are normalized by land price//
****Quantities and Equity are scaled by land flow
****Output prices and Equity are lagged one period.

sample 1 1824

read (e:\refutable_timeseries2.txt) t x1 DR1 DR3 DR13 DPRESQ x2 x3 r1  r2 r3  p1 &
         p2 p3 W0 pre d83
FILE OUTPUT (e:\refutable implications\final results\time_series_model.txt)
* crop price=p1; Livestock price=p2; Secondary output price=p3;
* capital price=r1;capital input=x1; material price=r2; material input=x2;
* labor price=r3; total labor=x3; Equity=w0; PRE=public research expenditure;
*DR1 DR3 DR13 and DPREsq (first difference of pre*pre) used in x1

* Create quadratic terms
```

```
genr PRE2=PRE*PRE
genr p11=0.5*p1*p1
genr p12=p1*p2
genr p13=p1*p3
genr p1r1=p1*r1
genr p1r2=p1*r2
genr p1r3=p1*r3
genr p1w0=p1*w0
genr p22=0.5*p2*p2
genr p23=p2*p3
genr p2r1=p2*r1
genr p2r2=p2*r2
genr p2r3=p2*r3
genr p2w0=p2*w0
genr p33=0.5*p3*p3
genr p3r1=p3*r1
genr p3r2=p3*r2
genr p3r3=p3*r3
genr p3w0=p3*w0
genr r11=0.5*r1*r1
genr r12=r1*r2
genr r13=r1*r3
genr r1w0=r1*w0
genr r22=0.5*r2*r2
genr r23=r2*r3
genr r2w0=r2*w0
genr r33=0.5*r3*r3
genr r3w0=r3*w0
genr W00=0.5*w0*w0

* Create cross-section dummy variables.
* Set the number of cross-sections
GEN1 NC=48
MATRIX CSDUM=SEAS(1824,-NC)
DO #=1,NC
   GENR D#=CSDUM:#
ENDO

* compute means

stat p1/mean=mp1
stat p11/mean=mp11
stat p12/mean=mp12
stat p13/mean=mp13
stat p1r1/mean=mp1r1
stat p1r2/mean=mp1r2
stat p1r3/mean=mp1r3
stat p1w0/mean=mp1w0
```

```
stat p2/mean=mp2
stat p22/mean=mp22
stat p23/mean=mp23
stat p2r1/mean=mp2r1
stat p2r2/mean=mp2r2
stat p2r3/mean=mp2r3
stat p2w0/mean=mp2w0
stat p3/mean=mp3
stat p33/mean=mp33
stat p3r1/mean=mp3r1
stat p3r2/mean=mp3r2
stat p3r3/mean=mp3r3
stat p3w0/mean=mp3w0
stat r1/mean=mr1
STAT DR1/MEAN=MDR1
stat r11/mean=mr11
stat r12/mean=mr12
stat r13/mean=mr13
STAT DR13/MEAN=MDR13
stat r1w0/mean=mr1w0
stat r2/mean=mr2
stat r22/mean=mr22
stat r23/mean=mr23
stat r2w0/mean=mr2w0
stat r3/mean=mr3
STAT DR3/MEAN=MDR3
stat r33/mean=mr33
stat r3w0/mean=mr3w0
stat x1/mean=mx1
stat x2/mean=mx2
stat x3/mean=mx3
stat w0/mean=mw0
stat w00/mean=mw00
STAT PRE/MEAN=MPRE
STAT PRE2/MEAN=MPRE2
stat Dpresq/mean=mDpresq
STAT D1-D48/mean=MD1-MD48
stat d83/mean=md83

****//Estimate system of equations and caculate input demand value
system 3/ dn noconstant
ols x1 D1-D48 d83 PRE DPRESQ  p1 p2 p3 Dr1 r2 Dr3 w0  &
            p11 p12 p13 p1r1 p1r2 p1r3 p1w0 &
               p22 p23 p2r1 p2r2 p2r3 p2w0 &
                  p33 p3r1 p3r2 p3r3 p3w0 &
                      r11  r12  Dr13 r1w0 &
                          r22  r23 r2w0 &
                              r33 r3w0 &
```

```
                              w00

ols x2 D1-D48 d83 PRE PRE2  p1 p2 p3 r1 r2 r3 w0  &
            p11 p12 p13 p1r1 p1r2 p1r3 p1w0 &
               p22 p23 p2r1 p2r2 p2r3 p2w0 &
                  p33 p3r1 p3r2 p3r3 p3w0 &
                      r11  r12  r13 r1w0 &
                          r22  r23 r2w0 &
                              r33 r3w0 &
                                  w00

ols x3 D1-D48 d83 PRE PRE2  p1 p2 p3 r1 r2 r3 w0  &
            p11 p12 p13 p1r1 p1r2 p1r3 p1w0 &
               p22 p23 p2r1 p2r2 p2r3 p2w0 &
                  p33 p3r1 p3r2 p3r3 p3w0 &
                      r11  r12  r13 r1w0 &
                          r22  r23 r2w0 &
                              r33 r3w0 &
                                  w00
************************************************
********//* Propostion 1: XHAT>=0*****************
************************************************
test (D1:1+  D2:1+ D3:1+ D4:1+ D5:1+ D6:1+ D7:1+ D8:1+ D9:1+D10:1 &
  +D11:1+D12:1+D13:1+D14:1+D15:1+D16:1+D17:1+D18:1+D19:1+D20:1 &
  +D21:1+D22:1+D23:1+D24:1+D25:1+D26:1+D27:1+D28:1+D29:1+D30:1 &
  +D31:1+D32:1+D33:1+D34:1+D35:1+D36:1+D37:1+D38:1+D39:1+D40:1 &
+D41:1+D42:1+D43:1+D44:1+D45:1+D46:1+D47:1+D48:1)*1/48 + d83:1*md83 &
+PRE:1*MPRE+DPRESQ:1*MDPRESQ+p1:1*mp1+p2:1*mp2+p3:1*mp3+Dr1:1*mDr1 &
+r2:1*mr2+Dr3:1*mDr3+w0:1*mw0 +p11:1*mp11+ p22:1*mp22+ p33:1*mp33+ r11:1*mr11&
+ r22:1*mr22+ r33:1*mr33+ w00:1*mw00 +p12:1*mp12+ p13:1*mp13+ p1r1:1*mp1r1 &
+ p1r2:1*mp1r2+p1r3:1*mp1r3+p1w0:1*mp1w0+p23:1*mp23+ p2r1:1*mp2r1 &
+ p2r2:1*mp2r2 + p2r3:1*mp2r3+p2w0:1*mp2w0+ p3r1:1*mp3r1 &
+p3r2:1*mp3r2+p3r3:1*mp3r3+p3w0:1*mp3w0+r12:1*mr12+Dr13:1*mDr13 &
+r1w0:1*mr1w0 +r23:1*mr23+r2w0:1*mr2w0+r3w0:1*mr3w0

test   (D1:2+ D2:2+ D3:2+ D4:2+ D5:2+ D6:2+ D7:2+ D8:2+D9:2+D10:2 &
   +D11:2+D12:2+D13:2+D14:2+D15:2+D16:2+D17:2+D18:2+D19:2+D20:2 &
   +D21:2+D22:2+D23:2+D24:2+D25:2+D26:2+D27:2+D28:2+D29:2+D30:2 &
   +D31:2+D32:2+D33:2+D34:2+D35:2+D36:2+D37:2+D38:2+D39:2+D40:2 &
   +D41:2+D42:2+D43:2+D44:2+D45:2+D46:2+D47:2+D48:2)*1/48 + d83:2*md83 &
   +PRE:2*MPRE+PRE2:2*MPRE2+p1:2*mp1+p2:2*mp2+p3:2*mp3+r1:2*mr1+r2:2*mr2 &
   + r3:2*mr3+w0:2*mw0 +p11:2*mp11+ p22:2*mp22+ p33:2*mp33+ r11:2*mr11 &
   + r22:2*mr22+ r33:2*mr33+ w00:2*mw00+p12:2*mp12+ p13:2*mp13+ p1r1:2*mp1r1&
   + p1r2:2*mp1r2 +p1r3:2*mp1r3+ p1w0:2*mp1w0+p23:2*mp23+ p2r1:2*p2r1 &
   + p2r2:2*mp2r2+ p2r3:2*mp2r3+p2w0:2*mp2w0+ p3r1:2*mp3r1 &
   +p3r2:2*mp3r2+p3r3:2*mp3r3+p3w0:2*mp3w0+r12:2*mr12+r13:2*mr13  &
   +r1w0:2*mr1w0+r23:2*mr23+r2w0:2*mr2w0+r3w0:2*mr3w0
```

```
test ( D1:3+ D2:3+D3:3+ D4:3+ D5:3+  D6:3+ D7:3+ D8:3+ D9:3+D10:3 &
  +D11:3+D12:3+D13:3+D14:3+D15:3+D16:3+D17:3+D18:3+D19:3+D20:3 &
  +D21:3+D22:3+D23:3+D24:3+D25:3+D26:3+D27:3+D28:3+D29:3+D30:3 &
  +D31:3+D32:3+D33:3+D34:3+D35:3+D36:3+D37:3+D38:3+D39:3+D40:3 &
  +D41:3+D42:3+D43:3+D44:3+D45:3+D46:3+D47:3+D48:3)*1/48 +d83:3*md83 &
  +PRE:3*MPRE+PRE2:3*MPRE2+p1:3*mp1+p2:3*mp2+p3:3*mp3+r1:3*mr1 &
  +r2:3*mr2+r3:3*mr3+w0:3*mw0 +p11:3*mp11+ p22:3*mp22+ p33:3*mp33 &
  + r11:3*mr11+ r22:3*mr22+ r33:3*mr33+w00:3*mw00 +p12:3*mp12+ p13:3*mp13 &
  + p1r1:3*mp1r1+ p1r2:3*mp1r2+p1r3:3*mp1r3+ p1w0:3*mp1w0+p23:3*mp23 &
  + p2r1:3*mp2r1+ p2r2:3*mp2r2+ p2r3:3*mp2r3+p2w0:3*mp2w0+ p3r1:3*mp3r1  &
  +p3r2:3*mp3r2+p3r3:3*mp3r3+p3w0:3*mp3w0+r12:3*mr12+r13:3*mr13+r1w0:3*mr1w0 &
  +r23:3*mr23+r2w0:3*mr2w0+r3w0:3*mr3w0

**************************************************************
****************Proposition 2.1 diag(-omiga)<=0***********-*********
**************************************************************
****************fist diagonal element of omiga*******************
test (2*(Dr1:1+r11:1*mDr1+p1r1:1*mp1+p2r1:1*mp2+p3r1:1*mp3+r12:1*mr2+Dr13:1*mr3 &
+r1w0:1*mw0)+mx1*(w0:1+w00:1*mw0+p1w0:1*mp1+p2w0:1*mp2+p3w0:1*mp3 &
+r1w0:1*mDr1+r2w0:1*mr2+r3w0:1*mDr3))

test (2*(r2:2+r22:2*mr2+p1r2:2*mp1+p2r2:2*mp2+p3r2:2*mp3+r12:2*mr1+r23:2*mr3 &
+r2w0:2*mw0) +mx2*(w0:2+w00:2*mw0+p1w0:2*mp1+p2w0:2*mp2+p3w0:2*mp3 &
+r1w0:2*mr1+r2w0:2*mr2+r3w0:2*mr3))

test  (2*(r3:3+r33:3*mr3+p1r3:3*mp1+p2r3:3*mp2+p3r3:3*mp3+r13:3*mr1+r23:3*mr2 &
+r3w0:3*mw0) +mx3*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2+p3w0:3*mp3 &
+r1w0:3*mr1 +r2w0:3*mr2+r3w0:3*mr3))

*****************************************************************************
*********** **Propostion 2.2: second order principal of (-Omiga)>>0*******************
*****************************************************************************
test ((2*(Dr1:1+r11:1*mDr1+p1r1:1*mp1+p2r1:1*mp2+p3r1:1*mp3+r12:1*mr2 &
+Dr13:1*mDr3 +r1w0:1*mw0) +mx1*(w0:1+w00:1*mw0+p1w0:1*mp1+p2w0:1*mp2 &
+p3w0:1*mp3 +r1w0:1*mDr1+r2w0:1*mr2+r3w0:1*mDr3))* &
 (2*(r2:2+r22:2*mr2+p1r2:2*mp1+p2r2:2*mp2+p3r2:2*mp3+r12:2*mr1+r23:2*mr3 &
+r2w0:2*mw0) +mx2*(w0:2+w00:2*mw0+p1w0:2*mp1+p2w0:2*mp2+p3w0:2*mp3 &
+r1w0:2*mr1+r2w0:2*mr2+r3w0:2*mr3))  -(2*(r2:1+r22:1*mr2+p1r2:1*mp1 &
+p2r2:1*mp2+p3r2:1*mp3+r12:1*mDr1+r23:1*mDr3+r2w0:1*mw0) &
+mx2*(w0:1+w00:1*mw0+p1w0:1*mp1+p2w0:1*mp2+p3w0:1*mp3+r1w0:1*mDr1 &
+r2w0:1*mr2+r3w0:1*mDr3))* (2*(r1:2+r11:2*mr1+p1r1:2*mp1+p2r1:2*mp2 &
+p3r1:2*mp3+r12:2*mr2+r13:2*mr3+r1w0:2*mw0) +mx1*(w0:2+w00:2*mw0+p1w0:2*mp1&
+p2w0:2*mp2+p3w0:2*mp3+r1w0:2*mr1+r2w0:2*mr2+r3w0:2*mr3)))

*****************************************************************
***************Determinant of (-Omiga)<=0***************************
*****************************************************************
```

```
test (2*(Dr1:1+r11:1*mDr1+p1r1:1*mp1+p2r1:1*mp2+p3r1:1*mp3+r12:1*mr2 &
+Dr13:1*mDr3+r1w0:1*mw0) +mx1*(w0:1+w00:1*mw0+p1w0:1*mp1&
+p2w0:1*mp2+p3w0:1*mp3+r1w0:1*mDr1+r2w0:1*mr2+r3w0:1*mDr3))&
*(((2*(r2:2+r22:2*mr2+p1r2:2*mp1+p2r2:2*mp2+p3r2:2*mp3+r12:2*mr1+r23:2*mr3 &
+r2w0:2*mw0) +mx2*(w0:2+w00:2*mw0+p1w0:2*mp1+p2w0:2*mp2 &
+p3w0:2*mp3+r1w0:2*mr1+r2w0:2*mr2+r3w0:2*mr3)) &
*(2*(r3:3+r33:3*mr3+p1r3:3*mp1+p2r3:3*mp2+p3r3:3*mp3+r13:3*mr1+r23:3*mr2 &
+r3w0:3*mw0) +mx3*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2 &
+p3w0:3*mp3+r1w0:3*mr1+r2w0:3*mr2+r3w0:3*mr3))) &
- (2*(r3:2+r33:2*mr3+p1r3:2*mp1+p2r3:2*mp2+p3r3:2*mp3+r13:2*mr1 &
+r23:2*mr2+r3w0:2*mw0) +mx3*(w0:2+w00:2*mw0+p1w0:2*mp1+p2w0:2*mp2 &
+p3w0:2*mp3+r1w0:2*mr1+r2w0:2*mr2+r3w0:2*mr3))* &
(2*(r2:3+r22:3*mr2+p1r2:3*mp1+p2r2:3*mp2+p3r2:3*mp3+r12:3*mr1+r23:3*mr3 &
+r2w0:3*mw0) +mx2*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2 &
+p3w0:3*mp3+r1w0:3*mr1+r2w0:3*mr2+r3w0:3*mr3))) &
 - (2*(r1:2+r11:2*mr1+p1r1:2*mp1+p2r1:2*mp2+p3r1:2*mp3+r12:2*mr2 &
+r13:2*mr3+r1w0:2*mw0)+mx1*(w0:2+w00:2*mw0+p1w0:2*mp1+p2w0:2*mp2 &
+p3w0:2*mp3+r1w0:2*mr1+r2w0:2*mr2+r3w0:2*mr3)) &
*((2*(r2:1+r22:1*mr2+p1r2:1*mp1+p2r2:1*mp2+p3r2:1*mp3+r12:1*mr1+r23:1*mr3 &
+r2w0:1*mw0) +mx2*(w0:1+w00:1*mw0+p1w0:1*mp1+p2w0:1*mp2+p3w0:1*mp3&
+r1w0:1*mDr1+r2w0:1*mr2+r3w0:1*mDr3))* (2*(r3:3+r33:3*mr3+p1r3:3*mp1+p2r3:3*mp2&
+p3r3:3*mp3+r13:3*mr1+r23:3*mr2+r3w0:3*mw0) +mx3*(w0:3+w00:3*mw0+p1w0:3*mp1&
+p2w0:3*mp2+p3w0:3*mp3+r1w0:3*mr1+r2w0:3*mr2+r3w0:3*mr3)))&
-(2*(Dr3:1+r33:1*mDr3+p1r3:1*mp1+p2r3:1*mp2+p3r3:1*mp3+Dr13:1*mDr1 &
+r23:1*mr2+r3w0:1*mw0) +mx3*(w0:1+w00:1*mw0+p1w0:1*mp1 &
 +p2w0:1*mp2+p3w0:1*mp3+r1w0:1*mDr1+r2w0:1*mr2+r3w0:1*mDr3))* &
(2*(r2:3+r22:3*mr2+p1r2:3*mp1+p2r2:3*mp2+p3r2:3*mp3+r12:3*mr1+r23:3*mr3 &
+r2w0:3*mw0) +mx2*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2&
+p3w0:3*mp3+r1w0:3*mr1+r2w0:3*mr2+r3w0:3*mr3)) &
+(2*(r1:3+r11:3*mr1+p1r1:3*mp1+p2r1:3*mp2+p3r1:3*mp3+r12:3*mr2+r13:3*mr3 &
+r1w0:3*mw0) +mx1*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2 &
+p3w0:3*mp3+r1w0:3*mr1+r2w0:3*mr2+r3w0:3*mr3))* ((2*(r2:1+r22:1*mr2+p1r2:1*mp1&
+p2r2:1*mp2+p3r2:1*mp3+r12:1*mDr1+r23:1*mDr3+r2w0:1*mw0) &
+mx2*(w0:1+w00:1*mw0+p1w0:1*mp1+p2w0:1*mp2+p3w0:1*mp3+r1w0:1*mDr1 &
+r2w0:1*mr2+r3w0:1*mDr3)) *(2*(r3:2+r33:2*mr3+p1r3:2*mp1&
+p2r3:2*mp2+p3r3:2*mp3+r13:2*mr1+r23:2*mr2+r3w0:2*mw0) +mx3*(w0:2+w00:2*mw0 &
+p1w0:2*mp1+p2w0:2*mp2+p3w0:2*mp3+r1w0:2*mr1+r2w0:2*mr2+r3w0:2*mr3))&
 -(2*(Dr3:1+r33:1*mDr3+p1r3:1*mp1+p2r3:1*mp2+p3r3:1*mp3+Dr13:1*mDr1 &
+r23:1*mr2+r3w0:1*mw0) +mx3*(w0:1+w00:1*mw0+p1w0:1*mp1 &
+p2w0:1*mp2+p3w0:1*mp3+r1w0:1*mDr1+r2w0:1*mr2+r3w0:1*mDr3))* &
(2*(r2:2+r22:2*mr2+p1r2:2*mp1+p2r2:2*mp2+p3r2:2*mp3+r12:2*mDr1+r23:2*mr3 &
+r2w0:2*mw0) +mx2*(w0:2+w00:2*mw0+p1w0:2*mp1+p2w0:2*mp2 &
+p3w0:2*mp3+r1w0:2*mr1+r2w0:2*mr2+r3w0:2*mr3)))

*********test Symmetry of omiga*********
test
test (2*(r2:1+r22:1*mr2+p1r2:1*mp1+p2r2:1*mp2+p3r2:1*mp3+r12:1*mDr1+r23:1*mDr3 &
    +r2w0:1*mw0) +mx2*(w0:1+w00:1*mw0+p1w0:1*mp1+p2w0:1*mp2 &
```

```
    +p3w0:1*mp3+r1w0:1*mDr1+r2w0:1*mr2+r3w0:1*mDr3))&
    - (2*(r1:2+r11:2*mr1+p1r1:2*mp1+p2r1:2*mp2+p3r1:2*mp3 &
    + r12:2*mr2+r13:2*mr3+r1w0:2*mw0) &
    +mx1*(w0:2+w00:2*mw0+p1w0:2*mp1+p2w0:2*mp2+p3w0:2*mp3+r1w0:2*mr1 &
    +r2w0:2*mr2+r3w0:2*mr3))
test (2*(Dr3:1+r33:1*mDr3+p1r3:1*mp1+p2r3:1*mp2+p3r3:1*mp3+Dr13:1*mDr1 &
   +r23:1*mr2+r3w0:1*mw0) +mx3*(w0:1+w00:1*mw0+p1w0:1*mp1+p2w0:1*mp2 &
   +p3w0:1*mp3+r1w0:1*mDr1+r2w0:1*mr2+r3w0:1*mDr3))- (2*(r1:3+r11:3*mr1 &
    +p1r1:3*mp1 +p2r1:3*mp2+p3r1:3*mp3 + r12:3*mr2+r13:3*mr3+r1w0:3*mw0)&
   +mx1*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2+p3w0:3*mp3+r1w0:3*mr1 &
   +r2w0:3*mr2+r3w0:3*mr3))
test (2*(r3:2+r33:2*mr3+p1r3:2*mp1+p2r3:2*mp2+p3r3:2*mp3+r13:2*mr1+r23:2*mr2
     +r3w0:2*mw0) +mx3*(w0:2+w00:2*mw0+p1w0:2*mp1+p2w0:2*mp2 &
     +p3w0:2*mp3+r1w0:2*mr1+r2w0:2*mr2+r3w0:2*mr3))&
     - (2*(r2:3+r22:3*mr2+p1r2:3*mp1+p2r2:3*mp2+p3r2:3*mp3+r12:3*mr1 &
     +r23:3*mr3+r2w0:3*mw0) +mx2*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2 &
    +p3w0:3*mp3+r1w0:3*mr1+r2w0:3*mr2+r3w0:3*mr3))
end

*********test corollary**********
test
test
(w0:1+w00:1*mw0+p1w0:1*mp1+p2w0:1*mp2+p3w0:1*mp3+r1w0:1*mDr1+r2w0:1*mr2&
    +r3w0:1*mDr3)
test (w0:2+w00:2*mw0+p1w0:2*mp1+p2w0:2*mp2+p3w0:2*mp3+r1w0:2*mr1+r2w0:2*mr2 &
   +r3w0:2*mr3)
test (w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2+p3w0:3*mp3+r1w0:3*mr1+r2w0:3*mr2 &
   +r3w0:3*mr3)
end

************************************************
********//* caculate XHAT***********************
************************************************
genr x1hat=  D1:1*D1+D2:1*D2+D3:1*D3+D4:1*D4+D5:1*D5+D6:1*D6+D7:1*D7 &
+D8:1*D8 +D9:1*D9+D10:1*D10 +D11:1*D11+D12:1*D12+D13:1*D13+D14:1*D14 &
+D15:1*D15+D16:1*D16+D17:1*D17 +D18:1*D18 +D19:1*D19+D20:1*D20 &
+D21:1*D21+D22:1*D22+D23:1*D23+D24:1*D24+D25:1*D25+D26:1*D26 +D27:1*D27&
+D28:1*D28+D29:1*D29+D30:1*D30+D31:1*D31+D32:1*D32+D33:1*D33 &
+D34:1*D34+D35:1*D35+D36:1*D36+D37:1*D37+D38:1*D38 +D39:1*D39 &
+D40:1*D40+D41:1*D41+D42:1*D42 +D43:1*D43+D44:1*D44+D45:1*D45 &
+D46:1*D46 +D47:1*D47+D48:1*D48+d83:1*d83+PRE:1*PRE+DPRESQ:1*DPRESQ &
+p1:1*p1+p2:1*p2+p3:1*p3+Dr1:1*Dr1+r2:1*r2+Dr3:1*Dr3+w0:1*w0 +p11:1*p11 &
+ p22:1*p22+ p33:1*p33+ r11:1*r11+ r22:1*r22+ r33:1*r33+ w00:1*w00 &
 +p12:1*p12+ p13:1*p13+ p1r1:1*p1r1+ p1r2:1*p1r2+p1r3:1*p1r3 &
+p1w0:1*p1w0 +p23:1*p23+ p2r1:1*p2r1+ p2r2:1*p2r2 + p2r3:1*p2r3+p2w0:1*p2w0 &
+ p3r1:1*p3r1 +p3r2:1*p3r2+p3r3:1*p3r3+p3w0:1*p3w0+r12:1*r12+r13:1*r13 &
+r1w0:1*r1w0 +r23:1*r23+r2w0:1*r2w0+r3w0:1*r3w0
```

```
genr x2hat= D1:2*D1+D2:2*D2+D3:2*D3+D4:2*D4+D5:2*D5+D6:2*D6+D7:2*D7 &
+D8:2*D8 +D9:2*D9 +D10:2*D10 +D11:2*D11+D12:2*D12+D13:2*D13 &
+D14:2*D14+D15:2*D15+D16:2*D16+D17:2*D17+D18:2*D18 +D19:2*D19 &
+D20:2*D20+D21:2*D21+D22:2*D22+D23:2*D23+D24:2*D24+D25:2*D25 &
+D26:2*D26 +D27:2*D27+D28:2*D28+D29:2*D29+D30:2*D30+D31:2*D31 &
+D32:2*D32+D33:2*D33+D34:2*D34+D35:2*D35+D36:2*D36 &
+D37:2*D37+D38:2*D38 +D39:2*D39+D40:2*D40+D41:2*D41+D42:2*D42 &
+D43:2*D43+D44:2*D44+D45:2*D45+D46:2*D46+D47:2*D47+D48:2*D48+d83:2*d83 &
+PRE:2*T+PRE2:2*PRE2+p1:2*p1+p2:2*p2+p3:2*p3+r1:2*r1+r2:2*r2+r3:2*r3+w0:2*w0 &
+p11:2*p11+ p22:2*p22+ p33:2*p33+ r11:2*r11+ r22:2*r22+ r33:2*r33+ w00:2*w00 &
+p12:2*p12+ p13:2*p13+ p1r1:2*p1r1+ p1r2:2*p1r2+p1r3:2*p1r3+ p1w0:2*p1w0 &
+p23:2*p23+ p2r1:2*p2r1+ p2r2:2*p2r2+ p2r3:2*p2r3+p2w0:2*p2w0+ p3r1:2*p3r1&
+p3r2:2*p3r2+p3r3:2*p3r3+p3w0:2*p3w0+r12:2*r12+r13:2*r13+r1w0:2*r1w0 &
+r23:2*r23+r2w0:2*r2w0+r3w0:2*r3w0

genr x3hat = D1:3*D1+D2:3*D2+D3:3*D3+D4:3*D4+D5:3*D5+D6:3*D6+D7:3*D7 &
+D8:3*D8 +D9:3*D9+D10:3*D10+D11:3*D11+D12:3*D12+D13:3*D13+D14:3*D14 &
+D15:3*D15 +D16:3*D16+D17:3*D17+D18:3*D18+D19:3*D19+D20:3*D20 &
+D21:3*D21 +D22:3*D22+D23:3*D23+D24:3*D24+D25:3*D25+D26:3*D26 &
+D27:3*D27+D28:3*D28+D29:3*D29+D30:3*D30+D31:3*D31+D32:3*D32+D33:3*D33 &
+D34:3*D34+D35:3*D35+D36:3*D36+D37:3*D37+D38:3*D38+D39:3*D39+D40:3*D40  &
+D41:3*D41+D42:3*D42+D43:3*D43+D44:3*D44+D45:3*D45+D46:3*D46+D47:3*D47  &
+D48:3*D48+d83:3*d83+PRE:3*PRE+PRE2:3*PRE2+p1:3*p1+p2:3*p2+p3:3*p3+r1:3*r1  &
+r2:3*r2+r3:3*r3+w0:3*w0 +p11:3*p11+ p22:3*p22+ p33:3*p33+ r11:3*r11+ r22:3*r22 &
+ r33:3*r33+w00:3*w00 +p12:3*p12+ p13:3*p13+ p1r1:3*p1r1+ p1r2:3*p1r2+p1r3:3*p1r3 &
+ p1w0:3*p1w0 +p23:3*p23+ p2r1:3*p2r1+ p2r2:3*p2r2+ p2r3:3*p2r3+p2w0:3*p2w0 &
+ p3r1:3*p3r1+p3r2:3*p3r2+p3r3:3*p3r3+p3w0:3*p3w0+r12:3*r12+r13:3*r13+r1w0:3*r1w0 &
+r23:3*r23+r2w0:3*r2w0+r3w0:3*r3w0 &

print x1hat x2hat x3hat

*************************************************************
*****************fist diagonal element of omiga*********************
*************************************************************
genr omig11=(2*(Dr1:1+r11:1*Dr1+p1r1:1*p1+p2r1:1*p2+p3r1:1*p3+r12:1*r2+Dr13:1*Dr3 &
+r1w0:1*w0) +x1*(w0:1+w00:1*w0+p1w0:1*p1+p2w0:1*p2 &
+p3w0:1*p3+r1w0:1*Dr1+r2w0:1*r2+r3w0:1*Dr3))

genr omig22=(2*(r2:2+r22:2*r2+p1r2:2*p1+p2r2:2*p2+p3r2:2*p3+r12:2*r1 &
+r23:2*r3+r2w0:2*w0) +x2*(w0:2+w00:2*w0+p1w0:2*p1+p2w0:2*p2 &
+p3w0:2*p3+r1w0:2*r1+r2w0:2*r2+r3w0:2*r3))

genr omig33=(2*(r3:3+r33:3*r3+p1r3:3*p1+p2r3:3*p2+p3r3:2*p3+r13:3*r1 &
+r23:3*r2+r3w0:3*w0) +x3*(w0:3+w00:3*w0+p1w0:3*p1+p2w0:3*p2 &
+p3w0:3*p3+r1w0:3*r1+r2w0:3*r2+r3w0:3*r3))

print omig11 omig22 omig33
*********************************P2*****************************
```

```
genr p2= ((2*(Dr1:1+r11:1*Dr1+p1r1:1*p1+p2r1:1*p2+p3r1:1*p3+r12:1*r2 &
+Dr13:1*Dr3+r1w0:1*w0) +x1*(w0:1+w00:1*w0+p1w0:1*p1+p2w0:1*p2 &
 +p3w0:1*p3+r1w0:1*Dr1+r2w0:1*r2+r3w0:1*Dr3))* &
     (2*(r2:2+r22:2*r2+p1r2:2*p1+p2r2:2*p2+p3r2:2*p3+r12:2*r1+r23:2*r3+r2w0:2*w0) &
+x2*(w0:2+w00:2*w0+p1w0:2*p1+p2w0:2*p2+p3w0:2*p3+r1w0:2*r1+r2w0:2*r2 &
+r3w0:2*r3))  -(2*(r2:1+r22:1*r2+p1r2:1*p1+p2r2:1*p2 &
+p3r2:1*p3+r12:1*Dr1+r23:1*Dr3+r2w0:1*w0) &
+x2*(w0:1+w00:1*w0+p1w0:1*p1+p2w0:1*p2+p3w0:1*p3+r1w0:1*Dr1+r2w0:1*r2 &
+r3w0:1*Dr3))* (2*(r1:2+r11:2*r1+p1r1:2*p1+p2r1:2*p2+p3r1:2*p3 &
+r12:2*r2+r13:2*r3+r1w0:2*w0) +x1*(w0:2+w00:2*w0+p1w0:2*p1+p2w0:2*p2 &
+p3w0:2*p3+r1w0:2*r1+r2w0:2*r2+r3w0:2*r3)))
print p2
*************************************************************
***************Determinant of (-Omiga)*****************************
***************************************************___****************__

genr D=(2*(Dr1:1+r11:1*Dr1+p1r1:1*p1+p2r1:1*p2+p3r1:1*p3+r12:1*r2+r13:1*Dr3 &
+r1w0:1*w0) +x1*(w0:1+w00:1*w0+p1w0:1*p1+p2w0:1*p2+p3w0:1*p3 &
+r1w0:1*Dr1+r2w0:1*r2+r3w0:1*Dr3)) *(((2*(r2:2+r22:2*r2+p1r2:2*p1+p2r2:2*p2 &
+p3r2:2*p3+r12:2*r1+r23:2*r3+r2w0:2*w0) +x2*(w0:2+w00:2*w0 &
+p1w0:2*p1+p2w0:2*p2+p3w0:2*p3+r1w0:2*r1+r2w0:2*r2+r3w0:2*r3))&
  *(2*(r3:3+r33:3*r3+p1r3:3*p1+p2r3:3*p2+p3r3:3*p3+r13:3*r1+r23:3*r2+r3w0:3*w0) &
+x3*(w0:3+w00:3*w0+p1w0:3*p1+p2w0:3*p2+p3w0:3*p3+r1w0:3*r1+r2w0:3*r2 &
+r3w0:3*r3))) -(2*(r3:2+r33:2*r3+p1r3:2*p1+p2r3:2*p2+p3r3:2*p3+r13:2*r1 &
+r23:2*r2+r3w0:2*w0) +x3*(w0:2+w00:2*w0+p1w0:2*p1+p2w0:2*p2+p3w0:2*p3 &
+r1w0:2*r1+r2w0:2*r2+r3w0:2*r3))* (2*(r2:3+r22:3*r2+p1r2:3*p1+p2r2:3*p2+p3r2:3*p3 &
+r12:3*r1+r23:3*r3+r2w0:3*w0) +x2*(w0:3+w00:3*w0+p1w0:3*p1 &
+p2w0:3*p2+p3w0:3*p3+r1w0:3*r1+r2w0:3*r2+r3w0:3*r3))) +x1*(w0:2+w00:2*w0 &
+p1w0:2*p1-(2*(r1:2+r11:2*r1+p1r1:2*p1+p2r1:2*p2+p3r1:2*p3+r12:2*r2+r13:2*r3 &
+r1w0:2*w0)+p2w0:2*p2+p3w0:2*p3+r1w0:2*r1+r2w0:2*r2+r3w0:2*r3)) &
      *((2*(r2:1+r22:1*r2+p1r2:1*p1+p2r2:1*p2+p3r2:1*p3+r12:1*r1+r23:1*r3+r2w0:1*w0) &
+x2*(w0:1+w00:1*w0+p1w0:1*p1+p2w0:1*p2+p3w0:1*p3+r1w0:1*Dr1+r2w0:1*r2 &
+r3w0:1*Dr3))*  (2*(r3:3+r33:3*r3+p1r3:3*p1+p2r3:3*p2+p3r3:3*p3+r13:3*r1 &
+r23:3*r2+r3w0:3*w0) +x3*(w0:3+w00:3*w0+p1w0:3*p1+p2w0:3*p2 &
+p3w0:3*p3+r1w0:3*r1+r2w0:3*r2+r3w0:3*r3)))  -  (2*(Dr3:1+r33:1*Dr3+p1r3:1*p1 &
+p2r3:1*p2+p3r3:1*p3+r13:1*Dr1+r23:1*r2+r3w0:1*w0) +x3*(w0:1+w00:1*w0 &
+p1w0:1*p1+p2w0:1*p2+p3w0:1*p3+r1w0:1*Dr1+r2w0:1*r2+r3w0:1*Dr3))*&
  (2*(r2:3+r22:3*r2+p1r2:3*p1+p2r2:3*p2+p3r2:3*p3+r12:3*r1+r23:3*r3+r2w0:3*w0)&
+x2*(w0:3+w00:3*w0+p1w0:3*p1+p2w0:3*p2+p3w0:3*p3+r1w0:3*r1+r2w0:3*r2 &
+r3w0:3*r3)) &
     +(2*(r1:3+r11:3*r1+p1r1:3*p1+p2r1:3*p2+p3r1:3*p3+r12:3*r2+r13:3*r3+r1w0:3*w0)&
+x1*(w0:3+w00:3*w0+p1w0:3*p1+p2w0:3*p2+p3w0:3*p3+r1w0:3*r1+r2w0:3*r2
+r3w0:3*r3))* ((2*(r2:1+r22:1*r2+p1r2:1*p1+p2r2:1*p2+p3r2:1*p3+r12:1*Dr1+r23:1*r3 &
+r2w0:1*w0) +x2*(w0:1+w00:1*w0+p1w0:1*p1+p2w0:1*p2+p3w0:1*p3+r1w0:1*Dr1&
 +r2w0:1*r2+r3w0:1*Dr3))*(2*(r3:2+r33:2*r3+p1r3:2*p1+p2r3:2*p2+p3r3:2*p3&
+r13:2*r1+r23:2*r2+r3w0:2*w0) +x3*(w0:2+w00:2*w0+p1w0:2*p1+p2w0:2*p2&
+p3w0:2*p3+r1w0:2*r1+r2w0:2*r2+r3w0:2*r3))&
-(2*(Dr3:1+r33:1*Dr3+p1r3:1*p1+p2r3:1*p2+p3r3:1*p3+r13:1*Dr1+r23:1*r2+r3w0:1*w0) &
```

```
+x3*(w0:1+w00:1*w0+p1w0:1*p1+p2w0:1*p2+p3w0:1*p3+r1w0:1*Dr1+r2w0:1*r2 &
+r3w0:1*Dr3))* (2*(r2:2+r22:2*r2+p1r2:2*p1+p2r2:2*p2 &
 +p3r2:2*p3+r12:2*r1+r23:2*r3+r2w0:2*w0) +x2*(w0:2+w00:2*w0+p1w0:2*p1 &
+p2w0:2*p2+p3w0:2*p3+r1w0:2*r1+r2w0:2*r2+r3w0:2*r3)))
PRINT D
end
stop
```

(b) Traditional Model

```
*// all prices in data are normalized by land prices//
****Quantities and Equity are scaled by land flow
****Output prices and Equity are lagged one period.

Sample 1 1872

Read (E:\TRANSFORMEDdata.txt) T x1 PK1 PK2 PK3 RK1 RK2 RK3 WK x2 PM1 & PM2
PM3 RM1 RM2 RM3 WM x3 P1 P2 P3 R1 R2 R3 W0
* file output (e:\refutable implications\final results\traditional_model.txt)
* crop price=p1; Livestock price=p2; Secondary output price=p3;
* capital price=r1;capital input=x1; material price=r2; material input=x2;
* labor price=r3; total labor=x3; Equity=w0
genr one=1
genr t2=0.5*t*t
* Create quadratic terms in capital equation

genr Pk11=0.5*Pk1*Pk1
genr pK12=pK1*pK2
genr pK13=pk1*pk3
genr Pk1r1=pk1*rk1
genr pk1r2=pk1*rk2
genr pk1r3=pk1*rk3
genr pk1w=pk1*wk
genr pk22=0.5*pk2*pk2
genr pk23=pk2*pk3
genr pk2r1=pk2*rk1
genr pk2r2=pk2*rk2
genr pk2r3=pk2*rk3
genr pk2w=pk2*wk
genr pk33=0.5*pk3*pk3
genr pk3r1=pk3*rk1
genr pk3r2=pk3*rk2
genr pk3r3=pk3*rk3
genr pk3w=pk3*wk
genr rk11=0.5*rk1*rk1
genr rk12=rk1*rk2
genr rk13=rk1*rk3
```

```
genr rk1w=rk1*wk
genr rk22=0.5*rk2*rk2
genr rk23=rk2*rk3
genr rk2w=rk2*wk
genr rk33=0.5*rk3*rk3
genr rk3w=rk3*wk
genr Wkk=0.5*wk*wk

*compute means

stat Pk1/mean=mPk1
stat Pk11/mean=mPk11
stat Pk12/mean=mPk12
stat Pk13/mean=mPk13
stat Pk1r1/mean=mPk1r1
stat Pk1r2/mean=mPk1r2
stat Pk1r3/mean=mPk1r3
stat Pk1w/mean=mPk1w
stat Pk2/mean=mPk2
stat Pk22/mean=mPk22
stat Pk23/mean=mPk23
stat Pk2r1/mean=mPk2r1
stat Pk2r2/mean=mPk2r2
stat Pk2r3/mean=mPk2r3
stat Pk2w/mean=mPk2w
stat Pk3/mean=mPk3
stat Pk33/mean=mPk33
stat Pk3r1/mean=mPk3r1
stat Pk3r2/mean=mPk3r2
stat Pk3r3/mean=mPk3r3
stat Pk3w/mean=mPk3w
stat rk1/mean=mrk1
stat rk11/mean=mrk11
stat rk12/mean=mrk12
stat rk13/mean=mrk13
stat rk1w/mean=mrk1w
stat rk2/mean=mrk2
stat rk22/mean=mrk22
stat rk23/mean=mrk23
stat rk2w/mean=mrk2w
stat rk3/mean=mrk3
stat rk33/mean=mrk33
stat rk3w/mean=mrk3w
stat wk/mean=mwk
stat wkk/mean=mwkk

* Create quadratic terms in Mat equation
genr pm11=0.5*Pm1*Pm1
```

```
genr pm12=pm1*pm2
genr pm13=pm1*pm3
genr pm1r1=pm1*rm1
genr pm1r2=pm1*rm2
genr pm1r3=pm1*rm3
genr pm1w=pm1*wm
genr pm22=0.5*pm2*pm2
genr pm23=pm2*pm3
genr pm2r1=pm2*rm1
genr pm2r2=pm2*rm2
genr pm2r3=pm2*rm3
genr pm2w=pm2*wm
genr pm33=0.5*pm3*pm3
genr pm3r1=pm3*rm1
genr pm3r2=pm3*rm2
genr pm3r3=pm3*rm3
genr pm3w=pm3*wm
genr rm11=0.5*rm1*rm1
genr rm12=rm1*rm2
genr rm13=rm1*rm3
genr rm1w=rm1*wm
genr rm22=0.5*rm2*rm2
genr rm23=rm2*rm3
genr rm2w=rm2*wm
genr rm33=0.5*rm3*rm3
genr rm3w=rm3*wm
genr Wmm=0.5*wm*wm

stat Pm1/mean=mPm1
stat Pm11/mean=mPm11
stat Pm12/mean=mPm12
stat Pm13/mean=mPm13
stat Pm1r1/mean=mPm1r1
stat Pm1r2/mean=mPm1r2
stat Pm1r3/mean=mPm1r3
stat Pm1w/mean=mPm1w
stat Pm2/mean=mPm2
stat Pm22/mean=mPm22
stat Pm23/mean=mPm23
stat Pm2r1/mean=mPm2r1
stat Pm2r2/mean=mPm2r2
stat Pm2r3/mean=mPm2r3
stat Pm2w/mean=mPm2w
stat Pm3/mean=mPm3
stat Pm33/mean=mPm33
stat Pm3r1/mean=mPm3r1
stat Pm3r2/mean=mPm3r2
stat Pm3r3/mean=mPm3r3
```

```
stat Pm3w/mean=mPm3w
stat rm1/mean=mrm1
stat rm11/mean=mrm11
stat rm12/mean=mrm12
stat rm13/mean=mrm13
stat rm1w/mean=mrm1w
stat rm2/mean=mrm2
stat rm22/mean=mrm22
stat rm23/mean=mrm23
stat rm2w/mean=mrm2w
stat rm3/mean=mrm3
stat rm33/mean=mrm33
stat rm3w/mean=mrm3w
stat wm/mean=mwm
stat wmm/mean=mwmm

* Create quadratic terms in Labor equation
genr p11=0.5*p1*p1
genr p12=p1*p2
genr p13=p1*p3
genr p1r1=p1*r1
genr p1r2=p1*r2
genr p1r3=p1*r3
genr p1w0=p1*w0
genr p22=0.5*p2*p2
genr p23=p2*p3
genr p2r1=p2*r1
genr p2r2=p2*r2
genr p2r3=p2*r3
genr p2w0=p2*w0
genr p33=0.5*p3*p3
genr p3r1=p3*r1
genr p3r2=p3*r2
genr p3r3=p3*r3
genr p3w0=p3*w0
genr r11=0.5*r1*r1
genr r12=r1*r2
genr r13=r1*r3
genr r1w0=r1*w0
genr r22=0.5*r2*r2
genr r23=r2*r3
genr r2w0=r2*w0
genr r33=0.5*r3*r3
genr r3w0=r3*w0
genr W00=0.5*w0*w0

* compute means
```

```
stat p1/mean=mp1
stat p11/mean=mp11
stat p12/mean=mp12
stat p13/mean=mp13
stat p1r1/mean=mp1r1
stat p1r2/mean=mp1r2
stat p1r3/mean=mp1r3
stat p1w0/mean=mp1w0
stat p2/mean=mp2
stat p22/mean=mp22
stat p23/mean=mp23
stat p2r1/mean=mp2r1
stat p2r2/mean=mp2r2
stat p2r3/mean=mp2r3
stat p2w0/mean=mp2w0
stat p3/mean=mp3
stat p33/mean=mp33
stat p3r1/mean=mp3r1
stat p3r2/mean=mp3r2
stat p3r3/mean=mp3r3
stat p3w0/mean=mp3w0
stat r1/mean=mr1
stat r11/mean=mr11
stat r12/mean=mr12
stat r13/mean=mr13
stat r1w0/mean=mr1w0
stat r2/mean=mr2
stat r22/mean=mr22
stat r23/mean=mr23
stat r2w0/mean=mr2w0
stat r3/mean=mr3
stat r33/mean=mr33
stat r3w0/mean=mr3w0
stat w0/mean=mw0
stat w00/mean=mw00
genr x1x1=0.5*x1*x1
genr x1x2=x1*x2
genr x1x3=x1*x3
genr x2x2=0.5*x2*x2
genr x2x3=x2*x3
genr x3x3=0.5*x3*x3
* Create cross-section dummy variables.
stat x1/mean=mx1
stat x1x1/mean=mx1x1
stat x1x2/mean=mx1x2
stat x1x3/mean=mx1x3
stat x2/mean=mx2
stat x2x2/mean=mx2x2
```

```
stat x2x3/mean=mx2x3
stat x3/mean=mx3
stat x3x3/mean=mx3x3
STAT T/MEAN=MT
STAT T2/MEAN=MT2
* Create cross-section dummy variables.
GEN1 NC=48
MATRIX CSDUM=SEAS(1872,-NC)
DO #=1,NC
   GENR D#=CSDUM:#
ENDO
STAT D1-D48/mean=MD1-MD48

****//Estimate system of equations and caculate input demand value
system 3/ dn noconstant
ols x2 D1-D48  t t2  pm1 pm2 pm3 rm1 rm2 rm3 wm  &
            pm11 pm12 pm13 pm1r1 pm1r2 pm1r3 pm1w &
               pm22 pm23 pm2r1 pm2r2 pm2r3 pm2w &
                  pm33 pm3r1 pm3r2 pm3r3 pm3w &
                     rm11  rm12  rm13 rm1w &
                        rm22  rm23 rm2w &
                           rm33 rm3w &
                              wmm
ols x1 D1-D48 t t2  pk1 pk2 pk3 rk1 rk2 rk3 wk  &
            pk11 pk12 pk13 pk1r1 pk1r2 pk1r3 pk1w &
               pk22 pk23 pk2r1 pk2r2 pk2r3 pk2w &
                  pk33 pk3r1 pk3r2 pk3r3 pk3w &
                     rk11  rk12  rk13 rk1w &
                        rk22  rk23 rk2w &
                           rk33 rk3w &
                              wkk

ols x3 D1-D48  t t2  p1 p2 p3 r1 r2 r3 w0  &
            p11 p12 p13 p1r1 p1r2 p1r3 p1w0 &
               p22 p23 p2r1 p2r2 p2r3 p2w0 &
                  p33 p3r1 p3r2 p3r3 p3w0 &
                     r11  r12  r13 r1w0 &
                        r22  r23 r2w0 &
                           r33 r3w0 &
                              w00

*************************************************
********//* Propostion 1: XHAT>=0*******************
*************************************************
test (D1:2+D2:2+D3:2+D4:2+D5:2+D6:2+D7:2+D8:2+D9:2+D10:2+D11:2+D12:2 &
+D13:2+D14:2+D15:2+D16:2+D17:2+D18:2+D19:2+D20:2 &
+D21:2+D22:2+D23:2+D24:2+D25:2+D26:2+D27:2+D28:2+D29:2+D30:2 &
+D31:2+D32:2+D33:2+D34:2+D35:2+D36:2+D37:2+D38:2+D39:2+D40:2 &
```

```
+D41:2+D42:2+D43:2+D44:2+D45:2+D46:2+D47:2+D48:2)*1/48 &
+T:2*MT+T2:2*MT2+pk1:2*mpk1+pk2:2*mpk2+pk3:2*mpk3+rk1:2*mrk1 &
+rk2:2*mrk2+rk3:2*mrk3+wk:2*mwk +pk11:2*mpk11+ pk22:2*mpk22 &
+ pk33:2*mpk33+ rk11:2*mrk11+ rk22:2*mrk22+ rk33:2*mrk33+ wkk:2*mwkk &
+pk12:2*mpk12+ pk13:2*mpk13+ pk1r1:2*mpk1r1+ pk1r2:2*mpk1r2 &
+pk1r3:2*mpk1r3 +pk1w:2*mpk1w+pk23:2*mpk23+ pk2r1:2*mpk2r1 &
+ pk2r2:2*mpk2r2+ pk2r3:2*mpk2r3+pk2w:2*mpk2w+ pk3r1:2*mpk3r1 &
+pk3r2:2*mpk3r2+pk3r3:2*mpk3r3+pk3w:2*mpk3w+rk12:2*mrk12 &
+rk13:2*mrk13+rk1w:2*mrk1w+rk23:2*mrk23+rk2w:2*mrk2w+rk3w:2*mrk3w

test (D1:1+ D2:1+ D3:1+ D4:1+ D5:1+ D6:1+ D7:1+ D8:1+D9:1+D10:1 &
   +D11:1+D12:1+D13:1+D14:1+D15:1+D16:1+D17:1+D18:1+D19:1+D20:1 &
   +D21:1+D22:1+D23:1+D24:1+D25:1+D26:1+D27:1+D28:1+D29:1+D30:1 &
   +D31:1+D32:1+D33:1+D34:1+D35:1+D36:1+D37:1+D38:1+D39:1+D40:1 &
   +D41:1+D42:1+D43:1+D44:1+D45:1+D46:1+D47:1+D48:1)*1/48 &
+T:1*MT+T2:1*MT2+pm1:1*mpm1+pm2:1*mpm2+pm3:1*mpm3+rm1:1*mrm1 &
+rm2:1*mrm2+rm3:1*mrm3+wm:1*mwm+pm11:1*mpm11+ pm22:1*mpm22 &
+ pm33:1*mpm33 + rm11:1*mrm11+ rm22:1*mrm22+ rm33:1*mrm33 &
+ wmm:1*mwmm +pm12:1*mpm12+ pm13:1*mpm13+ pm1r1:1*mpm1r1 &
+ pm1r2:1*mpm1r2+pm1r3:1*mpm1r3+ pm1w:1*mpm1w+pm23:1*mpm23 &
+ pm2r1:1*pm2r1+ pm2r2:1*mpm2r2+ pm2r3:1*mpm2r3+pm2w:1*mpm2w &
+ pm3r1:1*mpm3r1+pm3r2:1*mpm3r2+pm3r3:1*mpm3r3+pm3w:1*mpm3w &
+rm12:1*mrm12+rm13:1*mrm13+rm1w:1*mrm1w &
+rm23:1*mrm23+rm2w:1*mrm2w+rm3w:1*mrm3w

test ( D1:3+ D2:3+D3:3+ D4:3+ D5:3+  D6:3+ D7:3+ D8:3+ D9:3+D10:3 &
  +D11:3+D12:3+D13:3+D14:3+D15:3+D16:3+D17:3+D18:3+D19:3+D20:3 &
  +D21:3+D22:3+D23:3+D24:3+D25:3+D26:3+D27:3+D28:3+D29:3+D30:3 &
  +D31:3+D32:3+D33:3+D34:3+D35:3+D36:3+D37:3+D38:3+D39:3+D40:3 &
  +D41:3+D42:3+D43:3+D44:3+D45:3+D46:3+D47:3+D48:3)*1/48 &
+T:3*MT+T2:3*MT2+p1:3*mp1+p2:3*mp2+p3:3*mp3+r1:3*mr1+r2:3*mr2 &
+r3:3*mr3+w0:3*mw0 +p11:3*mp11+ p22:3*mp22+ p33:3*mp33 &
+ r11:3*mr11+ r22:3*mr22+ r33:3*mr33+w00:3*mw00 &
+p12:3*mp12+ p13:3*mp13+ p1r1:3*mp1r1+ p1r2:3*mp1r2+p1r3:3*mp1r3 &
+ p1w0:3*mp1w0 +p23:3*mp23+ p2r1:3*mp2r1+ p2r2:3*mp2r2 &
+ p2r3:3*mp2r3+p2w0:3*mp2w0+ p3r1:3*mp3r1+p3r2:3*mp3r2+p3r3:3*mp3r3 &
+p3w0:3*mp3w0+r12:3*mr12+r13:3*mr13+r1w0:3*mr1w0 &
+r23:3*mr23+r2w0:3*mr2w0+r3w0:3*mr3w0

*************************************************************
***************Proposition 2.1 diag(-omiga)<=0**********-*********
*************************************************************
test (2*(rm2:1+rm22:1*mrm2+pm1r2:1*mpm1+pm2r2:1*mpm2 &
+pm3r2:1*mpm3+rm12:1*mrm1+rm23:1*mrm3+rm2w:1*mwm) &
+mx2*(wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3))

test (2*(rk1:2+rk11:2*mrk1+pk1r1:2*mpk1+pk2r1:2*mpk2+pk3r1:2*mpk3 &
```

```
+rk12:2*mrk2+rk13:2*mrk3+rk1w:2*mwk) +mx1*(wk:2+wkk:2*mwk+pk1w:2*mpk1&
+pk2w:2*mpk2+pk3w:2*mpk3+rk1w:2*mrk1+rk2w:2*mrk2+rk3w:2*mrk3))

test (2*(r3:3+r33:3*mr3+p1r3:3*mp1+p2r3:3*mp2+p3r3:3*mp3+r13:3*mr1 &
+r23:3*mr2+r3w0:3*mw0) +mx3*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2&
+p3w0:3*mp3+r1w0:3*mr1+r2w0:3*mr2+r3w0:3*mr3))

************************************************************
********* Propostion 2.2: second order principal of (-Omiga)>>0********
************************************************************
test ((2*(rk1:2+rk11:2*mrk1+pk1r1:2*mpk1+pk2r1:2*mpk2+pk3r1:2*mpk3 &
+rk12:2*mrk2+rk13:2*mrk3+rk1w:2*mwk) &
+mx1*(wk:2+wkk:2*mwk+pk1w:2*mpk1+pk2w:2*mpk2+pk3w:2*mpk3 &
+rk1w:2*mrk1+rk2w:2*mrk2+rk3w:2*mrk3))* &
(2*(rm2:1+rm22:1*mrm2+pm1r2:1*mpm1+pm2r2:1*mpm2+pm3r2:1*mpm3 &
+rm12:1*mrm1+rm23:1*mrm3+rm2w:1*mwm) &
+mx2*(wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3)) &
-(2*(rk2:2+rk22:2*mrk2+pk1r2:2*mpk1+pk2r2:2*mpk2+pk3r2:2*mpk3 &
+rk12:2*mrk1+rk23:2*mrk3+rk2w:2*mwk) &
+mx2*(wk:2+wkk:2*mwk+pk1w:2*mpk1+pk2w:2*mpk2+pk3w:2*mpk3 &
+rk1w:2*mrk1+rk2w:2*mrk2+rk3w:2*mrk3))*&
(2*(rm1:1+rm11:1*mrm1+pm1r1:1*mpm1+pm2r1:1*mpm2+pm3r1:1*mpm3 &
+rm12:1*mrm2+rm13:1*mrm3+rm1w:1*mwm) &
+mx1*(wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3)))

************************************************************
***************Determinant of (-Omiga)<=0***********************
*************************************************___*********
test ((2*(rk1:2+rk11:2*mrk1+pk1r1:2*mpk1+pk2r1:2*mpk2+pk3r1:2*mpk3 &
+rk12:2*mrk2+rk13:2*mrk3+rk1w:2*mwk) &
+mx1*(wk:2+wkk:2*mwk+pk1w:2*mpk1+pk2w:2*mpk2+pk3w:2*mpk3 &
+rk1w:2*mrk1+rk2w:2*mrk2+rk3w:2*mrk3))&
*(((2*(rm2:1+rm22:1*mrm2+pm1r2:1*mpm1+pm2r2:1*mpm2+pm3r2:1*mpm3 &
+rm12:1*mrm1+rm23:1*mrm3+rm2w:1*mwm)&
+mx2*(wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3)) &
*(2*(r3:3+r33:3*mr3+p1r3:3*mp1+p2r3:3*mp2+p3r3:3*mp3+r13:3*mr1 &
+r23:3*mr2+r3w0:3*mw0) &
+mx3*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2+p3w0:3*mp3 &
+r1w0:3*mr1+r2w0:3*mr2+r3w0:3*mr3))) &
-(2*(rm3:1+rm33:1*mrm3+pm1r3:1*mpm1+pm2r3:1*mpm2+pm3r3:1*mpm3 &
+rm13:1*mrm1+rm23:1*mrm2+rm3w:1*mwm) &
+mx3*(wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3))* &
(2*(r2:3+r22:3*mr2+p1r2:3*mp1+p2r2:3*mp2+p3r2:3*mp3+r12:3*mr1 &
+r23:3*mr3+r2w0:3*mw0) &
```

```
+mx2*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2+p3w0:3*mp3+r1w0:3*mr1 &
+r2w0:3*mr2+r3w0:3*mr3))) &
- (2*(rm1:1+rm11:1*mrm1+pm1r1:1*mpm1+pm2r1:1*mpm2+pm3r1:1*mpm3 &
+rm12:1*mrm2+rm13:1*mrm3+rm1w:1*mwm)&
+mx1*(wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3)) &
*((2*(rk2:2+rk22:2*mrk2+pk1r2:2*mpk1+pk2r2:2*mpk2+pk3r2:2*mpk3 &
+rk12:2*mrk1+rk23:2*mrk3+rk2w:2*mwk) &
+mx2*(wk:2+wkk:2*mwk+pk1w:2*mpk1+pk2w:2*mpk2+pk3w:2*mpk3 &
+rk1w:2*mrk1+rk2w:2*mrk2+rk3w:2*mrk3))* &
(2*(r3:3+r33:3*mr3+p1r3:3*mp1+p2r3:3*mp2+p3r3:3*mp3+r13:3*mr1+r23:3*mr2 &
+r3w0:3*mw0)&
+mx3*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2+p3w0:3*mp3+r1w0:3*mr1 &
+r2w0:3*mr2+r3w0:3*mr3)))&
-(2*(rk3:2+rk33:2*mrk3+pk1r3:2*mpk1+pk2r3:2*mpk2+pk3r3:2*mpk3 &
+rk13:2*mrk1+rk23:2*mrk2+rk3w:2*mwk) &
+mx3*(wk:2+wkk:2*mwk+pk1w:2*mpk1+pk2w:2*mpk2+pk3w:2*mpk3 &
+rk1w:2*mrk1+rk2w:2*mrk2+rk3w:2*mrk3))*&
(2*(r2:3+r22:3*mr2+p1r2:3*mp1+p2r2:3*mp2+p3r2:3*mp3+r12:3*mr1+r23:3*mr3 &
+r2w0:3*mw0)&
+mx2*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2+p3w0:3*mp3+r1w0:3*mr1 &
+r2w0:3*mr2+r3w0:3*mr3)) &
+(2*(r1:3+r11:3*mr1+p1r1:3*mp1+p2r1:3*mp2+p3r1:3*mp3+r12:3*mr2+r13:3*mr3 &
+r1w0:3*mw0)&
+mx1*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2+p3w0:3*mp3+r1w0:3*mr1 &
+r2w0:3*mr2+r3w0:3*mr3))* &
((2*(rk2:2+rk22:2*mrk2+pk1r2:2*mpk1+pk2r2:2*mpk2+pk3r2:2*mpk3&
+rk12:2*mrk1 +rk23:2*mrk3+rk2w:2*mwk) &
+mx2*(wk:2+wkk:2*mwk+pk1w:2*mpk1+pk2w:2*mpk2+pk3w:2*mpk3 &
+rk1w:2*mrk1+rk2w:2*mrk2+rk3w:2*mrk3))&
*(2*(rm3:1+rm33:1*mrm3+pm1r3:1*mpm1+pm2r3:1*mpm2+pm3r3:1*mpm3 &
+rm13:1*mrm1+rm23:1*mrm2+rm3w:1*mwm) &
+mx3*(wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3))&
 -(2*(rk3:2+rk33:2*mrk3+pk1r3:2*mpk1+pk2r3:2*mpk2+pk3r3:2*mpk3 &
+rk13:2*mrk1+rk23:2*mrk2+rk3w:2*mwk) &
+mx3*(wk:2+wkk:2*mwk+pk1w:2*mpk1+pk2w:2*mpk2+pk3w:2*mpk3 &
+rk1w:2*mrk1+rk2w:2*mrk2+rk3w:2*mrk3))* &
(2*(rm2:1+rm22:1*mrm2+pm1r2:1*mpm1+pm2r2:1*mpm2+pm3r2:1*mpm3 &
+rm12:1*mrm1+rm23:1*mrm3+rm2w:1*mwm)&
+mx2*(wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3))))

**********test Symmetry of omiga**********
test

test (2*(rm2:1+rm22:1*mrm2+pm1r2:1*mpm1+pm2r2:1*mpm2+pm3r2:1*mpm3 &
+rm12:1*mrm1+rm23:1*mrm3+rm2w:1*mwm) &
```

```
+mx2*(wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3))&
-(2*(rk1:2+rk11:2*mrk1+pk1r1:2*mpk1+pk2r1:2*mpk2+pk3r1:2*mpk3 &
+rk12:2*mrk2+rk13:2*mrk3+rk1w:2*mwm)&
+mx1*(wk:2+wkk:2*mwk+pk1w:2*mpk1+pk2w:2*mpk2+pk3w:2*mpk3 &
+rk1w:2*mrk1+rk2w:2*mrk2+rk3w:2*mrk3))

test (2*(rm3:1+rm33:1*mrm3+pm1r3:1*mpm1+pm2r3:1*mpm2+pm3r3:1*mpm3 &
+rm13:1*mrm1+rm23:1*mrm2+rm3w:1*mwm) &
+mx3*(wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3))&
-(2*(r1:3+r11:3*mr1+p1r1:3*mp1+p2r1:3*mp2+p3r1:3*mp3+r12:3*mr2 &
+r13:3*mr3+r1w0:3*mw0)&
+mx1*(w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2+p3w0:3*mp3+r1w0:3*mr1 &
+r2w0:3*mr2+r3w0:3*mr3))

test (2*(rk3:2+rk33:2*mrk3+pk1r3:2*mpk1+pk2r3:2*mpk2+pk3r3:2*mpk3 &
+rk13:2*mrk1+rk23:2*mrk2+rk3w:2*mwk) &
+mx3*(wk:2+wkk:2*mwk+pk1w:2*mpk1+pk2w:2*mpk2+pk3w:2*mpk3 &
+rk1w:2*mrk1+rk2w:2*mrk2+rk3w:2*mrk3))&
-(2*(r2:3+r22:3*mr2+p1r2:3*mp1+p2r2:3*mp2+p3r2:3*mp3+r12:3*mr1 &
+r23:3*mr3+r2w0:3*mw0) +mx2*(w0:3+w00:3*mw0+p1w0:3*mp1 &
+p2w0:3*mp2+p3w0:3*mp3+r1w0:3*mr1+r2w0:3*mr2+r3w0:3*mr3))
end

*********test corollary**********
test

test (wk:2+wkk:2*mwk+pk1w:2*mpk1+pk2w:2*mpk2+pk3w:2*mpk3+rk1w:2*mrk1 &
+rk2w:2*mrk2+rk3w:2*mrk3)

test (wm:1+wmm:1*mwm+pm1w:1*mpm1+pm2w:1*mpm2+pm3w:1*mpm3 &
+rm1w:1*mrm1+rm2w:1*mrm2+rm3w:1*mrm3)

test (w0:3+w00:3*mw0+p1w0:3*mp1+p2w0:3*mp2+p3w0:3*mp3+r1w0:3*mr1 &
+r2w0:3*mr2+r3w0:3*mr3)
end

end
stop
```

(c) Shazam program for testing hypothesis using Saha and Shumway (1998)' data

```
sample 1 107
read (e:\ksfarm.txt) id year W0 q p x1 r1 x2 r2

* Create quadratic terms
genr pP=0.5*p*p
```

```
GENR PR1 = P*R1
GENR PR2 = p*R2
genr pw0=p*w0
genr r11=0.5*r1*r1
genr r12=r1*r2
genr r1w0=r1*w0
genr r22=0.5*r2*r2
genr r2w0=r2*w0
genr W00=0.5*w0*w0
GENR ONE = 1
* compute means
stat p/mean=mp
stat pP/mean=mpP
stat pr1/mean=mpr1
stat pr2/mean=mpr2
stat pw0/mean=mpw0
stat r1/mean=mr1
stat r11/mean=mr11
stat r12/mean=mr12
stat r1w0/mean=mr1w0
stat r2/mean=mr2
stat r22/mean=mr22
stat r2w0/mean=mr2w0
stat x1/mean=mx1
stat x2/mean=mx2
stat w0/mean=mw0
stat w00/mean=mw00

** Estimate system of equations and caculate input demand value **
system 2/ dn noconstant
ols x1 ONE p r1 r2 w0  pP pR1 pr2 pw0  r11  r12  r1w0 r22 r2w0 w00
ols x2 ONE p r1 r2 w0  pP pR1 pr2 pw0  r11  r12  r1w0 r22 r2w0 w00

**************************************************
********//* Propostion 1: XHAT>=0*****************
**************************************************
test ONE:1 + p:1*mp+r1:1*mr1+r2:1*mr2+w0:1*mw0 +pP:1*mpP+r11:1*mr11 &
        + r22:1*mr22+ w00:1*mw00+pr1:1*mpr1+ pr2:1*mpr2+pw0:1*mpw0 &
        +r12:1*mr12+r1w0:1*mr1w0 + r2w0:1*mr2w0

test ONE:2 + p:2*mp+r1:2*mr1+r2:2*mr2+w0:2*mw0 +pP:2*mpP+r11:2*mr11 &
        + r22:2*mr22+ w00:2*mw00 +pr1:2*mpr1+ pr2:2*mpr2+pw0:2*mpw0 &
        +r12:2*mr12+r1w0:2*mr1w0 + r2w0:2*mr2w0

***********Proposition 2.1 diag(-omiga)<=0****
**********fist diagonal element of omiga***********

test (2*(r1:1+r11:1*mr1+pr1:1*mp+r12:1*mr2+r1w0:1*mw0)&
```

```
 +mx1*(w0:1+w00:1*mw0+pw0:1*mp+r1w0:1*mr1+r2w0:1*mr2))

***********************************************************
**Propostion 2.2: second order principal of (-Omiga)>>0**

test ((2*(r1:1+r11:1*mr1+pr1:1*mp+r12:1*mr2+r1w0:1*mw0)&
  +mx1*(w0:1+w00:1*mw0+pw0:1*mp+r1w0:1*mr1+r2w0:1*mr2))* &
     (2*(r2:2+r22:2*mr2+pr2:2*mp+r12:2*mr1+r2w0:2*mw0) &
+mx2*(w0:2+w00:2*mw0+pw0:2*mp+r1w0:2*mr1+r2w0:2*mr2)) &
  -(2*(r2:1+r22:1*mr2+pr2:1*mp+r12:1*mr1+r2w0:1*mw0) &
+mx2*(w0:1+w00:1*mw0+pw0:1*mp+r1w0:1*mr1+r2w0:1*mr2))*&
     (2*(r1:2+r11:2*mr1+pr1:2*mp+r12:2*mr2+r1w0:2*mw0)&
+mx1*(w0:2+w00:2*mw0+pw0:2*mp+r1w0:2*mr1+r2w0:2*mr2)))

**********test Symmetry of omiga**********
test (2*(r2:1+r22:1*mr2+pr2:1*mp+r12:1*mr1+r2w0:1*mw0) &
+mx2*(w0:1+w00:1*mw0+pw0:1*mp+r1w0:1*mr1+r2w0:1*mr2))&
   -(2*(r1:2+r11:2*mr1+pr1:2*mp+r12:2*mr2+r1w0:2*mw0)&
    +mx1*(w0:2+w00:2*mw0+pw0:2*mp+r1w0:2*mr1+r2w0:2*mr2))

**********test corollary**********
test
test (w0:1+w00:1*mw0+pw0:1*mp+r1w0:1*mr1+r2w0:1*mr2)
test (w0:2+w00:2*mw0+pw0:2*mp+r1w0:2*mr1+r2w0:2*mr2)
end
************************************************
********//* caculate XHAT***********************
************************************************
genr x1hat=  p:1*p+r1:1*r1+r2:1*r2+w0:1*w0 &
          +pP:1*pP+ r11:1*r11+ r22:1*r22+ w00:1*w00 &
          + pr1:1*pr1+ pr2:1*pr2+pw0:1*pw0 &
          +r12:1*r12+r1w0:1*r1w0 &
          +r2w0:1*r2w0
genr x2hat= p:2*p+r1:2*r1+r2:2*r2+w0:2*w0 &
          +pP:2*pP+ r11:2*r11+ r22:2*r22+ w00:2*w00 &
          + pr1:2*pr1+ pr2:2*pr2+ pw0:2*pw0 &
          +r12:2*r12+r1w0:2*r1w0 &
         +r2w0:2*r2w0
print x1hat x2hat

***************Proposition 2.1 DIAG(-omiga)<=0*******
*********fist diagonal element of omiga***************

genr omig11=(2*(r1:1+r11:1*r1+pr1:1*p+r12:1*r2+r1w0:1*w0)&
 +x1*(w0:1+w00:1*w0+pw0:1*p+r1w0:1*r1+r2w0:1*r2))
genr omig22=(2*(r2:2+r22:2*r2+pr2:2*p+r12:2*r1+r2w0:2*w0) &
 +x2*(w0:2+w00:2*w0+pw0:2*p+r1w0:2*r1+r2w0:2*r2))
print omig11 omig22
```

```
***************second order principal component***********
genr p2= ((2*(r1:1+r11:1*r1+pr1:1*p+r12:1*r2+r1w0:1*w0)&
     +x1*(w0:1+w00:1*w0+pw0:1*p+r1w0:1*r1+r2w0:1*r2))* &
      (2*(r2:2+r22:2*r2+pr2:2*p+r12:2*r1+r2w0:2*w0) &
        +x2*(w0:2+w00:2*w0+pw0:2*p+r1w0:2*r1+r2w0:2*r2)) &
  -(2*(r2:1+r22:1*r2+pr2:1*p+r12:1*r1+r2w0:1*w0) &
        +x2*(w0:1+w00:1*w0+pw0:1*p+r1w0:1*r1+r2w0:1*r2))*&
      (2*(r1:2+r11:2*r1+pr1:2*p+r12:2*r2+r1w0:2*w0)&
       +x1*(w0:2+w00:2*w0+pw0:2*p+r1w0:2*r1+r2w0:2*r2)))
print p2
end
stop
```

APPENDIX B

COMPUTER PROGRAMS FOR CHAPTER 3

APPENDIX B

COMPUTER PROGRAMS FOR CHAPTER 3

I Stata program for unit root tests

```
/* all variables are in logarithm form */
Set memory 5000
use "E:\Induced Innovation\program\IIH.dta"
tsset state year
hadrilm R1
hadrilm R2
hadrilm P1
hadrilm P2
hadrilm Rpri
hadrilm Rpub
hadrilm Ext
hadrilm Size

Set memory 5000
use "E:\Induced Innovation\program\IIHPri.dta"
tsset state year
hadrilm Rpri

Set memory 5000
use "E:\Induced Innovation\program\IIHPub.dta"
tsset state year
hadrilm Rpub

Set memory 5000
use "E:\Induced Innovation\program\IIHExt.dta"
tsset state year
hadrilm Ext
```

II Rats program for panel cointegration tests

```
calendar( panelobs=39 ) 1961:01
allocate 48//1999:01
```

```
open data "e:\IIH_coint.xls"
data(for=xls,org=col) / R1 dR2 P1 P2 dfs Rpri13 Rpub16 dext3
@pancoint( mlag=3,block=39,trend,notdum,unweightd )
# R1 P1 P2 dfs Rpri13 Rpub16 dext3

calendar( panelobs=39 ) 1961:01
allocate 48//1999:01
open data "e:\IIH_coint.xls"
data(for=xls,org=col) / P1 dx2 P1 P2 dfs Rpri13 Rpub16 dext3
@pancoint( mlag=3,block=39,trend,notdum,unweightd )
# dR2 P1 P2 dfs Rpri13 Rpub16 dext3
```

III Rats program for testing IIH using A&F (2003) method

```
dis ' '
display '**************** ln(A/M) ******************'
display '** nt = f(research activities) **  '
dis '** OLS ** '
calendar( panelobs=39 )
allocate 48//39
open data "e:\IIH_estimate_funk.xls"
data(for=xls,org=col) / state year x1 r1 F1 sumrpri13 sumrpub16 sumext3
linreg x1
# constant r1 f1 sumrpri13 sumrpub16 sumext3
set resnew = log(%resids**2)
linreg resnew
# constant r1 f1 sumrpri13 sumrpub16 sumext3
cdf(title='Breusch-Pagan Test') chisqr %trsquared 4

display ' *** Robusterrors for heter. and Auto.*** '
**
display ' *** Strong Test of IIH*** '

linreg(vcv,robusterrors,lags=3,lwindow=neweywest) x1
# constant r1 f1 sumrpri13 sumrpub16 sumext3
restrict 1
# 2 3
# 1.0 1.0 -1.0

display ' *** Weak Test of IIH*** '
 compute [vect] cbeta = || 0, -0.000914325, -2.591403424, 0, 0, 0 ||
 declare symmetric varb
```

```
compute varb = || 0.008196 | 0.002955,0.002051 | 1.318409e-06,8.923053e-
08,9.842141e-10 | -2.526354e-05,-1.504662e-05,-6.133362e-09,5.573128e-07 |
8.074574e-05,1.601437e-05,3.286839e-08,-2.753683e-07,7.027452e-06 | $
-9.204124e-05,-1.861684e-05,-3.335994e-08,2.283829e-07,-7.330213e-06,7.677319e-06
||
 declare real varcbeta
compute varcbeta=%QFORM(varb,cbeta)
com secbeta=sqrt(varcbeta)
compute tweak=0.00035283/secbeta
com pvalue = %ttest(tweak,1866)
display 'Statistic' tweak 'Standard Error' secbeta 'P-value' pvalue

dis ' '
display '**************** ln(L/K) *******************'

display '** nt = f(research activities) **  '
dis '** OLS ** '
calendar( panelobs=38 )
allocate 48//38
open data "e:\IIH_estimate_funk.xls"
data(for=xls,org=col) / state year x1 dx2 r1 r2 dF1 dF2 dsumrpri13 dsumrpub16
dsumext3
linreg dx2
# constant r2 df2 dsumrpri13 dsumrpub16 dsumext3
set resnew = log(%resids**2)
linreg resnew
# constant r2 df2 dsumrpri13 dsumrpub16 dsumext3
cdf(title='Breusch-Pagan Test') chisqr %trsquared 4

display ' *** Robusterrors for heter. *** '
**
display ' *** Strong Test of IIH*** '
linreg(vcv,robusterrors) dx2
# constant r2 df2 dsumrpri13 dsumrpub16 dsumext3
restrict 1
# 2 3
# 1.0 1.0 -1.0

display ' *** Weak Test of IIH*** '
 compute [vect] cbeta = || 0, 0.637399112, -2.080078807, 0, 0, 0 ||
 declare symmetric varb
 compute varb = || 0.0037 | -0.0001,0.0001 | -0.0001,0.00001,0.00003 | 0.00006,-
0.000004,-0.000002,0.000004 | -0.00005,-0.0000001,-0.000002,-0.000001,0.00003 | -
0.0002,0.00001,0.000006,-0.000004,-0.00003,0.00004 ||
```

```
declare real varcbeta
compute varcbeta=%QFORM(varb,cbeta)
com secbeta=sqrt(varcbeta)
compute tweak=-0.306430271/secbeta
com pvalue = %ttest(tweak,1818)
display 'Statistic' tweak 'Standard Error' secbeta 'P-value' pvalue
```

III Gams program for testing IIH and computing marginal cost using nonparametric approach (Washington State)

```
set t /1930*1999/;
set m(t) /1960*1999/;
set j /0*28/;
set x /1*5/;
set n1(x) /1/;
set n2(x) /2*5/;
set r /pub,pri,EXT/;
set m1(m) /1960*1970/
   m2(m) /1970*1980/
   m3(m) /1980*1990/
   m4(m) /1990*1999/
   j1(j) /0*7/
   j2(j) /7*14/
   j3(j) /14*21/
   j4(j) /21*28/;

alias (m,s);
table data(t,*) data matrix
            output          outp          pk          qk          pmat          Qmat          pland
qland          plabor          qlabor          PubRes          PriRes          Ext          MTPI
1930     0.0000000000     0.0000000000     0.2765462311     0.1320812889     0.4927775001
0.1337914626     0.0286997819     0.3319227520     0.1190478830     1.3474117111
0.2735440687     0.9810240198     0.0000000000     0.1923076923
1931     0.0000000000     0.0000000000     0.2578413454     0.1287956847     0.4508389895
0.1070331701     0.0257511742     0.3253500243     0.0923346995     1.3763438644
0.2559514019     1.0635924865     0.0000000000     0.1600000000
1932     0.0000000000     0.0000000000     0.2351436191     0.1222244763     0.3984158512
0.0668957313     0.0216231233     0.3154909326     0.0662022374     1.3267458873
0.2402841602     0.9838819433     0.0000000000     0.1255769231
1933     0.0000000000     0.0000000000     0.2335487637     0.1126962241     0.3669619682
0.0802748776     0.0175933594     0.3187772965     0.0662022374     1.3267458873
0.2396855154     0.7923511252     0.0000000000     0.1223076923
1934     0.0000000000     0.0000000000     0.2654818849     0.1077678178     0.4089004788
0.0936540238     0.0181830810     0.3154909326     0.0662022374     1.1903514503
0.1884876513     0.5800871816     0.0000000000     0.1284615385
```

1935 0.0000000000 0.0000000000 0.2876327865 0.1090820595 0.4089004788
0.1070331701 0.0186745156 0.3253500243 0.0789781078 1.2358162627
0.3258640419 0.5063737046 0.0000000000 0.1434615385
1936 0.0000000000 0.0000000000 0.3082458563 0.1136819054 0.3879312235
0.1337914626 0.0186745156 0.3253500243 0.0789781078 1.2027509446
0.2388451365 0.4017176511 0.0000000000 0.1432692308
1937 0.0000000000 0.0000000000 0.3062614409 0.1241958388 0.4089004788
0.1471706089 0.0192642372 0.3286363881 0.0923346995 1.2978137340
0.2439990794 0.4201096827 0.0000000000 0.1575000000
1938 0.0000000000 0.0000000000 0.2981863229 0.1284671243 0.3984158512
0.1471706089 0.0192642372 0.3319227520 0.0923346995 1.2110172741
0.3751796048 0.3869730449 0.0000000000 0.1557692308
1939 0.0000000000 0.0000000000 0.2859959139 0.1297813660 0.3984158512
0.1471706089 0.0186745156 0.3352091159 0.0923346995 1.2151504389
0.3667868079 0.5567000441 0.0000000000 0.1544230769
1940 0.0000000000 0.0000000000 0.2778661735 0.1337240910 0.3879312235
0.1739289014 0.0186745156 0.3384954798 0.0923346995 1.2110172741
0.3751744504 0.5090933905 0.0000000000 0.1525000000
1941 0.0000000000 0.0000000000 0.2691866071 0.1396381786 0.3879312235
0.1873080476 0.0186745156 0.3352091159 0.1056912913 1.1903514503
0.3837392487 0.5206047905 0.0000000000 0.1625000000
1942 0.0000000000 0.0000000000 0.2719579458 0.1616517268 0.4298697342
0.2006871939 0.0251614526 0.3286363881 0.1318237534 1.2234167684
0.3819584111 0.4201957369 0.0000000000 0.1901923077
1943 0.0000000000 0.0000000000 0.2802227418 0.1747941436 0.4613236172
0.2274454864 0.0222128449 0.3220636604 0.1846693991 1.2068841094
0.4023288221 0.3850850747 0.0000000000 0.2344230769
1944 0.0000000000 0.0000000000 0.2801639176 0.1849795166 0.4613236172
0.2675829252 0.0251614526 0.3220636604 0.2241584530 1.1944846151
0.4346287271 0.2873160704 0.0000000000 0.2632692308
1945 0.0000000000 0.0000000000 0.2732304687 0.1879365604 0.4718082448
0.2675829252 0.0275203388 0.3220636604 0.2508716365 1.1200876494
0.4919759741 0.2673911138 0.0000000000 0.2830769231
1946 0.0000000000 0.0000000000 0.2868476639 0.1780797478 0.4718082448
0.2809620715 0.0310586681 0.3352091159 0.2642282282 1.0746228371
0.5482470381 0.1806119740 0.0000000000 0.2942307692
1947 0.0000000000 0.0000000000 0.3268480999 0.1895793625 0.5242313831
0.3077203640 0.0350884320 0.3384954798 0.2903606904 1.0167585305
0.6812857874 0.2522301898 0.0000000000 0.3257692308
1948 0.0000000000 0.0000000000 0.2861163441 0.2106006418 0.6157019547
0.3528865808 0.0445865408 0.3478548097 0.3087652853 0.9795801758
0.8298335858 0.2680043787 0.0000000000 0.3521153846
1949 0.0000000000 0.0000000000 0.2823706207 0.2394970625 0.5750478945
0.3929868958 0.0377166440 0.3411763932 0.3119872287 0.9559721746
0.8841402695 0.5660502967 0.0000000000 0.3434615385
1950 0.0000000000 0.0000000000 0.2818513660 0.2673462108 0.5409262606
0.3976561342 0.0382023877 0.3419914010 0.2989341517 0.9197463932
0.6609510492 0.9212059592 0.0000000000 0.3288461538
1951 0.0000000000 0.0000000000 0.3151683847 0.2916141141 0.5945396003
0.4155781139 0.0432055712 0.3423219360 0.3175102881 0.8844056483
0.7393764628 0.7979296940 0.9279112715 0.3567307692

1952 0.0000000000 0.0000000000 0.7953075710 0.2992695641 0.6199646632
0.4210059216 0.0417085280 0.3421374062 0.3202977893 0.8646411486
0.7628171704 1.0034829136 0.8197153219 0.4465384615
1953 0.0000000000 0.0000000000 0.3323976135 0.3227699738 0.5683743155
0.4251626852 0.0570035587 0.3413584568 0.3147564393 0.8287246204
0.8024964112 0.9261935590 0.8363022788 0.3526923077
1954 0.0000000000 0.0000000000 0.3214054948 0.3364216105 0.5895844305
0.4046474365 0.0568541099 0.3398195278 0.3153378677 0.8121294407
0.7612294162 0.7759418908 0.8347546584 0.3559615385
1955 0.0000000000 0.0000000000 0.3268824708 0.3431879025 0.5388120830
0.4403732486 0.0633301178 0.3372835159 0.3187235799 0.7940555011
0.8809209720 0.7082901252 0.8789956915 0.3475000000
1956 0.0000000000 0.0000000000 0.3557142801 0.3482165794 0.5256763294
0.4555547685 0.0848512739 0.3339136524 0.3468053091 0.7442089257
0.9072023480 0.9273337081 0.9527882138 0.3659615385
1957 0.0000000000 0.0000000000 0.4059600619 0.3450484809 0.5131953868
0.4695943732 0.1400919725 0.3300133412 0.3778703492 0.6900622076
0.9503986320 0.8532133954 0.9701318904 0.3959615385
1958 0.0000000000 0.0000000000 0.4219392233 0.3435445388 0.5310377926
0.4932159528 0.1600816246 0.3262052350 0.3967403836 0.6578002220
1.1068398345 0.7993182022 1.1001931227 0.4151923077
1959 0.0000000000 0.0000000000 0.4527501586 0.3470859212 0.5227713171
0.5172032562 0.1861654707 0.3233074042 0.4172603625 0.6532700706
1.1651489700 0.7215148545 1.1090564487 0.4313461538
1960 1.3369126827 0.4810311892 0.4290587985 0.3630061396 0.5257872895
0.5158492304 0.1719393771 0.3190137706 0.3987861567 0.6319691513
1.0984327379 0.6647201240 1.0990189971 0.4180769231
1961 1.3454700688 0.4791744774 0.4810263584 0.3556607534 0.5426755322
0.5028885568 0.2416910777 0.3218136894 0.4481074890 0.5994937512
1.2476479426 0.6441992317 1.1605717713 0.4644230769
1962 1.4176043103 0.4884580365 0.4630074557 0.3499347831 0.5503958717
0.5252237404 0.2040883090 0.3229734418 0.4852038756 0.5802208229
1.2850857569 0.8257862850 1.1579228781 0.4688461538
1963 1.4959755995 0.4773177655 0.4812875019 0.3476437058 0.5563469667
0.5459902882 0.2170052906 0.3220366517 0.5176632140 0.5739318870
1.4076377140 0.7042661734 1.2194838856 0.4876923077
1964 1.5403911078 0.4618927749 0.4682303260 0.3468299770 0.5552210839
0.5418364812 0.1926065476 0.3185145440 0.5703569450 0.5592230690
1.3952841053 0.7321264106 1.1942574002 0.4976923077
1965 1.5565578599 0.4827450770 0.4878160898 0.3459101762 0.5677666356
0.5654424897 0.2161441585 0.3121433962 0.5998654344 0.5242858010
1.6418628987 0.8220736619 1.2785252386 0.5196153846
1966 1.6313555196 0.5271633371 0.5144527285 0.3455697504 0.5915710158
0.5669265695 0.2637934684 0.3036105590 0.6483436670 0.5017114838
1.6137162261 0.8444918947 1.1859142722 0.5571153846
1967 1.7031970933 0.5287344009 0.5447453765 0.3493814476 0.5920535370
0.6123448829 0.3407212698 0.2937848889 0.7541526790 0.4387215430
1.8280913816 0.7977979420 1.2704001696 0.6080769231
1968 1.6397707727 0.5488725832 0.5423950849 0.3563339464 0.6221306931
0.5713073095 0.3476103267 0.2835934213 0.7828180687 0.4313188598
1.7896378427 0.6740770420 1.1808772084 0.6278846154

1969	1.6482378378	0.5558709585	0.6019358067	0.3549730089	0.6327461599	0.5759958080	0.4753449223	0.2740962722	0.8966365278	0.4380964687	2.1024486039	0.8693038422	1.3347298283	0.6994230769
1970	1.6867880849	0.5568707264	0.6256998668	0.3504279985	0.6485085198	0.5974773503	0.5172533515	0.2662828368	0.9075968238	0.4742473535	2.0113184961	0.7663039538	1.4266205014	0.7205769231
1971	1.7871437764	0.5564422545	0.5990632281	0.3487369744	0.6679702090	0.5980574284	0.4302790088	0.2603276530	0.9122338722	0.4456768296	2.1043473910	1.0038161543	1.5135646776	0.7090384615
1972	1.8593158267	0.6471354864	0.5901843485	0.3471945275	0.7054460237	0.6300767456	0.3688515853	0.2561206330	0.9602905549	0.4246802617	2.0605273323	0.8646248166	1.4173944090	0.7248076923
1973	1.7847219143	0.9559209469	0.6494639268	0.3471945275	0.9565178986	0.6441758146	0.4736226581	0.2535457667	1.0218368328	0.4305685333	1.9153327963	1.0014381166	1.4041539347	0.8707692308
1974	1.9626332055	1.0447574670	0.9134800226	0.3593008973	1.1131764547	0.6924230192	0.9394951273	0.2525455718	0.9130769719	0.4329355132	1.1027754988	1.0819136014	1.4599129254	1.0350000000
1975	2.1465595928	0.9723457055	0.9461229622	0.3776724045	1.2706392128	0.5943220486	0.9828387766	0.2530082186	1.0045532890	0.4413193378	1.0292360493	1.1304086686	1.4634597528	1.1355769231
1976	2.2872747513	0.8712263225	0.9385498002	0.3861397792	1.2420096204	0.6788343940	0.9664772666	0.2543951138	1.0243661319	0.4831578062	1.1924214665	1.1909487653	1.5973459999	1.1257692308
1977	2.0525459733	0.9067894953	1.0383066237	0.3922827615	1.2717650957	0.6451121465	1.2526601697	0.2560373705	1.1773887269	0.4021804316	1.2820572980	1.2677709166	1.5896503126	1.2448076923
1978	2.3489233592	1.0478995947	1.1179553964	0.3935000998	1.3200172177	0.8298617415	1.4136918735	0.2573086040	1.3232449744	0.3964556045	1.3341078561	1.2007885600	1.6745406422	1.3419230769
1979	2.3597296673	1.1240247800	1.3104181684	0.4063053190	1.5278230231	0.8506003113	1.8281834604	0.2577517416	1.2477875516	0.4381666858	1.2771205235	1.1113289928	1.6177285311	1.5192307692
1980	2.4414974447	1.1594451288	1.6039434816	0.4202133802	1.6971879713	0.8048213920	2.4938385780	0.2573838538	1.2520030500	0.4621166410	1.2781071765	1.4426071196	1.9552010737	1.7521153846
1981	2.7113960852	1.2047203328	1.9280225862	0.4151560078	1.7819508657	0.8727968481	3.2338381008	0.2563435953	1.2174359625	0.4507723124	1.3377312368	1.3405399818	2.0995466693	1.9540384615
1982	2.6501822781	1.2001499652	1.9110482576	0.4077753919	1.7671535482	0.8805218970	3.0013324323	0.2548072457	1.9108854633	0.3935451539	1.3035775871	1.2674418740	2.1593090641	2.0669230769
1983	2.7439802476	1.2164318997	1.6530384628	0.3936168938	1.8240910522	0.8458639393	1.8497117630	0.2529643229	1.4269462372	0.4220665732	1.6120152816	1.1030769632	2.1111442160	1.7728846154
1984	2.7860215049	1.2548515523	2.3134704173	0.3830357389	1.8152448298	0.8755554832	3.6204864163	0.2509527848	1.6427797596	0.4205177647	1.3685235727	1.2810871656	2.1081492725	2.2001923077
1985	2.6487903551	1.2378554978	2.4704176711	0.3732748226	1.7623283360	0.8412973008	3.6500519519	0.2488816740	2.1073276927	0.3550080744	1.2977369999	1.5877893498	2.0955203116	2.3113461538

```
1986	2.6330254962	1.2425686894	2.1230967934	0.3526168333	1.6264181924
0.8527285079	2.4212164371	0.2468788454	2.1102785416	0.3446584088
1.2578087941	1.5467958169	1.9252508908	1.9984615385
1987	2.8453609769	1.1957224216	2.2800440472	0.3327342796	1.7047474704
0.8251465085	2.5693311593	0.2451163981	1.7397362248	0.3836658952
1.4307696293	1.7465207922	1.9015747700	2.0107692308
1988	3.0863373049	1.1941513577	2.5910659759	0.3241068397	1.8393708908
0.9037144521	2.9832486581	0.2437497088	2.2637226864	0.3530436567
1.4221829721	1.7909503264	2.0164848918	2.3061538462
1989	3.0763753928	1.3028404120	2.4393415926	0.3156088305	1.9949035641
0.9122116950	2.4757548038	0.2426906379	2.0761330039	0.4398912742
1.2733461612	2.5554302956	1.8677122489	2.2471153846
1990	3.4088580584	1.2894149572	2.4811245553	0.3088029943	1.9757635557
0.9426343984	2.6040634876	0.2417653443	2.1368361820	0.4692607546
1.2959047870	2.5113405099	1.8643710058	2.2763461538
1991	3.2628321674	1.4410940317	2.3492470792	0.3087137713	1.9435954744
1.0227013435	2.4128921601	0.2407749039	2.0672804570	0.4790109657
1.3537939855	2.5158533146	1.9507221313	2.1971153846
1992	3.3071853613	1.4583757342	2.2440062418	0.3024704611	1.9839664165
1.0276242358	2.1823957998	0.2395120315	3.0440114560	0.3671613228
1.3792115412	2.3921081631	2.0220967931	2.3886538462
1993	3.7993302827	1.3989609555	2.1912552514	0.2967130905	2.0822399049
1.1287773001	2.0121786869	0.2378175180	2.7050853778	0.3969874514
1.5770705518	2.2440679105	2.0617486068	2.3461538462
1994	3.7609837829	1.3712531020	2.6714981792	0.2936362383	2.1255059743
1.0972914309	3.0906031273	0.2357230658	2.2510761910	0.4536746975
1.6299891395	2.3102909907	2.0617486068	2.4765384615
1995	3.9865649378	1.4222412654	2.6231866285	0.2874070965	2.1496320353
1.2099956971	2.8965613595	0.2333112407	3.1097732324	0.4093947622
1.5638196177	2.5317429789	2.0617486068	2.6467307692
1996	4.0026476704	1.5220752325	2.7294720400	0.2812526263	2.3317033757
1.1087972461	3.2232174715	0.2306639117	2.9006845075	0.4682226804
0.0000000000	2.8703530918	2.0617486068	2.7598076923
1997	4.1054406275	1.4238123293	2.6649695913	0.2843918962	2.2950317630
1.1960899874	3.2418753338	0.2278643413	3.3412040992	0.4451577925
0.0000000000	0.0000000000	0.0000000000	2.8323076923
1998	4.1546809557	1.3923910521	2.6226643415	0.2844167868	2.2120381131
1.1985949549	3.1675309287	0.2250024110	3.5216274344	0.4233648776
0.0000000000	0.0000000000	0.0000000000	2.8075000000
1999	4.1030187654	1.3569707032	2.7668155629	0.2859366407	2.1742406176
1.2464243540	3.6618207574	0.2221084300	4.1467858597	0.4207853487
0.0000000000	0.0000000000	0.0000000000	2.9911538462
;
parameter price(x,m,j)
	res(m,j,r)
	time(m)
	jt(j)
	input(n2,m);
input('2',m)=data(m,'qk');
input('3',m)=data(m,'qmat');
input('4',m)=data(m,'qland');
```

```
input('5',m)=data(m,'qlabor');

loop(m,time(m)=ord(m)+1959;);
loop(j,jt(j)=ord(j)-1;);
loop(j,
loop(m,
price('1',m,j)=sum(t$(ord(t)=ord(m)+31-ord(j)),data(t,'outp'));
price('2',m,j)=sum(t$(ord(t)=ord(m)+31-ord(j)),data(t,'pk')/data(t,'MTPI'));
price('3',m,j)=sum(t$(ord(t)=ord(m)+31-ord(j)),data(t,'pmat')/data(t,'MTPI'));
price('4',m,j)=sum(t$(ord(t)=ord(m)+31-ord(j)),data(t,'pland')/data(t,'MTPI'));
price('5',m,j)=sum(t$(ord(t)=ord(m)+31-ord(j)),data(t,'plabor')/data(t,'MTPI'));
res(m,j,'pub')=sum(t$(ord(t)=ord(m)+31-ord(j)),data(t,'PubRes'));
res(m,j,'pri')=sum(t$(ord(t)=ord(m)+31-ord(j)),data(t,'PriRes'));
res(m,j,'EXT')=sum(t$(ord(t)=ord(m)+31-ord(j)),data(t,'EXT'));
);
);
display price;
variables alpha(x,m)
        beta(x,j,r)
        gamma(x,j,r)
        a(x,m)
        obj
        aa1
        aa2
        aa3
        aa4
        ba1
        ba2
        ba3
        ba4
        ab1
        ab2
        ab3
        ab4
        bb1
        bb2
        bb3
        bb4
        ag1
        ag2
        ag3
        ag4
        bg1
        bg2
```

```
        bg3
        bg4
        ;
equations object
        constraint(m,s)
        conInp(n2,m)
        conOut(n1,m)
        conout2(n1,m)
        bound1(n1,m)
        bound2(n2,m)
        bound3(n2,m,j,r)
        bound4(n1,m,j,r)
        conal1(n2,m1)
        conal2(n2,m2)
        conal3(n2,m3)
        conal4(n2,m4)
        conbeta1(x,j1,r)
        conbeta2(x,j2,r)
        conbeta3(x,j3,r)
        conbeta4(x,j4,r)
        congamma1(x,j1,r)
        congamma2(x,j2,r)
        congamma3(x,j3,r)
        congamma4(x,j4,r)
        congamma5(n2,j,r)
        ;
object..obj=e=-
sum(x,sum(m,alpha(x,m)**2)+sum(j,sum(r,beta(x,j,r)**2+gamma(x,j,r)**2)));

        constraint(m,s)..(data(m,'output')-a('1',m))*data(m,'outp')-
(data(m,'qk')+a('2',m))*data(m,'pk')-(data(m,'Qmat')+a('3',m))*data(m,'Pmat')-
(data(m,'qland')+a('4',m))*data(m,'pland')-(data(m,'qlabor')+a('5',m))*data(m,'plabor')
          =g=(data(s,'output')-a('1',s))*data(m,'outp')-(data(s,'qk')+a('2',s))*data(m,'pk')-
(data(s,'Qmat')+a('3',s))*data(m,'Pmat')-(data(s,'qland')+a('4',s))*data(m,'pland')-
(data(s,'qlabor')+a('5',s))*data(m,'plabor');
        coninp(n2,m)..a(n2,m)=e=alpha(n2,m)+sum(j,sum(r,(beta(n2,j,r)+(price(n2,m,j)-
1)*gamma(n2,j,r))*res(m,j,r)));
        conout(n1,m)..a(n1,m)=e=alpha(n1,m)+sum(j,sum(r,beta(n1,j,r)*res(m,j,r)));
        conout2(n1,m)$(ord(m)>5)..a(n1,m)=g=(a(n1,m-1)+a(n1,m-2)+a(n1,m-3)+a(n1,m-
4)+a(n1,m-5))/5;
        bound1(n1,m)..data(m,'output')-a(n1,m)=g=0;
        bound2(n2,m)..input(n2,m)+a(n2,m)=g=0;
        bound3(n2,m,j,r)..beta(n2,j,r)+(price(n2,m,j)-1)*gamma(n2,j,r)=g=0;
        bound4(n1,m,j,r)..beta(n1,j,r)=g=0;
```

```
        conal1(n2,m1)..a(n2,m1)=e=aa1+ba1*time(m1);
        conal2(n2,m2)..a(n2,m2)=e=aa2+ba2*time(m2);
        conal3(n2,m3)..a(n2,m3)=e=aa3+ba3*time(m3);
        conal4(n2,m4)..a(n2,m4)=e=aa4+ba4*time(m4);
        conbeta1(x,j1,r)..beta(x,j1,r)=e=ab1+bb1*jt(j1);
        conbeta2(x,j2,r)..beta(x,j2,r)=e=ab2+bb2*jt(j2);
        conbeta3(x,j3,r)..beta(x,j3,r)=e=ab3+bb3*jt(j3);
        conbeta4(x,j4,r)..beta(x,j4,r)=e=ab4+bb4*jt(j4);
        congamma1(x,j1,r)..gamma(x,j1,r)=e=ag1+bg1*jt(j1);
        congamma2(x,j2,r)..gamma(x,j2,r)=e=ag2+bg2*jt(j2);
        congamma3(x,j3,r)..gamma(x,j3,r)=e=ag3+bg3*jt(j3);
        congamma4(x,j4,r)..gamma(x,j4,r)=e=ag4+bg4*jt(j4);
        congamma5(n2,j,r)..gamma(n2,j,r)=g=0.0000001 /* this constraint is included
                                                      when computing marginal cost */

model IIH /object,constraint,conInp,conout,conout2,bound1,bound2,bound3,bound4/;

beta.fx(x,'0',r)=0;
beta.fx(x,'1',r)=0;
beta.fx(x,'2',r)=0;
beta.fx(x,'28',r)=0;
gamma.fx(x,'0',r)=0;
gamma.fx(x,'1',r)=0;
gamma.fx(x,'2',r)=0;
gamma.fx(x,'28',r)=0;
beta.fx(x,'21','pri')=0;
beta.fx(x,'22','pri')=0;
beta.fx(x,'23','pri')=0;
beta.fx(x,'24','pri')=0;
beta.fx(x,'25','pri')=0;
beta.fx(x,'26','pri')=0;
beta.fx(x,'27','pri')=0;
gamma.fx(x,'21','pri')=0;
gamma.fx(x,'22','pri')=0;
gamma.fx(x,'23','pri')=0;
gamma.fx(x,'24','pri')=0;
gamma.fx(x,'25','pri')=0;
gamma.fx(x,'26','pri')=0;
gamma.fx(x,'27','pri')=0;
beta.fx(x,'3','pub')=0;
gamma.fx(x,'3','pub')=0;

beta.fx(x,'10','EXT')=0;
gamma.fx(x,'10','EXT')=0;
```

```
beta.fx(x,'11','EXT')=0;
gamma.fx(x,'11','EXT')=0;
beta.fx(x,'12','EXT')=0;
gamma.fx(x,'12','EXT')=0;
beta.fx(x,'13','EXT')=0;
gamma.fx(x,'13','EXT')=0;
beta.fx(x,'14','EXT')=0;
gamma.fx(x,'14','EXT')=0;
beta.fx(x,'15','EXT')=0;
gamma.fx(x,'15','EXT')=0;
beta.fx(x,'16','EXT')=0;
gamma.fx(x,'16','EXT')=0;
beta.fx(x,'17','EXT')=0;
gamma.fx(x,'17','EXT')=0;
beta.fx(x,'18','EXT')=0;
gamma.fx(x,'18','EXT')=0;
beta.fx(x,'19','EXT')=0;
gamma.fx(x,'19','EXT')=0;
beta.fx(x,'20','EXT')=0;
gamma.fx(x,'20','EXT')=0;
beta.fx(x,'21','EXT')=0;
gamma.fx(x,'21','EXT')=0;
beta.fx(x,'22','EXT')=0;
gamma.fx(x,'22','EXT')=0;
beta.fx(x,'23','EXT')=0;
gamma.fx(x,'23','EXT')=0;
beta.fx(x,'24','EXT')=0;
gamma.fx(x,'24','EXT')=0;
beta.fx(x,'25','EXT')=0;
gamma.fx(x,'25','EXT')=0;
beta.fx(x,'26','EXT')=0;
gamma.fx(x,'26','EXT')=0;
beta.fx(x,'27','EXT')=0;
gamma.fx(x,'27','EXT')=0;
solve IIH using NLP maximizing obj;
```

APPENDIX C

COMPUTER PROGRAMS FOR CHAPTER 4

APPENDIX C

COMPUTER PROGRAMS FOR CHAPTER 4

I Rats program for computing critical values of Pedroni's Cointegration Test[57]

```
allocate 10000
DECLARE vector sumstat sumsstat
dim sumstat(7) sumsstat(7)
**********************************************************************
procedure PanCoint startp endp
type integer startp endp

option integer mlag 3
option switch  trend
option integer block

*** 07/07 Revision: New options:
option switch unweighted 0
option switch tdum 0

*** MAIN SOURCE CODE ***
local vector muvec vivec tvecreal
local vec[series] dvec rvec tdumseries
local vec[real] N D N2 D2 N3 D3 Nadf Dadf Sadf S N3adf D3adf $
  S3adf S3  V3 DD  DD3  NN3 GR GP GA Lbar statvec Tval tsizes
local integer pull i j k maxlag klag
local series time ehat ehatlag icount u
local series dehat nhat destar estar uresid
local integer llags start end nsecs
local integer nsec
local real su st lambda mtratio L11var sum
local vect[integer] datavec rhs tvec savecal
local integer m
local integer unbal
local integer tperiods offset tperiodsmax entry i
```

---

[57] This code is an extension of PANCOINT.PRG developed by Estima

```
local vector[real] offsettemp
*
* Lookup tables with and without trend
*
*
* Pull in list of series. Set m to the number of variables - 1
*
enter(varying) datavec
compute m=%rows(datavec)-1
*
* Create list to be used for RHS (that is, datavec w/o the
* first entry, which will be used for the dependent variable)
*
dim rhs(m)
ewise rhs(i)=datavec(i+1)
*
* Generate appropriate lookup values
*
if .not.%defined(block)
  compute tperiods=2//1-1//1
else
  compute tperiods=block

compute tperiodsmax = tperiods

*
* Get the data range
*
inquire(reglist) start<<startp end<<endp
# datavec
*
* Normalize start to begin at the first entry in an individual's
* record, and end to end at the last entry.
*
compute start=(start-1)/tperiods*tperiods+1
compute end  =((end-1)/tperiods+1)*tperiods
compute nsecs=(end-start+1)/tperiods

display ' '
display '     Currently computing panel statistics. Please wait. '
display ' '

*** 07/07 Revision: New treatment for observation counts
***              and determining if unbalanced:
```

```
*
* Run an OLS mainly to figure out what data points are available.
*
linreg(noprint) datavec(1) start end u
# rhs

* NOTE: If using Version 6, you can uncomment this line
* and the CALENDAR statement below if you want the procedure
* to reset back to your original CALENDAR setting:
*
* compute savecal = %calendar()
*
dim tvec(nsecs)
calendar(panelobs=tperiods)
panel(icount=1,compress) u / icount
ewise tvec(i) = fix(icount(i))
*
* calendar(recall=savecal)
*
*
* Create in tsizes the observation counts for the individuals
*
dim tvecreal(nsecs) tsizes(nsecs)
ewise tvecreal(i) = tvec(i)
compute unbal = fix(%minvalue(tvecreal)<%maxvalue(tvecreal))
if unbal
   ewise tsizes(i)=tvec(i)
else
   ewise tsizes(i)=TPeriods
dim dvec(m+1) rvec(m+1)
dim N(Nsecs) D(Nsecs) N2(Nsecs) D2(Nsecs) N3(Nsecs) D3(Nsecs) $
  Nadf(Nsecs) Dadf(Nsecs) Sadf(Nsecs) S(Nsecs) N3adf(Nsecs) D3adf(Nsecs) $
  S3adf(Nsecs) S3(Nsecs) V3(Nsecs) DD(Nsecs) DD3(Nsecs) NN3(Nsecs) $
  GR(Nsecs) GP(Nsecs) GA(Nsecs) Lbar(Nsecs) statvec(7)

          ***  SETUP DATA VARIABLES ***

if tdum == 1
{
 dim tdumseries(m+1)
 *compute savecal = %calendar()
 calander(panelobs=tperiods)
 * Write transformed series to TDUMSERIES
 * so we don't overwrite original data:
```

```
 do K=1,m+1
  panel(entry=1,time=-1) datavec(K) / tdumseries(K)
 end do K
 *calander(recall=savecal)
 * Reset DATAVEC to point to the new series:
 ewise datavec(i) = tdumseries(i)
}

* Dimension array used to hold temporary data when
* determining offset:
dim offsettemp(m+1)

do J=1,Nsecs
   if unbal == 1 ; {; compute Tperiods = fix(Tsizes(J)); }

   * Need to allow for possibility of NA's at the beginning of
   * individual. Compute offset from entry indiv//1 to first entry
   * in that individual for which all series contain data:

   do entry=((j-1)*tperiodsmax+1),j*tperiodsmax
      ewise offsettemp(i) = ([series]datavec(i))(entry)
      * If using Version 6, you can replace the next
      * 5 lines with the single command:
      *if %valid(offsettemp)

      compute sum = 0
      do i=1,%rows(offsettemp)
        compute sum = sum + offsettemp(i)
      end do i
      if %valid(sum)
        {
        compute offset = entry-((j-1)*tperiodsmax)
        break
        }
   end do
   dis 'offset = ' offset

   do K=1,M+1
*       move datavec(K) ((j-1)*Tperiods+offset) (j*Tperiods+offset-1) dvec(K) 1
      move datavec(K) ((j-1)*Tperiodsmax+offset) (j*Tperiodsmax+offset-1) dvec(K) 1
      diff dvec(K) 2 Tperiods rvec(K)
   end do K
   set time = T
```

```
      *** DO INDIVIDUAL COINTEGRATING REGRESSIONS ***

if m >= 1
{
 linreg(noprint) dvec(1) 1 Tperiods ehat
 # dvec(2) to dvec(m+1)
}

if trend == 1 .and. m>=1
{
 linreg(noprint) dvec(1) 1 Tperiods ehat
 # dvec(2) to dvec(m+1) time
 }

if m == 0
{
 linreg(noprint) dvec(1) 1 Tperiods ehat
 # constant
}

if m == 0 .and. trend == 1
{
 linreg(noprint) dvec(1) 1 Tperiods ehat
 # time
}

if m>=1
{
 linreg(noprint) rvec(1) 2 Tperiods nhat
 # rvec(2) to rvec(m+1)
}

diff ehat / dehat

if m==0
{
 linreg(noprint) dehat 2 Tperiods nhat
 # ehat
}

       *** COMPUTE ADF LAG TRUNCATIONS ***

 do llags=mlag,1,-1
   linreg(noprint) dehat 2 Tperiods
```

```
  # ehat{1} dehat{1 to llags}
  compute mtratio = %tstats(llags+1)
  if abs(mtratio) >= 1.64
     { ; compute maxlag=llags ; break ; }
end do llags

if llags == 1 .and. abs(mtratio) < 1.64
  compute maxlag = 0

compute klag = fix(%round((4.0*(Tvec(J)/100.0)**(2.0/9.0)),0))

      *** COMPUTE INDIVIDUAL MEMBER SAMPLE STATS ***

if maxlag == 0 {
  linreg(noprint) dehat 2 Tperiods
  # ehat{1}
  compute sadf(J) = %seesq
  cmoment(noprint) 2+maxlag Tperiods
  # dehat ehat{1}
  compute nadf(J) = %cmom(2,1)
  compute dadf(J) = %cmom(2,2)
}

if maxlag >= 1 {
  linreg(noprint) dehat 2 Tperiods
  # ehat{1} dehat{1 to maxlag}
  compute sadf(J) = %seesq
  linreg(noprint) dehat 2 Tperiods destar
  # dehat{1 to maxlag}
  set ehatlag 1 Tperiods = ehat{1}
  linreg(noprint) ehatlag 2 Tperiods estar
  # dehat{1 to maxlag}
  cmoment(noprint) 2+maxlag Tperiods
  # destar estar
  compute nadf(J) = %cmom(2,1)
  compute dadf(J) = %cmom(2,2)
}

linreg(noprint) dehat 2 Tperiods uresid
# ehat{1}
compute d(J) = 1.0/%xx(1,1)
cmoment(noprint,lastreg) 2 Tperiods
compute n(J) = %cmom(2,1)
mcov(damp=1.0,lags=klag) 2 Tperiods
```

```
  # uresid
  compute su = sqrt(%seesq*%ndf/(Tvec(J)-1.0))
  compute st = sqrt(%cmom(1,1)/(Tvec(J)-1.0))
  compute lambda = 0.5*(st**2-su**2)
  compute S(J) = st**2

  mcov(damp=1.0,lags=klag,noprint) 2 Tperiods
  # nhat
  compute L11var = (1.0/(tvec(j)-1.0))*%CMOM(1,1)

       *** CONSTRUCT NUMERATOR AND DENOMINATOR TERMS ***

  if unweighted == 1
  {
   compute Lbar(J) = L11var
   compute L11var = 1.0
   }
  compute N2(J) = N(J) - lambda*Tvec(j)
  compute D2(J) = D(J)
  compute N3(J) = N2(J)/L11var
  compute D3(J) = D2(J)/L11var
  compute N3adf(J) = Nadf(J)/L11var
  compute D3adf(J) = Dadf(J)/L11var
  compute S3adf(J) = Sadf(J)/L11var
  compute S3(J) = S(J)/L11var
  compute DD(J) = D(J)*S(J)
  compute DD3(J) = D3(J)*S3(J)

  compute GR(J) = N2(J)/D2(J)
  compute GP(J) = N2(J)/sqrt(D2(J)*S(J))
  compute GA(J) = Nadf(J)/sqrt(Dadf(J)*Sadf(J))

end do J

      *** CONSTRUCT PANEL COINTEGRATION STATISTICS ***

ewise V3(I) = D3(I)*(1.0/(Tsizes(I)**2))
ewise NN3(I) = N3(I)*(Tsizes(I)/1.0)
ewise GR(I) = GR(I)*(Tsizes(I)/1.0)

compute statvec(1) = sqrt(Nsecs**3)/%sum(V3)
if unweighted == 1
{
 compute statvec(1) = (sqrt(Nsecs**3)*%sum(Lbar))/(%sum(V3)*Nsecs)
```

```
}
compute statvec(2) = (sqrt(Nsecs)*%sum(NN3))/%sum(D3)
compute statvec(3) = %sum(N3)/(sqrt(%sum(D3)*%sum(S3)/Nsecs))
compute statvec(4) = %sum(N3adf)/(sqrt(%sum(D3adf)*(%sum(S3adf)/Nsecs)))
compute statvec(5) = %sum(GR)/sqrt(Nsecs)
compute statvec(6) = %sum(GP)/sqrt(Nsecs)
compute statvec(7) = %sum(GA)/sqrt(Nsecs)

*do K=1,7
*   compute statvec(K) = (statvec(K) - muvec(K)*sqrt(Nsecs))/sqrt(vivec(K))
*end do K
      do l=1,7
         compute sumstat(l)=sumstat(l)+statvec(l)
         compute sumsstat(l)=sumsstat(l)+statvec(l)**2
      end do l

end

compute sumstat=||0.0,0.0,0.0,0.0,0.0,0.0,0.0||
compute sumsstat=||0.0,0.0,0.0,0.0,0.0,0.0,0.0||

*** Simulate 9 independent random walks.

do draw=1,10000
         set y1 = 0.0
         set y2 = 0.0
         set y3 = 0.0
         set y4 = 0.0
         set y5 = 0.0
         set y6 = 0.0
         set y7 = 0.0
         set y8 = 0.0
         set y9 = 0.0

EQUATION(variance=1,NOCONSTANT,coeffs=||1||) w1  Y1  1 0
EQUATION(variance=1,NOCONSTANT,coeffs=||1||) w2  Y2  1 0
EQUATION(variance=1,NOCONSTANT,coeffs=||1||) w3  Y3  1 0
EQUATION(variance=1,NOCONSTANT,coeffs=||1||) w4  Y4  1 0
EQUATION(variance=1,NOCONSTANT,coeffs=||1||) w5  Y5  1 0
EQUATION(variance=1,NOCONSTANT,coeffs=||1||) w6  Y6  1 0
EQUATION(variance=1,NOCONSTANT,coeffs=||1||) w7  Y7  1 0
EQUATION(variance=1,NOCONSTANT,coeffs=||1||) w8  Y8  1 0
EQUATION(variance=1,NOCONSTANT,coeffs=||1||) w9  Y9  1 0
```

```
simultate 9 100001 2
        # w1 y1
        # w2 y2
        # w3 y3
        # w4 y4
        # w5 y5
        # w6 y6
        # w7 y7
        # w8 y8
        # w9 y9
sample y1 2 10001 x1 1
sample y2 2 10001 x2 1
sample y3 2 10001 x3 1
sample y4 2 10001 x4 1
sample y5 2 10001 x5 1
sample y6 2 10001 x6 1
sample y7 2 10001 x7 1
sample y8 2 10001 x8 1
sample y9 2 10001 x9 1
@pancoint( mlag=3,notrend,block=10000,notdum,unweighted ) 1 10000
# x1 x2 x3 x4 x5 x6 x7 x8 x9

end do draw
do li=1,7
        compute sumstat(li)=sumstat(li)/10000
        compute sumsstat(li)=sumsstat(li)/10000-sumstat(li)**2
end do li
display sumstat
display sumsstat
```

II Rats program for Pendroi's cointegration test

```
calendar( panelobs=39 )
allocate 48//39
open data "e:\TFPCOINT.xls"
data(for=xls,org=col) / year TFP DlnFsize dlnedu dlnMds LnPub25 DLnPri15 DLnExt7
LnPubSpill DLnPriSpill LnInter15
@pancoint( mlag=3,block=39,trend,notdum,unweightd )
# TFP DlnFsize dlnedu dlnmds LnPub25 DLnPri15 DLnExt7 LnPubSpill DLnPriSpill
LnInter15
```