Induced Innovation Tests on Western American Agriculture:

A Cointegration Analysis

Qinghua Liu

C. Richard Shumway

Department of Agricultural & Resource Economics
Washington State University

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Contact Information: Qinghua Liu, Department of Agricultural & Resource Economics, Washington State University. E-mail: liu2@wsunix.wsu.edu. C. Richard Shumway, Department of Agricultural & Resource Economics, Washington State University. E-mail: shumway@wsu.edu.

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Introduction

U.S. agricultural productivity has experienced rapid growth for many decades. The average annual rate of total factor productivity growth was 1.99 percent for the period of 1960-1993 (Ball et al. 1997). Factor productivity is measured as a ratio of output to input. Technological change can lead to productivity growth by either increasing total output or increasing usage of relatively cheap inputs and reducing relatively expensive inputs. Determination of the magnitude and the direction of technological change in agricultural production has attracted much attention and become the subject of intense research efforts over the last thirty years (Huffman and Evenson 1993). This topic is frequently studied in two different ways. One is to consider effects of investment in research and development on technological change (Huffman and Evenson 1993; Alston, Craig, and Pardey 1998). The other is to explain technological change by testing induced innovation hypothesis (Hicks 1932; Hayami and Ruttan 1970; Binswanger 1974; Lee 1983; Kawagoe, Otsuka, and Hayami 1986; Clark and Youngblood 1992; Lambert and Shonkwiler 1995).

The theory of induced innovation, first proposed by Hicks (1932), is the most important theory in the field of technological change. This theory hypothesized that changes in relative factor prices will lead to biased technological change. Based on the hypothesis, when relative factor prices change, a cost-minimizing producer will adopt new technology which saves inputs which are relatively more expensive. So the technological change induced by input prices makes the isoquant shift along a long-run equilibrium path. Ahmad (1966) introduced the innovation possibility curve (IPC), the envelope curve of all the isoquants (representing different technologies), to represent such a path.

A considerable number of researchers have attempted to test Hicks' induced innovation hypothesis in agriculture and have used a variety of methods. Hayami and Ruttan (1970) made the pioneering contribution in the field of testing the induced innovation hypothesis. Their basic model regressed the logarithms of the factor ratios on the logarithms of the factor price ratios using aggregate data of U.S. and Japan for 1880-1960. If the coefficient of the relative price ratio is negative and significantly different from zero, the result is considered to accept the inducement hypothesis. Consistency with induced innovation hypothesis was found in their empirical result.

Hayami and Ruttan's tests were ad hoc, and the most important limitation was the failure to distinguish between technological change effects and the effects of factor substitution under a given technology (Oniki 2000). In order to distinguish these two effects, Binswanger (1974) incorporated a time trend variable (proxy for technological change) in a translog cost function. His tests were based on a two-step process. He first estimated the production technology (primal or dual representation) and computed indices of biased technological changes. He then compared those indices to the indices of relative input prices. Like Hayami and Ruttan, Binswanger found consistency with the induced innovation hypothesis. This approach has been applied in subsequent empirical studies with modest variation (e.g., Kawagoe, Otsuka, and Hayami 1986; Kuroda 1987; Yuhn 1991; Lin 1991; Terrel 1993). All of these studies found significant induced innovation.

Assuming all dependent and independent variables are stationary, a linear deterministic time trend has been used as a proxy of technological change in these traditional models since there is no direct measure of technological change. Then the technological change bias is measured as the first derivative of input quantity (or share) with respect to time. However, Nelson and Kang (1984) pointed out that spurious results may be achieved from estimation procedures inappropriately incorporating time as an independent variable. When some or all of the data in the model are nonstationary, coefficient estimates will not have a regular distribution, and the use of normal statistical tests may incorrectly reject the null hypothesis (Durlauf and Phillips 1988).

In order to solve this problem, Clark and Youngblood (1992) proposed a time series approach to test for induced innovation. According to their method, if cointegration exists among the nonstationary variables, there is no bias in technological change since the residual of the translog share function is stationary. On the other hand, if there is no cointegration among the variables, the residual is nonstationary and the technological change effects are included in the residual. They concluded that technological change was neutral for central Canadian agriculture by using this time series approach. Machado (1995) and Lambert and Shonkwiler (1995) also applied this method to test the induced innovation hypothesis in their empirical studies of U.S. agriculture. Although Lambert and Shonkwiler found technological bias in labor and material factor shares, Clark and

Youngblood, Machado found little support for the induced innovation hypothesis. Some other studies also found little evidence to support the induced innovation hypothesis (e.g., Olmstead and Rhode 1993, 1998).

Although Clark and Youngblood proposed a more appropriate way to test the induced innovation hypothesis than the traditional model, specifics of their ideas was questioned by Oniki (2000). Oniki argued that the residual of a cointegration part does not represent technological change effects. Therefore, the long-run relationship does not imply a lack of technological change. He concluded that the induced innovation hypothesis is supported by the existence of a difference in the elasticities of factor substitution along the isoquant curve and the innovation possibility curve. Thirtle, Townsend and Zyl (1998) also applied a time series model to test for the induced innovation hypothesis by comparing long-run and short-run effect of changes in relative factor prices.

Although markedly different from traditional models used to test the induced innovation hypothesis, a time series model may misspecify the relationships among prices and shares by failing to account for the effects of investment in research and development. The reason is that relative price changes are only part of the explanation of changes in input ratios. Research and extension (R&E) expenditures, an important determinant of productivity growth, should also be considered in the estimation of technical biases. This paper tests for the IIH following the general logic of Oniki's test procedure. Two augmentations are made to Oniki's method. First, the IIH is tested while simultaneously measuring the effect of R&E on input bias. The second augmentation is an empirical objective – to examine the sensitivity of IIH test conclusions to geographic aggregation. Because valuable information can be lost in aggregate data for large and diverse areas, the consistency of IIH test conclusions is examined for a state (WA), two regions (Pacific Northwest and West), and the U.S.

The model used to conduct the induced innovation tests is specified in the next section. It is sequentially followed by testing methods, data description, and empirical results. The final section concludes.

Model

A translog, twice-differentiable cost function is used to estimate factor bias in this paper. The dual cost function provides a useful summary of behavioral responses to changes in relative input prices. Moreover, this model allows us to estimate the effects of research investment on input shares.

We assume that producers minimize a static cost function, $C(y, \mathbf{w}, R)$ by choosing input combinations that satisfy

$$C(y, \mathbf{w}, R) = \min_x\{\mathbf{w}'\mathbf{x} : F(\mathbf{x}, y, R) = 0\} \tag{1}$$

Where y is output, $\mathbf{w}$ is the vector of input prices, R is R&E expenditure (treated as a fixed input), and $F(\cdot)$ is the production function. Under competitive, cost-minimizing behavior, $C(y, \mathbf{w}, R)$ is non-decreasing in y and $\mathbf{w}$, non-increasing in R, concave and homogeneous of degree one in $\mathbf{w}$.

Considering one output (aggregate of crop and livestock commodities) and two inputs (labor and capital), the variable cost function in (1) is approximated by the following translog function:

$$\ln C = \alpha_0 + \sum_{i=1}^{2} \alpha_i \ln w_i + \beta_1 \ln y + \gamma_1 \ln R$$
$$+ \frac{1}{2} \sum_{i=1}^{2} \sum_{j=1}^{2} \alpha_{ij} \ln w_i \ln w_j + \frac{1}{2} \beta_2 (\ln y)^2 + \frac{1}{2} \gamma_2 (\ln R)^2 \tag{2}$$
$$+ \sum_{i=1}^{2} \delta_i \ln w_i \ln y + \sum_{i=1}^{2} \theta_i \ln w_i \ln R + \phi_1 \ln y \ln R$$

Homogeneity of degree one in variable input prices requires:

$$\sum_{i=1}^{2} \alpha_i = 1, \quad \sum_{i=1}^{2} \alpha_{ij} = \sum_{i=1}^{2} \delta_i = \sum_{i=1}^{2} \theta_i = 0 . \tag{3}$$

Using Shephard's lemma, the ith input's cost share is given by:

$$\frac{\partial \ln C}{\partial \ln w_i} = \frac{w_i x_i}{C} = s_i , \tag{4}$$

from which we get the input share equation:

$$s_i = \alpha_i + \sum_{j=1}^{2} \alpha_{ij} \ln w_j + \delta_i \ln y + \theta_i \ln R . \tag{5}$$

For equation (5), the symmetry constraints are:

$$\alpha_{ij} = \alpha_{ji}, \forall i, j \tag{6}$$

The Allen-Uzawa partial elasticities of substitution (σ_{ij}) for this cost function are given by:

$$\sigma_{ii} = \frac{\alpha_{ii} + s_i^2 - s_i}{s_i^2} \tag{7}$$

$$\sigma_{ij} = \frac{\alpha_{ij} + s_i s_j}{s_i s_j} . \tag{8}$$

Test Procedure

Oniki's (2000) challenge of Clark and Youngblood's time series method for testing the induced innovation hypothesis rested on the argument that the residual of a cointegrated series does not represent technological change effects. Instead, the short-run effects (represented by an isoquant) plus the technical change effects are equal to long-run effects (represented by the IPC). Therefore, Oniki argued that the existence of the IPC is a necessary condition for induced innovation, which counters Clark and Youngblood's statement that the existence of the long-run relationship (cointegration) "implies that technical change in neutral" (p. 354). In Oniki's study, the induced innovation hypothesis was tested by comparing the long-run Allen-Uzawa's partial elasticities of factor substitution (AUES) with the short-run AUES. If the long-run elasticity is greater than the short-run elasticity, the curvature of the isoquant is greater than the curvature of the IPC, which implies that induced innovation exists in the production process.

Although Oniki's procedure for testing the induced innovation hypothesis is an important correction to Clark and Youngblood's time series method, his model didn't include technology variables. Technology variables, such as research and extension investments, could be indispensable for explaining some biases due to technical change. Based on the Oniki's testing logic and explicitly incorporating R&E investments in the model, we test the induced innovation hypothesis on domestic agriculture by the following procedures.

First, since cointegration techniques are used to determine whether long-run relationships exist among the variables, stationarity properties of the data series in equation (5) are checked to determine whether each is nonstationary and integrated of the same order.

The augmented Dickey-Fuller (ADF) test is commonly used to test for the unit root of the series. This test is generated from the following regression:

$$\Delta X_t = \delta + \rho X_{t-1} + \sum_{j=1}^{k} \phi_j \Delta X_t + \varepsilon_t \qquad (9)$$

where X represents the variables (input share, input prices, output level, and R&E expenditure) in equation (5), $\Delta X_t = X_t - X_{t-1}$, and k is the lag order chosen such that $k / t^{1/3} \rightarrow 0$ as k and $t \rightarrow \infty$ and regression residuals behave like a white noise series. The ADF test statistic is the ratio of ρ to its standard error. The null hypothesis of this test is that a process has a unit root (nonstationary), and it is rejected when the test statistic exceeds the critical value at the specified significant level (α) or the p-value is less than the specified significance level. The deterministic part, δ, can be zero, a constant, or a constant plus a linear time trend.

A problem with the ADF test is that the stochastic trend is the null hypothesis. This ensures that a unit root is accepted unless there is strong evidence against it. One way to overcome this weakness is to increase the specified significance level (type I error) which can lead to a decrease of type II error. Then the power of a test (1 - type II error) will increase. The other way is to reverse the null and alternative hypotheses. Kwiatkowski and colleagues (1991) provided a test (KPSS) in which the null hypothesis is stationary (no unit root). When both ADF and KPSS tests are applied, consistent results (the null hypothesis of ADF is not rejected and the null of KPSS test is rejected or the null hypothesis of ADF is rejected and the null of KPSS test is not rejected) will increase the reliability of either test. However, we may also get inconsistent results when the null hypotheses of both tests are rejected or both are not rejected. In this situation, the tests give indeterminate results and we can't conclude whether or not the time series is stationary. In order to simplify the test procedures, we use the first method to increase the power of the ADF test. We use a 10% rather than a 5% significance level for our ADF tests.

Second, based on the outcome of the unit root tests, a cointegration test can be applied to determine whether there exists a linear combination of variables that are integrated to the same order. Johansen's cointegration test is used to estimate all cointegrating relationships and conduct tests for the number of cointegrating vectors under a multivariate framework.

Consider a vector of n time-ordered variables X_t, where X_t follows an unrestricted vector autoregression (VAR):

$$X_t = \pi_1 X_{t-1} + \pi_2 X_{t-2} + \ldots + \pi_p X_{t-p} + \mu + \varepsilon_t \tag{10}$$

where each of the π_i is an n×n matrix of parameters, μ is a constant term and ε_t are identically and independently distributed with zero mean and contemporaneous covariance matrix Ω. The above VAR system can be written in error correction form (ECM) as:

$$\Delta X_t = \mu + \Pi X_{t-p} + \sum_{i=1}^{p} \Gamma_i \Delta X_{t-i} + \varepsilon_t \tag{11}$$

where $\Pi = \boldsymbol{I} - \pi_1 - \pi_2 - \ldots - \pi_p$, and $\Gamma_i = [(\boldsymbol{I} + \pi_1), (\boldsymbol{I} + \pi_1 + \pi_2), \ldots, (\boldsymbol{I} + \pi_1 + \pi_2 + \ldots + \pi_p)]$, and p is chosen so that ε_t is a multivariate normal white noise process with mean 0 and finite covariance matrix. The rank of Π, r, can be used to investigate the cointegration relationship. If r = n, the variables in levels are stationary. If r = 0, none of the linear combinations is stationary. When $0 < r < n$, there exist r cointegration vectors or r stationary linear combinations of X_t. The matrix Π can be factored as $\Pi = \alpha\beta'$, where both α and β are $n\times r$ matrices, and β may be interpreted as the matrix of cointegrating vectors representing the long-run relationship, and α is the matrix of adjustment parameters.

Johansen suggested two statistics to test the null hypothesis that there are at most r cointegration vectors in the system. One is the maximal eigenvalue test and the other is the trace test. The alternative hypothesis is that there are exactly r+1 cointegration vectors for the former while there exist more than r cointegration vectors for the latter. The statistic for each test follows a non-standard distribution. The critical values for the tests were simulated by Johansen and Joselius (1990). We apply both tests in this study.

Third, if there exists cointegration among the variables in equation (5), the short-run and the long-run relationships of the variables can be estimated by the error correction model (ECM). If all variables are integrated to the order d, the pth order of the vector ECM for the translog share input equations can be represented by the following equation:

$$\begin{aligned} \Delta s_t &= \Phi(L)\Delta s_{t-d} + \Gamma_w(L)\Delta w_t + \gamma_y(L)\Delta y_t + \gamma_R(L)\Delta R_t \\ &\quad + \mathrm{A}(s_{t-d} - \beta_0 - \mathrm{B}_w w_{t-p} - \beta_y y_{t-p} - \beta_R R_{t-p}) + \varepsilon_t \end{aligned} \tag{12}$$

where $\Phi(L) = \sum_{i=1}^{d-1}(\sum_{j=1}^{i}\Phi_j^*)L^i$ for d > 1, or null otherwise;

$\Gamma_w(L) = \sum_{i=1}^{p-1}(\sum_{j=1}^{i}\Gamma_{wj}^*)L^i$; $\gamma_y(L) = \sum_{i=1}^{p-1}(\sum_{j=1}^{i}\gamma_{yj}^*)L^i$;

$\gamma_R(L) = \sum_{i=1}^{p-1}(\sum_{j=1}^{i}\gamma_{Rj}^*)L^i$ for p > 0, or null otherwise; and

A is the loading matrix of adjustment parameters.

Suppose all the variables are integrated to the first order and the lag order is 1, i.e., d =

p = 1, equation (12) can be rewritten in the following form:

$$\Delta s_t = \Gamma_w \Delta w_t + \gamma_y \Delta y_t + \gamma_R \Delta R_t + \mathrm{A}(s_{t-1} - \beta_0 - \mathrm{B}_w w_{t-1} - \beta_y y_{t-1} - \beta_R R_{t-1}) + \varepsilon_t \qquad (13)$$

The differenced terms in the above model are stationary (I(0)) and cover the short-run situation while the terms enclosed in parentheses are I(1) and describe the long-run relationship. As the relative factor prices change, the input shares s will change immediately owing to the substitution effects (short-run effects), which are reflected by the matrix of Γ_w. According to Oniki, the stochastic part, δ=A(s_{t-1} - β_0 - $\mathrm{B}_w w_{t-1}$ - $\beta_y y_{t-1}$- $\beta_R R_{t-1}$), represents the technological change and its value tends to zero in the long-run equilibrium. In the short run, changes in relative factor prices will make δ non-zero, which shifts the short-run production process until the shares reach a new long-run equilibrium, where $\delta = 0$. Therefore, the long-run effects of relative factor price changes are B_w while the short-run effects are Γ_w.

The curvature of the isoquant and the IPC can be represented by the short-run AUES and the long-run AUES, respectively. From equation (8), the short-run and long-run AUES, respectively, of factor i for factor j are estimated by:

$$\sigma_{ij}^{SR} = \frac{\gamma_{ij} + s_i s_j}{s_i s_j}, \quad \sigma_{ij}^{LR} = \frac{\beta_{ij} + s_i s_j}{s_i s_j}, \qquad (14)$$

where γ_{ij} and β_{ij} are the ijth element of the matrix Γ_w and B_w, respectively, in equation (13). Following Oniki (2000), technological change is the difference between the long-run and the short-run production process. Therefore, induced innovation exists if the estimated long-run elasticities of substitution are significantly greater than the estimated short-run elasticities.

Based on equation (13), biased technological change can be induced by changes in output levels and by R&E investments in addition to changes in relative factor prices. The possibility of output- and R&E investment-induced technological change can be tested in a similar way to testing for price-induced innovation. If the long-run input-output elasticity is significantly greater than the short-run input-output elasticity, output-induced technological change occurs. Similarly, R&E investment-induced technological change exists when the long-run input-RE investment elasticity is significantly greater than the short-run input-RE investment elasticity.

Data

Annual U.S. and state-level data for the period, 1960-1999, were used in this study. The data source was Ball's (2002) agricultural output and input series for the U.S. and the contiguous 48 states. State-level data were used for 11 Western states – AZ, CA, CO, ID, MT, NV, NM, OR, UT, WA, WY. This data set includes price and quantity data for 26 individual inputs (25 for WA, 20 for the U.S.) and 20-75 individual outputs for each of the Western states (68 for the U.S.).[1] Although the number of outputs varies considerably among states, virtually every Western state produces one or more commodity within the broad categories of livestock, milk, poultry, feed grains, food grains, oilseeds, vegetables,

[1] The number of outputs in each state are: AZ – 34, CA – 75, CO – 36, ID – 30, MT – 20, NV – 22, NM – 28, OR – 42, UT – 29, WA – 43, WY – 21.

fruits and nut crops.[2] Detailed input data cover the broad categories of labor, capital, land, chemicals, energy, and materials.[3]

The research and extension investment data for the period, 1927-1995, were from Huffman (2002). Current investments in research and extension are very unlikely to affect current production technology and costs. It is the cumulative effect of lagged investments. Research and extension investments incurred at least seven years earlier and sometimes as much as 25-30 years earlier have been estimated to affect agricultural production costs in the United States (Evenson and Pray 1991, Pardey and Craig 1989, Chavas and Cox 1992). A seven-year lag was considered in this paper. In other words, current investments in research and extension are expected to affect production technology seven years later.

In this study, all outputs were aggregated into one group and inputs were aggregated into two groups (labor and capital). In order to examine the sensitivity of IIH test conclusions to geographic aggregation, four geographic entities were tested: (1) Washington State, (2) Pacific Northwest (PNW) – WA, ID, and OR, (3) Western States, including CA, AZ, NV, UT, MT, WY, CO, NM, plus WA, ID, and OR, and (4) the U.S.

Commodity group and regional price indices were created as Törnqvist indices

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[2] For example, in Washington, outputs include: cattle, hogs, lamb, wool, honey, milk sold to plant and dealer, milk utilized on farm, broiler, chickens, eggs, corn, oats, barley, wheat, hay, fresh asparagus, processed asparagus, processed green beans, carrots, fresh sweet corn, processed sweet corn, processed cucumbers, dry beans, lettuce, peas, onions, potatoes, apples, apricots cherries, cranberries, grapes, peaches, plums, pears, strawberries, filberts, sugar beets, hops, mint, mushrooms, forestry, and nursery. California's larger number of outputs are mainly vegetables, fruit and nuts.

[3] Except as noted, separate data series are included in each state for the following inputs: hired labor, self-employed labor, automobiles, trucks, tractors, other machinery, inventories, buildings, land, Bureau of Land Management public land (not in Washington), Forest Service public land, fuel (composite of four types), electricity, feed, seed, purchased livestock, fertilizer (hedonic index of N,P,K), pesticides (hedonic index of 34 herbicides, insecticides, and fungicides), equipment repairs, building repairs, custom services, contract labor, storage-transportation-marketing services, irrigation, insurance, miscellaneous inputs.

computed by the following formula:

$$D_t = \exp\left[.5\sum_{i=1}^{K}(s_{it} + s_{i,t-1})\log(p_{it} / p_{i,t-1}) \right] \tag{15}$$

where $s_{it} = (p_{it}x_{it}) / (p_t x_t)$, p_{it} and x_{it} are the price and quantity for individual commodity or state i in period t, i = 1,2,…,K, and K is the number of outputs, inputs, or states in the respective category. The year 1987 was used as the base year for computing group and regional price indices. The aggregate group or regional quantity indices were computed by dividing output revenue or input expenditure by the corresponding group or regional price indices.

Empirical Results

The time series properties of the variables (labor cost share, logarithm of relative labor:capital price, logarithm of output, logarithm of R&E investments) were examined first. Using the relative labor:capital price is a consequence of maintaining linear homogeneity of the cost function in input prices. Because of the singularity of the share equations (Anderson and Blundell 1982), it was unnecessary to examine the capital share equation.

The ADF unit root test results are reported in Table 1. All three cases (zero mean, non-zero mean, and non-zero mean with linear trend) in equation (9) were considered since each variable may or may not have a constant or a trend, which alters the distribution of the statistic under the null hypothesis. Test statistics and P values for the four variables in each region indicated that the null hypothesis of a unit root could not be rejected at the 10% significance level for any variable. That is, the implication of these tests is that all the variables are nonstationary.

Further tests rejected the presence of unit roots in first differences for each variable (Table 2). This means that all the data series of each region are nonstationary in the levels but stationary in first differences, i.e., the series are integrated to order one, I (1).

Concluding that the variables were integrated to the same order, we proceeded with Johansen's cointegration tests to determine whether cointegrating vectors existed which would imply non-spurious long-run relationships among the variables. The results of the cointegration analysis are presented in Table 3. Test statistics from both the maximal eigenvalue and the trace tests were consistent in suggesting that there is one integrating vector among the variables in Washington and the West and two integrating vectors among the variables in the PNW and the U.S. Therefore, it was concluded that there existed long-run relationships among the labor cost share, relative input price, output level, and R&E investments for each geographic unit examined. Specifying labor cost share as the normalized variable, the estimated cointegrating vectors were [1, -0.24, 0.11, 0.02] for Washington, [1, -0.19, 0.06, 0.12] for the PNW, [1, -0.20, 0.02, 0.10] for the West, and [1, -0.29, -0.06, 0.18] for the U.S. Thus, the long-run relationship among the four variables was very similar for the three regions – Washington, the PNW, and the West. The sign on the output variable caused these to be fundamentally different from the long-run relationship among the four variables for the U.S.

Having determined that the variables are cointegrated, we next estimated the error correction model (ECM). Based on the AIC criterion, the "best" estimated lag length of the underlying vector autoregression (VAR) was estimated to be one for each variable in each geographic unit. Since all the variables were integrated of order one, the specified dynamic form of the model for each geographic unit was equation (13). This model allowed us to separate the short-run and the long-run effects of changes in relative input price, output level, and R&E investments on the cost share. The estimated results of the ECM model are presented in Table 4. The differenced terms in equation (13) represent short-run effects because they are stationary and the lagged terms within the parentheses represent the long-run effects since they are nonstationary. Except for the PNW, the estimates of long-run effects of relative input price, output level, and R&E investments were statistically significant at the 5% level. Except for the U.S., the estimates of short-run effects were not significant.

As previously noted, greater curvature of the isoquant curve than the curvature of the IPC implies the existence of induced innovation (Oniki 2000). The curvature of these curves can be measured by the short-run and long-run elasticities of substitution. If a small change in relative prices gives us a large change in the factor input ratio, the isoquant is relatively flat which means that the elasticity of substitution is large. Therefore, in order to test for the existence of the induced innovation, we only need to test whether the long-run elasticity of substitution is significantly greater than the short-run elasticity of substitution.

By equation (13), it can be inferred that biased technical change can be induced not only by changes in relative factor prices but also by changes in output level or R&E investments. The formulas for the short-run and long-run elasticities of the i^{th} factor with respect to output level y was derived by Oniki (2000):

$$\pi_i^{SR} = \frac{\gamma_{iq}}{s_i} + 1 \text{ (short-run effect)}, \quad \pi_i^{LR} = \frac{\beta_{iq}}{s_i} + 1 \text{ (long-run effect)} \tag{16}$$

Similarly, the formulas for the elasticities of the ith factor with respect to R&E investment R are:

$$\omega_i^{SR} = \frac{\gamma_{iR}}{s_i} + 1 \text{ (short-run effect)}, \quad \omega_i^{LR} = \frac{\beta_{iR}}{s_i} + 1 \text{ (long-run effect)} \tag{17}$$

Since all elasticity functions are nonlinear of parameter estimates, the Delta method was used to compute standard errors and confidence intervals for the short-run and long-run elasticities. This method is based on a first-order Taylor-series approximation to the statistic and was used to find standard errors of the nonlinear functions of parameter estimates. Confidence intervals were then derived based on the estimated parameters and estimated standard errors. Confidence intervals for the estimated elasticity of substitution, output elasticity, and R&E investment elasticity are presented in Table 5.[4] Since the estimated AUES in the long-run was significantly greater than those in the short-run in the three regions of Washington, PNW, and the West, we conclude that induced innovation existed in their production processes. However, for the most aggregated data (U.S.), the elasticities of substitution in the short-run and in the long-run were not significantly different, which means that the induced innovation hypothesis was not supported with the national data. None of the long-run output elasticities or long-run R&E investment elasticities were significantly greater than their corresponding short-run elasticities. This finding implies that neither output nor R&E investment changes induced technical change in any of the four geographic units.

Conclusions

A variety of methods have been applied to test the induced innovation hypothesis (IIH) in agriculture. The traditional method, which has used a time trend as a proxy for technology in estimating technical biases, has previously been discredited when the time series properties of variables were not considered.

This paper tested for the IIH following the general logic of Oniki's (2000) recent time series test procedure with two augmentations. First, research and extension (R&E) investments were included in the time series model. Second, the sensitivity of IIH test conclusions to geographic aggregation was examined. The consistency of the IIH test conclusions was examined for a state (WA), two regions (Pacific Northwest and West), and the U.S. A translog, twice-differentiable cost function with one output and two inputs (labor and capital) was used to estimate factor biases. An error correction model was implemented to separate short-run and long-run effects of relative price changes as well as changes in output level and R&E investments. A significantly larger elasticity of factor substitution along the innovation possibility curve than along the isoquant would imply IIH. Significantly larger factor elasticities with respect to output level or R&E investment along the IPC than along the isoquant would imply that those respective variables also induce innovation.

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[4] The mean values of the variables were used to calculate elasticities.

All four variables in each of the four geographic units exhibited similar time series properties. Each variable was integrated of order 1 and the system of four variables was cointegrated in each geographic unit. The latter implied that a long-run relationship and a corresponding IPC existed among these variables in each area. The error correction model endogenized technical changes in terms of the relative factor prices, output, and R&E investments. The induced innovation hypotheses were tested by comparing the short-run and long-run elasticities of substitution, output elasticities, and R&E investment elasticities. The estimated results showed that the induced innovation hypothesis was supported for the three regions of Washington, PNW, and the West, but not for the nation. However, while changes in relative input prices induced innovation, changes in output level or R&E investments did not. The empirical tests failed to find any significant impact of changes in the latter variables on agricultural technology in any of the geographic units.

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Table 1. Unit Root Tests for Stationarity of Data Series

Data Series	With Zero Mean		With Non-Zero Mean		With Non-Zero Mean and Linear Trend	
	Statistic	P-value	Statistic	P-value	Statistic	P-value
Washington						
Labor Share	-0.64	0.43	-1.38	0.58	-0.79	0.96
Price	-0.87	0.33	-1.74	0.40	-1.65	0.76
Output	3.83	0.99	-0.82	0.80	-2.89	0.18
Investments	0.60	0.84	-2.16	0.23	-1.70	0.73
PNW						
Labor Share	-0.65	0.43	-1.34	0.60	-0.62	0.97
Price	-0.97	0.29	-1.45	0.55	-1.38	0.85
Output	3.47	0.99	0.12	0.96	-2.85	0.19
Investments	1.27	0.95	-2.26	0.19	-1.44	0.83
West						
Labor Share	-0.41	0.53	-1.37	0.58	-0.44	0.98
Price	-0.85	0.34	-1.55	0.50	-1.63	0.76
Output	3.93	0.99	-0.69	0.84	-2.70	0.24
Investments	2.72	0.99	-2.56	0.11	-1.67	0.75
U.S.						
Labor Share	-0.62	0.44	-1.44	0.55	-1.04	0.93
Price	-0.64	0.43	-1.28	0.63	-1.36	0.86
Output	4.01	0.99	1.61	0.99	-0.67	0.97
Investments	3.09	0.99	-2.03	0.27	-2.13	0.51

Table 2. Unit Root Tests for Stationarity of First-order Difference of Data Series

Data Series	With Zero Mean		With Non-Zero Mean		With Non-Zero Mean and Linear Trend	
	Statistic	P-value	Statistic	P-value	Statistic	P-value
Washington						
Labor Share	-4.47	0.00	-4.44	0.00	-4.72	0.00
Price	-5.73	0.00	-5.70	0.00	-5.69	0.00
Output	-2.44	0.02	-4.33	0.00	-4.26	0.01
Investments	-4.01	0.00	-4.01	0.00	-4.24	0.01
PNW						
Labor Share	-4.14	0.00	-4.13	0.00	-4.60	0.00
Price	-4.41	0.00	-4.39	0.00	-4.41	0.01
Output	-1.66	0.09	-3.80	0.01	-3.77	0.03
Investments	-4.14	0.00	-4.39	0.00	-4.93	0.00
West						
Labor Share	-5.00	0.00	-4.95	0.00	-5.82	0.00
Price	-5.49	0.00	-5.54	0.00	-5.51	0.00
Output	-3.15	0.00	-7.99	0.00	-7.87	0.00
Investments	-2.25	0.03	-3.05	0.04	-4.27	0.01
U.S.						
Labor Share	-3.34	0.00	-3.306	0.02	-3.51	0.05
Price	-4.40	0.00	-4.37	0.00	-4.32	0.01
Output	-2.89	0.01	-4.91	0.00	-5.57	0.00
Investments	-2.51	0.01	-3.35	0.02	-4.13	0.01

Table 3. Johansen's Cointegration Test Statistics

Hypothesis	WA		PNW		West		U.S.	
	λ_{trace}	λ_{max}	λ_{trace}	λ_{max}	λ_{trace}	λ_{max}	λ_{trace}	λ_{max}
H_0: r=0, H_1: r>0 (or r=1)[a]	65.50*[b]	30.78*	73.64*	32.60*	64.04*	32.88*	91.97*	39.33*
H_0: r=1, H_1: r>1 (or r=2)	34.72	18.20	41.04*	23.73*	31.16	16.73	52.65*	33.23*
H_0: r=2, H_1: r>2 (or r=3)	16.52	11.28	17.31	12.88	14.43	8.63	19.41	13.39
H_0: r=3, H_1: r>0 (or r=4)	5.24	5.24	4.43	4.43	5.80	5.80	6.02	6.02

[a] The alternative hypothesis of the max eigenvalue test is in parentheses.

[b] An asterisk indicates that the null hypothesis is rejected; critical values are taken at a significance level of 5%.

Table 4. Estimated Error Correction Models

Variable	WA	PNW	West	U.S.
Constant	-0.86*[a]	-0.28	-1.05*	-7.27*
Short-run effects:				
Δw_t	0.02	-0.05	-0.01	0.24*
Δq_t	-0.001	-0.04	0.02	0.09
ΔR_t	0.005	0.02	-0.01	-0.41*
Long-run effects:				
s_{t-1}	0.40*	0.09	0.43*	2.27*
w_{t-1}	-0.09*	-0.02	-0.09*	-0.66*
q_{t-1}	0.04*	0.005	0.01*	-0.14*
R_{t-1}	0.01*	0.01	0.04*	0.41*

[a] An asterisk indicates the parameter is significant at the 5% level.

Table 5. Confidence Intervals of Estimates of the AUES, Output elasticity, and R&E Investment Elasticity along the Isoquant and the Innovation Possibilities Curve

Region		Confidence Interval[a]		
		AUES	Output Elasticity	R&E Elasticity
Washington	IQC[b]	(0.705, 1.037)	(0.456, 1.536)	(0.791, 1.245)
	IPC	(2.072, 2.364)	(0.559, 0.601)	(0.935, 0.941)
PNW	IQC	(0.284, 1.244)	(0.132, 1.538)	(0.760, 1.360)
	IPC	(1.833, 2.151)	(0.774, 0.792)	(0.523, 0.553)
West	IQC	(0.534, 1.388)	(0.540, 1.606)	(0.639, 1.245)
	IPC	(2.105, 2.203)	(0.886, 0.902)	(0.528, 0.614)
U.S.	IQC	(0.944, 3.110)	(1.205, 1.299)	(-1.576, 1.394)
	IPC	(1.694, 2.794)	(1.161, 1.171)	(0.499, 0.535)

[a]: Significance level is 5%.

[b]: IQC is the isoquant and IPC is the innovation possibility curve.