School of Economic Sciences

Working Paper Series
WP 2008-3

Induced Innovation in U.S. Agriculture: Time-series, Direct Econometric, and Nonparametric Tests

By

Y. Liu and C.R. Shumway

2008

WASHINGTON STATE UNIVERSITY
World Class. Face to Face.

Induced Innovation in U.S. Agriculture:

Time-series, Direct Econometric, and Nonparametric Tests

Yucan Liu and C. Richard Shumway

Abstract

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, direct econometric, and nonparametric. We find little support for the hypothesis. That conclusion is robust across testing techniques. However, as with all empirical tests of this hypothesis conducted to date, ours focus only on the demand side of the hypothesis. The hypothesis could have been rejected simply because the marginal cost of developing and implementing input-saving technologies for the relatively expensive inputs is greater than for the relatively cheap inputs.

Key words**:** econometric, induced innovation, nonparametric, time series, 2-stage CES

Suggested Running Head**:** Three Tests of Induced Innovation in U.S. Agriculture

---

Yucan Liu is a market analyst for Federal Express and a former graduate research assistant in the School of Economic Sciences, Washington State University. C. Richard Shumway is a professor in the School of Economic Sciences, Washington State University.

Induced Innovation in U.S. Agriculture:

Time-series, Direct Econometric, and Nonparametric Tests

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 expensive ones. It clearly is a result of choices and decisions made both by researchers who discover new technologies and by producers who choose technologies to implement from among those currently available.

The processes by which output-augmenting and input-saving technologies are developed are varied and diffuse. They include both fortuitous discoveries and planned 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 inputs.

First proposed by Hicks in 1932, this theory has been extensively examined during the last four decades. Based on the microeconomic foundations of induced innovation theory proposed by Ahmad (1966),[1] Hayami and Ruttan (1970) conducted the first formal test of the induced innovation hypothesis (IIH) and concluded that the evolution of relative input 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 (1974) 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 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, Otsuka, and Hayami (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.

Based on the overall consistency of 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 regional and national technological developments as well as a subsequent econometric test (Olmstead and Rhode 1998) failed to support the IIH. 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: direct econometric, time series, and nonparametric methods.[2] Direct 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, Schimmelpfennig, and Townsend (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.[3] The most recently developed and least-used procedures for testing the IIH have involved nonparametric economic models. 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.

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.[4]

To shed light on both of these issues, the objectives of this paper are to conduct comprehensive tests of the IIH for U.S. agriculture using a rich state-level panel data set and three state-of-the-art testing procedures. They include time-series, direct econometric, and nonparametric tests. The high-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 analysis of the IIH to be conducted in any country for any industry using a single high-quality data set.

Methodology

In this section we sequentially describe the three procedures we use to test the IIH 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, Townsend, and van Zyl (1998), Oniki (2000), and Thirtle, Schimmelpfennig, and Townsend (2002). Thirtle, Schimmelpfennig, and Townsend (2002) argue that each of 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 cointegration, (b) cointegration must exist among the series, (c) the correlation between factor price ratios and the factor quantity ratios must be negative, (d) the change in factor quantity ratios cannot be fully explained by factor substitution, and (e) causality must run unidirectionally 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 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, Sadoulet, and Fafchamps 1989; Thirtle, Schimmelpfennig, and Townsend 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, the logarithms of the first-order conditions of profit maximization can be expressed as:[5]

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

where R_i and P_i, are the factor quantity and price ratios, respectively; R_{pri} is stock of private research investment, R_{pub} is stock of public research investment, Ext is stock of public extension investment; 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 augmenting variables. The agricultural private and public research and public extension stocks were constructed based on the weighting procedure of Huffman and Evenson (1989).[6] This specification provides a straightforward approach for directly testing the IIH. Hereafter, we refer to equation (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).

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 (1). The pooled mean group estimation procedure (PMGE) developed by Pesaran, Shin, and Smith (1999) is used for this purpose.[7] The structure of the ARDL model is:

(2) $\Delta \ln R_{iht} = \mu_i + \lambda_i (\ln R_{iht-1} - \boldsymbol{\theta}_i' \mathbf{x}_{iht}) + \boldsymbol{\beta}_i' \mathbf{Z}_i + \varepsilon_{iht},\ i = A/M$ and L/K,

where $\mathbf{x}_{iht} = (\ln P_{iht}, \ln R_{pri,ht}, \ln R_{pub,ht}, \ln Ext_{ht})'$; $\mathbf{Z}_i$ is a vector of the lagged terms of $\ln\mathbf{R}_{iht}$ and $\mathbf{x}_{iht}$ where the optimal number of lags is selected based on the Akaike Information Criterion (AIC); h identifies the state; t is time; Δ is the differencing operator; $\boldsymbol{\theta}$ 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 error correction coefficient; μ and $\boldsymbol{\beta}$ are parameters; ε is a disturbance term.

Since all the variables are in logarithms, the absolute values 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 (IPC). Induced innovation requires the estimated long-run elasticities of substitution to be significantly greater than the estimated short-run elasticities (Oniki 2000). It implies that part of the factor ratio changes are induced by lagged effects of relative prices, which cause technology-induced substitution around the IPC. From estimation of the ECM, short-run and long-run elasticities are used to decompose the factor ratio changes into those that are technology-induced by lagged effects of relative price changes and those that are factor substitutions due to changes in current prices (Thirtle, Schimmelpfennig, and Townsend 2002).

The final step of the time series analysis is to examine whether the factor price ratio Granger causes factor-saving technical bias. To do that, we use Nair-Reichert and Weinhold's (2001) mixed fixed and random coefficients estimation algorithm for the dynamic panel model.

Direct Econometric Approach

The direct 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 include 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 that equates the slope of the IPF to the market relative shares measured in efficiency units (Funk 2002; Armanville and Funk 2003). Armanville and Funk argue 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 develop two tests of the IIH – a "weak" test that innovative decisions move in the direction predicted by the IIH, and a "strong" test that innovation decisions satisfy the first-order conditions for profit-maximizing choices.

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:

(3)

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

where $F_{iht} = P_{iht}R_{iht}$; $R_{pri,s}$, $R_{pub,s}$, and Ext_s are investments in year s for private research, public research investment, and extension, respectively; τ, γ, δ are parameters. As with the stock variables used in the time series procedure, the maximum number of lags is 27 for public research investment, 20 for private research investment, and nine for extension investment.

By estimating equation (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 or between L and K is less than 1, the hypothesis is $\gamma_i > 0$. 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. If the elasticity of substitution is greater than 1, $\gamma_i < 0$ and the equivalent test is to determine whether this ratio is significantly negative. 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 A (Liu and Shumway 2008).

Nonparametric Approach

The nonparametric testing procedure follows Chavas, Aliber, and Cox (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 $\mathbf{X}_t = (X_{1,t},...,X_{m,t})'$ with associated price vector $\mathbf{P}_t = (P_{1,t},...,P_{m,t})'$. In our case, the netput vector is 5x1: $\mathbf{X}_t = (Y_t,\ -X_{A,t},\ -X_{M,t},\ -X_{L,t},\ -X_{K,t})$. The feasible netput choices satisfy $\mathbf{X}_t \in F$, where F is the feasible technology set.

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

$$(4) \qquad x_{i,t} = g(X_{i,t}, B_{i,t}), \quad i = Y, A, M, L, K, \quad t \in T.$$

We follow Chavas, Aliber, and Cox (1997) in treating $g(X,\cdot)$ as a reversible function, specifying augmentation following the translating hypothesis, i.e., $X_i = x_i + B_i$, and in specifying three augmentation restrictions needed to implement nonparametric testing of the IIH.[8]

The first augmentation restriction is that the relationship between innovation investments and input augmentation is presumed to take the following form:[9]

$$(5) \qquad B_{i,t} = \alpha_{i,t} + \sum_{j=0}^{\mathbf{r}} \left\{ [\boldsymbol{\beta}_{i,j} + (p_{i,t-j} - 1)\boldsymbol{\gamma}_{i,j}]\mathbf{R}_{t-j} \right\}, \ i = A, M, L, K, \quad t \in T,$$

where $\mathbf{r}$ 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 $\mathbf{R}_{t-j} = (R_{pri,t-j}, R_{pub,t-j}, Ext_{t-j})'$, $\alpha_{i,t}$ is a scalar that measures the impact of exogenous shocks on augmentation in the absence of innovation investments, $\boldsymbol{\beta}_{i,j}$ is a $1 \times k$ parameter vector measuring the marginal effect of $\mathbf{R}_{t-j}$ on $B_{i,t}$ for constant relative prices (i.e., $p_{i,t-j} = 1$); the 1xk parameter vector $\boldsymbol{\gamma}_{i,j}$ measures the interaction effect of $p_{i,t-j}$ and $\mathbf{R}_{t-j}$ on $B_{i,t}$. The maximum number of lags on each innovation variable is the same in this model as in the others. Thus, the $\boldsymbol{\beta}_{i,j}$'s and $\boldsymbol{\gamma}_{i,j}$'s are allowed to be nonzero for $3 < j < 28$ for public research, $2 < j < 21$ for private research, and $2 < j < 10$ for extension. The IIH is corroborated by $\gamma_{i,j,k} > 0$ for some j with no $\gamma_{i,j,k} < 0$; this constitutes the critical test via this nonparametric method.

The second restriction smoothes output augmentation variables to maintain the hypothesis of nonregressive technical change subject to random weather effects that can 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 WAPM under the three augmentation restrictions. Following Chavas, Aliber, and Cox (1997), we solve the following quadratic programming problem:

$$\tag{6} \min_{B,\alpha,\boldsymbol{\beta},\boldsymbol{\gamma}} \left[\sum_{i \in N} \left\{ \sum_{t \in T} w_1 \alpha_{i,t}^2 + \sum_j (w_2 \boldsymbol{\beta}_{i,j} \boldsymbol{\beta}'_{i,j} + w_3 \boldsymbol{\gamma}_{i,j} \boldsymbol{\gamma}'_{i,j}) \right\} : \begin{array}{l} (X_{i,t} - B_{i,t}) \ge 0, i = Y; \\ (X_{i,t} - B_{i,t}) \le 0,\ i = A, M, L, K;\ \ t \in T; \\ \text{WAPM; the three augmentation restrictions} \end{array} \right]$$

where w_1, w_2, w_3 are positive weights.[10] Equation (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 the WAPM

(Chavas, Aliber, and Cox 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 Appendix B (Liu and Shumway 2008).

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 United States and include Florida, North Carolina, and New York in the east, Texas, Iowa, Kansas, and Michigan in the center, and California and Washington in the west.

Data

Panel data on input quantities and prices for the 48 contiguous states for the period 1960-1999 come from Ball, Hallahan, and Nehring (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).[11] They were 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. 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 are 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 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.

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.[12] Consequently, we created state-level input price proxies for the period 1932-1959 using Ball et al.'s (1997) U.S. input price data, which were developed using the same procedures as the state-level data for the period 1948-1999 and Thirtle, Schimmelpfennig, and Townsend's (2002) U.S. input price data for earlier years. Details of the construction of state-level input price proxies in this data set are provided in the linked Appendix C (Liu and Shumway 2008).

Empirical Results

The empirical results from each estimation procedure are presented sequentially in this section. All test statistics are reported for a 0.05 significance level.

Time-Series Test Results

The Hadri stationarity test results for all variables are reported in Table 1. Accounting for heteroskedastic errors across units, the associated p-values for all series imply that stationarity was rejected for each series in levels. Three variables were found to be stationary in first differences, i.e., they followed I(1) processes. Two series were found to be I(2) processes and two were I(3) processes.

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 (1) 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, first differences for I(2) series, and second differences for I(3) series to capture the long-run relationships in the data for both time-series and direct econometric models. 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).

The results of the cointegration tests are reported in the last four rows of Table 1. Pedroni's (1999) seven test statistics are reported for each cointegration test. Weak evidence was found to support cointegration for the land-material equation. Three of the test statistics rejected the hypothesis of no cointegration for this equation. For the labor-capital equation in the time-series model, all statistics but one supported rejection of the hypothesis of no cointegration. Thus, based on the preponderance of test evidence, it is concluded that a long-run relationship exists for the labor-capital equation but is inconclusive for the land-material equation.[13]

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 and second differences for each I(3) variable.

Using the Hausman test, we failed to reject the hypothesis of long-run homogeneity for either 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 chosen by this process for each factor ratio equation.

The Pesaran PMGE parameter estimates of the ECM are reported in Table 2. 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 -1.290, significantly different from -1.0, and 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 (0.062) is significantly larger than the long-run elasticity (0.048).[14] Failure of the long-run elasticity (along the IPF) to exceed the short-run elasticity (along the isoquant) implies that changes in the labor-capital quantity ratio can’t be separated into two parts, which is a crucial inconsistency with the IIH (Thirtle et al. 2002; Oniki 2000). Based on requirement (d), the IIH is rejected for labor and capital inputs.

The estimated value of the error correction term in the land-material equation is -0.131, which implies that, when the system is not in equilibrium, there is a 13.1% correction towards the long-run equilibrium in the current period. Thus, its long-run elasticity of substitution (0.053) is larger than its short-run elasticity (0.007), which is consistent with the IIH.

Two of the innovation variables (private and public research investments) have significantly negative long-run and short-run effects on the land-material ratio. The significantly negative coefficients on these two innovation variables imply that increased research investments lead to land-saving technical change both in the long run and short run. The significantly positive coefficients on extension investments imply that this innovation variable increases both the short-run and long-run bias toward material-saving technical change.

The final time-series test of the IIH was conducted to determine whether causality ran unidirectionally from the factor price ratio and innovation variables to the factor quantity ratio for both equations. We estimated a dynamic model in which the factor quantity ratio was modeled as a function of its lags, lags of the hypothesized causal variables (i.e., the own-price ratio and the three types of innovation investment) and other explanatory variables. Following Lütkepohl (1993, p. 306), maximum lag length was set equal to the integer of $T^{1/3}$, i.e., 3 in our application. Based on the AIC, optimal lag length was 2 for all the causal variables in the land-materials equation and 1 in the labor-capital equation. Lagged terms of the dependent variable were included to proxy omitted variables (Nair-Reichert and Weinhold 2001). Although a shorter lag structure was chosen as optimal by the AIC, causality test inferences can be sensitive to the number of lags, so we estimated the model using lags ranging from 1 to 3. The Nair-Reichert and Weinhold mixed-fixed-and-random-coefficients estimates are reported in Table 3 for all three lag lengths.

In none of the estimated results did we reject the causality relation from the own-price ratio to the quantity ratio for land-materials. In this equation, all but one of the lagged own-price ratio for lags 1 to 3 were negative as expected and statistically significant. However, evidence of reverse causality was also found for each lag option (see Appendix Table D.1 in Liu and Shumway 2008). Thus, the bidirectional causality results are robust to lag length and imply rejection of the IIH for land and materials by time-series procedures based on requirement (e). Evidence of causality running from public research and extension to the land-materials quantity ratio implies that investments in public research tended to induce land-saving technical change and investments in extension induced materials-saving technical change. However, reverse causality was found for public research such that land-saving technical change stimulated additional public research investment. No causal evidence was found running from private research to the land-materials quantity ratio.

We rejected the causality relation from the own-price ratio to the quantity ratio for labor-capital for at least one lagged variable in each lag option. Only two of the six coefficients on lagged own-price ratios were significantly negative. These results imply rejection of the IIH for labor and capital by time-series procedures based on requirement (e). Evidence of causality from all three innovation variables to the labor-capital quantity ratio was found and was robust to lag length. Reverse causality was found in public research. These findings imply that extension and private research investments tended to induce labor-saving technical change. Public research investments were found to induce capital-saving technical change, and capital-saving technical change stimulated public innovation policy that further increased research investment.

Thus, none of the inputs fully satisfied the necessary conditions for supporting the hypothesis of induced innovation using this robust, panel time-series testing procedure. Land and materials were ambiguous in supporting the hypothesis at the second step (existence of a cointegrated relationship), and capital and labor failed to support it at the fourth step (long-run elasticity of substitution greater in absolute value than the short-run elasticity). All four inputs failed to support the hypothesis at the fifth step (causality running unidirectionally from the own-price ratio to the quantity ratio). Despite evidence supporting the IIH at other steps, these violations necessitate rejection by time series methods of the IIH for both pairs of inputs. [15]

Direct Econometric Model Results

Before estimating the direct econometric model, we first tested for AR(1) and heteroskedasticity in each equation's residuals.[16] Finding evidence of both autocorrelation and heteroskedasticity in the residuals of the land-material and labor-capital equations specified in equation (3), we estimated both equations using a heteroskedasticity- and autocorrelation-consistent covariance matrix estimator

(HACCME).[17] This estimator computes the coefficients using a least-squares approach. The parameter estimates and test statistics are reported in Table 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). Thus, 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. The test results for the weak and strong hypotheses are reported in the last two rows of Table 4. The weak hypothesis was accepted (i.e., the tested null hypothesis was rejected) only for the land-material equation but not for the labor-capital equation. The strong hypothesis that $\gamma_i = 1$, i= A/M, L/C, was soundly rejected for both equations. Thus, our econometric test results provided support for the weak version of the IIH in only one input pair but no support for the strong version in either pair.

Generalized Model Results

To determine whether test conclusions were sensitive to the restrictive CES functional form, all time-series and direct 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. Each equation included three price ratios ($P_{A/M}$, $P_{L/K}$, and $P_{A/L}$), output level, and the three efficiency variables (R_{pri}, R_{pub}, Ext). This generalization was treated only as an approximation to an unknown but more general functional form. Conclusions from both models were qualitatively unaffected by this generalization.

Nonparametric Test Results

The nonparametric findings regarding the validity of the IIH are reported in Table 5 for each input for 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, Aliber, and Cox (1997). In no state did a majority of the tests support the hypothesis, and in one state all tests rejected the hypothesis. For each innovation investment types, about one-quarter of the tests supported the hypothesis and three-quarters rejected it.

Thus, nonparametric test results were consistent with both the time series and direct econometric model test results. Findings from all approaches imply that relative input prices failed to play a major role in inducing 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 (1974), Antle (1984), Thirtle (1985), Kawagoe, Otsuka, and Hayami (1986), Huffman and Evenson (1989), Lambert and Shonkwiler (1995), and

Thirtle, Schimmelpfennig, and Townsend (2002).

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. This hypothesis has been empirically tested in many ways, using a wide variety of data 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 this highly intuitive hypothesis in U.S. agriculture as well as in many other industries and countries. However, while most early tests supported the hypothesis, recent tests with a wider variety of testing methods and data have resulted in nearly even support for and against the IIH. Thus, no stylized fact on induced innovation in this industry currently exists.

Possible reasons for the recent conflicting test results are inadequate data, low power of traditional testing methods, and inflexibility of specification. 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, direct econometric, and nonparametric methods.

With the exception of the weak direct econometric test for land-materials, our empirical finding was robust to test procedures and to functional specification. The IIH proved inadequate to explain input-saving technologies developed and implemented in

U.S. agriculture between 1960 and 1999. The hypothesis was 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 impacted development and implementation of factor-saving inputs, they were not exclusively motivated by relative prices.

However, it should be clearly noted that all empirical tests conducted to date, including ours, focus only on the demand side of the hypothesis. A possible and very plausible explanation for rejecting the hypothesis 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. All the tests impose the assumption 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.[18]

Footnotes

[1] 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.

[2] These three categories are not all-inclusive; e.g., they don't capture the notable work of Olmstead and Rhode (1993).

[3] Liu and Shumway (2006) rejected the IIH for the U.S. but not for the state of Washington or two western regions.

[4] For example, an anonymous reviewer suggested that rejection of the IIH by Machado (1995) and Tiffin and Dawson (1995) may have been due to the use of low quality data.

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

[6] We used a trapezoidal stock variable for public research starting in year 4 with increasing weights for 7 years, constant for 5, and declining for 12 to year 27; a trapezoidal stock variable for private research starting in year 3 with increasing weights for 6, constant for 5, and declining for 7 to year 20; and a stock variable for extension with half the weight in year 3 and declining geometrically to year 9.

[7] The PMGE allows short-run coefficients and error variances to vary across groups. This weak homogeneity assumption is preferable to traditional procedures such as fixed effects, instrumental variables, and generalized method of moments which presume strong homogeneity across groups (Pesaran *et al*., 1999).

[8] Another augmentation specification maintained in analysis of technical change relies on the scaling hypothesis: $x_i = X_i B_i$. We don't use this specification because it renders the weak axiom of profit maximization (WAPM) nonlinear in *B*.

[9] 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: $B_{y,t} = \alpha_{y,t} + \sum_{j=0}^{\mathbf{r}} \boldsymbol{\beta}_{y,t} \mathbf{R}_{t-j}$, $t \in T$.

[10] Following Chavas, Aliber, and Cox (1997), we use unit weights on all three parameters. That is, each of the terms in equation (5) is treated as being equally important to the augmentation indices.

[11] The capital input category includes machinery, equipment, buildings, and inventories; land includes land and land improvements, labor includes family and hired labor, materials includes chemicals, energy, seed, feed, and other operational inputs. Prices of capital and land are rental rates. One could argue that buildings and livestock inventories, which are included in the capital category, are misplaced for our tests because they are more likely to be land-enhancing than labor-substituting. The seriousness of such a possible misplacement is not entirely clear. The combined portion of capital rents represented by these inputs is typically about one-quarter. Many buildings are indeed labor-substituting (e.g., milking parlors, machine storage, and even livestock barns). As a further caution, an anonymous reviewer noted that constructed price ratio data often fare poorly in time series tests.

[12] Some input prices are available prior to 1960, but data such as marketing and inventories that are required to construct input aggregates consistent with those used in this study are not available.

[13] We also ran state-specific tests. In 26 of the 48 states, the hypothesis of no long-run relationship was not rejected for the land-materials equation. Thus, the IIH would be rejected in 26 states by these individual tests for these inputs. The hypothesis of no long-run relationship was rejected in all states for the labor-capital equation.

[14] In the state-specific analyses, only 3 states exhibited larger long-run than short-run elasticities of substitution for labor and capital.

[15] If the micro units underlying the aggregated data are heterogeneous, their time series characteristics can differ significantly from that of the aggregate data (Granger, 1980). Therefore, possible inappropriateness of pooling all 48 states in the sample may bias the results. To determine whether test conclusions were sensitive to the sample used for land and materials, we re-ran all tests using the sub-sample of 22 states for which a long-run relationship could not be rejected (i.e., each had a significant error correction coefficient estimated by the PMGE). Their results were not qualitatively different than reported for the entire sample.

[16] We first attempted to specify the direct 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 severe multicollinearity.

[17] 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.

[18] See Appendix E (Liu and Shumway 2008) for additional insights.

References

Afriat, S.N. 1972. "Efficiency Estimation of Production Functions." *International Economic Review* 13:568-598.

Ahmad, S. 1966. "On the Theory of Induced Invention." *Economic Journal* 76:344-57.

Antle, J.M. 1984. "The Structure of US Agricultural Technology, 1910-1978." *Journal of American Agricultural Economics* 33:414-21.

Armanville, I. and P. Funk. 2003. "Induced Innovation: An Empirical Test." *Applied Economics* 35:1627-1647.

Ball, V.E., J.C. Bureau, R. Nehring, and A. Somwaru. 1997. "Agricultural Productivity Revisited." *American Journal of Agricultural Economics* 79:1045-1063.

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.

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

Funk, P. 2002. "Induced Innovation Revisited." *Economica* 69:155-171.

Granger, C.W.J. 1980. “Long memory relationships and the aggregation of dynamic models.” *Journal of Econometrics* 25:227-238.

Hadri, K. 2000. “Testing for Stationarity in Heterogeneous Panel Data.” *Econometrics Journal* 3:148-161.

Hayami, Y. and V.W. Ruttan. 1970. “Factor Prices and Technical Change in Agricultural Development: The United States and Japan, 1880-1960.” *The Journal of Political Economy* 78:1115-1141.

——. 1985. *Agricultural Development*: *an International Perspective*, revised ed. Baltimore: John Hopkins University Press.

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

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 . 1989. “Supply and Demand Functions for Multiproduct U.S. Cash Grain Farms: Bias Caused by Research and Other Policies.” *American Journal of Agricultural Economics* 71:761-73.

——. 2003. “New Econometric Evidence on Agricultural Total Factor Productivity Determinants: Impact of Funding Sources.” Working Paper # 03029, Department of Economics, Iowa State University.

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

Johnson, D.K.N. 1999. “150 Years of American Invention; Methodology and a First Geographical Application.” Working paper 99-01, Wellesley College.

Johnson, D.K.N. and R.E. Evenson. 1997. “Introduction: Invention Input-Output Analysis.” *Economic Systems Research* 9:2.

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.

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

Lin, N. 1998. “Technical Change and Aggregation in U.S. Agriculture.” Ph.D. Dissertation, Texas A&M University.

Liu, Q. and C.R. Shumway. 2006. “Geographic Aggregation and Induced Innovation in American Agriculture.” *Applied Economics* 38:671-682.

Liu, Y. and R. Shumway. 2008. “*AJAE* Appendix: Induced Innovation in U.S. Agriculture: Time Series, Direct Econometric, and Nonparametric Tests.” Unpublished manuscript. Available at: http://agecon.lib.umn.edu/, forthcoming.

Lütkepohl, H. 1993. *Introduction to Multiple Time Series*, 2nd ed. Berlin: Spring-Verlag.

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.

Olmstead, A.L. and P.W. Rhode . 1993. “Induced Innovation in American Agriculture: A Reconsideration.” *Journal of Political Economy* 101:100-118.

——. 1998. “Induced Innovation in American Agriculture: An Econometric Analysis." *Research in Economic History* 18:103-19.

Oniki, S. 2000. “Testing the Induced Innovation Hypothesis in A Cointegrating Regression model.” *The Japanese Economic Review* 51:544-54.

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.P. Smith. 1999. “Pooled Mean Group Estimation of Dynamic Heterogeneous Panels.” *Journal of American Statistical Association* 94:621-634.

Thirtle, C.G. 1985. “Accounting for Increasing Land-Labour Ratios in Developed Country Agriculture.” *Journal of Agricultural Economics* 36:161-9.

Thirtle, C.G., D.E. Schimmelpfennig, and R.E. 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.G., R.E. 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.J. 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/MannUsda/viewDocumentInfo.do?documentID=1259

Varian, H.R. 1984. "The Nonparametric Approach to Production Analysis." *Econometrica* 52:579-598.

Table 1. Stationarity and Cointegration Test Results [a]

Stationarity Test Results

Data Series [b]	Levels		1st Differences		2nd Differences		3nd Differences	
	Statistic	P-value	Statistic	P-value	Statistic	P-value	Statistic	P-value
Ln$R_{A/M}$	64.045	0.000	-2.294	0.960				
Ln$R_{L/K}$	101.568	0.000	6.006	0.000	-7.130	1.000		
Ln$P_{A/M}$	78.049	0.000	-3.776	1.000				
Ln$P_{L/K}$	51.773	0.000	-3.735	1.000				
LnR_{pri}	93.761	0.000	62.009	0.000	25.940	0.000	-4.802	1.000
LnR_{pub}	95.863	0.000	66.692	0.000	55.960	0.000	-2.675	0.996
LnExt	87.589	0.000	16.567	0.000	-6.519	1.000		

Cointegration Test Results [c]

Test Statistic	Land-Materials		Labor-Capital	
	Panel	Group	Panel	Group
v-statistic	1.905*		0.137	
ρ-statistic	2.187	3.121	-14.739*	-12.678*
t-statistic (nonparametric)	-2.142*	-2.538*	-41.239*	-45.998*
t-statistic (parametric)	-0.773	-0.321	-25.637*	-28.260*

[a] A time trend was included when testing for stationarity in levels and in testing for cointegration.

[b] 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.

[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 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*)$_t$	-0.053*	0.018	-0.048*	0.006
$\Delta^2 \mathrm{Ln} R_{pri,t}$	-7.802*	2.489	-1.388*	0.546
$\Delta^2 \mathrm{Ln} R_{pub,t}$	-7.699*	1.791	2.764*	0.336
$\Delta \mathrm{Ln} Ext_t$	0.944*	0.219	-0.312*	0.044
Error correction coefficient	-0.131*	0.024	-1.290*	0.059
Short-run effects:				
Ln(*own-price ratio*)$_t$	-0.007*	0.001	-0.062*	0.003
$\Delta^2 \mathrm{Ln} R_{pri,t}$	-1.021*	0.184	-1.790*	0.083
$\Delta^2 \mathrm{Ln} R_{pub,t}$	-1.008*	0.182	3.565*	0.164
$\Delta \mathrm{Ln} Ext_t$	0.124*	0.022	-0.402*	0.019
ΔLn(*own-quantity ratio*)$_{t-1}$ [c]	-0.113*	0.032	0.114*	0.038
ΔLn(*own-quantity ratio*)$_{t-2}$ [c]	-0.011	0.016	0.036*	0.017
ΔLn(*own-price ratio*)$_t$	0.010	0.008	-0.108*	0.019
ΔLn(*own-price ratio*)$_{t-1}$	0.026*	0.007	0.028*	0.013

ΔLn(*own-price ratio*)$_{t-2}$	0.009	0.005	0.007	0.012
Δ^3Ln $R_{pri,t}$	0.148	1.041	0.869	1.318
Δ^3Ln $R_{pri,t\text{-}1}$	-0.275	0.806	-0.670	1.742
Δ^3Ln $R_{pri,t\text{-}2}$	0.242	0.551	-0.603	0.892
Δ^3Ln$R_{pub,t}$	1.249*	0.315	-1.645*	0.577
Δ^3Ln $R_{pub,t\text{-}1}$	0.970*	0.337	-1.334*	0.400
Δ^3Ln $R_{pub,t\text{-}2}$	-1.194*	0.362	-0.732*	0.353
Δ^2LnExt_t	-0.150*	0.039	0.309*	0.084
Δ^2Ln$Ext_{t\text{-}1}$	-0.033	0.018	0.041	0.029
Δ^2Ln$Ext_{t\text{-}2}$	0.004	0.025	-0.051	0.031
Constant	-0.070*	0.018	-0.035*	0.003
$\overline{R}^2$	0.373		0.611	

[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 LnExt_t are respectively stock of private research, public research, and extension investments.

[c] These variables are twice differenced and the dependent variable is first differenced in the labor-capital equation.

Table 3. Causality Test Results [a]

Number of lags	Variable	Land-Materials Estimated Coefficient	Land-Materials Standard Error	Labor-Capital Estimated Coefficient	Labor-Capital Standard Error
Causal variable: own price ratio					
1	Ln(*own-price ratio*)$_{t-1}$	-0.0358*	0.0063	0.0065	0.0111
2	Ln(*own-price ratio*)$_{t-1}$	-0.0147*	0.0058	0.0149	0.0133
	Ln(*own-price ratio*)$_{t-2}$	-0.0307*	0.0084	-0.0374*	0.0204
3	Ln(*own-price ratio*)$_{t-1}$	-0.0031	0.0088	0.0421	0.0194
	Ln(*own-price ratio*)$_{t-2}$	-0.0313*	0.0102	-0.0290	0.0250
	Ln(*own-price ratio*)$_{t-3}$	-0.0240*	0.0094	-0.0489*	0.0227
Causal variable: private research					
1	Ln$R_{pri,t-1}$	0.5829	1.4011	-4.0540*	0.9939
2	Ln$R_{pri,t-1}$	-0.8454	0.8987	-4.7723*	1.2665
	Ln$R_{pri,t-2}$	0.6916	1.3183	-2.1179	1.9874
3	Ln$R_{pri,t-1}$	-0.0124	1.5889	-4.9388*	1.9722
	Ln$R_{pri,t-2}$	1.1583	1.9445	-1.6823	2.4355
	Ln$R_{pri,t-3}$	-0.2782	1.7463	1.9072	2.1079
Causal variable: public research					
1	Ln$R_{pub,t-1}$	-3.3452*	0.8242	1.7046*	0.5831
2	Ln$R_{pub,t-1}$	-1.7290*	0.6522	2.0240*	0.7456
	Ln$R_{pub,t-2}$	-1.2715	0.7267	0.8604	0.8889

3	Ln$R_{pub,t\text{-}1}$	-1.8976*	1.6589	2.5874*	0.9068
	Ln$R_{pub,t\text{-}2}$	-2.3474*	1.0176	1.8282	1.0809
	Ln$R_{pub,t\text{-}3}$	1.3269	0.9375	1.7781	0.9965
Causal variable: extension					
1	Ln$Ext_{t\text{-}1}$	0.2246*	0.0738	-0.3485*	0.0567
2	Ln$Ext_{t\text{-}1}$	0.1935*	0.0552	-0.3906*	0.0721
	Ln$Ext_{t\text{-}2}$	0.1050	0.0597	-0.1502*	0.0759
3	Ln$Ext_{t\text{-}1}$	0.1920*	0.0834	-0.4043*	0.0735
	Ln$Ext_{t\text{-}2}$	0.0430	0.1343	-0.1566*	0.0775
	Ln$Ext_{t\text{-}3}$	0.0720	0.1320	-0.0110	0.0753

[a] The critical values at the 0.05 significance level are -1.645 for the 1-tailed tests on price ratios and 1.96 for the 2-tailed tests on innovation variables. Significant coefficients are identified by an asterisk.

Table 4: Estimated Direct 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
$\bar{R}^2$ [b]	0.488		$\bar{R}^2$	0.357	
Hypothesis	Tested Null	Statistic	Hypothesis	Tested Null	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-tailed t-ratios on the coefficients, 1.65 for the 1-tailed standard normal statistics for the weak test, and 3.84 for the 1-tailed Wald chi-square statistics for the strong test. Significant coefficients are identified by an asterisk.

[b] $\overline{R}^2$ is an average of state-specific adjusted R-square values.

Table 5. Nonparametric Tests of the Induced Innovation Hypothesis, Selected States [a]

	Land			Materials			Labor			Capital		
State	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 stock of private research investments, R_{pub} is stock of public research investments, *Ext* is stock of extension investments. A means accept the IIH, R means rejected the IIH.