Demand and Supply of Induced Innovation:
An Application to U.S. Agriculture:

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Abstract

The hypothesis of induced innovation (Hicks, 1932) is tested for U.S. agriculture using a high-quality state-level panel data set and three disparate testing techniques – time series, econometric, and nonparametric. The conclusion of little support for the hypothesis is robust across testing techniques. However, each test maintains the hypothesis that the relative marginal cost of developing and implementing technologies that save one input is the same as for any other input. Lacking data on development and implementation costs of input-saving technologies, we use nonparametric procedures to estimate relative differences required for technological change to be consistent with the induced innovation hypothesis.

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

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I. Introduction

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

The processes by which output-augmenting and input-saving technologies are developed are varied and diffuse. They include both fortuitous (or accidental) discoveries and planned (organized) research and development activities. Their implementation also includes both fortuitous and planned elements.

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

Although first proposed by Hicks in 1932, this theory has been empirically examined only during the last four decades. Based on the microeconomic foundations of induced innovation theory proposed by Ahmad (1966),[1] Hayami and Ruttan (1970) conducted the first formal test of the induced innovation hypothesis (IIH) and concluded that the evolution of relative factor demand "represents a process of dynamic factor substitutions accompanying changes in the production function induced by changes in relative factor prices" (p. 1135). Since that time it has been tested in a wide variety of countries and industries using various analytical tools and data.

Using a four-factor econometric model, Binswanger (1974a) extended the Hayami-Ruttan methodology to the measurement of technical change bias with many factors of production. He incorporated a linear time trend variable in a translog cost function to measure the bias of factor usage. He found support for the IIH in U.S. agriculture for labor and fertilizer, but not for machinery. Modifications of Binswanger's econometric approach were used by Antle (1984), Hayami and Ruttan (1985), Thirtle (1985), Kawagoe *et al*. (1986), and Huffman and Evenson (1989). All of these couched their tests within a static framework and concluded that their findings were consistent with the IIH for U.S. agriculture. Under the assumption that firms use lagged prices to form expectations, Antle (1986) found support for the IIH, but concluded that it depended on the specification of expectations.

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[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.

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

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

Most analytical tools that have been used to test the IIH can be broadly grouped into three methodological classes: econometric, time series, and nonparametric methods.[2] Econometric models have been used most frequently. While most have built on the modeling approach of Binswanger, important variants include tests using a dynamic econometric model (Lin, 1998) and input demand equations jointly estimated with the innovation possibility frontier (Armanville and Funk, 2003). Lin rejected the IIH for U.S. agriculture, and Armanville and Funk found that support was sensitive to the specification of the innovation possibility frontier. Several have tested the hypothesis using time series procedures. Lambert and Shonkwiler (1995) and Thirtle *et al*. (2002) concluded their evidence confirmed the IIH in this industry, while Machado (1995), Tiffin and Dawson (1995), and Liu and Shumway (2006) failed to find clear evidence

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

supporting the hypothesis. The most recently developed and least-used procedures for testing the IIH have involved nonparametric economic models. Chavas *et al.* (1997) found evidence supporting the IIH for actively traded inputs but not for land and farm labor in the U.S.

Because the IIH has such strong theoretical and intuitive underpinnings, many regard the recent failures to consistently support the hypothesis as data or methodological inadequacies. However, it should be cautioned that all the tests conducted to date have only tested the demand side of the hypothesis. Although both Binswanger (1974a) and Olmstead and Rhode (1993) acknowledged the demand-side nature of the hypothesis tests, most others who have tested the IIH have generally been silent about this important limitation (Coxhead, 1997, is an exception). [3] All tests of the hypothesis have implicitly maintained the hypothesis that the marginal cost of developing and implementing technologies that save one input is the same as the marginal cost of saving an equal percent of any other input. Since it is highly unlikely that innovation possibilities are this neutral, it is possible that the IIH is in fact a valid explanation and yet producers augment cheaper factors because the marginal costs of developing and implementing input-saving technologies for the relatively expensive inputs are greater than for the relatively cheap ones. That is, technical change may not bias toward saving a particular input even when it tends to be relatively expensive.

Unfortunately, data on the development and implementation costs of various input-saving

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

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

The objectives of this paper are to (a) conduct comprehensive demand-side tests of the IIH for U.S. agriculture using a rich state-level panel data set, and (b) if the hypothesis is not unambiguously supported, estimate relative differences in the marginal cost of developing and implementing input-saving technology required for consistency with the hypothesis. The hypothesis is tested using three state-of-the-art testing procedures. They include time-series, econometric, and nonparametric tests. The high-quality, 40-year panel data set permits tests to be conducted that have higher power than those previously used. Consequently, this is the most comprehensive and theoretically complete analysis of the IIH to be conducted in any country for any industry using a single high-quality data set.

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

II. Methodology

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

A. Time-series Approach

The procedure used in our time-series method follows the testing logic developed by

Thirtle *et al.* (1998), Oniki (2000), and Thirtle *et al.* (2002).[4] Thirtle *et al.* (2002) argue that five requirements must be satisfied for the IIH to be supported via time-series properties: (a) the affected series must have time-series properties allowing for 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 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 *et al.*, 1989; Frisvold, 1991; Thirtle *et al.*, 2002). Letting A, M, L, K represent the quantities of land, materials, labor, and capital, respectively, and explicitly incorporating efficiency augmenting variables of research and extension investments and farm size, the logarithms of the first-order conditions of profit maximization can be expressed as:[5]

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

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

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

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

ratio are explained by the own-price ratio and four efficiency augmenting variables. [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). These tests allow for both parametric and dynamic heterogeneity across groups and are considerably more powerful than conventional methods (Harris and Tzavalis, 1999).

If a cointegrated relationship exists among nonstationary variables in the input demand equations, the short-run and long-run relationships of the variables are estimated by an error correction model (ECM) in the second step of the analysis. Our ECM is based on a re-parameterization of an autoregressive distributed lag model (ARDL) of the input demand equations defined in (1). The pooled mean group estimation procedure (PMGE) developed by

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

Pesaran *et al.* (1999) is used for this purpose.[7] The structure of the ARDL model is given as:

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

where $x_{iht} = (\ln(P_{iht}), \ln(R_{pri,ht}), \ln(R_{pub,ht}), \ln(Ext_{ht}), \ln(Size_{ht}))'$; Z_i is a vector of the lagged terms of $\ln(R_{iht})$ and x_{iht} where the optimal lags are selected based on the Akaike Information Criterion (AIC); h identifies the state; t is time; Δ is the differencing operator; θ is a vector of long-run parameters accounting for the long-run equilibrium relationship between factor quantity ratio and the explanatory variables; λ is the corresponding error correction coefficient; [8] μ and β are vectors of parameters; ε is a disturbance term

Since all the variables are in logarithms, the absolute value of long-run coefficients are estimates of long-run elasticities of substitution, and the short-run elasticities of substitution are estimated by the associated absolute value of short-run parameters. The short-run elasticities of

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

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

substitution are curvature measures along the isoquant, while the long-run elasticities are curvature measures along the innovation possibility curve. Induced innovation requires the estimated long-run elasticities of substitution to be significantly greater than the estimated short-run elasticities (Oniki, 2000).

The next step of the analysis is to examine whether the factor price ratio Granger causes factor-saving technical bias. We use the mixed fixed and random coefficients estimation algorithm initially developed by Hsiao *et al.* (1989) and extended to the dynamic panel model by Nair-Reichert and Weinhold (2001).[9]

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

B. Econometric Approach

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

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

rate of augmentation for other inputs.

The first-order conditions of this maximization problem imply that the profit maximizer will choose the set of factor augmentations such that the slope of the IPF equals the market relative shares measured in efficiency units (Funk, 2002; Armanville and Funk, 2003). Armanville and Funk argued that it is the market relative shares (in efficiency units) rather than the relative prices *per se* that play the essential role in determining direction of technical change. They developed two tests of the IIH – a "weak" test that innovative decisions move in the same direction predicted by the IIH, and a "strong" test that innovation decisions satisfy the first-order conditions for profit-maximizing choice of innovations.

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

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

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

By estimating equation (3), all the parameters concealed in the production function and the IPF can be recovered. With this specification, a strong test of the IIH is equivalent to testing the null hypothesis that $\gamma_i = 1$ for i = A/M, L/K. The null was tested by the equivalent hypothesis that the sum of the coefficients on the price ratio and F_{iht}, i = A/M, L/K, equals negative one. The null hypothesis for the weak test is dependent on the magnitude of the elasticity of substitution. If the elasticity of substitution between A and M (for i = A/M) or between L and K (for i = L/K) is less (greater) than 1, the hypothesis is that $\gamma_i > 0$ ($\gamma_i < 0$). Testing this hypothesis is

equivalent to testing whether the ratio of the coefficient on F_{iht} and the negative of (1 plus the coefficient on the price ratio) is significantly positive (negative) when the elasticity of substitution is less (greater) than 1. This model not only provides a simple specification for joint estimates of the production function and IPF but an empirically tractable approach for directly conducting strong and weak tests of the IIH. Additional details of the econometric estimation equations and hypothesis tests are in Reviewers' Appendix A.[10]

C. Nonparametric Approach

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

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

[10] Reviewers' appendices are provided for completeness. They are not intended for publication. Upon acceptance of the manuscript, references to appendices will be changed to making them available upon request or by directing the readers to a website where they will be maintained for a minimum of 5 years.

augmentations, $B_{i,t}$:

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

We follow Chavas *et al.* (1997) in treating $g(X,\cdot)$ as a reversible function, specifying augmentation following the translating hypothesis, i.e., $X_i = x_i + B_i$,[11] and in specifying three augmentation restrictions needed to implement nonparametric testing of the IIH.

The first augmentation restriction is that the relationship between innovation investments and input augmentation is presumed to take the following form:[12]

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

where r is a vector of the maximum number of lags on innovation investments, j is the lag number, $p_{i,t-j}$ is the price of the ith input relative to a Tornqvist index of all input prices at time t-j (so it equals 1 if the ith input price moves in proportion to the index of all input prices), the $k \times 1$ vector $R_{t-j} = (R_{pri,t-j}, R_{pub,t-j}, Ext_{t-j})'$, $\alpha_{i,t}$ is a scalar that measures the impact of exogenous shocks on augmentation in the absence of innovation investments, $\beta_{i,j}$ is a $1 \times k$ parameter vector

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

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

measuring the marginal effect of R_{t-j} on $B_{i,t}$ for constant relative prices (i.e., $p_{i,t-j} = 1$);[13] the 1xk parameter vector $\gamma_{i,j}$ measures the interaction effect of $p_{i,t-j}$ and R_{t-j} on $B_{i,t}$. We set the maximum number of lags at 28 for public research, 21 for private research, and 10 for extension and allowed the $\beta_{i,j}$'s and $\gamma_{i,j}$'s to be nonzero for $3 < j < 28$ for public research, $2 < j < 21$ for private research, and $3 < j < 10$ for extension. The IIH is corroborated by $\gamma_{i,j} > 0$ for some j with no $\gamma_{i,j} < 0$ and constitutes the critical test via this nonparametric method.

The second restriction 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 the weak axiom of profit maximization (WAPM) under the three augmentation restrictions. Following Chavas *et al*. (1997), we solve the following quadratic programming problem:

$$\min_{B,\alpha,\beta,\gamma}\left[\sum_{i\in N}\left\{\sum_{t\in T} w_1\alpha_{i,t}^2 + \sum_{j}(w_2\beta_{i,j}^2 + w_3\gamma_{i,j}^2)\right\}:\right.$$

$$(X_{i,t} - B_{i,t}) \geq 0, i = Y; \tag{6}$$

$$\left.\begin{array}{l}(X_{i,t} - B_{i,t}) \leq 0,\ i = A, M, L, K;\ \ t \in T;\\ \text{WAPM; the three augmentation restrictions}\end{array}\right]$$

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

where w_1, w_2, w_3 are positive weights.[14] 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 WAPM (Chavas *et al.,* 1997). Thus, with observed data on actual netputs and associated prices, we seek to reveal the nature of technical change. Additional details of the nonparametric test are in the Reviewers' Appendix B.

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

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

As have all other tests of the IIH, our three testing procedures focus exclusively on the demand for innovation. Each test implicitly maintains the hypothesis that the marginal cost of developing and implementing technologies that save one input is the same as the marginal cost of saving an equal percent of any other input. Although, as early as 1974, Binswanger recognized this limitation in his comments about neutral innovation possibilities, it appears that none of the empirical tests of the IIH have attempted to surmount it. Unfortunately, data on the development and implementation costs of various input-saving technologies are generally lacking, so it is not possible to conduct explicit tests of the induced innovation accounting for differences in these costs. Consequently, it is possible that the IIH is correct and yet we may observe producers

[14] Following Chavas *et al.* (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.

augmenting cheap factors because the marginal costs of developing and implementing input-saving technologies for the relatively expensive inputs are greater than for the relatively inexpensive ones. That is, technical change may not bias toward saving a particular input even when the input is relatively expensive, even when the elasticity of substitution is less than 1.

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

In equation (5), the parameter $\beta_{i,j}$ was interpreted as the marginal impact of innovation investments in lagged period j on the current input augmentation index given constant relative input prices. That is, this parameter can be viewed as the marginal effect of a unit investment in an innovation activity on the productivity of the input given constant relative input prices. Thus, the inverse of $\beta_{i,j}$ could be interpreted as the marginal cost in the lagged period j of a 1% change in current productivity of the input given constant relative input prices. Consequently their ratios would be measures of the implied relative marginal costs for augmenting associated inputs under revealed consistency with the IIH.

Making use of the marginal cost information embodied in the inverse of the β's, we compute minimum differences in the marginal costs of developing and implementing input-saving technology by including one additional restriction in the optimization problem in equation (6). This restriction assures that actual observations are consistent with the IIH:

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

where ε is an arbitrarily small positive number, 0.0000001. The weights (w_1, w_2, w_3) and all other

implementation conditions in (6) remain the same. To create summary marginal cost measures for each input, the implied marginal cost for the ith input at each lag j, i.e., the inverse of $\beta_{i,j}$, is discounted to the current period ($j = 0$) using a discount rate of 0.03,[15] and they are summed across j for each innovation investment type.

The optimization problem (6) and (7) provides a simple framework for investigating relative differences in the marginal costs of technology development and implementation that must have existed over our data period for the IIH to have been the sole motivation for input-saving technologies in the U.S. farm sector.

III. Data

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

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

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

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 in the U.S. for use in agriculture. Johnson's patent classification since 1976 follows the international protocol, and the Yale Technology Concordance (Johnson and Evenson, 1997) was used to calculate industries of manufacture and sectors of use. Prior to 1976, the Wellesley Technology Concordance (Johnson, 1999) was followed to classify patents.

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

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

input price proxies this data set are provided in Reviewers' Appendix C.

IV. Empirical Results

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

A. Time-Series Test Results

The Hadri stationarity test results for all variables are reported in Table 1.[16] Accounting for heteroskedastic errors across units and associated P-values for all series imply that stationarity was rejected at a 0.05 significance level for each series in levels. Five variables (Ln($R_{A/M}$), Ln($P_{A/M}$), Ln($P_{L/K}$), Ln(R_{pri}), Ln(R_{pub})) were found to be stationary in first differences, i.e., they followed I(1) processes, at the 0.05 level. Three series, Ln($R_{L/K}$), Ln(*Ext*), Ln(*Size*), were found to be I(2) processes at the 0.05 level. Again, A is land, M is materials, L is labor, K is capital, P_i is price of the ith input, R_{pri} is private research investments, R_{pub} is public research investments, *Ext* is extension investments, *Size* is average farm size.

Because investments in research and extension may not induce technological change for several years, Akaike's information criterion (AIC) was used to determine optimal lags on extension, public and private research investments for both the time-series and econometric testing procedures. The optimal lag on public research investments was chosen from lags of 7-30 years. The optimal lag on private research investments was chosen from lags between 3 years and the optimal lag on public research investments. Because of the more limited data series, the

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

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

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

The results of the cointegration analysis are reported in the last four rows of Table 1. The seven test statistics recommended by Pedroni (1999) are reported for each cointegration test. [17] Five of the seven test statistics for the land-material equation in the time-series model resulted in rejection of the hypothesis of no cointegration at the 0.05 significance level and another at a 0.10 significance level. For the labor-capital equation in the time-series model, all statistics but one supported rejection of the hypothesis of no cointegration at the 0.01 significance level. Thus,

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

based on the preponderance of test evidence, it is concluded that cointegration, and consequently a long run relationship, exists for both the land-material and the labor-capital time-series equations, which is consistent with the IIH.

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

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

The Pesaran PMGE parameter estimates of the ECM are reported in Table 2.[18] Consistent with the IIH, the own-price parameter is negative both in the short-run and the long-run for each factor ratio equation. The error correction term, λ_i, is negative and significant in each equation which indicates that the system adjusts toward equilibrium. However, in the labor-capital equation, the estimated value is -1.3109, which implies that the error correction over-adjusts towards the long-run equilibrium. As a result, the short-run direct elasticity of substitution

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

between labor and capital (0.049) is smaller than the long-run elasticity (0.037).[19] The failure of the long-run elasticity (along the IPF) to exceed the short-run elasticity (along the isoquant) is a crucial inconsistency with the IIH (Oniki, 2000). Based on requirement (d), it **necessitates rejection of the IIH for labor and capital inputs by time series procedures**. Additional testing with time-series procedures will be restricted to the land and materials inputs.

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

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

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

The final time-series test of the IIH was conducted to determine whether causality ran from the factor price ratio and innovation variables to the factor quantity ratio for land and materials. We estimated a dynamic model in which the land-material ratio was modeled as a function of its lags, other explanatory variables, and their lags. We selected a lag length of two for all the variables. The lagged terms of the dependent variable were included to proxy omitted variables (Nair-Reichert and Weinhold, 2001). The Nair-Reichert and Weinhold mixed-fixed-and-random-coefficients estimates are reported in Table 3.[20] Insignificance of the coefficients on the two terms representing lagged own-price ratios result in rejection of the hypothesis that causality runs from the factor price ratio to the factor quantity ratio as required for consistency with the IIH. The hypothesis that research and extension activities Granger-cause the change in factor quantity ratio was also rejected. Thus, based on requirement (e), the **testing results for causal relationships in the land-material equation fail to support the IIH**. Despite other evidence supporting the IIH in land and materials inputs, this violation **necessitates rejection of the IIH in all four inputs using this robust, panel time-series testing procedure**.

B. Econometric Model Results

Before estimating the econometric model, we first tested for AR(1) and heteroskedasticity in each equation's residuals.[21] 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-

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

[21] We first attempted to specify the econometric model to be consistent with the non-rejected time-series properties of the variables. Unfortunately, the use of differenced data as required for some of the variables resulted in serious multicollinearity.

consistent covariance matrix estimator (HACCME).[22] HACCME 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). Therefore, the weak test of the IIH is that $\gamma_i > 0$ for i = A/M, L/C, which is tested by determining whether the alternate hypothesis that $\gamma_i = 0$ is rejected by a one-sided test at the 0.05 level. The test results for the weak and strong hypotheses are reported in the last two rows of Table 4. The weak hypothesis was rejected (i.e., the tested null hypothesis was not rejected) for both equations. In addition, the strong hypothesis that $\gamma_i = 1$, i= A/M, L/C, was soundly rejected for both equations. We failed to find support for the strong hypothesis in either equation. Thus, **our econometric test results provide no support for either test of the IIH for either pair of inputs**.

C. Generalized Model Results

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

[22] 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.

to be consistent with the weak version of the IIH, but the strong hypothesis conclusions were unaffected by the generalization.

D. Nonparametric Test Results

The nonparametric findings regarding the validity of the IIH are reported in Table 5 for each input and each of nine states. To provide nonparametric support for the IIH, we required that $\gamma_{i,j} > 0$ for some *j* with no $\gamma_{i,j} < 0$. With four inputs, three innovation investments, and nine states, there were 108 individual tests of the hypothesis. Of these tests, 79 rejected the hypothesis and 29 supported the hypothesis. The only input that received support by a majority of the tests was materials. Land received the least support, followed in succession by labor and capital. Frequent rejections of the hypothesis in the less actively traded inputs (land, labor, and capital) were consistent with the findings of Chavas *et al*. (1997). In no state did a majority of the tests support the hypothesis, and in one state all tests rejected the hypothesis. For each of the innovation investment types, approximately ¼ of the tests supported the hypothesis and ¾ rejected the hypothesis.

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

E. Marginal Cost of Developing and Implementing Input-Saving Technologies

Having failed to find support for the IIH relying exclusively on the demand for innovation and lacking essential data to distinguish differences in innovation supply, we calculated relative differences in the marginal costs of developing and implementing saving technologies for the various inputs to be consistent with the hypothesis. The qualitative pairwise results of these nonparametric computations are reported for the nine representative states in Table 6.

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

For consistency with the IIH, the marginal cost of developing and implementing land-saving technology must have been greater than for labor-saving technology in most states for all types of innovation investment. The marginal cost of land-saving technology must also have been greater than for capital-saving technology in all states for research investments and in a majority of states for extension investments. This same observation also applies in nearly all states for labor vs. material-saving technologies. However, the order ranking of required marginal cost differences for labor and capital was less clear. For private research investments, 2/3 of the states required higher marginal costs for labor-saving technologies than for capital-

saving technologies. Nearly the reverse was found for extension investments, and neither dominated for public research investments.

V. Conclusions

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

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

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

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

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

marginal costs for labor-saving and capital-saving innovations must have differed for consistency with the hypothesis. Likewise, there was little evidence that marginal costs of extension investments had to differ between land and capital-saving innovations or between labor and materials-saving innovations for consistency with the hypothesis.

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

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Table 1. Stationarity and Cointegration Test Results

	Stationary Test Results					
	Levels		1st Differences		2nd Differences	
Data Series [a]	Statistic [b]	P-value	Statistic [b]	P-value	Statistic [b]	P-value
Ln($R_{A/M}$)	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		
Ln(R_{pri})	211.161	0.000	-2.451	0.993		
Ln(R_{pub})	79.132	0.000	-2.529	0.994		
Ln(*Ext*)	81.702	0.000	2.324	0.010	-7.168	1.000
Ln(*Size*)	125.088	0.000	35.034	0.000	-6.645	1.000

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

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

Table 2. Estimated Error Correction Model [a]

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

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

Table 3. Causality Test for the Land-Materials Ratio [a]

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

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

Table 4: Estimated Econometric Model [a]

Land-Materials Equation			Labor-Capital Equation		
Variable	Coefficient	Standard Error	Variable	Coefficient	Standard Error
Constant	-1.4467*	0.0900	Constant	0.8118*	0.0332
Ln($P_{A/M}$)	-0.6167*	0.0446	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	Wald Statistic	Hypothesis	Tested Null	Wald Statistic
Weak Test, $\gamma_{A/M} > 0$	$\gamma_{A/M} \leq 0$	3.677	Weak Test, $\gamma_{L/K} > 0$	$\gamma_{L/K} \leq 0$	-9.664
Strong Test, $\gamma_{A/M} = 1$	$\gamma_{A/M} = 1$	73.838*	Strong Test, $\gamma_{L/K} = 1$	$\gamma_{L/K} = 1$	473.041*

[a] Critical values at the 0.05 significance level are 1.96 for the 2-tail t-ratios and 3.84 for the 1-tail Wald chi-square statistics. Significant coefficients are identified by an asterisk.
[b] $\bar{R}^2$ 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		
	R_{pri}	R_{pub}	*Ext*	R_{pri}	R_{pub}	*Ext*	R_{pri}	R_{pub}	*Ext*	R_{pri}	R_{pub}	*Ext*
CA	R	R	A	R	A	A	R	R	R	R	R	R
FL	R	R	R	A	A	A	R	R	R	A	R	R
IA	R	R	R	R	R	A	R	R	R	R	A	R
KS	R	R	R	A	A	A	R	R	R	R	A	R
MI	R	R	R	R	R	A	R	R	A	R	R	R
NC	R	R	R	A	A	A	A	R	R	R	A	R
NY	R	R	R	R	R	R	R	R	R	R	R	R
TX	R	R	R	A	A	A	R	R	R	R	R	R
WA	R	R	R	A	A	A	A	R	R	A	R	A

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

Table 6. Nonparametric Estimates of Relative Marginal Cost of Developing and Implementing Input-Saving Technology Required for Consistency with the Induced Innovation Hypothesis [a]

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

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

Reviewer's Appendix A: Structure of the Econometric Model

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

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

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

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

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

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

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

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

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

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

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

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

Following Armanville and Funk (2003) and using notation (E_i) to represent the efficiency variables (factor augmentations), we define the IPF as the following set of instantaneous rates of

factor augmentation ($(\hat{E}_{A,t},\ \hat{E}_{M,t}),(\hat{E}_{L,t},\hat{E}_{K,t})$) that producers can choose: [23]

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

where the circumflexes ($^{\wedge}$) denote relative rates of change, i.e., $\hat{E}_{i,t} = (E_{i,t} - E_{i,t-1}) / E_{i,t-1}$; $\phi_1(\cdot)$ and $\phi_2(\cdot)$ are the first-level innovation possibility frontiers which are assumed to be differentiable, decreasing, strictly concave, and ellipses centered at (-1,-1), [24] i.e.,

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

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

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

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

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

Generally, innovations can be viewed as activities that reallocate resources among factor

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

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

augmentations for the purpose of profit maximization. The hypothesis of induced innovation is that a firm chooses a feasible set of factor augmentations on the IPF to maximize profit given the amount of employed factors (Funk, 2002; Armanville and Funk, 2003). Letting π denote profit, the firms' innovative decisions are made as follows:

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

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

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

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

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

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

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

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

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

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

As demonstrated by Funk (2002), the hypothesis of induced innovation can be derived

from a microeconomic model with fully rational firms. Suppose firms can make profits with an innovation chosen from their perceived IPF until this innovation is imitated by other firms. With the aggregate technology defined in (A2), the IPF defined in (A7), and profit-maximizing choice of innovations in a continuous-time setting,[25] the slopes of the IPF are:[26]

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

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

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

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

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[25] In this case, the length of the period between innovation and imitation tends to zero.

[26] See Funk (2002) for details and discussion of the derivation.

H_0: $corr(\hat{E}_{A,t} - \hat{E}_{M,t}, (P_{A,t} / E_{A,t}) / (P_{M,t} / E_{M,t})) > 0$ or H_0: $corr(\hat{E}_{A,t} - \hat{E}_{M,t}, \Phi_{1,t}) > 0$

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

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

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

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

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

From equations (A10-11) and (A17-18), we derive the following relationships: [27]

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

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

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

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

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

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

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

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

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

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

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

Assuming that innovation investments are allocated evenly for factor augmentation at the starting period, i.e., $E_{A,0}/E_{M,0} = 1$ and $E_{L,0}/E_{K,0} = 1$, rewriting equations (A21-22) gives equation (3) in the paper.

Reviewer's Appendix B:

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

(B1) $P_t' x_t \geq P_t' x_s, \ \forall s,t \in T$, or

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

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

We follow Chavas *et al*. (1997) in specifying three augmentation restrictions needed to conduct nonparametric testing of the IIH. The first restriction specified in equation (5) in the text, treats the technology indices as functions of a constant term and a weighted sum of a finite lag of past innovation investments. The idea for this model specification is that R&D investments can generate technical progress, and the process of technical change takes time. Also the Hicksian IIH emphasizes the crucial role of relative price changes in determining the direction of research investments towards augmenting particular factors, which suggests that the marginal impact of

R&D depends on relative prices. Thus, it provides an approach to directly investigate the Hicksian IIH.

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

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

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

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

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

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

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

Reviewer's Appendix C: Construction of Input Price Proxies for the Period 1932-1959

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