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Testing the Induced Innovation Hypothesis: Accounting for Innovation Creation and Innovation Implementation Incentives

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Despite extensive empirical literature on the induced innovation hypothesis in US agriculture, this article reports only the second set of tests for this industry that account for supply as well as demand for new input-saving technology. Rather than assuming a specific innovation production function, we examine the relationship between research intensity and input prices in several different reduced-form specifications. Considering four inputs in the innovation-implementing industry—land, labor, fertilizer, and energy—we find non-trivial but limited support for the induced innovation hypothesis in public agricultural research. The most support for the hypothesis is found for research decisions aimed at saving fertilizer, followed in turn by energy, labor, and land.

Key words: demand, direct test, induced innovation, public research, supply, US agriculture.

The induced innovation hypothesis (IIH) that "a change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind—directed to economizing the use of a factor which has become relatively expensive" (Hicks, 1932, pp. 124-125), holds a respected, almost exalted, position in both macroeconomic and microeconomic theory. It is a hypothesis with important policy relevance. If valid, a direct policy implication of the hypothesis is that distortionary taxes and/or subsidies aimed at synchronizing market and social input price would have more than contemporary effects on input use. They would also have effects on future input use through research investment decisions to create innovation that saves relatively more of the inputs for which public cost exceeds private cost (Nordhaus, 2002). Thus, it is possible that taxes and/or subsidies proposed without consideration of their possible impact on research investments may overshoot social optimality. This is particularly important for public agricultural research. While agricultural production is a source of renewable energy, it also uses large quantities of fossil energy with socially important environmental consequences. Food safety issues are also not fully endogenized in market prices (Pouliot & Sumner, 2008).

The policy relevance of the IIH depends on its validity as an accurate representation of innovation creation decision making. However, despite considerable empirical support for the hypothesis being provided by early demand-side tests, recent tests with improved methods and data have found greater evidence of empirical inconsistency with the hypothesis (e.g., Liu & Shumway, 2006, 2009; Machado, 1995; Lin, 1998; Olmstead & Rhode, 1993; Tiffin & Dawson, 1995). A variety of testing procedures has been employed, but until recently all treated the innovation possibilities function as exogenous. Largely because of limited data on the marginal cost of creating input-saving technology, the supply side of innovation creation was consistently ignored. Recent studies by Popp (2002); Crabb and Johnson (2010); and Cowan, Lee, and Shumway (2015) appear to be the only exceptions.

Noting that Hicks' statement of the hypothesis did not imply that implemented technical change would substitute relative cheap inputs for expensive ones but only that factor prices would spur invention to economize the use of expensive factors, Popp (2002) and Crabb and Johnson (2010) explicitly incorporated supply-side control variables (but not innovation prices or marginal costs) in their examination of the IIH for the energy private innovation sector. With similar motivation, Cowan et al. (2015) tested the IIH using research investments in the agricultural public innovation sector as signals of intent to create input-saving technology for the agricultural production sector. Their testing procedure using a pseudo Poisson maximum likelihood estimator assumed a homothetic two-level constant elasticity of transformation (CET) production function in the innovation creating sector. Both Popp (2002) and Crabb and Johnson (2010) found limited evidence of support for the IIH in the energy sector by accounting for both demand and supply variables. Cowan et al. (2015) found considerably more support for the IIH in the public agricultural research sector.

To determine whether the level of support found for the IIH in the agricultural research sector was due to the assumed production function or estimation method, we extend the testing initiated by Cowan et al. (2015) by loosening the connection to the two-level CET production function and using panel data and pooled OLS estimators. We still use research expenditure and price ratios as implied by the two-level CET in our tests but relax the CET implication that they be specified as logarithms. We use two estimation procedures. In one, zero observations are converted to ones so that all observations can be included in the estimation. In the other, we approach the expenditure decision in two separate steps: 1) funding at least one project, and 2) conditional on funding a project, how much to invest. We also consider alternative specifications in our robustness section.

Empirical Model

Following Cowan et al. (2015), our empirical testing procedure is constructed to determine whether states with relatively higher prices of an input in the innovation implementing industry (agriculture) devote a relatively greater portion of the research budget in the innovation creating industry (public research) to developing technology to save that input and/or whether states with more rapidly rising prices of an input increase the portion of the research budget to projects to save that input.

We use a panel dataset of agricultural input prices and public agricultural research investments aimed to save usage of four non-exhaustive input categories. We initially regress relative research investments on relative expected output prices (input prices in the innovation implementing industry) and time dummy variables:

$$R_{ist} / R_{jst} = b_0 + b_1 E(P_{ist}) / E(P_{jst}) + \sum_{t=1}^{T-1} d_t D_t + \mu_s + e_{st}, \quad (1)$$

where R is research expenditure, $E(P)$ is expected output price, D is a time dummy variable, b and d are parameters to be estimated, subscripts i and j are two of the factors of production (land, labor, energy, or fertilizer) that research is seeking to save, s is state, and t is year. This specification allows for time fixed effects. We use a panel data estimator and conduct Hausman tests to determine whether a random-effects or fixed-effects model is most appropriate. Observations of zero expenditure are initially recorded as ones for this estimation in order to use all observations.

In order to isolate the effect of induced innovation, we need to control for marginal cost differences across states and time. If the marginal cost of innovation to save an input (in the implementing industry) is identical across states at a point in time, then differences in relative input prices across states identify differences in relative benefits of innovation. Inclusion of the time dummy variables in our models allows for secular change in marginal cost to save an input. If marginal costs differ across states but relative differences do not change over time, then inclusion of state fixed effects in the model will control for such effects. We analyzed fixed-effect models but found that they are not significantly different from random-effects models—which do not control for time-invariant heterogeneity across state—in the large majority of our specifications (see below).

The critical test of the induced innovation hypothesis is the one-sided test, $b_1 > 0$. A significant negative coefficient on the input price ratio in the innovation implementing industry is typically used to test the IIH when input quantity ratios in the innovation implementing industry are used as the dependent variable. However, that does not constitute a critical test unless innovation possibilities are neutral. By using the ratio of research investments, we are able to conduct an unambiguous critical test of the hypothesis for public agricultural research regardless of whether innovation possibilities are neutral or non-neutral. If b_1 is significantly positive, that is clear evidence that factor prices in the innovation implementing industry spur invention efforts in the innovation creating industry to economize the use of expensive factors in the implementing industry.[1]

Expected price is defined as a geometrically lagged function of historical prices and is designed to capture expected input prices by giving more weight to recent than to earlier prices. Because of likely lags in the impact of any price changes, we begin the geometric lag with prices lagged two years and consider the previous 10 years of price data. Thus, expected price in t is constructed as $E(P_{ist}) \approx \sigma P_{ist-2} + \sigma (1-\sigma) P_{ist-3} + \sigma$

1. The claim of unambiguity of the test is subject to several caveats: it assumes that the data are measured accurately, that there are no omitted variables bias due to failing to control appropriately for other variables that could affect relative research investments, and that public agricultural research in each state can be treated as though it were a competitive firm. Because it is not completely clear how variables should be specified or what control variables are needed in the model, we consider several alternatives in the robustness checks. We do not, however, relax the assumption that public agricultural research in each state mimics the decisions of a competitive firm.

$(1-\sigma)^2 P_{ist-4} + \ldots + \sigma(1-\sigma)^9 P_{ist-11}$, where σ is the geometric lag coefficient. The optimal lag is selected based on the Akaike criterion from values of 0.5 to 0.9 in 0.1 intervals. Our temporal data period is too short to conduct meaningful time series tests or even tests for autocorrelated errors. We find considerable evidence of heteroskedasticity and compute standard errors that are robust to both heteroskedasticity and autocorrelation.

For robustness checks on our conclusions, we consider several alternatives to this specification. (A) The first alternative generalizes the specification to include all three price ratios as regressors (with the denominator fixed across the three). (B) As noted in the next section, our data periods do not match perfectly. Our price data are available for two inputs through 2008 and only though 2004 for the other two inputs; we have research expenditure data through 2010. To utilize more of the available data, a second alternative uses four more years of observations but starts the geometric lag of prices at six years because of the lack of recent input price data for two of the inputs. (C) To capture investment stickiness in adjustment toward a new equilibrium, a third alternative includes the lagged dependent variable as a regressor. A pooled data estimator with fixed time effects is used for this estimation.[2] (D) To determine whether total research budgets impact research expenditure ratios, another alternative includes total public research expenditures as an additional regressor. Inclusion of this variable permits us to treat homotheticity of the innovation creating production function as a local rather than a global property. This alternative also includes the lagged dependent variable and is estimated with a pooled data estimator with fixed time effects. (E) To utilize all available data, a fifth alternative uses the four additional observations available for two of the inputs. We check variance inflation factors and do not find evidence of serious collinearity among the regressors in any model.

A final alternative is the way we deal with the large number of zero investments. Because we use investment ratios as the dependent variable, a zero investment in research for the denominator input produces a dependent variable with infinite value. In the previous models we approached this problem by converting all zero research expenditures to ones. In this specification, we approach the expenditure decision in two steps: 1) use a Probit binary choice model to model the decision to fund or not fund at least one project:

$$Pr\,(DP_{ist}) = \Phi[b_0 + b_1\,E(P_{ist})\,/\,E(P_{jst}) + c_2 R_{st} + \textstyle\sum_{t=1}^{T-1} d_t D_t + e_{st}], \qquad (2)$$

where DP is a binary variable (1 if the decision is to fund at least one project, 0 otherwise) and R_{st} is total public research expenditures in state s in year t; and 2) conditional on funding a project, use a panel data estimator to model the decision of how much to invest, Equation 1. We include total public research expenditures to control for the effect of the state's research scale on the decision to fund.

The robustness Alternative F is combined with several of the other alternative specifications. Robustness of the binary choice decision to fund model is addressed with alternatives A, B, C, and E. Robustness of the resource allocation model is addressed with Alternatives A-E. A random effects panel data model with fixed time effects is used to estimate the initial resource allocation model and robustness Alternatives A, B, and E. A pooled ordinary least squares (OLS) estimator with fixed time effects is used to estimate Alternatives C and D, both of which include the lagged dependent variable.

Data

The data used for this study were also used by Cowan et al. (2015), and additional details can be found there. They include total public research expenditures for agricultural productivity research, public research expenditures on technology aimed to save four agricultural inputs (land, labor, fertilizer, and energy), and agricultural input prices for the same array of inputs.

Land-saving research projects were funded in most years and states (96% of observations) while research projects aimed at saving other inputs were funded in only about half of the observations (44-56%). Further, aggregate funding for land-saving research was about 10 times as great as for any of the other inputs.

For our initial model, Equation 1, annual data for each of the 48 states for the period 1998-2006 were used for the dependent variables, 1987-2004 for prices (because of the geometric lag structure), and 1998-2006 for total research expenditure. For the robustness checks that included the lagged dependent variable as a regressor, the period of observations were adjusted to accommodate the loss of the 1998 observation in the dependent variable. Additional data were used in other robustness checks. The extremes of the data periods

2. *This model is estimated via pooled OLS since the inclusion of the lagged dependent variable is designed to account for unobserved time-invariant heterogeneity across states.*

Table 1. Statistical estimates of induced innovation, initial model.[a]

Input ratio equation	Own-price ratio Coefficient	Own-price ratio Robust std. error	Intercept Coefficient	Intercept Robust std. error	Optimal geometric lag coefficient	R-square, overall
Energy/land	0.0112	0.0300	0.1566***	0.0591	0.5	0.037
Fertilizer/land	-4.332	3.855	6.856	4.666	0.5	0.020
Labor/land	-0.0245	0.0242	0.1501***	0.0549	0.5	0.021
Energy/labor	-134.5	69.11	357.1**	164.1	0.5	0.036
Fertilizer/labor	61.46	72.66	127.6	95.86	0.7	0.045
Land/labor	90.37	615.0	1167.0	885.1	0.5	0.003
Energy/fertilizer	56.11	71.52	36.62	135.9	0.5	0.011
Labor/fertilizer	447.5*	298.0	-368.4	265.8	0.5	0.109
Land/fertilizer	466.0	377.0	417.9	514.1	0.9	0.037
Fertilizer/energy	346.0	358.2	-132.8	237.4	0.5	0.024
Labor/energy	421.5*	266.9	-247.2	175.0	0.7	0.077
Land/energy	238.6	953.5	748.2	895.4	0.5	0.036

[a] Random effects, geometric-lagged prices beginning with Year 2, zero funding level converted to one, own-price only. All models were estimated with 432 observations. Significance of own-price ratio is based on 1-sided test and significance of others on 2-sided tests.

, **, * delineates coefficients significant at the 10%, 5%, and 1% levels, respectively.*

used in robustness checks were 1998-2010 for the dependent variable, 1983-2008 for prices, and 1998-2009 for the lagged dependent variable and for total research expenditures.

Test Results

Based on Hausman tests, the random effects panel data estimator was tested against fixed effects, and the null of random effects was not rejected for 70% of the models. Because of the large number of models estimated, we limit the panel data estimates to those based on the random effects estimator with fixed time effects when the lagged dependent variable is not included. With the lagged dependent variable included as a regressor, the estimates are based on pooled OLS with fixed time effects.

The critical test results for the induced innovation hypothesis based on Equation 1 are reported in Table 1. Twelve equations were estimated for an exhaustive permutation of expenditure ratios as the dependent variable. With 1) zero expenditures converted to ones, 2) beginning the geometric lag specification of expected price with price lagged two years, and 3) limiting independent price ratio variables to own prices, the initial panel data estimator with random effects provided no support for the hypothesis at the 5% level of significance.

Results of the first sets of robustness checks are reported in Table 2. Including all three price ratios as regressors (Alternative A) resulted in three equations being consistent with the hypothesis. Extending the starting point of the geometric lag (Alternative B) did not result in any equations supporting the hypothesis.

Including the lagged dependent variable as a regressor and using pooled OLS with fixed time effects (Alternative C), one equation was consistent with the hypothesis when the geometric lag started at two years and only one price ratio was included as a regressor and two when all three price ratios were included. Two were consistent with the hypothesis when the geometric lag started at six years with one price ratio and three when all three price ratios were included.

Including total research expenditure as a regressor (Alternative D), one equation was consistent with the hypothesis when the geometric lag started at two years and only one price ratio was included as a regressor and three when all three price ratios were included. Two were consistent with the hypothesis when the geometric lag started at six years with one price ratio and three when all three price ratios were included. When additional data were used for energy and fertilizer (Alternative E), one of two equations was consistent with the hypothesis.

Of the 146 resource allocation equations estimated in the base model and this set of robustness checks, 21 equations (14%) were found to be supportive of the IIH. Among the twelve ratios, labor/fertilizer showed the most robust support for the IIH with six equations

Table 2. Own-price ratios with significant (5% level) positive parameters, alternative models. [a]

Panel data estimator	# of price ratios	Geometric lag begins with year	Lagged dep. variable	Total research expend.	Own-price ratio	Est. coeff.	Robust std. error	R^2 value	Geometric lag coeff.	# of obs.[b]
Alternative A: All price ratios										
Random effects	3	2	No	No	Energy/land	0.1358	0.0615	0.0547	0.5	432
					Fertilizer/labor	373.6	194.4	0.0879	0.5	432
					Labor/energy	458.1	269.4	0.0863	0.7	432
Alternative B: Longer price lags										
Random effects	1	6	No	No	None					
	3	6	No	No	None					
Alternative C: Lagged dependent variable										
Pooled	1	2	Yes	No	Labor/fertilizer	182.3	99.97	0.4788	0.5	384
	3	2	Yes	No	Fertilizer/labor	199.2	70.52	0.0925	0.5	384
					Labor/fertilizer	250.4	142.8	0.4826	0.5	384
	1	6	Yes	No	Labor/fertilizer	107.0	61.00	0.4531	0.9	576
					Fertilizer/energy	132.4	78.11	0.3361	0.5	576
	3	6	Yes	No	Energy/land	0.0282	0.0168	0.3362	0.9	576
					Fertilizer/labor	136.3	54.02	0.0645	0.5	576
					Fertilizer/energy	145.1	80.00	0.3368	0.5	576
Alternative D: Total research expenditure										
Pooled	1	2	Yes	Yes	Labor/fertilizer	184.5	100.2	0.4792	0.5	384
	3	2	Yes	Yes	Fertilizer/labor	206.5	71.51	0.0936	0.5	384
					Labor/fertilizer	243.0	145.5	0.2923	0.9	384
					Labor/energy	249.2	159.8	0.2922	0.8	384
	1	6	Yes	Yes	Labor/fertilizer	122.3	68.01	0.4354	0.9	528
					Fertilizer/energy	145.7	83.65	0.4903	0.9	528
	3	6	Yes	Yes	Energy/land	0.0365	0.0191	0.3833	0.9	528
					Fertilizer/labor	138.2	56.78	0.0989	0.5	528
					Fertilizer/energy	180.0	84.70	0.4920	0.9	528
Alternative E: More data										
Random effects	1	2	No	No	Energy/fertilizer	58.94	30.13	0.0237	0.5	624

[a] *All models estimated with time-fixed effects.*

[b] *The number of observations used in estimation varies over the alternatives. Starting the geometric lag price expectation with prices lagged six years allows four more years of data to be used, including the lagged dependent variable reduces the number of observations by one year, and including total research expenditure reduces the number of observations by one year when the geometric lag price expectation starts with prices lagged six years.*

(50%), followed by fertilizer/labor with five (42%), fertilizer/energy with four (31%), and energy/land with three (25%). No empirical support was found for six ratios, five of which included land as the numerator or denominator.

The equations that were consistent with the hypothesis showed a wide range of R^2 values and selected geometric lag coefficients. Except for equations that included the lagged dependent variable, all R^2 values were less than 0.1. When the lagged dependent variable was included as a regressor, most R^2 values ranged from 0.3 to 0.5. Those for the fertilizer/labor equations remained less than 0.1. More than half of the geometric lag coefficients selected by the Akaike criterion between 0.5 and 0.9 were 0.5, and a majority of the remainder were 0.9.

For the final set of robustness checks, we approach the funding decision in two steps. Considering the same set of initial and alternative models as above, we first estimated the decision to fund at least one project as a limited dependent variable problem using a Probit model, Equation 2.[3] Twelve equations were estimated

3. *Because we include total public research expenditures in all the binary models, Alternative D is excluded from the robustness checks.*

Table 3. Own-price ratios with significant positive parameters, two-step decision model (Alternative F), decision to fund, alternative models.

Estimator	# of price ratios	Geometric lag begins with year	Lagged dep. variable	Total research expend.	Own-price ratio	Est. coeff.	Robust std. error	Log-likelihood value	Geometric lag coeff.	# of obs.
Initial										
Probit	1	2	No	Yes	Fertilizer/land	0.555	0.292	-223.6	0.5	432
					Fertilizer/labor	1.712	0.610	-221.1	0.5	432
					Fertilizer/energy	2.181	1.288	-223.8	0.5	432
Alternative A: All price ratios										
Probit	3	2	No	Yes	Fertilizer/labor	1.729	0.940	-220.6	0.5	432
Alternative B: Longer price lags										
Probit	1	6	No	Yes	Fertilizer/land	0.682	0.287	-289.3	0.5	576
					Fertilizer/labor	1.085	0.466	-289.3	0.5	576
					Energy/fertilizer	0.730	0.365	-291.1	0.9	576
					Fertilizer/energy	2.643	1.381	-219.8	0.5	576
	3	6	No	Yes	Fertilizer/land	1.337	0.704	-286.5	0.6	576
					Fertilizer/labor	1.223	0.545	-288.6	0.5	576
Alternative C: Lagged dependent variable										
Probit	1	2	Yes	Yes	Fertilizer/land	0.326	0.122	-153.2	0.5	384
					Fertilizer/labor	0.765	0.305	-153.2	0.8	384
	3	2	Yes	Yes	Energy/land	0.465	0.270	-166.7	0.9	384
	1	6	Yes	Yes	Fertilizer/land	0.364	0.103	-208.2	0.5	528
					Fertilizer/labor	0.468	0.282	-211.0	0.8	528
	3	6	Yes	Yes	Fertilizer/land	0.504	0.240	-207.8	0.5	528
Alternative E: More data										
Probit	1	2	No	Yes	Energy/fertilizer	0.205	0.113	-291.0	0.9	576

for each model except Alternative E, for which two equations were estimated. For the probability of funding at least one research project to save an input, three equations were estimated, each with a different price in the denominator. The estimation results are reported in Table 3.

Of the 98 decision-to-fund binary model equations, 17 equations (17%) were consistent with the IIH. The input ratios that showed the most support were fertilizer/land and fertilizer/labor with six equations (50%) each. In terms of individual inputs, the most support for the IIH was found with the decisions to fund a fertilizer research project (16 equations, 32%). Support for the IIH in decisions to fund a research project to save other inputs ranged from 10 to 15%.

Conditional on funding at least one project, we next examined the decision of how much to invest using the random-effects panel data estimator (pooled OLS estimator when the lagged dependent variable was included as a regressor) with fixed time effects. The estimation results are presented in Table 4.

Of the 146 resource allocation equations, 22 equations (15%) were consistent with the IIH. The input ratios that showed the most support were energy/fertilizer (10 equations, 77%) and labor/energy (6 equations, 46%). In terms of individual inputs, the most support for the IIH was found with resource allocation decisions for energy (18 equations, 24%) and fertilizer (14 equations, 19%). Support for the IIH in decisions to fund a research project to save land and labor ranged from 7 to 10%.

Overall, a total of 35 models were estimated—10 using a random effects panel data estimator, 16 using a pooled OLS estimator, and nine using a Probit estimator. Except for three models, each included 12 equations for an exhaustive combination of price ratios. This resulted in a total of 390 separate equations being estimated. Among those 390 equations, 60 rendered significantly positive parameters at the 5% level on the own-price ratio for consistency with the induced innovation hypothesis. With random observations and a normal distribution, we would have expected 19-20 of the estimated equations to be consistent with the hypothesis. Thus, we find three times the evidence in support of the induced innovations than would be expected from random observations. This is nontrivial—but not overwhelming—support for induced innovation.

The evidence in support of induced innovation is considerably stronger than that provided by Liu and

Table 4. Own-price ratios with significant positive parameters, two-step decision model (Alternative F), allocation decision, alternative models.[a]

Panel data est.	# of price ratios	Geometric lag begins with year	Lagged dep. variable	Total research expend.	Own-price ratio	Est. coeff.	Robust std. error	R^2 value	Geometric lag coeff.	# of obs. [b]
Initial										
Random effects	1	2	No	No	None					
Alternative A: All price ratios										
Random effects	3	2	No	No	Energy/land	0.0477	0.0232	0.0375	0.5	413
					Energy/fertilizer	4.992	1.792	0.0411	0.5	216
Alternative B: Longer price lags										
Random effects	1	6	No	No	Energy/fertilizer	3.352	1.647	0.0357	0.8	306
					Labor/fertilizer	1.774	1.003	0.0720	0.5	306
					Labor/energy	33.28	20.12	0.0620	0.5	276
	3	6	No	No	Energy/land	0.0262	0.0141	0.0306	0.7	599
					Energy/fertilizer	3.345	1.997	0.0399	0.8	306
					Labor/energy	35.93	20.65	0.0648	0.5	276
Alternative C: Lagged dependent variable										
Pooled	1	2	Yes	No	Energy/fertilizer	5.295	1.852	0.2167	0.5	163
	3	2	Yes	No	None					
	1	6	Yes	No	Fertilizer/land	0.0184	0.0080	0.2823	0.9	546
					Energy/fertilizer	3.615	1.155	0.1751	0.6	240
					Labor/energy	41.38	22.13	0.0782	0.5	192
	3	6	Yes	No	Energy/fertilizer	2.318	0.9185	0.1933	0.5	240
					Labor/energy	45.06	23.35	0.0819	0.5	192
Alternative D: Total research expenditure										
Pooled	1	2	Yes	Yes	Fertilizer/land	0.0152	0.0089	0.2871	0.9	364
					Energy/fertilizer	5.279	1.984	0.2167	0.5	163
	3	2	Yes	Yes	None					
	1	6	Yes	Yes	Fertilizer/land	0.0177	0.0079	0.2884	0.9	499
					Energy/fertilizer	3.438	1.262	0.190	0.6	219
					Labor/energy	47.01	25.94	0.0800	0.5	171
	3	6	Yes	Yes	Energy/fertilizer	1.705	0.912	0.2140	0.5	219
					Labor/energy	49.64	26.19	0.0835	0.5	171
Alternative E: More data										
Random effects	1	2	No	No	Energy/fertilizer	1.510	0.912	0.0245	0.5	306

[a] All panel-data models estimated with time-fixed effects.

[b] The number of observations depends on the number of non-zero research funding observations in the denominator as well as the issues described in Footnote B of Table 2.

Shumway's (2009) demand-side hypothesis tests. Thus, it is apparent that these tests based on reduced-form equations accounting for both supply and demand for new technology provide clearer evidence in support of induced innovation. However, the support we found for the IIH in this less structured specification and broader set of robustness checks is not as strong as Cowan et al.'s (2015) hypothesis tests.[4] They used the same data we have but maintained additional structure (i.e., two-level CET) on the innovation production function and used the pseudo-Poisson maximum likelihood (PPML) estimator. Thus, the structure they imposed on the production function and their estimation method did not limit evidence in support of a valid hypothesis, but rather clarified support.

4. *Fifty-six percent of their estimated equations were consistent with the IIH at the 5% level of significance.*

Considering evidence from all 60 equations, the greatest support for the induced innovation hypothesis was found for project selection and resource allocation decisions governing the fertilizer-labor and energy-fertilizer input-saving research pairs. Eighteen significant positive coefficients on the own-price ratio for the first pair (28% of its estimated equations) and 19 models for the second pair (27% of its estimated equations) were found. No significant negative own-price coefficients were found for either pair. Support for the induced innovation hypothesis for the fertilizer-land, energy-labor, and energy-land input-saving research funding decisions ranged from 9 to 14% of their estimated equations. The support from these input ratios dropped to 5 to 9% when the number of equations with a significant negative own-price coefficient was subtracted from the number with a significant positive own-price coefficient. No support was found for the hypothesis for the labor-land input-saving research funding decisions. Our finding that fertilizer provides the greatest support for the IIH (with 23% of estimated equations) and is followed by energy (with 17% of estimated equations) is consistent with the findings of Cowan et al. (2015). We rank labor next (with 14% of estimated equations supporting the IIH) and land (with support from 8%) last, whereas they reverse the rank order of the inputs providing least support. Our rank order remains the same when the number of equations with a significant negative own-price coefficient is subtracted from the number with a significant positive own-price coefficient.

In terms of model specification, robustness Alternative E provided the greatest support (50%) for the induced innovation hypothesis, and the initial model specification provided least support (8%). The other robustness alternatives provided a similar level of support (14-17%). With the exception of Alternative E that used additional data for two inputs, models with longer lags in initiating the geometric price expectation provided greater support (19%) than did those with shorter lags (10%).

Each of the models was estimated subject to a geometric lag coefficient being selected based on the Akaike criterion. Five alternatives between 0.5 and 0.9 in 0.1 increments were considered. Of all the models estimated, 0.5 was selected for a majority of the equations. Thus, it appears that induced funding decisions give relatively heavy weight to highly lagged input prices for the implementing industry in formulating output price expectations in the innovation creating industry.

Conclusions and Policy Implications

We join Cowan et al. (2015) in reporting what we believe to be the first legitimate tests of the induced innovation hypothesis for US agriculture. They are the first tests conducted for this industry that account for supply as well as demand for new technology aimed at saving inputs. We relax the strict CET specification of the two-level production function in the innovation creating industry and conduct a larger set of robustness checks. We find important but less support for the induced innovation hypothesis than did Cowan et al. (2015). Although the support is smaller, our tests are qualitatively consistent with their finding of support for the induced innovation hypothesis in the input-saving research funding decisions that affect energy and fertilizer resource allocations. We found relatively more support than they did for the induced innovation hypothesis in research resource allocations to save labor but less for decisions to save land.

We found very little support for the hypothesis in public research investment decisions to create innovations to save the land input. On reflection, this may not be particularly surprising. Because land prices are based on productivity and consequently vary so much more than do the prices of other inputs, it is possible that the use of local land prices (even partially accounting for quality differences as with this series) are not appropriate for testing the induced innovation hypothesis. Prices could just be reflecting local differences in productivity. Thus, there may be little difference in the incentive to invest in research to save high-valued, more productive land than to save low-valued, less productive land. This possibility seems to have some support in the fact that research funding for land-saving research was much larger and much more stable across states and over time than funding to save the other inputs.

The greatest support for the hypothesis in public research decisions came from energy and fertilizer. Both are largely fossil-based inputs. Consequently, even the modest support found for the hypothesis in research investment decisions aimed at saving these inputs documents the potential for taxes and/or subsidies to be used in public policy to induce public innovation that has socially beneficial environmental effects. Since support has been found in public research decisions, it is likely that private research decisions will also be responsive (and likely more so) to tax-subsidy policy that seeks to synchronize private with social prices. Consequently, not only can we expect input combinations to change through substitution effects to save the input with the greatest relative disparity between private and social prices but also through non-neutral technical change.

References

Cowan, B.W., Lee, D., & Shumway, C.R. (2015). The induced innovation hypothesis and U.S. public agricultural research. *American Journal of Agricultural Economics*, *97*(3), 727-742.

Crabb, J.M., & Johnson, D.K.N. (2010). Fueling innovation: The impact of oil prices and CAFÉ standards on energy-efficient automotive technology. *The Energy Journal*, *31*(1), 199-216.

Hicks, J.R. (1932). *The theory of wages*. London: Macmillan.

Lin, N. (1998). *Technical change and aggregation in U.S. agriculture*. Ph.D. dissertation, Texas A&M University.

Liu, Q., & Shumway, C.R. (2006). Geographic aggregation and induced innovation in American agriculture. *Applied Economics*, *38*(April 10), 671-682.

Liu, Y., & Shumway, C.R. (2009). Induced innovation in U.S. agriculture: Time-series, econometric, and nonparametric tests. *American Journal of Agricultural Economics*, *91*(1), 224-236.

Machado, F.S. (1995). Testing the induced innovation hypothesis using cointegration analysis. *Journal of Agricultural Economics*, *46*(3), 349-360.

Nordhaus, W. (2002). Modeling induced innovation in climate-change policy. In A. Grubler, N. Nakicenovic, & W.D. Nordhaus (Eds.), *Technological change and the environment* (pp. 182-209). Washington, DC: Resources for the Future Press.

Olmstead, A.L., & Rhode, P.W. (1993). Induced innovation in American agriculture: A reconsideration. *Journal of Political Economy*, *101*(1), 100-118.

Popp, D. (2002). Induced innovation and energy prices. *The American Economic Review*, *92*(1), 160-180.

Pouliot, S., & Sumner, D.A. (2008). Traceability, liability, and incentives for food safety and quality. *American Journal of Agricultural Economics*, *90*(1), 15-27.

Tiffin, R., & Dawson, P.J. (1995). Induced innovation in American agriculture. *Oxford Agrarian Studies*, *23*(2), 87-98.

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