Induced Innovation in the Agricultural Sector:

Evidence from a State Panel

Yucan Liu and C. Richard Shumway*

* Yucan Liu: Ph.D. Student, School of Economic Sciences, Washington State University, Pullman, WA 99164-6210. Phone: 509-338-4902, Email: yucanliu@yahoo.com.

C. Richard Shumway: Professor, School of Economic Sciences, Washington State University, Pullman, WA 99164-6210. Phone: 509-335-1007, Email: shumway@wsu.edu.

Selected Paper prepared for presentation at the American Agricultural Economics Association Annual Meeting, Long Beach, California July 23-26, 2006

Induced Innovation in the Agricultural Sector:

Evidence from a State Panel

Yucan Liu and C. Richard Shumway

Abstract

This paper uses recently developed panel cointegration techniques and error correction modeling to test the hypothesis of induced innovation in a state-level panel of U.S. agricultural production. These methods provide greatly improved power compared to conventional approaches. A 5-step testing procedure is used to test the induced innovation hypothesis based on a 2-stage CES production function with aggregate output and four input categories. For both pairs of inputs, the test fails to support the hypothesis of induced innovation at one or more of the critical steps.

Key words: induced innovation, panel cointegration, error correction, 2-stage CES

The authors are, respectively, a graduate research assistant and a professor in the School of Economic Sciences, Washington State University.

Induced Innovation in the Agricultural Sector:

Evidence from a State Panel

Introduction

One of the fundamental issues in the literature concerning the economics of technology is the induced innovation theory which was developed to explain the nature of technical change. This refutable hypothesis suggests that high prices can induce associated input-saving innovations. Much research has been devoted to testing the induced innovation hypothesis (IIH) since it was first proposed by Hicks in 1932. The hypothesis has been examined in a wide variety of countries and industries and using various analytical tools. Nearly all of the early tests found strong support for the IIH, but many have been criticized for inadequate testing procedure or data. With the recent development of high quality panel data for U.S. agriculture and the development of new techniques for handling non-stationarity properties of data, this paper reexamines this refutable hypothesis.

Several studies have examined the IIH in the last decade using a time-series approach. Yet, their findings have not always agreed. Some concluded their evidence confirmed the IIH (e.g., Khatri, Thirtle, and Townsend, 1998; Thirtle *et al*., 1998; Oniki, 2000; Thirtle *et al*., 2002; Liu and Shumway, 2006), while others failed to find clear evidence supporting the hypothesis (e.g., Machado, 1995; Tiffin and Dawson, 1995), even for the same industry and country.

Similar ambiguity appears in recent studies using a variety of other testing methods. For example, Olmstead and Rhode (1993) concluded that the induced technical change model held only for the central grain growing regions of the U.S. based on regional tests. In a later paper (1998) using state-level data they found little support for the induced technical change. Using a nonparametric approach, Chavas, Aliber and Cox (1997) found evidence supporting the IIH for actively traded inputs but not for land and farm labor in the U.S. Armanville and Funk (2003) empirically tested the IIH by imposing parametric restrictions on an input demand equation jointly estimated with the innovation possibility frontier. They found conflicting results for different sectors in a variety of countries.

The work presented in this paper attempts to bridge these divergent strands of research by using recently developed time-series techniques designed for panel data and a high-quality state panel for agriculture. Panel data have several important advantages over time-series or cross-sectional data for economic research. For example, they enlarge the sample size, enhance the power of statistical tests, and facilitate analysis of dynamic properties of relationships.

As Dickey and Fuller (1979) and many other time series papers have demonstrated, traditional unit root tests have extremely low power unless the number of observations is very large. Therefore, it is possible that the conclusions based on conventional unit root and cointegration tests could be spurious. The most obvious way to overcome a low power problem is to increase the number of observations, such as using very long time-series data. For example, Thirtle *et al*. (2002) obtained evidence supporting IIH using data spanning 110 years. Unfortunately it is not always possible to obtain such a long data set. Additionally, analysis for long periods may suffer from serious structural changes that can cause the cointegration relation implied by the model to be unstable over the entire sample. Alhough the sample size can be dramatically increased by simple transformation from annual data to quarterly or monthly data, the test power remains low since cointegration is a long run concept (Hakkio and Rush, 1991).

Therefore, test results for the IIH will be more reliable when panel data and panel time-series techniques are employed.[1] We test the IIH for the U.S. agriculture sector following the testing logic of Thirtle *at al* (1998), Oniki (2000) and Thirtle *at al* (2002). Using time series data for South Africa, Japan, and the United States, they found evidence supporting the induced innovation hypothesis in each of those countries. Thirtle *at al* (2002) argue that five requirements must be satisfied for the IIH to be validated via time-series properties: (a) the affected series have time-series properties allowing cointegration, (b) cointegration occurs among the series if a valid long-run relationship exists, (c), the correlation between factor price ratios and the factor quantity ratios is negative, (d) the change in factor quantity ratios cannot be fully explained by factor substitution, and (e) causality runs from factor prices to factor quantity ratios. Although this method is appealing both because of its logic and its rigor, it has only been applied in a traditional time-series approach to an aggregate country-level data set. Application of the method to state-level panel data using panel time-series techniques could offer a more robust test for the IIH.

We test the IIH using a two-stage CES production function. The two-stage CES model (de Janvry, Sadoulet, and Fafchamps, 1989) and its extensions have gained much attention in empirical tests of the IIH because of its simplicity.[2] With the two-stage CES model, a system of input demand equations is estimated. The logarithms of input quantity

[1] It appears that no extant literature has examined the IIH using such techniques.
[2] Hayami and Ruttan (1985), Thirtle (1985), Kawagoe, Otsuka, and Hayami (1986), Karagiannis and Furtan (1990), and Thirtle, Schimmelpfenning, and Townsend (2002) have all used the two-stage CES model to test the IIH.

ratios serve as the dependent variables, and the explanatory variables include a constant term, the own-price ratio, and an efficiency term. The benefits of using the two-stage CES are that the dependent variables are linear in parameters and symmetrically distributed around a zero mean. One shortcoming is that the conventional two-stage CES model is not locally flexible. Among potentially relevant regressors that are excluded from the input ratio demand equations are output quantity and other input prices.

The remainder of this paper is organized as follows. The next section develops the specification of the CES model and the panel testing methodologies. The subsequent section describes the data. The following section reports the empirical application of the model and panel testing methodology to a state-level panel data set for U.S. agriculture. The last section summaries our main findings and concludes.

Methodology

Following de Janvry *at al.* (1989), Frisvold (1991), and Thirtle *at al.* (2002), our basic model is represented by the following input demand equations based on a two-stage CES functional form:

(1) $$\ln(A/M) = \beta_0 + \beta_1 \ln(P_A / P_M) + \beta_2 \ln(E_{A/M})$$

(2) $$\ln(L/K) = \alpha_0 + \alpha_1 \ln(P_L / P_K) + \alpha_2 \ln(E_{L/K})$$

where A, M, L, K are the quantities of land, materials, labor and capital respectively; P_A P_M, P_L, and P_K are the prices of land, materials, labor and capital respectively; $E_{A/M}$ and $E_{L/K}$ represent efficiency variables associated with land saving and labor saving techniques, respectively; α and β are parameters to be estimated. We treat the efficiency variables as functions of research activities, extension, and farm size:

(3) $$E_i = E_i(R_{pri}, R_{pub}, Ext, Size), \quad i = A/M, L/K,$$

where R_{pri} is private research investment, R_{pub} is public research investment, *Ext* is public extension investment, *Size* is average farm size, and E_i is general functional notation.

In this model, the land-material ratio and the labor-capital ratio are presumed to be explained by a constant term, the own-price ratio, and efficiency variables, thus providing a clear-cut approach to a direct test of the induced innovation hypothesis. Additionally, significantly negative coefficients associated with current price ratios are direct partial elasticities of substitution.

In the first step of the analysis, each series is tested for a unit root. Several tests have been proposed to test for the null of nonstationarity in heterogeneous panels. They include the early work of Levin and Lin (1993) which allows for heterogeneous, serially-correlated errors but assumes identical first-order autoregressive coefficients in all series. Also included is the recent contribution of Im, Pesaran and Shin (2003) which allows for residual serial correlation and heterogeneous autoregressive coefficients across units. In this study, we apply the procedure of Im, Pesaran and Shin (2003), hereafter IPS, because of its stronger theoretical foundation and superior performance relative to alternative panel data testing procedures. The IPS statistic is the average of the individual ADF t-statistics and is distributed as standard normal.

In the second step of the analysis, a panel cointegration test is performed for nonstationary variables involved in equations (1) and (2). We use Pedroni's (1999) testing procedure which allows cointegration vectors to vary across units and is considerably more powerful than conventional methods (Harris and Tzavalis, 1999). Seven statistics are proposed by Pedroni (1999) and are categorized into two groups –

between-dimension statistics and within-dimension statistics. The asymptotic distribution of each statistic can be expressed in the following form:

$$(4) \qquad \frac{Z_{N,T} - \mu\sqrt{N}}{\sqrt{V}} \Rightarrow N(0,1)$$

where $Z_{N,T}$ is the statistic, and μ and V are the mean and variance, respectively. They are tabulated in Pedroni (1999, Table 2) up to seven explanatory variables. Under the alternative hypothesis, all the statistics diverge to negative infinity except one named ‘panel v statistic’. 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 tests result in rejection of the null hypothesis of no cointegrated relation among the variables.

If a cointegrated relationship exists among nonstationary variables in the input demand equations, the short-run and the long-run relationships of the variables are estimated by an error correction model (ECM) in the third step of the analysis. The ECM we estimate is based on a re-parameterization of an autoregressive distributed lag model (ARDL) of each input demand equation defined in (1) and (2). Suppose the model for the land-material quantity ratio and the labor-capital quantity ratio is ARDL (p_1, q_1, q_2, q_3, q_4, q_5) and ARDL (p_2, r_1, r_2, r_3, r_4, r_5) respectively. The ECM can then be written as follows:

$$(5) \qquad \begin{aligned} \Delta \ln\left[\frac{A}{M}\right]_{i,t} &= \lambda_{1i}\left(\ln\left[\frac{A}{M}\right]_{i,t-1} - \theta_{1i}' x_{1i,t-1}\right) + \nu_1 ' x_{1i,t} + \Gamma_i(L)\Delta \ln\left[\frac{A}{M}\right]_{i,t} + A_i(L)\Delta \ln\left[\frac{P_A}{P_M}\right]_{i,t} \\ &+ C_i(L)\Delta \ln[R_{pri}]_{i,t} + D_i(L)\Delta \ln\left[R_{pub}\right]_{i,t} + E_i(L)\Delta \ln\left[Ext\right]_{i,t} \\ &+ F_i(L)\Delta \ln\left[Size\right]_{i,t} + \mu_{1i} + \varepsilon_{1it} \end{aligned}$$

$$
\begin{aligned}
\Delta \ln\left[\frac{L}{K}\right]_{i,t} &= \lambda_{2i}(\ln\left[\frac{L}{K}\right]_{i,t-1} - \theta_{2i}{}' x_{2i,t-1}) + v_2{}' x_{2i,t} + \Phi_i(L)\Delta\ln\left[\frac{L}{K}\right]_{i,t} + H_i(L)\Delta\ln\left[\frac{P_L}{P_K}\right]_{i,t} \\
&+ J_i(L)\Delta\ln[R_{pri}]_{i,t} + K_i(L)\Delta\ln\left[R_{pub}\right]_{i,t} + M_i(L)\Delta\ln\left[Ext\right]_{i,t} \qquad (6) \\
&+ R_i(L)\Delta\ln\left[Size\right]_{i,t} + \mu_{2i} + \varepsilon_{2it}
\end{aligned}
$$

where $x_{1i,t} = (\ln\left[\frac{P_A}{P_M}\right]_{i,t}, \ln\left[R_{pri}\right]_{i,t}, \ln\left[R_{pub}\right]_{i,t}, \ln\left[Ext\right]_{i,t}, \ln\left[Size\right]_{i,t})'$;

$x_{2i,t} = (\ln\left[\frac{P_L}{P_K}\right]_{i,t}, \ln\left[R_{pri}\right]_{i,t}, \ln\left[R_{pub}\right]_{i,t}, \ln\left[Ext\right]_{i,t}, \ln\left[Size\right]_{i,t})'$; Δ is the differencing

operator; L is the lag operator; $\Gamma_i(L) = \sum_{j=1}^{p_1-1}\varphi_{i,j}L^j$; $A_i(L) = \sum_{j=0}^{q_1-1}\alpha_{i,j}L^j$; $C_i(L) = \sum_{j=0}^{q_2-1}\eta_{i,j}L^j$;

$D_i(L) = \sum_{j=0}^{q_3-1}\gamma_{i,j}L^j$; $E_i(L) = \sum_{j=0}^{q_4-1}\delta_{i,j}L^j$; $F_i(L) = \sum_{j=0}^{q_5-1}\kappa_{i,j}L^j$; $\Phi_i(L) = \sum_{j=1}^{p_2-1}\phi_{i,j}L^j$;

$H_i(L) = \sum_{j=0}^{r_1-1}\sigma_{i,j}L^j$; $J_i(L) = \sum_{j=0}^{r_2-1}\varpi_{i,j}L^j$; $K_i(L) = \sum_{j=0}^{r_3-1}\kappa_{i,j}L^j$; $M_i(L) = \sum_{j=0}^{r_4-1}\tau_{i,j}L^j$;

$R_i(L) = \sum_{j=0}^{r_5-1}\zeta_{i,j}L^j$; θ_1 and θ_2 are vectors of long-run parameters accounting for the long-run equilibrium relationship between factor quantity ratios and the explanatory variables; λ_1 and λ_2 are corresponding error correction coefficients. The term associated with the error correction coefficient represents the deviation of the set of variables from the long-run equilibrium path. Thus, the error correction coefficient measures the speed of adjustment for the system to move back to the 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.

Since all the variables are in logarithms, the long-run elasticities are represented by the long-run coefficients, and the short-run elasticities are represented by associated short-run parameters. The short-run elasticities of substitution may be viewed as movements around the curvature of the isoquant, while the long-run elasticities can be explained as movements around the innovation possibility curve (IPC). Induced innovation requires the estimated long-run elasticities of substitution to be significantly greater than the estimated short-run elasticities (Oniki, 2000).

The dynamic panel data models specified in (5) and (6) are estimated by the pooled mean group estimation procedure (PMGE) developed by Pesaran *at al.* (1999). This estimation method uses a maximum likelihood approach which involves maximizing the log-likelihood function by means of the Newton-Raphson algorithm to estimate the ECM. The main benefit of the PMGE procedure is that it constraints only 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 (GMM) which presume strong homogeneity across groups (Pesaran *at al.*, 1999).

As proposed by Pesaran et al. (1999), a Hausman-type test is conducted to test for the validity of homogeneity restrictions of the long-run coefficients and the error correction term in each panel. Reference results are provided by mean group (MG) estimates, which impose no restrictions on estimates and are defined as the average of state-specific coefficients. The PMGE parameter estimates are consistent and efficient only if homogeneity holds. Otherwise, the MG estimation method is preferred. Thus, we are able to evaluate whether imposing long-run homogeneity helps to reveal significant adjustment of the factor demands to long-run equilibrium.

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 *at al.* 2002).

The last step of the analysis is to examine whether the factor price ratio Granger causes factor-saving technical bias. Several approaches have been developed to conduct Granger causality tests for a panel data model. Holtz-Eakin *et al.* (1988) applied an instrumental variable estimation approach to a panel vector autoregression (VAR) model to test for Granger causality in panels. We use a mixed fixed and random coefficients (MFR) estimation algorithm which as developed by Hsiao (1989) for a non-dynamic, non-fixed-effects panel data model and extended by Nair-Reichert and Weinhold (2001) to the dynamic panel model. This procedure is followed since it results in least bias among the estimators, including Holtz-Eakin *et al.* (1988). In the MFR 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.

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 include 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. For example, labor inputs were constructed by incorporating a demographic cross-classification of the agricultural labor force. Capital stocks for depreciable assets and land were developed using the perpetual inventory method. Implicit asset rental prices were based on the correspondence between the asset's purchase price and the discounted value of future service flows. Using data on land area and average value for each agricultural statistical district in each state, a constant-quality stock of land was compiled (Ball *et al.* 1999). In this study, all outputs were aggregated into one group.

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 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 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.

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 are from Huffman, Ahearn, and Yee (2005). They are total cooperative extension investments in current dollars divided 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. 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). Farm numbers data 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).

Empirical Results

Panel Unit Root and Cointegration Test Results

The IPS unit root test results are reported in Table 1. They indicate the order of integration for each series. 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, Regression Analysis of Time-Series (RATS), version 6, routine IPSHIN. As suggested by Newey and West (1994), the number of lags included in each test was set equal to the integer of $4(T/100)^{2/9}$, i.e., 3 in our application. Test statistics and associated P-values for all series imply that a unit root could not be rejected at a 0.05 significance level for any variable except extension investments. Thus, only extension investments are concluded to be stationary. Most variables (Ln(A/M), $Ln(P_A/P_M)$, $Ln(R_{pri})$, $Ln(R_{pub})$) are stationary in first differences, i.e., they are I(1) processes, at a 0.05 significance level. A few series including Ln(L/K), $Ln(P_L/P_K)$ and Ln(*Size*) are I(2) processes.

Based on the integration order of the time series, we proceed to analyze the long-run relationship between the factor ratios and associated explanatory variables. If the data are cointegrated for a factor ratio equation, the factor ratio can be formulated using the original (i.e., untransformed) data for I(1) and I(0) series and first differences for I(2) series to capture the long-run relationships in the data (Lim and Shumway, 1997; Tiffin and Dawson, 1995). If the data are not cointegrated, we will fail to support the IIH from a time series perspective since a long-run relationship is a necessary condition for induced innovation to occur (Oniki 2000).

Investments in research activities have been shown to affect the technology, or the nature of the production function, at least seven years later and sometimes up to 30 years later (Chavas and Cox 1992; Evenson and Pray 1991; Pardey and Craig 1989). Because investments in research and extension may not induce technological change for several years, Akiake's information criterion (AIC) is used in the cointegration analysis to determine 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 between 3 years and the optimal lag on public research investments. 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 capital-labor ratio equation. In both equations, a lag of 13 years on private research investments minimized the AIC. The optimal lag on extension investments was 3 for the land-material equation and 4 for the capital-labor equation. For convenience in subsequent analysis, identical lags were selected for both 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.

Table 2 reports the results of the cointegration analysis. Except one test, all tests for the land-material equation resulted in failure to reject the hypothesis of no cointegration. For the capital-labor equation, 5 of the 7 statistics supported rejection of the hypothesis of no cointegration at a 0.05 significance level and another at a 0.10 significance level. Thus, it is concluded that a long run relationship exists for the capital-labor equation but not for the land-material equation. Consequently, the IIH is rejected based on these time series testing procedures for the inputs of land and materials. Additional testing will focus on capital and labor only.

Estimation of the Error Correction Model

Having concluded that a cointegration relationship exists among the variables in the capital-labor equation, we next estimated the ECM. Based on the previous test results, the dynamic form of the model specified in (6) was modified by replacing the I(2) variables, Ln(L/K), Ln(P_L/P_K) and Ln(*Size*), with their first differences. Although considered redundant from a time series analysis perspective, the stationary variable, extension investments, was included in the ECM to determine whether it induces biased technical change.

The pooled mean group estimation (PMGE) estimates were computed using a GAUSS program by Pesaran, Shin, and Smith (1999). 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(2,2,2,2,2,2) was determined by this process.

The ECM parameter estimates are reported in Table 3. As noted previously, the estimated coefficients are elasticity estimates. Using the Hausman test, the hypothesis of long-run homogeneity among the variables was not rejected at a 0.05 significance level.

Thus, it was concluded that the PMGE is an appropriate method for estimating the ECM specified in (6). The capital/labor model performed quite well with an average adjusted R-square of 0.625, which is reasonably high for an ECM. The estimated error correction coefficient λ_2 was negative and highly significant indicating that the system moves toward equilibrium. However, it has an estimated value of -1.361 which implies that the error correction overadjusts towards the long-run equilibrium.

In the long-run, the negative coefficient with regard to the price ratio indicates that a reduction in the ratio between the prices of capital and labor generates a labor-saving technical change that is consistent with the hypotheses of induced innovation. In agreement with de Janvry *et al.* (1989), and Thirtle *at al.* (2002), the long-run coefficient on public research investments is significantly positive. In addition, as expected, private research and extension investments have significantly positive impacts on the capital-labor ratio. The significantly positive coefficients on all three variables that represent the technology creation and dissemination sector imply that increased research and extension investments would lead to capital using and/or labor saving technical bias. The farm size parameter is negative and significant. This result suggests that a decrease in farm size would increase the capital/labor ratio, so it is the smaller farms that increase the bias towards labor-saving technical change. Also, in state-specific regressions, all of the long-run coefficients are significant and have the same signs as in the panel estimates. As shown in Table 3, most of the variables exhibited significant short-run effects at a 0.05 level, and all the research and extension variables were significantly positive and consistent with theoretical expectations. Due to the over-adjustment of the system, however, the short-run direct elasticity of substitution had a value of -0.143 which was greater in absolute value than the long-run elasticity of -0.108.[3] As noted by Oniki (2000), a crucial requirement to support the IIH is that the curvature of the isoquant is greater than that of IPC, i.e., the long-run elasticity has a greater absolute value than the short-run elasticity. Despite the other supporting evidence for the IIH in capital and labor inputs, this violation results in rejection of the IIH in all four inputs using a robust, panel time series testing procedure.[4]

In contrast with other empirical studies, our conclusion that the IIH is not supported in U.S. agriculture is consistent with the earlier conclusions of Olmstead and Rhode (1993, 1998), Machado (1995), Tiffin and Dawson (1995), and Antle (1986). However, it is counter to the earlier conclusions of Binswanger (1974), Kawagoe *et al*. (1986), Lambert and Shonkwiler (1995), Thirtle *at al* (2002) and others who found evidence supporting the IIH in U.S. agriculture.

In order to determine whether inclusion of potentially relevant variables would affect conclusions relative to the IIH, we also conducted all tests using a generalization of

---

[3] In the state-specific analyses, only two states, Colorado and Nevada, exhibited smaller short-run elasticities than long-run elastisticies in absolute value, which would be required for a partial adjustment process.

[4] Although the IIH has now been rejected for all inputs by this time-series testing procedure, we also carried out the final test, the FMR causality test, to determine whether causality ran from the factor price ratio and research and extension variables to the factor quantity ratio for capital and labor. We used a dynamic model in which the capital-labor ratio was modeled as a function of its lags and other explanatory variables:

$$\begin{aligned}\ln(L/K)_{it} &= \alpha_0 + \gamma_{1i}\ln(L/K)_{it-1} + \gamma_{2i}\ln(L/K)_{it-2} + \beta_{1i}\ln(P_L/P_K)_{it-1} + \beta_{2i}\ln(P_L/P_K)_{it-2} \\ &\quad + \beta_{3i}\ln(R_{pri})_{it-1} + \beta_{4i}\ln(R_{pri})_{it-2} + \beta_{5i}\ln(R_{pub})_{it-1} + \beta_{6i}\ln(R_{pub})_{it-2} \\ &\quad + \beta_{7i}\ln(Ext)_{it-1} + \beta_{8i}\ln(Ext)_{it-2} + \beta_{9i}\ln(Size)_{it-1} + \beta_{10i}\ln(Size)_{it-2} + \varepsilon_{it}\end{aligned} \tag{7}$$

Consistent with previous ARDL models, 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 estimates were computed using a GAUSS program distributed by Nair-Reichert and Weinhold, (2001). Insignificance of the coefficients on the two terms representing lagged own-price ratio indicated that the hypothesis of causality running from the factor price ratio to the factor quantity ratio was clearly rejected. 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 capital-labor equation also failed to support the IIH. This finding is consistent with Liu and Shumway (2006).

the two-stage CES model. This generalization includes a term representing output level and all input prices as regressors. That is, the factor ratio is explained not only by its own price ratio and an efficiency variable but also by other price ratios and a term representing aggregate output level. This generalization is treated only as an approximation to an unknown but more general functional form. The model has the following form:

(1') $\ln(A/M) = \beta_0 + \beta_1 \ln(P_A / P_M) + \beta_2 \ln(P_k / P_L) + \beta_3 \ln(P_A / P_L) + \beta_4 \ln(y) + \beta_5 \ln(E_{A/M})$

(2') $\ln(L/K) = \alpha_0 + \alpha_1 \ln(P_K / P_L) + \alpha_2 \ln(P_A / P_M) + \alpha_3 \ln(P_A / P_L) + \alpha_4 \ln(y) + \alpha_5 \ln(E_{L/K})$

where y represents aggregate output level, and other variables are the same as in above sections. The conclusions regarding cointegrated relationships were the same for this generalization of the CES model as for the traditional two-stage CES model. An ECM was also estimated using this generalization, and the results were qualitatively the same as for the traditional CES model. The system over-adjusted, and the long-run elasticity was smaller than that of the short-run, thus the IIH was not supported by this model either.

Conclusions

The hypothesis of induced innovations is that technology is developed and implemented in ways that facilitate replacement of scarce and expensive production factors by abundant and cheap factors. This hypothesis has been widely tested in many sectors, and especially in the agricultural sector in many countries. Surprisingly, we do not yet have a stylized fact based on the broad testing, even for the agricultural sector in the U.S. Part of the reason for conflicting test results is due to the low power of traditional testing methods and part is due to inadequate data.

In this paper, both issues are addressed in a rigorous fashion. A high quality state-level panel data set is used for the tests, and recent time-series testing procedures for panel data are used that result in much higher power than traditional time-series methods. In addition, a 5-step sequential testing logic is employed that assures a more powerful approach for examining the induced innovation hypothesis. Based on a two-stage CES model with aggregate output and four factors of production, none of the inputs satisfied the necessary conditions for supporting the hypothesis. Land and materials failed to support the hypothesis at the 2nd step (existence of a cointegrated relationship) and capital and labor failed to support it at the 3rd step (long-run elasticity of substitution greater in absolute value than the short-run elasticity). While other steps in the testing procedure supported the hypothesis, these did not and resulted in rejection of the hypothesis. The test conclusions were confirmed using a generalization of the CES functional form.

Despite rejection of the induced innovation hypothesis, one of the significant results from this study is that both research and extension investments have positive impacts on innovation of labor-saving inputs. That is true in both the short run and the long run. This finding suggests that policies encouraging investment in public and/or private research and development will help lead producers' decisions toward more economical and efficient technical progress in saving relative expensive inputs. Our results also make clear that policy makers cannot rely exclusively on price signals to induce efficient technical change. One possible implication is that input substitution is inelastic and results in augmentation of the relatively more expensive input even after the development of new technologies (Armanville and Funk 2003). Another possibility is that the marginal costs of developing and implementing input-saving technologies for the relatively expensive inputs are greater than for the relatively cheap inputs. Available data impose the assumption on tests of the induced innovation hypothesis that the marginal cost of developing and implementing input-saving technologies are the same for each input, so we cannot definitively rule out this possibility. It begs for data that would permit the supply side of technology development to be explicitly incorporated into future tests of the hypothesis.

References

Ahearn, M., J. Yee, and J. Bottum. 2003. "Regional Trends in Extension System Resources." Washington, DC: USDA, ERS, AIB-781.

Antle, J. 1986. "Aggregation, Expectations, and the Explanation of Technology Change." *Journal of Econometrics* 33: 213-236.

Alston, J., B. Craig, and P. Pardey. 1998. "Dynamics in the creation and depreciation of knowledge, and the returns to research." International Food Policy Research Institute, EPTD Discussion Paper No. 35.

Armanville, I. and P. Funk. 2003. "Induced innovation: an empirical test." *Applied Economics* 35: 1627-47.

Ball, V. E., F. M. Gollop, A. Kelly-Hawke, and Swinand, G. P. 1999. "Patterns of State Productivity Growth in the U.S. Farm Sector: Linking State and Aggregate Models." *American Journal of Agricultural Economics* 81: 164-79.

Ball, V.E., C. Hallahan, and R. Nehring. 2004. "Convergence of Productivity: An Analysis of the Catch-up Hypothesis within a Panel of States." *American Journal of Agricultural Economics* 86: 1315-1321.

Binswanger, H. P. 1974. "The Measurement of Technical Change Biases with Many Factor of Production." *American Economic Review* 64: 964-967.

Chavas, J. P., M. Aliber, and T.L. Cox. 1997. "An Analysis of the Source and Nature of Technical Change: The Case of U.S. Agriculture." *Review of Economics and Statistics* 79: 482-492.

Chavas, J. P. and T.L. Cox. 1992. "A nonparametric analysis of the influence of research on agricultural productivity." *American Journal of Agricultural Economics* 74: 583-91.

de Janvry, A., E. Sadoulet, and M. Fafchamps. 1989. "Agrarian Structure, Technological Innovations and the State." in Pranab Bardhan, ed. *The Economic Theory of Agrarian Institutions.* Oxford University Press.

Dickey, D.A. and W.A Fuller. 1979. "Distribution of the estimators for autoregressive time series with unit root." *Journal of the American Statistical Association* 74: 427-31.

Evenson, R. and C.E. Pray, ed. 1991. *Research and productivity in Asian agriculture*, Ithaca NY: Cornell University Press.

Frisvold, G.B. 1991. "Endogenous Technological Change in U.S. Agriculture. A Direct

Test of the Induced Innovation Hypothesis." Washington D.C.: U.S. Department of Agriculture, ERS, Technical Bulletin No. 1790.

Hakkio, C.S., and M. Rush. 1991. "Cointegration: How Short Is the Long Run?" *Journal of International Money and Finance* 10: 571-581.

Harris, R. D. F. and E. Tzavalis. 1999. "Inference for Unit Roots in Dynamic Panels where the Time Dimension is Fixed." *Journal of Econometrics* 91: 201-226.

Hayami, Y. and V.W. Ruttan. 1985. "*Agricultural development: an international perspective*, revised edition, Johns Hopkins University Press, Baltimore.

Hicks, J. R. 1932. *The Theory of Wages*, London: Macmillan.

Holtz-Eakin, D., W. Newey, and H. Rosen. 1988. "Estimating Vector Autoregressive with Panel Data." *Econometrica* 56: 1371-1395.

Hsiao, Cheng. 1989. "Modeling Ontario Regional Electricity System Demand Using a Mixed Fixed and Random Coefficients Approach." Regional Science and Urban Economics 19:565-87.

Huffman, W.E. 2005. "Agricultural Public Research Expenditure Data." Unpublished, Ames: Iowa State University.

Huffman, W.E., M. Ahearn, and J. Yee. 2005. "Agricultural Extension Expenditure Data." Unpublished, Ames: Iowa State University, and Washington: U.S. Department of Agriculture Economic Research Service.

Huffman, W.E. and R.E. Evenson. .1993. *Science for agriculture*, Ames: Iowa State University Press.

Im, K.S., M.H. Pesaran, and Y. Shin. 2003. "Testing for Unit Roots in Heterogeneous Panels." *Journal of Econometrics* 115: 53-74.

Johnson, K.N.D. 2005. *USHiPS*: *The U.S. Historical Patent Set*. Retrieved from http://faculty1.coloradocollege.edu/~djohnson/uships/histstat.xls.

Johnson, D.K.N. 1999. "150 years of American invention; Methodology and a first geographical application." Wellesley College Working paper 99-01, Wellesley, MA, January.

Johnson, D.K.N. and R.E. Evenson, ed. 1997. *Economic Systems Research* 9, Issue 1, June.

Karagiannis, G. and W.H. Furtan. 1990. "Induced Innovation in Canadian Agriculture: 1926-1987." *Canadian Journal of Agriculture Economics* 38: 1-21.

Kawagoe, T., K. Otsuka, and Y. Hayami. 1986. "Induced bias of technical change in agriculture: the United States and Japan 1880-1980." *Journal of Political Economy* 94: 523-544.

Khatri, Y., C. Thirtle, and R. Townsend. 1998. "Testing the Induced Innovation Hypothesis: An Application to UK Agriculture, 1953-1990." *Econ. Innovation and New Technology* 6: 1-28.

Lambert, D.K., and J.S. Shonkwiler. 1995. "Factor Bias Under Stochastic Technical Change." American Journal of Agricultural Economics 77: 578-590.

Levin, A. and C. Lin. 1993. "Unit Root Tests in Panel Data: Asymptotic and Finite-Sample Properties." Working Paper, San Diego: University of California.

Lim, H. and C.R. Shumway. 1997. "Technical Change and Model Specification: U.S. Agricultural Production." *American Journal of Agricultural Economics* 79: 543-554.

Liu, Q. and C.R. Shumway. 2006. "Geographic Aggregation and Induced Innovation in American Agriculture." *Applied Economics*, in press.

Machado, F.S. 1995. "Testing the induced innovation hypothesis using cointegration analysis." *Journal of Agricultural Economics* 46: 349-60.

Nair-Reichert, U., and D. Weinhold. 2001. "Causality Test for Cross-country Panels: A New Look at FDI and Economic Growth in Developing Countries." *Oxford Bulletin of Economics and Statistics* 63: 153-171.

Newey, W. and K. West. 1994. "Autocovariance Lag Selection in Covariance Matrix Estimation." *Review of Economic Studies* 61: 631-653.

Olmstead, A. L., and P. W. Rhode. 1998. "Induced Innovation in American Agriculture: An Econometric Analysis." *Research in Economic History* 18: 103-19.

_____. 1993. "Induced Innovation in American Agriculture: A Reconsideration." *Journal of Political Economy* 101: 100-118.

Oniki, S. 2000. "Testing the induced innovation hypothesis in a cointegrating regression model." *The Japanese Economic Review* 51: 544-54.

Pardey, P.G. and B. Craig. 1989. "Causal relationships between public sector agricultural research expenditures and output." *American Journal of Agricultural Economics* 71: 9-19.

Pedroni, P. 1999. "Critical Values for Cointegration Tests in Heterogeneous Panels with

Multiple Regressors." *Oxford Bulletin of Economics and Statistics* 61: 653-678.

Pesaran, M.H., Y. Shin, and R. Smith. 1999. :Pooled Mean Group Estimation of Dynamic Heterogeneous Panels." *Journal of American Statistical Association* 94: 621-634.

Strickland, R. 2005. "Personal communication." Unpublished, Washington DC: U.S. Department of Agriculture, ERS.

Thirtle, C.G. 1985. "Accounting for Increasing Land-Labour Ratios in Developed Country Agriculture." *Journal of Agriculture Economics* 36: 161-169.

Thirtle, C.G., D.E Schimmelpfennig, and R.F. Townsend. 2002. "Induced innovation in United States agriculture, 1880-1990: Time series tests and an error correction model." *American Journal of Agricultural Economics* 84: 598-614.

Thirtle, C., R. Townsend, and J. van Zyl, 1998. "Testing the induced innovation hypothesis: an error correction model of South African agriculture." *Agricultural Economics* 19: 145-57.

Tiffin, R. and P. Dawson. 1995. "Induced innovation in American agriculture." *Oxford Agrarian Studies* 23: 87-98.

U.S. Department of Agriculture/Economic Research Service. 1960-2003. *Farm Balance Sheet*. Annual Series, http://www.ers.usda.gov/Data/FarmBalanceSheet/50STBSHT.htm.

U.S. Department of Agriculture / National Agricultural Statistics Service. 1960-2005. *Farms, Land in Farms, & Livestock Operations.* Annual Series. http://usda.mannlib.cornell.edu/reports/nassr/other/zfl-bb/

Table 1. Panel Unit Root Test Results

Data Series [a]	Z_{tbar} statistic [b]	P-value
Ln(A/M)	-1.535	0.062
Δ Ln(A/M)	-2.194	0.014
Ln(L/K)	1.220	0.111
Δ Ln(L/K)	-1.533	0.063
Δ^2 Ln(L/K)	-4.073	0.000
Ln(P_A/P_M)	0.847	0.199
Δ Ln(P_A/P_M)	-2.071	0.019
Ln(P_L/P_K)	1.101	0.136
Δ Ln(P_L/P_K)	-1.560	0.057
Δ^2 Ln(P_L/P_K)	-5.347	0.000
Ln(R_{pri})	-0.536	0.296
Δ Ln(R_{pri})	-2.862	0.002
Ln(R_{pub})	-0.225	0.411
Δ Ln(R_{pub})	-2.041	0.021
Ln(Ext)	1.765	0.038
Ln($Size$)	0.568	0.285
Δ Ln($Size$)	-0.196	0.422
Δ^2 Ln($Size$)	-2.878	0.002

[a] Δ^2 indicates the variable is second differenced.

[b] When testing for unit root in levels, a time trend was included. For the differences, the unit root was tested without time trend.

Table 2. Panel Cointegration Test Results

Test Statistic	Equation	
	Ln(A/M)	ΔLn(K/L)
Panel v-statistic [a]	2.073**	-0.523
Panel ρ-statistic [b]	0.369	-1.962**
Panel t-statistic (nonparametric) [b]	0.441	-4.556***
Panel t-statistic (parametric) [b]	0.612	-4.349***
Group ρ-statistic [b]	1.098	-1.349*
Group t-statistic (nonparametric) [b]	0.760	-4.883***
Group t-statistic (parametric) [b]	0.952	-4.649***

[a] Critical 1-tailed test values for rejecting hypothesis of no cointegration (Pedroni 1999): 10% level* 1.282, 5% level** 1.645, 1% level*** 2.326.

[b] Critical 1-tailed test values for rejecting hypothesis of no cointegration (Pedroni 1999): 10% level* -1.282, 5% level** -1.645, 1% level*** -2.326.

Table 3. Estimated Error Correction Model

Variable		PMGE			MGE		Hausman test	
	Coef.[a]	S. E.[b]	t-ratio	Coef.	S. E.	t-ratio	h-value	p-value
Long-run Coefficients								
$\Delta Ln(P_L/P_K)_{t-1}$	-0.108	0.011	-10.237	-0.115	0.055	-2.106	0.02	0.90
$\Delta Ln(Size)_{t-1}$	-0.052	0.021	-2.439	0.088	0.175	0.501	0.65	0.42
$Ln(R_{pri})_{t-1}$ [c]	0.020	0.007	3.055	0.072	0.040	1.797	1.73	0.19
$Ln(R_{pub})_{t-1}$	0.019	0.005	3.670	-0.030	0.043	-0.693	1.32	0.25
$Ln(Ext)_{t-1}$	0.051	0.009	5.511	0.088	0.033	2.677	1.35	0.25
Error Correction Coef. λ_2	-1.319	0.055	-23.903	-1.415	0.068	-20.788		
Short-run Coefficients								
$\Delta Ln(P_L/P_K)_t$	-0.143	0.006	-23.903	-0.127	0.044	-2.873		
$\Delta Ln(Size)_t$	-0.069	0.003	-23.903	0.005	0.137	0.034		
$Ln(R_{pri})_t$	0.026	0.001	23.903	0.068	0.029	2.365		
$Ln(R_{pub})_t$	0.025	0.001	23.903	0.002	0.023	0.079		
$Ln(Ext)_t$	0.068	0.003	23.903	0.132	0.041	3.191		
$\Delta^2 Ln(L/K)_{t-1}$	0.123	0.038	3.238	0.164	0.043	3.804		
$\Delta^2 Ln(L/K)_{t-2}$	0.020	0.021	0.953	0.018	0.025	0.694		
$\Delta^2 Ln(P_L/P_K)_t$	-0.042	0.018	-2.343	-0.048	0.040	-1.205		
$\Delta^2 Ln(P_L/P_K)_{t-1}$	-0.043	0.021	-2.027	-0.048	0.037	-1.286		
$\Delta^2 Ln(P_L/P_K)_{t-2}$	-0.034	0.016	-2.101	-0.045	0.021	-2.119		
$\Delta^2 Ln(Size)_t$	0.183	0.038	4.850	0.144	0.113	1.273		
$\Delta^2 Ln(Size)_{t-1}$	0.123	0.039	3.159	0.028	0.076	0.368		
$\Delta^2 Ln(Size)_{t-2}$	0.012	0.032	0.394	-0.016	0.056	-0.296		
$\Delta Ln(R_{pri})_t$	-0.008	0.016	-0.534	-0.042	0.026	-1.600		
$\Delta Ln(R_{pri})_{t-1}$	-0.021	0.010	-2.038	-0.029	0.014	-2.020		
$\Delta Ln(R_{pri})_{t-2}$	0.016	0.008	2.090	0.028	0.014	2.076		
$\Delta Ln(R_{pub})_t$	0.032	0.024	1.298	0.074	0.036	2.075		
$\Delta Ln(R_{pub})_{t-1}$	-0.006	0.014	-0.470	0.004	0.014	0.279		
$\Delta Ln(R_{pub})_{t-2}$	0.037	0.016	2.266	0.051	0.021	2.460		
$\Delta Ln(Ext)_t$	-0.018	0.036	-0.506	-0.036	0.065	-0.562		
$\Delta Ln(Ext)_{t-1}$	-0.203	0.050	-4.029	-0.280	0.068	-4.128		
$\Delta Ln(Ext)_{t-2}$	-0.111	0.032	-3.480	-0.176	0.046	-3.860		
Constant	-0.665	0.028	-23.658	-0.968	0.216	-4.489		
$\bar{R}^2$		0.6252			0.727			

Note: The critical t values are 1.68 for 95% confidence level and 2.02 for 97.5% confidence level. $\bar{R}^2$ is an average of state-specific adjusted R-square.

[a] Coef. represents coefficient

[b] S.E. represents standard error

[c] $Ln(R_{pri})_t$, $Ln(R_{prub})_t$ and $Ln(Ext)_t$ are lagged values on private research, public research, and extension expenditures with optimal lags 13 years, 16 years, and 3 years respectively which were selected by minimizing the AIC.

Table 4. MFR Causality Test

Variable	Estimated Coefficient	Standard Error	t-value
Constant	-1.152	0.538	-2.142
$Ln(L/K)_{t-1}$	-0.212	0.519	-0.408
$Ln(L/K)_{t-2}$	-0.081	0.527	-0.154
$Ln(P_L/P_K)_{t-1}$	0.045	0.396	0.114
$Ln(P_L/P_K)_{t-2}$	0.033	0.409	0.081
$Ln(R_{pri})_{t-1}$ [a]	0.031	0.256	0.121
$Ln(R_{pri})_{t-2}$	0.003	0.253	0.011
$Ln(R_{pub})_{t-1}$	0.047	0.447	0.106
$Ln(R_{pub})_{t-2}$	-0.019	0.448	-0.042
$Ln(Ext)_{t-1}$	-0.036	0.331	-0.107
$Ln(Ext)_{t-2}$	0.111	0.332	0.336
$Ln(Size)_{t-1}$	0.034	0.824	0.042
$Ln(Size)_{t-2}$	-0.151	0.840	-0.180

[a] $Ln(R_{pri})_t$, $Ln(R_{prub})_t$ and $Ln(Ext)_t$ are lagged values on private research, public research, and extension expenditures with optimal lags 13 years, 16 years, and 3 years respectively which were selected by minimizing the AIC.

Note: The critical t values are 1.68 for 95% confidence level and 2.02 for 97.5% confidence level.