Non-Neutral Marginal Research Costs and Induced Innovation

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Abstract
Allowing for a non-neutral innovation function, we test whether the Hicks' Induced Innovation Hypothesis (IIH) holds in U.S. agriculture for the period 1960-2004 using state-level input price and quantity data. A multi-stage cost minimization model is set forth that includes introduction of an innovation function reflecting non-neutral marginal research costs across inputs. With homothetic production and innovation functions, we derive a structural relationship between the expected input price ratio and input allocation under cost minimization which permits the effect of the IIH to be distinguished from general input substitution. Our major contributions to the literature are fourfold: (1) we document that the IIH's implication of factor-saving behavior depends crucially on the magnitude of the elasticity of substitution, (2) we demonstrate that, when the innovation function is accounted for, the relationship between factor augmentation and expected relative price is not a monotonic function of the elasticity of substitution, (3) we find that the relationship between factor-saving behavior and marginal research cost is also not a monotonic function of the elasticity of substitution, and (4) we provide a test procedure that is robust to a time-variant and non-neutral innovation function. Considerable supporting evidence for the IIH is found in the data for all inputs except land.

Keywords: demand, difference in differences, factor augmentation, induced innovation, innovation function, supply, U.S. agriculture

JEL Classification: O300, D240

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Introduction

The induced innovation hypothesis (IIH) postulated by Hicks (1932) more than 80 years ago has captured much attention because of the theoretical appeal that prices may be important not only for input choices but also for technology development to save inputs that become relatively more expensive. Although it took more than 30 years before the theoretical foundations began to be established (e.g., Kennedy 1964, Samuelson 1965, Ahmad 1966, Kamien and Schwartz 1968, Binswanger 1974), Hayami and Ruttan's (1970) tests of the IIH soon after inaugurated a large body of literature devoted to determining the empirical validity of the IIH in a wide range of industries and countries.

Part of that attention may be due to its important policy implications. Whether the IIH is valid in a sector or a country is important to policy makers because of the dynamic effects of economic policies. Taxes and subsidies are sometimes used to correct market failures when prices fail to reflect externalities. Provided the IIH is valid, price interventions would be expected to have inter-temporal effects through research resource allocation decisions. If those secondary effects actually occur but are not considered in the policy implementation, a tax intended to curb use of a polluting input, for example, could overshoot the initial reduction goal due to development of technology that further saves the polluting input.

Despite the large body of literature that reports empirical tests of the IIH, most of it has implicitly maintained the untenable hypothesis of a neutral innovation function.[1] Statistical tests of the hypothesis have generally focused exclusively on the demand for innovation and ignored

[1] A neutral innovation function implies that the marginal research cost to augment 1 percent of an input is identical across inputs.

its supply dimensions. Previous efforts to surmount this limitation have required data from the innovation creating industry specific to efforts to create technology to save particular inputs in the innovation implementing industry. For example, Popp (2002) and Crabb and Johnson (2010) attempted to account for heterogeneities in innovation supply among different inputs in their IIH tests of the energy sector by adding a knowledge stock variable to the regression equation. Linn (2008) used entry, survival, and exit rate as proxies for unobserved heterogeneous productivity in the same sector. Cowan, Lee, and Shumway (2015) tackled the problem in U.S. agriculture by focusing on public research investment decisions. Both sets of test procedures, however, depend on availability of high quality data from the innovation creating industry, and such data are seldom available or sufficiently complete.

In this article, we develop both a theoretical foundation and a test procedure that accounts for the non-neutral innovation function without requiring data that is often difficult or impossible to obtain. We postulate a representative firm that makes or influences two distinct, inter-temporal decisions – a research resource allocation decision that is based on expected input prices and a subsequent input choice decision based on existing technology and realized input prices. We develop a multi-stage decision model that parametrically distinguishes effects of the IIH from those of contemporaneous input substitution. We explicitly introduce an innovation function that is permitted to be non-neutral. We show how a difference-in-differences estimation procedure can control for the effect of non-neutral marginal research costs in empirical estimation. [2]

[2] Although the use of a difference-in-differences method in the induced innovation literature is not new (e.g., Deininger 1995, Jaffe and Palmer 1997, Finkelstein 2004, Bhattacharya and Packalen 2008, Calel and Dechezleprêtre 2014, Dechezleprêtre and Glachant 2014), none formally addresses the identification role of the method in terms of non-neutrality of innovation creation.

Our procedure allows marginal cost of research on technology that aims to augment use of an input to vary across observational units and over time. We impose only one simplifying assumption – that the trend in the rate of change in relative marginal research cost is the same across states. This difference-in-differences formulation permits the cost-minimizing input ratio effects of different marginal research costs across observational units and over time to be controlled for, which could have otherwise caused omitted variables bias. While our simplifying assumption is still restrictive, this assumption is much more flexible than the assumption of a neutral innovation function maintained in most previous tests. We implement our empirical test using a state-level panel for the period 1960-2004 of readily available data – input prices and quantities and total output for the innovation-implementing agricultural production industry and total research expenditures for the innovation-creating public agricultural research industry. The research resource allocation decision is based on rational expectations of future input prices. Alternative expectation-generating mechanisms are considered as robustness checks.

Our analytical results show that when the elasticity of substitution between two inputs is less than one plus the magnitude of the innovation concavity parameter (which itself must be greater than one), a rise in the relative expected price of an input results in its relatively lower use. However, when the elasticity of substitution is greater than this magnitude, the IIH implies relatively greater use of the input that is expected to become more expensive. We document that the relationship between factor augmentation and expected relative price is not a monotonic function of the elasticity of substitution when the innovation function is accounted for. We also find that the relationship between factor-saving behavior and marginal research cost is not a monotonic function of the elasticity of substitution.

The empirical results of this research indicate that the state-level U.S. agricultural data during the 1960-2004 period provide moderate (57 percent) overall support for the IIH and strong support with some inputs. Empirical evidence of consistency with the IIH was concentrated in input decisions involving pairs of three inputs – capital, intermediate inputs, and labor (with 75-88 percent support). Less support was found for input pairs involving land. The level of support for the IIH is similar to other recent tests for the IIH in this industry when innovation supply is accounted for. It is considerably greater than that found in several other studies that treated innovation supply as input neutral (e.g., Olmstead and Rhode 1993, Machado 1995, Liu and Shumway 2006, Liu and Shumway 2009).

The remainder of the paper is organized as follows. In the next section we develop a multi-period model of research investment and input choice for a price-taking, cost-minimizing representative firm. We subsequently develop an empirical model based on the optimization conditions and show how unobserved non-neutral marginal costs of research can be addressed by a difference-in-differences formulation. We then describe the data and variable specifications used for estimation. Empirical estimates from the initial model and robustness checks are reported in the following two sections, and we conclude in the final section.

Theoretical Model

We propose a $k+1$ period model for a cost-minimizing firm that makes input choice decisions and makes or influences research resource allocation decisions. We start with input choice decisions in the final period t without imposing any restrictions on factor augmentation. We then turn to the research resource allocation decision in period $t-k$ and its factor augmentation implications. By combining both components, we show how earlier optimal research decisions impact the subsequent input choice decisions under the IIH. In doing so, we document that the range of elasticities of substitution that give rise to factor-saving behavior under the IIH is limited and their relationship to factor augmentation is more complex than previously documented.

We initiate the input choice decision using one of the common assumptions in the induced innovation literature, that the production technology can be approximated by a two-level constant elasticity of substitution (CES) functional form (e.g., Kawagoe, Otsuka, and Hayami 1986, de Janvry, Sadoulet, and Fafchamps 1991, Thirtle, Schimmelpfennig, and Townsend 2002, Liu and Shumway 2009, Cowan, Lee, and Shumway 2015). Consider a representative firm that produces a single output Y at time t:

$$(1) \quad Y_t = \left[\delta X_{1t}^{\frac{\rho-1}{\rho}} + (1-\delta) X_{2t}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}} \text{ for } \rho \in [0,\infty)$$

where ρ is the elasticity of substitution between input indices $X_{it},\ i \in (1,2)$. We suppress the firm subscript throughout to reduce notational clutter. The input indices are produced respectively by pairs of inputs that also follow a CES form:

$$(2) \quad X_{it} = \left[\delta_i (a_{i1t} x_{i1t})^{\frac{\rho_i-1}{\rho_i}} + (1-\delta_i)(a_{i2t} x_{i2t})^{\frac{\rho_i-1}{\rho_i}} \right]^{\frac{\rho_i}{\rho_i-1}} \text{ for } \rho_i \in [0,\infty),$$

where x_{ij} is input $j \in (1,2)$ used in production of input index i, and a is a factor-augmenting parameter that captures technical progress.

The firm selects optimal input quantities x_{ij} that minimize the cost of producing a given output level with known input prices and technology. Since the two-level CES production function maintains homotheticity, minimizing cost provides the same optimal input ratios as maximizing profit for a given output price with the same input prices and technology. Taking the first-order conditions and with a little reorganization documented in Appendix I, we obtain the following optimal input demand relationship:

$$(3) \quad \frac{x^*_{i1t}}{x^*_{i2t}} = \left(\frac{\delta_i}{1-\delta_i}\right)^{\rho_i} \left(\frac{w_{i1t}}{w_{i2t}}\right)^{-\rho_i} \left(\frac{a_{i1t}}{a_{i2t}}\right)^{\rho_i - 1}, \; i \in \{1,2\}.$$

where w_{ij} is the price of input x_{ij}, and the asterisk on *x* denotes the cost-minimizing input level.

Equation (3) documents that the qualitative effect of technical change (represented by the ratio of factor augmentation parameters) on the input ratio is dependent on the magnitude of the elasticity of substitution. Specifically, for two inputs, say labor and capital, without relative price changes, labor-augmenting technical change (that augments labor relatively more than capital) results in a labor-saving production decision if and only if the elasticity of substitution is less than one (Acemoglu 2002, Funk 2002, Armanville and Funk 2003). When the elasticity of substitution is greater than one, labor-augmenting technical change results in relatively greater use of labor because it is more easily substituted for capital. When the elasticity of substitution is exactly one (as in the Cobb-Douglas production function), technical change does not lead to changes in the input ratio.

We now turn to the research resource allocation decision made in period *t-k*. In doing so, we show that the relationship between factor-saving behavior and factor augmentation is not a monotonic function of the elasticity of substitution. We also document that the sign of the IIH test depends crucially on the magnitude of the elasticity of substitution.

We consider a simple but very general homothetic innovation function that can accommodate both non-neutral and time-varying marginal research costs, where innovation is defined as augmentation of at least one factor.[3] For a given research budget $\overline{R}$, the innovation function is given by:[4]

(4) $$R_{i(t-k)} = \left(c_{i1(t-k)}\hat{a}_{i1t}\right)^{\theta_i} + \left(c_{i2(t-k)}\hat{a}_{i2t}\right)^{\theta_i}.$$

where $R_{i(t-k)}$ is expenditure on research in period *t-k* to augment the *i*th input index, the total research budget is assumed to be exogenously given and is fully expended, i.e., $\overline{R}_{t-k} \equiv R_{1(t-k)} + R_{2(t-k)}$, $\hat{a}_{ij}$ is the factor-augmentation parameter, which is assumed to be nonregressive, i.e., $\hat{a}_{ijt} \geq \hat{a}_{ij\tau}$ if $t > \tau$; $c_{ij(t-k)} > 0$ denotes marginal research costs (or degree of research difficulty) for technology that augments x_{ij} by 1 percent; and $\theta_i > 1$ is a parameter representing the trade-off between the two research outcomes $\hat{a}_{i1t}$ and $\hat{a}_{i2t}$, i.e., the larger the parameter, the more concave the frontier toward the origin (hereafter referred to as the "concavity parameter"). Given a research budget, the condition $\theta_i > 1$ is sufficient to ensure that $\frac{\partial \hat{a}_{i2t}}{\partial \hat{a}_{i1t}} < 0$ and $\frac{\partial^2 \hat{a}_{i2t}}{\partial \hat{a}_{i1t}^2} < 0$ on the innovation function, as demonstrated in Appendix II.

This simple formulation of the innovation function results in an inverse relationship between degree of research difficulty and research outcome. An increase in the marginal cost of research shifts the innovation function toward the origin. Further, the innovation function is output-homothetic on the frontier, so the share of research outputs measured by the ratio of the factor-augmenting parameters does not depend on the total research budget.

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[3] An increase in a factor augmentation parameter shifts the entire production function upward. But the shift may be greater in the region where the factor associated with the augmented parameter is used intensively, a feature similar to "localized" progress introduced by Atkinson and Stiglitz (1969) and revisited by Acemoglu (2015).

[4] This function is a modified version of the one employed by Armanville and Funk (2003).

The marginal research cost parameters represent the time-varying and non-neutral nature of the innovation function. At a point in time, the innovation function is neutral if and only if $c_{i1} = c_{i2}$. Figure 1 displays (a) a neutral innovation function and (b) a non-neutral innovation function. In panel (b) of the figure, the condition $c_{i1} > c_{i2}$ implies that research on the $i1$ input-augmenting technology is more difficult (more costly) than that on input $i2$ to achieve the same level of augmentation. Note that increases (decreases) in research funds expand (shrink) the innovation function radially parallel to the origin.[5]

Considering the opportunity to invest (or influence investment) in R&D *k* periods before production inputs are selected and assuming a two-level CES production function as in the input decision model, the firm's research resource allocation problem in period *t-k* can be written as follows:

$$(5) \qquad \min_{\tilde{x}_{ijt}, \hat{a}_{ijt}} \sum_i \sum_j E_{t-k}(w_{ijt})\tilde{x}_{ijt}$$

$$s.t.\ \overline{Y}_t = \left[\delta X_{1t}^{\frac{\rho-1}{\rho}} + (1-\delta) X_{2t}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}},$$

$$\overline{R}_{t-k} \equiv R_{1(t-k)} + R_{2(t-k)}$$

where $X_{it} = \left[\delta_i (\hat{a}_{i1t}\tilde{x}_{i1t})^{\frac{\rho_i-1}{\rho_i}} + (1-\delta_i)(\hat{a}_{i2t}\tilde{x}_{i2t})^{\frac{\rho_i-1}{\rho_i}} \right]^{\frac{\rho_i}{\rho_i-1}}$, a tilde on input levels denotes that these values are "*conceived*" at time *t-k* and thus distinguished from the values that are actually chosen by the firm at time *t*, E_{t-k} is the expectations operator $E_{t-k}\left[\cdot \middle| \Omega_{t-k}\right]$, Ω_{t-k} is the firm's

[5] Decision making on total resources devoted to R&D is out of the scope of this paper and, for this reason, the homothetic functional form is deliberately chosen for the sake of tractability. In estimation, we impose homotheticity only as a local property by including total public research expenditure as a control variable.

information set at time *t-k*, and $\hat{a}_{ijt}$ is expected factor augmentation in period *t*. The research resource allocation that minimizes this function results in induced innovation and is consistent with the IIH.

Combining and rearranging the first-order conditions, the optimal ratios of innovation are obtained (see Appendix I for derivation of this and the next two equations):

$$(6) \quad \frac{\hat{a}_{i1t}^*}{\hat{a}_{i2t}^*} = \left(\frac{\delta_1}{1-\delta_1}\right)^{\frac{\rho_i}{1+\theta_i-\rho_i}} \left(\frac{E_{t-k}(w_{i1t})}{E_{t-k}(w_{i2t})}\right)^{\frac{1-\rho_i}{1+\theta_i-\rho_i}} \left(\frac{c_{i1(t-k)}}{c_{i2(t-k)}}\right)^{\frac{-\theta_i}{1+\theta_i-\rho_i}},$$

where the asterisk denotes an optimal value. It is apparent that the effect of an expected relative price change on technical bias (the ratio of expected research outcomes) depends on the sign and magnitude of $D_i \equiv \dfrac{1-\rho_i}{1+\theta_i-\rho_i}$. Since $\rho_i \geq 0$ and $\theta_i > 1$, an increase in the (expected) relative price of x_{i1t} brings about factor-augmenting technical change such that the input that is expected to become more expensive is augmented more than the other whenever $0 \leq \rho_i < 1$ or $1+\theta_i < \rho_i$. Conversely, when $1 < \rho_i < 1+\theta_i$, the same increase will induce technical change that augments the input that is expected to become less expensive. Thus, the relationship between elasticity of substitution and factor augmentation is not monotonic.

The effect of a change in the marginal cost of research on technical bias depends on the sign and magnitude of $\dfrac{-\theta_i}{1+\theta_i-\rho_i}$. The ratio of marginal costs of research negatively affect the optimal ratios of innovation, i.e., a higher relative marginal cost of research on labor-augmenting technology leads to relatively more capital-augmenting technical change whenever $0 \leq \rho_i < 1+\theta_i$. It positively affects the optimal innovation ratios when $1+\theta_i < \rho_i$.

By further manipulating the first-order conditions, the expected optimal input ratio is obtained:

$$(7) \quad \frac{\tilde{x}^*_{i1t}}{\tilde{x}^*_{i2t}} = \left(\frac{\delta_1}{1-\delta_1}\right)^{\frac{\rho_i\theta_i}{1+\theta_i-\rho_i}} \left(\frac{E_{t-k}(w_{i1t})}{E_{t-k}(w_{i2t})}\right)^{\frac{\rho_i-\rho_i\theta_i-1}{1+\theta_i-\rho_i}} \left(\frac{c_{i1(t-k)}}{c_{i2(t-k)}}\right)^{\frac{(1-\rho_i)\theta_i}{1+\theta_i-\rho_i}}.$$

This concludes the *k* research resource allocation stages of the optimization model. However, recall that the firm is not constrained by the conceived value $\frac{\tilde{x}^*_{i1t}}{\tilde{x}^*_{i2t}}$ when time *t* has come. This is because it may still do better by adjusting input allocation decisions when the actual realized prices of inputs are different from the expectations that the firm formed at *t-k.* The whole process is illustrated conceptually in Appendix III.

Thus, the firm optimizes at time *t* by solving the input choice decision problem in which the research outcomes are taken as given. Substituting $\frac{\hat{a}^*_{i1t}}{\hat{a}^*_{i2t}}$ into the equilibrium condition (3) yields the following:

$$(8) \quad \frac{x^*_{i1t}}{x^*_{i2t}} = \left(\frac{\delta_i}{1-\delta_i}\right)^{\frac{\theta_i\rho_i}{1-\theta_i-\rho_i}} \left(\frac{w_{i1t}}{w_{i2t}}\right)^{-\rho_i} \left(\frac{E_{t-k}(w_{i1t})}{E_{t-k}(w_{i2t})}\right)^{\frac{-(1-\rho_i)^2}{1+\theta_i-\rho_i}} \left(\frac{c_{i1(t-k)}}{c_{i2(t-k)}}\right)^{\frac{\theta_i(1-\rho_i)}{1+\theta_i-\rho_i}}.$$

With this combined condition, it is now possible to distinguish optimal input ratio effects of technical change caused by changes in the expected price ratio from input substitution effects caused by changes in the current price ratio. Note that if the realized input price ratio is the same as the expected price ratio, i.e., if $\frac{w_{i1t}}{w_{i2t}} = \frac{E_{t-k}(w_{i1t})}{E_{t-k}(w_{i2t})}$, then the effects of relative prices on actual optimal choice of relative input quantities $\frac{x^*_{i1t}}{x^*_{i2t}}$ would be the same as the effects on optimal choice of the conceived production plan $\frac{\tilde{x}^*_{i1t}}{\tilde{x}^*_{i2t}}$.

Consider the parameter associated with the expected price ratio $H_i \equiv \frac{-(1-\rho_i)^2}{1+\theta_i-\rho_i}$ in equation (8). H_i reveals the relationship between the change in the expected price ratio and the optimal input demand ratio. H_i is negative for $\rho_i < 1+\theta_i$ and positive otherwise. Thus, when the concave innovation function is incorporated into the model, the range of elasticities of substitution for which the IIH implies a factor-saving input choice is more than twice as great as the range of elasticities for which factor augmentation implies a factor-saving input choice since $\theta_i > 1$.[6]

Further, note that $H_i = (\rho_i - 1)D_i$. Thus, when the conditions for the research allocation decision are combined with the input choice decision, additional important analytical results emerge. When $0 \le \rho_i < 1$, the expected price change leads to research resource allocation decisions that are expected to augment more the input that has become more expensive, and in turn, the augmentation of the more expensive input results in less use of it. When $1 < \rho_i < 1+\theta_i$, the expected price change leads to research decisions that augment more an input that has become less expensive, but the augmentation of the less expensive input leads to less use of the more expensive input. And when $1+\theta_i < \rho_i$, the expected price change again leads to research

[6] In an early challenge to the IIH, Salter (1960) contended that an increase in the price of one factor relative to another should only constrain the firm to seek ways to reduce use of the factor if knowledge to save it is easier to acquire than knowledge to save other inputs. We formally document that his argument has an element of validity, but only if the elasticity of substitution is very large.

decisions that augment more an input that has become more expensive; but its augmentation leads to more use of the more expensive input. Thus, because of the non-monotonic relationship between factor augmentation and the elasticity of substitution, consistency with the IIH requires H_i to be negative if $0 \le \rho_i < 1+\theta_i$, where $\theta_i > 1$ due to the assumption of concavity of the innovation function. In other words, unless the elasticity of substitution between inputs is greater than $1+\theta_i$, which is at least greater than 2, relative saving of an input that has become relatively more expensive is consistent with the IIH.

Finally, the impact of a non-neutral innovation function on factor-saving or factor-using behavior under the IIH is non-monotonic. If $0 \le \rho_i < 1$ or $1+\theta_i < \rho_i$, an increase in marginal cost of research to save one input induces factor-saving behavior for the other input. Conversely, if $1 < \rho_i < 1+\theta_i$, an increase in marginal cost induces factor-saving behavior for the same input.

Empirical Model – Difference-in-Differences Approach

In our empirical implementation, we focus on the agricultural production sector. We treat states as though they were price-taking profit-maximizing firms, a hypothesis previously not rejected by empirical testing (Lim and Shumway 1992). Although little formal research is conducted by agricultural firms, they do have influence on the allocation of public research funds. Thus, we treat public agricultural research in the state as an appendage to the representative state-level agricultural firm.

Including the state subscript *s* on variables and taking the natural logarithm of both sides of equation (8), we obtain the regression model:

$$(9)\quad \ln\left(\frac{x_{i1st}}{x_{i2st}}\right) = \beta_{i0} + \beta_{i1}\ln\left(\frac{w_{i1st}}{w_{i2st}}\right) + \beta_{i2}\ln\left(\frac{E_{t-k}(w_{i1st})}{E_{t-k}(w_{i2st})}\right) + \beta_{i3}\ln\left(\frac{c_{i1st}}{c_{i2st}}\right) + \Gamma_i^{'} Z_{ist} + \varepsilon_{ist},$$

where Z is a vector of other control variables, ε_{ijst} is an error term, and the β 's and the vector Γ are parameters. The parameters β_{i1}, β_{i2}, and β_{i3} correspond to $-\rho_i$, $H_i \equiv \frac{-(1-\rho_i)^2}{1+\theta_i-\rho_i}$, and $\frac{\theta_i(1-\rho_i)}{1+\theta_i-\rho_i}$, respectively, in equation (8).[7]

In order to conduct valid tests of the IIH, it is important that we accurately determine whether elasticities of substitution are less than or greater than $1+\theta_i$ (or at least to discern whether they are less than 2.0). In addition, we must account for the impact of non-neutral marginal cost of research on input saving or using behavior. The latter is particularly challenging because we lack data on the marginal cost of innovation to save individual inputs (as is usually the case).

If the marginal cost of research to augment 1 percent of an input is the same across inputs, i.e., $c_{i1t} = c_{i2t}$ (which represents a neutral innovation function), then the ratio of marginal research costs vanishes from the regression model and does not affect the optimal input ratio. As previously noted, this has been implicitly assumed in virtually all of the IIH testing literature until recently. Formal tests have been intrinsically limited to the demand side without accounting for possible non-neutrality in the supply of innovation. However, there is no reason to expect that the innovation function is neutral, so we must deal with the omitted variables problem due to the lack of explicit data on marginal research costs. To surmount this omitted variables problem, we

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[7] The three parameters in equation (9) overidentify the two parameters in equation (8). Since our subsequent estimation procedure does not require us to estimate β_{i3}, this overidentification disappears. Furthermore, since the constant in equation (8) is omitted, the empirical model presented in equation (9) no longer constitutes a fully specified structural model. However, it is still structural in the sense of explicitly identifying the effects of both intended technical change and current input prices on input substitution.

use a difference-in-differences (DID) approach in which we allow marginal costs to vary across inputs, across states, and over time.

The time-difference equation can be written as follows:

$$(10) \quad \Delta_t \ln\left(\frac{x_{i1st}}{x_{i2st}}\right) = \beta_{i1}\Delta_t \ln\left(\frac{w_{i1st}}{w_{12st}}\right) + \beta_{i2}\Delta_t \ln\left(\frac{E_{t-k}(w_{i1st})}{E_{t-k}(w_{i2st})}\right) + \beta_{i3}\Delta_t \ln\left(\frac{c_{i1st}}{c_{i2st}}\right) + \Gamma_i^{'}\Delta_t Z_{ist} + \Delta_t \varepsilon_{ist}$$

where Δ_t is the time difference operator. If the marginal research cost ratio varies across states but is invariant over time, then $\Delta_t \ln\left(\frac{c_{i1st}}{c_{i2st}}\right) = \ln\left(\frac{c_{i1st}}{c_{i2st}}\frac{c_{i2s(t-1)}}{c_{i1s(t-1)}}\right) = \ln\left(\frac{c_{i1s}}{c_{i2s}}\frac{c_{i2s}}{c_{i1s}}\right) = 0$ and the equation would be estimable in its current form. However, since it is unknown whether the marginal research cost is invariant over time, we estimate the DID formulation:

$$(11) \quad \Delta_{t,s} \ln\left(\frac{x_{i1st}}{x_{12st}}\right) = \beta_{i1}\Delta_{t,s} \ln\left(\frac{w_{i1st}}{w_{i2st}}\right) + \beta_{i2}\Delta_{t,s} \ln\left(\frac{E_{t-k}(w_{i1st})}{E_{t-k}(w_{i2st})}\right) + \beta_{i3}\Delta_{t,s} \ln\left(\frac{c_{i1st}}{c_{i2st}}\right) + \Gamma_i^{'}\Delta_{t,s} Z_{ist} + \Delta_{t,s} \varepsilon_{ist}$$

where $\Delta_{t,s}$ is the time and state difference operator. Thus

$\Delta_{t,s} \ln\left(\frac{c_{i1st}}{c_{i2st}}\right) = \ln\left(\left(\frac{c_{i1st}}{c_{i2st}}\frac{c_{i2s(t-1)}}{c_{i1s(t-1)}}\right)\left(\frac{c_{i2\bar{s}t}}{c_{i1\bar{s}t}}\frac{c_{i1\bar{s}(t-1)}}{c_{i2\bar{s}(t-1)}}\right)\right)$, where $\bar{s} \neq s$ is a reference state. We must still impose an assumption about how relative marginal costs of research change across states over time. We maintain the sufficient condition that the change rate in relative marginal costs of research over time is equal across states. More restrictive assumptions such as state-invariant marginal research costs (as typically assumed) and/or time-invariance (as shown in equation (10)) are sufficient but not necessary for the equation to be identified. Importantly, identification under our sufficient condition does not require identical marginal research costs across inputs, and thus the equation is estimable with a non-neutral innovation function. Further, the assumption still allows for differences in marginal research costs across states and for changes in the innovation function over time so long as the pattern of change is common across states. Equation (11) is estimated using a two-way fixed effects (state and year) panel data estimator which is sufficient to surmount the omitted variables problem caused by the lack of marginal research cost data and make estimation of β_{i3} unnecessary.

We include two additional control variables – total public agricultural research expenditures for each state *s* and year *t-k* and total agricultural output for each state *s* and year *t*. These variables are included to control for potential size effects of total research expenditures in the innovation creation industry and of total agricultural output in the innovation implementation industry. Inclusion of these control variables renders homotheticity as a local property rather than a global constraint for both the production function and the innovation function.

Data and Variable Specification

The data used for our test of the IIH include annual agricultural input quantities and prices for four exhaustive input categories (land, non-land capital, labor, and intermediate inputs), as well as total agricultural output and total public research expenditures for agricultural productivity research for each of the 48 contiguous U.S. states for the years 1960-2004. The panel data set is balanced over the entire period. Summary statistics are presented in Table 1.

The agricultural input prices and quantities and total output are from the U.S. Department of Agriculture (USDA ERS 2015). For details regarding original data sources and construction of this state-level aggregated series, see Ball, Hallahan, and Nehring (2004) and Ball et al. (1999). Total annual public expenditures for agricultural productivity research by state are from Huffman (2012). They were compiled following the procedures outlined in Huffman (2015). Specifically, research expenditure data collected by the USDA in its Current Research Information System (CRIS) were used. CRIS includes funding from all sources for agricultural research undertaken by both federal research organizations (U.S. Department of Agriculture) and state public research entities (state agricultural experiment stations and veterinary colleges at land grant universities). Expenditures on post-harvest research and research on households, families, and communities were excluded from Huffman's series.

Expected Prices and Forecasting

In the theory of induced innovation, it is the expectation of future input prices that drives invention to economize "the use of a factor which has become relatively expensive" (Hicks 1932). Thus, for consistency with the IIH, expected future prices should be a key determinant in research resource allocation decisions. The challenge is to determine how future price expectations are formulated. Much of the empirical IIH testing literature has relied on adaptive expectation formulations (e.g., Peeters and Surry 2000, Popp 2002, Esposti and Pierani 2006, Crabb and Johnson 2010, Cowan, Lee, and Shumway 2015). Although they are easy to implement, adaptive expectations suffer from the conceptual drawback that they are backward-looking. As such, they embed systematic errors from previous forecasts (Hommes 1998). To overcome this conceptual problem of adaptive expectations, we use rational expectations in our base model to forecast future input prices.[8] Rational expectations theory postulates that economic agents use all relevant information so their forecasting is not prone to systematic errors.

To obtain forecasted future input prices that are consistent with rational expectations theory, we identified the autoregressive (AR) structure for each input price to ensure that the forecasted prices based on the AR model give zero expected errors. To identify the AR structure, we first used the Im-Pesaran-Shin (2003) test for nonstationarity of the panel price data. Test

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[8] We do use adaptive expectations for a robustness check.

results for the prices of each input category are presented in Table 2.[9] Two Augmented Dickey-Fuller test statistics are provided – with and without a time trend.[10] The null hypothesis of nonstationarity was not rejected for prices of three inputs (land, non-land capital, and intermediate inputs) by both tests. Labor was found to be stationary but only when a time trend was included. The null hypothesis of nonstationarity was rejected (at the 1% level) for the first differences of all inputs. Thus, we fit an AR model with level values for labor price and with first differenced prices for the other three inputs.

The AR structure for each input price was identified using both a panel fixed effects estimator and an Arellano-Bond estimator (Arellano and Bond 1991).[11] AR order q for each input price was selected based on satisfying the following two conditions: (a) the qth lagged autoregressive term was statistically significant at the 5 percent level and the (q+1)th lagged term was not significant, and (b) the residuals from AR(q) estimates followed a white noise process. The AR structure was identical and the estimated parameters were almost identical for both panel fixed effect and Arellano-Bond estimations. The identified AR orders were, respectively, AR(7), AR(3), and AR(2) for first-differenced land, capital, and intermediate prices and AR(2) for the level of labor price with a time trend. The results are presented in Table 3. With the estimated

[9] Several test procedures for nonstationarity with panel data have been introduced in the time series literature such as LLC (Levin, Lin, and Chu 2002), HT (Harris and Tzavalis 1999), Breitung (Breitung 2000, Breitung and Das 2005) and Hadri (Hadri 2000). We chose the IPS test due to the following advantages: (a) the test allows heterogeneous non-stationarity structures among cross-section units, and (b) they provide exact critical values that assume both cross-sectional units and the time series are fixed. The latter advantage is particularly important in our case considering our fixed cross-sections (states) and the limited time dimension of our dataset.

[10] Test statistics also depend on whether the lagged terms are included in the specification. When the lag structure is specified, the test procedure assumes that the number of time and cross-section units sequentially go to infinity. Thus, with only 45 years and 48 states in our data set, we do not consider specifications with lags.

[11] The panel fixed-effects estimator can be subject to an endogeneity problem in dynamic models since the within-estimator or first-difference estimator can be correlated with the error term. To overcome this problem, the Arellano-Bond estimator makes use of lagged dependent and independent variables as instruments. However, because our ultimate purpose is to forecast, endogeneity is not a major concern.

results, the *k*-step-ahead forecasts at the forecast origin *t-k* with AR(*q*) were used as the expected input prices.

Research Lag

The importance of expected price rather than current price in testing the IIH comes from the fact that there is a lag between research efforts by the innovation creating industry and use of new technology by the innovation implementing industry. In our theoretical model, we treat both activities as embodied within the same firm. In reality, they may be entirely separate entities. The theoretical model still applies as long as the innovation implementing firm can influence decisions by the innovation creating unit.

We test the IIH allowing for the technology in any year to be affected most by research conducted 5 years earlier.[12] We considered two options: (a) a single price expectation given information available at *t-k*, where $k = 5$, which implies that research conducted five years earlier is primarily responsible for changes in current technology, and (b) a weighted average of price expectations for $k = 2, \ldots, 5$, which implies that research conducted between two and five years earlier is primarily responsible for changes in current technology. For the latter, we used weights for the first five years of Wang et al. (2013)'s trapezoidal structure for private research stock.[13] Specifically, weights of 0.1, 0.2, 0.3, and 0.4 were assigned to the expectations made between two and five years earlier, respectively. Using a weighted average of price expectations amounts

[12] The length of the lag is highly volatile and is a subject of research itself. A strand of literature has focused on measuring the lag between research and its impact on productivity in U.S. agriculture (e.g., Chavas and Cox 1992, Huffman and Evenson 2006, Wang et al. 2013). Our choice of five years is generally shorter than their findings and is due to the short length of our data series.

[13] Wang et al. (2013)'s trapezoidal weight pattern has a length of 19 years for private research stock and 35 years for public research stock. Based on the assumed five-year research lag, we chose the weight structure for private research stock over public research stock so that the lag pattern can reflect influences concentrated in the short term.

to solving the cost minimization problem, equation (5), with the objective function

$$\sum_{h=2}^{5}\sum_{i}\sum_{j}\omega_h E_{t-h}(w_{ijst})\tilde{x}_{ijst}$$ where ω denotes the weights.

Test Results

The difference-in-differences estimation model, equation (11), was estimated using a two-way fixed-effects panel data estimator. The statistical estimates based on rational price expectations are presented in Table 4. Estimation results are reported from two model specifications in which only price expectation differed: the first used a single price expectation lagged five years and the second used a weighted average of expected prices lagged two to five years. Each column contains estimates for one input pair.

For comprehensive coverage, we tested for consistency with the IIH by considering all six exhaustive pairs of the four inputs, i.e., labor/land, capital/land, intermediate inputs/land, capital/labor, intermediate inputs/labor, and intermediate inputs/capital. Due to potential heteroskedasticity and autocorrelation, robust standard errors were obtained using a clustered sandwich estimator with the state as the unit of cluster. Time and state fixed effects were included in all equations, but these estimates are not reported in the table to conserve space. Although our data were strongly balanced across inputs, the number of observations included in each of the regressions varied across input ratios due to the different number of lags involved in the calculation of rational expectations of future price. For example, for the ratio of labor to land, the first 12 years of observations were dropped from the estimation because land price was identified as AR(7) and the model used 5-year-ahead price forecasts.[14]

[14] For each equation, the number of observations depends on the input in the ratio that has the longer AR structure.

Estimates of the effect of the current price ratio on the input quantity ratio, β_{i1}, is the negative of the estimated elasticity of substitution, ρ_i, and estimates of the effect of the expected future price ratio on the input quantity ratio correspond to β_{i2} in equation (11). For all 12 estimated equations in this table, the elasticity of substitution was estimated to be substantially less than 2.0 (0.03-0.54).[15] Thus, support for the IIH is provided by a statistically significant negative β_{i2}. Therefore, the indicators of significance in the table were based on one-sided tests for price ratios with the null hypothesis of the coefficient being equal to or greater than zero. A two-sided test applied to total agricultural output, total public research funds, and the constant.

Using a single price expectation based on the information set available five years earlier, five of the six pairings of inputs (83%) supported the IIH: labor/land, capital/land, intermediate inputs/land, intermediate inputs/labor, and intermediate inputs/capital. Using a weighted average of price expectations given the information set available two-five years earlier, three equations (50%) supported the IIH: capital/labor, intermediate inputs/labor, and intermediate inputs/capital. Apart from statistical significance, the estimated signs on the expected future price ratio as well as on the current price ratio are negative for all 12 equations, and thus the directional impact of technical change are found to be consistent with the IIH in all the estimated equations.

Effects of total agricultural output were estimated to have a significantly positive effect in 10 of the 12 equations and an insignificantly negative effect in the other two. Based on the results, we conclude that increases in total output lead to more intense use of non-land inputs (i.e., labor, capital and intermediate inputs) than land – see the first three columns – and to more

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[15] Because each estimated elasticity of substitution is less than one, they also imply that an increase in marginal cost of research to save one input will induce factor-saving behavior for the other input.

intense use of intermediate inputs (energy, fertilizer, etc.) than labor and capital – see the last two columns. These results imply that the agricultural production function is not globally homothetic.

Total public research funds were estimated to have a significantly positive effect in two equations and a significantly negative effect in two while the rest are statistically insignificant. They imply that increases in total research funds lead to behavior that saves labor and intermediate inputs relative to capital. Consequently, the evidence implies that the innovation function is also not globally homothetic. Total public research funds are not found to be significant in any of the equations where land is included as an input (see the first three columns). Thus, unlike de Janvry, Sadoulet, and Fafchamps (1991), we fail to find evidence that total public research expenditures bias technical change toward land-saving technology in U.S. agriculture.

Derived estimates for the research concavity parameter θ_i are also reported in Table 4. The larger the parameter θ_i is, the more concave is the innovation function that augments inputs x_{i1st} and x_{i2st}. Except for the intermediate inputs and capital ratio, all estimates are greater than 1.0, as required for a concave function. The estimated concavity parameter is highly sensitive both to input pair and to the information used to estimate price expectations, but none is statistically significantly different from one. The variance of the input quantity ratio explained by the estimated models ranged from 44 to 89 percent of total variance.

Robustness Checks

We consider several alternative model specifications to examine the robustness of initial model results. Specifically, we consider variations in our price expectations assumption and the type of estimator used. To make the results of these alternatives directly comparable to the initial model results, we employ both price expectation structures (five years ahead and a weighted average of two-five years ahead). Thus, for each alternative, 12 equations are estimated – six exhaustive ratios for each of the price expectation structures.

Adaptive and Naïve Price Expectations

Despite the theoretical advantages of the rational expectation hypothesis over alternatives, the rational expectations theory is subject to the criticism that it assumes that economic agents have more information about the true structure and probability distribution of the economy than they actually do (Sargent 1993, Evans and Honkapohja 2001). Therefore, we apply the adaptive expectations hypothesis and the naïve expectations hypothesis as two alternative specifications in our robustness analysis.

To create adaptive expectations, we first forecast prices *one* year ahead at time *t-k* using geometrically declining distributed lags on five years of realized prices:[16]

$$E_{t-k}(w_{is(t-k+1)}) = \varphi w_{is(t-k)} + \varphi(1-\varphi) w_{is(t-k-1)} + \varphi(1-\varphi)^2 w_{is(t-k-2)} + \cdots + \varphi(1-\varphi)^4 w_{is(t-k-4)}$$

where φ denotes the weight. The subsequent, 2-, 3-, and *k*-year ahead forecasts are sequentially updated as $E_{t-h}(w_{ist}) = \sum_{p=1}^{h-1} \varphi(1-\varphi)^{p-1} E_{t-h}(w_{is(t-p)}) + \sum_{p=h}^{5} \varphi(1-\varphi)^{p-1} w_{is(t-p))}$ for $h = 2,...,k$. We select the optimal weight φ based on the Akaike Information Criterion. To ensure that the cumulative weights are over 0.9 within the assumed research period, i.e., $\sum_{t=1}^{5} \varphi(1-\varphi)^{t-1} > 0.9$, we only consider φ =0.4, 0.5, 0.6, 0.7, 0.8, and 0.9. When $\varphi = 1$, the expectation of future price

[16] To examine the IIH in the U.S. energy sector, Popp (2002) employed up to 20 years of lagged prices and Crabb and Johnson (2010) used up to 24 months of lagged prices in their adaptive expectation formulation. Cowan, Lee, and Shumway (2015) used 10 years of lagged prices to test the hypothesis in U.S. agriculture. To keep more observations in the statistical estimation and to retain data consistency with the rational expectations formulation, we truncated the lagged prices that are assumed to affect formulation of expected price at 5 years.

is the realized lagged price, $E_{t-k}(w_{ist}) = w_{is(t-k)}$, which implies that investors expect the current price to persist. This is the naïve expectation. Forecasts of future prices from these two expectation hypotheses are presented using a single price expectation lagged five years and a weighted average of expected prices lagged two to five years.

Estimates based on adaptive and naïve expectations are reported in Tables 5 and 6, respectively. Coefficient estimates for variables other than current price ratio and expected price ratio are suppressed.[17] Except for the capital/land and intermediate inputs/land equations estimated with weighted naïve expectations, substitution elasticities are all found to be between zero and one (and nearly all significant at the 10% level) with both expectation hypotheses.[18] Compared to the test results with the rational expectation hypothesis, somewhat less support for the IIH was found with both the adaptive and naïve expectations.[19] For capital/labor, intermediate inputs/labor and intermediate inputs/capital equations, all four of these estimated equations were found to be supportive of the IIH.

Estimation as Systems of Equations

Based on the two-level CES production function, there are three alternative ways the pairs of input ratios could be combined: labor/land and intermediate inputs/capital, capital/land and

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[17] The number of observations included in the estimation with the naïve and adaptive expectation hypotheses differ from each other and from the number with the rational expectation hypothesis because the number of lags used in each expectation hypothesis differs and because the rational expectations are based on a unique number of autoregressive parameters for each input.

[18] In both exceptions, the elasticity of substitution is estimated to be negative. One is statistically significant at the 10 percent level while the other is not significant. Negative elasticities of substitution violate the convexity hypothesis, a necessary condition for cost-minimizing input choices.

[19] To see whether the different test results were driven by different data used in estimation, we also performed the tests using the same number of observations across models with the three expectations hypotheses. To do so, we restricted data included in estimation to be the largest intersection of data used in the original estimation based on each expectation hypothesis. As a result, 1,584 observations were used to estimate the labor/land, capital/land, and intermediate inputs/land equations, and 1,728 observations are used to estimate the capital/labor, intermediate inputs/labor, and intermediate inputs/capital equations with all price expectation specifications. Except for the capital/labor equation, test conclusions were not different from the results using all available data.

intermediate inputs/labor, and intermediate inputs/land and capital/labor. Because the error terms between pairs of equations could be correlated, we estimated the three systems of equations based on the rational expectations hypothesis using seemingly unrelated regressions (SUR). The results provided the same support for the IIH as previously (50 percent) when using the weighted average of price expectations and slightly lower support as previously (67 percent vs. 83 percent) when using a single price expectation lagged five years.

Overall, a moderate level of support for the IIH was found using the 1960-2004 U.S. agricultural state-level data. Twenty-seven of the 48 estimated equations tested (57 percent) provided support for the IIH. However, empirical evidence of consistency with the IIH was concentrated in three pairs: intermediate inputs/labor, intermediate inputs/capital, and capital/labor with 88 percent, 88 percent, and 75 percent support, respectively. All input ratios that included land provided much less consistency with the IIH with support ranging from 25 to 38 percent. The overall level of support for the IIH found here is slightly lower than the 59 percent support found by Cowan, Lee, and Shumway (2015) in their recent tests based on public research expenditures data. In both cases, the greatest support was found for intermediate inputs and least support for land and labor. Ours differed from theirs only in that relative support was reversed for labor and land. Thus, the emerging evidence of support for the IIH in this industry when innovation supply is accounted for is considerably greater than that found in several other studies that treated innovation supply as input neutral (e.g., Olmstead and Rhode 1993, Machado 1995, Liu and Shumway 2006, Liu and Shumway 2009). Our lower level of support for the IIH in land choices may be attributed to the relative fixity of this input. Land is often documented in the dynamic adjustment literature on the agricultural industry as a quasi-fixed input (e.g., Vasavada and Chambers 1986, Taylor and Kalaitzandonakes 1990). Quasi-fixity implies that high adjustment costs hinder immediate response to shocks such as prices and possibly new technology. In such a case, the adjustment rate toward the optimal input utilization would be sluggish.

It is also apparent that the price expectations mechanism matters in the IIH implications. We find more support (67 percent) for the IIH when input prices are assumed to be formulated via rational expectations than when they are based on adaptive or naïve expectations (50 percent).

Conclusions

We test whether the Hicks' induced innovation hypothesis (IIH) holds in U.S. agriculture for the period 1960-2004 using only state-level panel input price and quantity and total output data for the agricultural production sector and total public agricultural research expenditures. Considering a two-level CES production function and a homothetic innovation function, we derive the complete set of multi-stage optimization conditions that build a parametric connection between expected price ratios and factor augmentation, between factor augmentation and cost-minimizing input allocations, and thus between the expected price ratio and subsequent cost-minimizing input allocations.

Our analytical results show that when the elasticity of substitution between two inputs is less than one plus the magnitude of the innovation concavity parameter (which must be greater than one), a rise in the relative expected price of an input results in its relatively lower use. However, when the elasticity of substitution is greater than this magnitude, the IIH implies relatively greater use of the input that is expected to become more expensive. We document that the relationship between factor augmentation and expected relative price is not a monotonic function of the elasticity of substitution when the innovation function is accounted for. We also find that the relationship between factor-saving behavior and marginal research cost is not a monotonic function of the elasticity of substitution.

We apply a difference-in-differences estimation procedure which allows for a time-varying and non-neutral innovation function. We impose only one simplifying assumption – that the trend in the rate of change in marginal research cost is the same across states. This difference-in-differences formulation permits the cost-minimizing input ratio effects of unobserved differences in marginal research costs across states and over time to be controlled for, which could have otherwise caused omitted variables bias. Consequently, provided that the remaining simplifying assumption is valid, the test results reported in the paper constitute a valid test in the sense that potential biases emanating from non-neutral innovation supply are accounted for.

We implement our test using a rational expectations specification of future input prices at the time research resource allocation decisions are made. Homotheticity conditions on both innovation creating and innovation implementing industries are imposed only as local conditions. We then conduct several robustness checks, including alternative price expectations specifications and estimation as systems of equations.

The empirical results of this research indicate that the state-level U.S. agricultural data during the 1960-2004 period provide moderate (57 percent) overall support for the IIH and strong support with some inputs. We find more support (67 percent) for the IIH when input prices are assumed to be formulated via the rational expectations hypothesis than when they are based on adaptive or naïve expectations (50 percent). Considering all models estimated, empirical evidence of consistency with the IIH was concentrated in input decisions involving pairs of three inputs – capital, intermediate inputs, and labor. Considerably less support was found for input pairs involving land. The overall level of support for the IIH is similar to other recent tests for the IIH in this industry when innovation supply is accounted for. It is considerably greater than that found in several other studies that treated innovation supply as input neutral.

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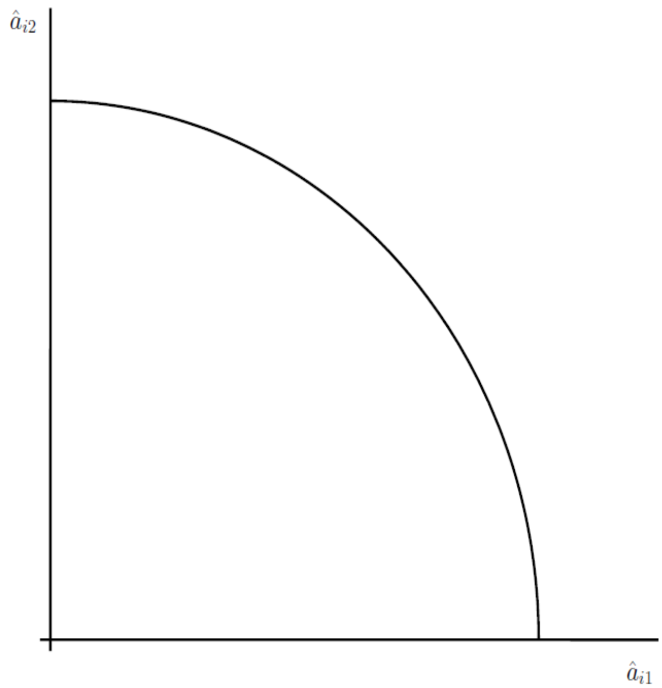
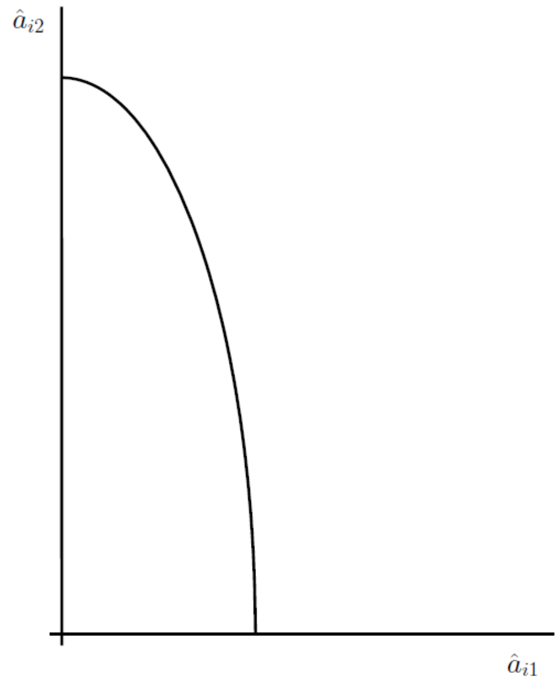
Figure 1. Neutral and Non-Neutral Innovation Function



(a) Neutral Innovation Function, $c_{i1} = c_{i2}$



(b) Non-Neutral Innovation Function, $c_{i1} > c_{i2}$

Table 1. Summary Statistics

Variable	Unit	Mean Value	Standard Deviation	Minimum Value	Maximum Value
Land price	Index [a]	0.606616	0.575	0.006	3.631
Labor price	Index [a]	0.439577	0.334	0.048	2.110
Capital price	Index [a]	0.638603	0.370	0.129	1.237
Intermediate inputs price	Index [a]	0.887015	0.382	0.224	2.022
Land quantity	Thousands of $ 1996 [b]	714,651	758,782	4,014	5,155,293
Labor quantity	Thousands of $ 1996 [b]	1,971,694	1,742,262	18,189	9,476,398
Capital quantity	Thousands of $ 1996 [b]	662,047	591,411	7,350	3,330,621
Intermediate inputs quantity	Thousands of $ 1996 [b]	1,761,636	1,636,347	12,918	9,454,613
Total agricultural output	Thousands of $ 1996 [b]	3,814,100	3,846,671	42,552	30,129,558
Total public research expenditure	Thousands of $ 1996	19,888	17,150	487	111,612

[a] Measured relative to a 1996 Alabama price of 1.00.
[b] Measured as the value of the input, in thousands of dollars, used for agricultural production in the state divided by the price index.

Table 2. Im-Pesaran-Shin Statistics for Nonstationarity[a]

Price series	Without time trend[b]	With time trend[c]
Level		
Land price	-0.7760	-1.4674
Labor price	0.0001	-2.6834***
Capital price	-0.4160	-1.2717
Intermediate inputs price	-0.5841	-1.9525
First-Differenced		
Land price	-3.6542***	-3.6165***
Labor price	-8.3984***	
Capital price	-3.7324***	-3.6815***
Intermediate inputs price	-5.3272***	-5.2745***

Notes: p-value of estimated parameters: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[a] The null hypothesis of IPS test is that each price series contains a unit root.

[b] Critical values of the statistics without time trend for 10%, 5% and 1% level of significance are -1.68, -1.73, and -1.81, respectively.

[c] Critical values of the statistics with time trend for 10%, 5% and 1% level of significance are -2.32, -2.36, and -2.44, respectively.

Table 3. Autoregressive Model Statistical Estimates

Lags	Land price		Labor price		Capital price		Intermediate inputs price	
	Arellano-Bond	Fixed effect	Arellano-Bond	Fixed effect	Arellano-Bond	Fixed effect	Arellano-Bond	Fixed effect
Lag1	0.683*** (0.024)	0.686*** (0.024)	0.581*** (0.023)	0.586*** (0.022)	0.620*** (0.021)	0.620*** (0.022)	0.217*** (0.022)	0.219*** (0.021)
Lag2	-0.387*** (0.028)	-0.386*** (0.028)	0.256*** (0.024)	0.256*** (0.024)	-0.342*** (0.024)	-0.342*** (0.025)	-0.279*** (0.022)	-0.277*** (0.021)
Lag3	0.257*** (0.028)	0.259*** (0.028)			0.253*** (0.022)	0.253*** (0.023)		
Lag4	0.003 (0.029)	0.004 (0.029)						
Lag5	-0.529*** (0.029)	-0.528*** (0.029)						
Lag6	0.357*** (0.030)	0.358*** (0.030)						
Lag7	-0.247*** (0.026)	-0.245*** (0.026)						
Time trend			0.005*** (0.000)	0.004*** (0.000)				
Constant	0.024*** (0.002)	0.023*** (0.002)	-0.021*** (0.005)	-0.020*** (0.005)	0.010*** (0.000)	0.010*** (0.000)	0.026*** (0.001)	0.026*** (0.001)

Notes: Standard errors are in parentheses; p-value of estimated parameters: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Statistical Estimates with Rational Expectation Price Forecasts[a]

Parameter	Labor /Land	Capital /Land	Intermediate inputs/Land	Capital /Labor	Intermediate inputs/Labor	Intermediate inputs/Capital
A single price expectation lagged five years						
Current price ($-\rho_i$)	-0.19787***	-0.04478	-0.08009**	-0.29171***	-0.35002***	-0.54031***
	(0.03419)	(0.03628)	(0.04247)	(0.03431)	(0.03573)	(0.08229)
Expected future price	-0.11118**	-0.13664***	-0.09704*	-0.15303*	-0.16168	-0.20492***
(H_i)	(0.06607)	(0.06682)	(0.06507)	(0.11034)	(0.13213)	(0.08504)
Total agricultural	0.36315***	0.19109***	0.82940***	-0.11165	0.50564***	0.62433***
output	(0.10030)	(0.05091)	(0.08701)	(0.09053)	(0.11606)	(0.06987)
Total public research	0.01343	0.06810	-0.00440	0.09368**	0.01005	-0.08779***
funds	(0.06747)	(0.04315)	(0.04068)	(0.04078)	(0.04598)	(0.02859)
Constant	-4.49910***	-2.76671***	-11.06790***	0.67070	-7.07749***	-7.65521***
	(1.44822)	(0.77475)	(1.32141)	(1.29626)	(1.72343)	(1.02867)
Research concavity	4.98499	5.72251	7.80056	2.56998	1.96304	0.57151
parameter (θ_i)[b]	(3.30485)	(3.12931)	(6.02332)	(2.33927)	(2.12083)	(0.40471)
R-square	0.43977	0.67243	0.66757	0.43559	0.75363	0.89067
Number of Obs.	1,584	1,584	1,584	1,776	1,824	1,776
A weighted average of price expectations lagged two-five years						
Current price ($-\rho_i$)	-0.19950***	-0.03171	-0.07112*	-0.28332***	-0.33322***	-0.53087***
	(0.03198)	(0.03322)	(0.04374)	(0.03289)	(0.03428)	(0.07833)
Expected future price	-0.01243	-0.05083	-0.03864	-0.08158**	-0.11449**	-0.18466***
(H_i)	(0.03947)	(0.04029)	(0.03809)	(0.04748)	(0.05232)	(0.07443)
Total agricultural	0.35015***	0.18702***	0.82752***	-0.10617	0.51089***	0.62681***
output	(0.10120)	(0.05132)	(0.08737)	(0.08916)	(0.11374)	(0.07005)
Total public research	0.01332	0.06898	-0.00392	0.09772**	0.01473	-0.08867***
funds	(0.06634)	(0.04291)	(0.04091)	(0.04082)	(0.04608)	(0.02872)
Constant	-4.22069***	-2.64218***	-11.07869***	0.54001	-7.17650***	-7.69130***
	(1.45744)	(0.75843)	(1.31140)	(1.27949)	(1.68790)	(1.03056)
Research concavity	50.75222	17.47722	21.40078	5.57935	3.21649	0.722698
parameter (θ_i)[b]	(163.13467)	(14.54639)	(22.56500)	(3.65881)	(1.75779)	(0.42064)
R-square	0.43655	0.66879	0.66621	0.43467	0.75404	0.89084
Number of Obs.	1,584	1,584	1,584	1,776	1,824	1,776

[a] Standard errors are in parentheses; p-value of estimated parameters: * p<0.1, ** p<0.05, *** p<0.01. The t-tests conducted for the coefficients on current and expected price ratios are one-tailed tests (with the null hypothesis that the coefficient is greater than or equal to zero). T-tests for coefficients on other regressors are two-tailed tests (null hypothesis that the coefficient is equal to zero). Time fixed effects and state fixed effects parameter estimates are suppressed.
[b] Standard errors of the research concavity parameter were obtained using the delta method.

Table 5. Statistical Estimates with Adaptive Expectation Price Forecasts[a]

Parameter	Labor /Land	Capital /Land	Intermediate inputs/Land	Capital /Labor	Intermediate inputs/Labor	Intermediate inputs/Capital
A single price expectation lagged five years						
Current price ($-\rho_i$)	-0.17727***	-0.05443*	-0.07624**	-0.28398***	-0.33933***	-0.52402***
	(0.03195)	(0.03895)	(0.04387)	(0.03168)	(0.03239)	(0.07305)
Expected future	-0.03764	0.02012	-0.01952	-0.06859*	-0.09735**	-0.24118**
price (H_i)	(0.03753)	(0.03565)	(0.03289)	(0.04244)	(0.04474)	(0.10721)
R-square	0.43397	0.64354	0.70179	0.40870	0.74274	0.89338
Number of Obs.	1,728	1,728	1,728	1,728	1,728	1,728
Opt. Coefficient δ[b]	0.4	0.4	0.9	0.4	0.4	0.5
A weighted average of price expectations lagged two-five years						
Current price ($-\rho_i$)	-0.17704***	-0.05458*	-0.07624**	-0.28378***	-0.33906***	-0.52380***
	(0.03197)	(0.03899)	(0.04387)	(0.03169)	(0.03241)	(0.07298)
Expected future	-0.03826	0.02052	-0.01952	-0.06957*	-0.09859**	-0.24170**
price (H_i)	(0.03760)	(0.03571)	(0.03289)	(0.04272)	(0.04496)	(0.10774)
R-square	0.43402	0.64355	0.70179	0.40878	0.74279	0.89338
Number of Obs.	1,728	1,728	1,728	1,728	1,728	1728
Opt. Coefficient δ[b]	0.4	0.4	0.9	0.4	0.4	0.5

[a] Notes: Standard errors are in parentheses; p-value of estimated parameters: * $p<0.1$, ** $p<0.05$, *** $p<0.01$. The t-tests conducted for the coefficients on current and expected price ratios are one-tailed tests (with the null hypothesis that the coefficient is greater than or equal to zero). T-tests for coefficients on other regressors are two-tailed tests (null hypothesis that the coefficient is equal to zero). Time fixed effects and state fixed effects are included in all models but are not reported. Other parameter estimates are suppressed.

[b] Optimal coefficient δ is selected based on Akaike Information Criterion.

Table 6. Statistical Estimates with Naïve Expectation Price Forecasts[a]

Parameter	Labor /Land	Capital /Land	Intermediate inputs/Land	Capital /Labor	Intermediate inputs/Labor	Intermediate inputs/Capital
A single price expectation lagged five years						
Current price ($-\rho_i$)	-0.18874***	-0.05651	-0.10740**	-0.28976***	-0.33850***	-0.55566***
	(0.03080)	(0.04510)	(0.04597)	(0.03568)	(0.03586)	(0.08844)
Expected future	-0.02365	-0.00420	-0.03493	-0.08041**	-0.08462**	-0.14099**
price (H_i)	(0.03105)	(0.03422)	(0.03368)	(0.03670)	(0.03584)	(0.07295)
R-square	0.45483	0.66254	0.76177	0.57516	0.77766	0.87950
Number of Obs.	1,920	1,920	1,920	1,920	1,920	1,920
A weighted average of price expectations lagged two-five years						
Current price ($-\rho_i$)	-0.23371***	0.14864†	0.01553	-0.22013***	-0.23512***	-0.20067***
	(0.04621)	(0.10810)	(0.09407)	(0.03704)	(0.03935)	(0.06859)
Expected future	0.03787	-0.21742**	-0.15301**	-0.12690**	-0.17325***	-0.52407***
price (H_i)	(0.06734)	(0.11015)	(0.08484)	(0.06264)	(0.06573)	(0.15029)
R-square	0.45443	0.66434	0.76199	0.57291	0.77722	0.88055
Number of Obs.	1,920	1,920	1,920	1,920	1,920	1,920

[a] Standard errors are in parentheses; p-value of estimated parameters: * p<0.1, ** p<0.05, *** p<0.01. The t-tests conducted for the coefficients on current and expected price ratios are one-tailed tests (with the null hypothesis that the coefficient is greater than or equal to zero). T-tests for coefficients on other regressors are two-tailed tests (null hypothesis that the coefficient is equal to zero). † p<0.1 is given to positive significant expected price ratios. The null hypothesis in this case is that the coefficient is less than or equal to zero. Time fixed effects and state fixed effects are included in all models but are not reported. Other parameter estimates are suppressed.

APPENDICES intended as links, not for publication

Appendix I.

We develop the multi-stage optimization conditions in this appendix. Subscripts for state are omitted to avoid notational clutter. A single output Y at time *t* is produced by the following two-level CES production function as in equation (1):

$$Y_t = \left[\delta X_{1t}^{\frac{\rho-1}{\rho}} + (1-\delta) X_{2t}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}},$$

where ρ is the elasticity of substitution between input indices and δ is a share parameter. The input indices X_{1t} and X_{2t} are produced respectively by pairs of inputs that also follow a CES form:

$$X_{it} = \left[\delta_i (a_{i1t} x_{i1t})^{\frac{\rho_i-1}{\rho_i}} + (1-\delta_i)(a_{i2t} x_{i2t})^{\frac{\rho_i-1}{\rho_i}} \right]^{\frac{\rho_i}{\rho_i-1}}, \; i \in \{1,2\}$$

as in equation (2), where x_{ij} is input *j* used in production of input index *i*, and *a* is a factor-augmenting parameter that captures technical progress.

A static cost minimization problem for period *t* can be stated as:

$$\min \sum_i \sum_j w_{ijt} x_{ijt} \quad \text{for } i, j \in \{1,2\}$$

$$s.t. \; \overline{Y}_t = \left[\delta X_{1t}^{\frac{\rho-1}{\rho}} + (1-\delta) X_{2t}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}}.$$

where w_{ij} is the price of input x_{ij}. This gives the Lagrangian:

$$L = \sum_i \sum_j w_{ijt} x_{ijt} + \lambda_Y \left(\overline{Y}_t - A_t^{\frac{\rho}{\rho-1}} \right)$$

where λ_Y is the Lagrangian multiplier. First order conditions for x_{11t} and x_{12t} are:

(A-1) $$\frac{\partial L}{x_{11t}} = w_{11t} - \lambda A_t^{\frac{1}{\rho-1}} \delta X_{1t}^{\frac{-1}{\rho}} A_{1t}^{\frac{1}{\rho_1-1}} \delta_1 \left(a_{11t}x_{11t}\right)^{\frac{-1}{\rho_1}} a_{11t} = 0\,,$$

(A-2) $$\frac{\partial L}{x_{12t}} = w_{12t} - \lambda A_t^{\frac{1}{\rho-1}} \delta X_{1t}^{\frac{-1}{\rho}} A_{1t}^{\frac{1}{\rho_1-1}} \left(1-\delta_1\right) \left(a_{12t}x_{12t}\right)^{\frac{-1}{\rho_1}} a_{12t} = 0$$

where $A_t = \left[\delta X_{1t}^{\frac{\rho-1}{\rho}} + (1-\delta) X_{2t}^{\frac{\rho-1}{\rho}}\right]$ and $A_{it} = \left[\delta_i (a_{i1t}x_{i1t})^{\frac{\rho_i-1}{\rho_i}} + (1-\delta_i)(a_{i2t}x_{i2t})^{\frac{\rho_i-1}{\rho_i}}\right]$. We only derive the static conditions for the input pair, x_{11t} and x_{12t}. The conditions for the other pair of inputs, x_{21t} and x_{22t}, can be obtained analogously. Dividing (A-1) by (A-2), we obtain:

(A-3) $$\frac{w_{11t}}{w_{12t}} = \frac{\delta_1}{1-\delta_1} \left(\frac{a_{11t}x_{11t}}{a_{12t}x_{12t}}\right)^{\frac{-1}{\rho_1}} \frac{a_{11t}}{a_{12t}}\,.$$

Solving for $\frac{x_{11t}}{x_{12t}}$, we obtain the condition for the optimal ratio of inputs:

(A-4) $$\frac{x_{11t}^*}{x_{12t}^*} = \left(\frac{\delta_1}{1-\delta_1}\right)^{\rho_1} \left(\frac{w_{11t}}{w_{12t}}\right)^{-\rho_1} \left(\frac{a_{11t}}{a_{12t}}\right)^{\rho_1-1}$$

which is equation (3).

Now, consider research and development opportunities. For a given research budget $\overline{R}$, the innovation function is given by equation (4):

$$R_{i(t-k)} = \left(c_{i1(t-k)}\hat{a}_{i1t}\right)^{\theta_i} + \left(c_{i2(t-k)}\hat{a}_{i2t}\right)^{\theta_i}$$

where $R_{i(t-k)}$ is expenditure on research in period *t-k* to augment the *i*th input index, the total research budget is assumed to be exogenously given and is fully expended, i.e.,

$\bar{R}_{t-k} \equiv R_{1(t-k)} + R_{2(t-k)}$, $\hat{a}_{ij}$ is the factor-augmentation parameter which is assumed to be nonregressive, i.e., $\hat{a}_{ijt} \geq \hat{a}_{ij\tau}$ if $t > \tau$; $c_{ij(t-k)} > 0$ denotes marginal research costs for technology that augments x_{ij} by 1 percent; and $\theta_i > 1$ is a concavity parameter.

In the multi-stage optimization problem, the cost minimization problem for the firm's research resource allocation in period *t-k* can be expressed, as in equation (5), by:

$$\min_{\tilde{x}_{ijt}, \hat{a}_{ijt}} \sum_i \sum_j E_{t-k}(w_{ijt})\tilde{x}_{ijt} \quad \text{for } i, j \in \{1,2\}$$

$$s.t.\ \bar{Y}_t = \left[\delta X_{1t}^{\frac{\rho-1}{\rho}} + (1-\delta) X_{2t}^{\frac{\rho-1}{\rho}} \right]^{\frac{\rho}{\rho-1}},$$

$$\bar{R}_{t-k} \equiv R_{1(t-k)} + R_{2(t-k)}$$

where $X_{it} = \left[\delta_i (\hat{a}_{i1t}\tilde{x}_{i1t})^{\frac{\rho_i-1}{\rho_i}} + (1-\delta_i)(\hat{a}_{i2t}\tilde{x}_{i2t})^{\frac{\rho_i-1}{\rho_i}} \right]^{\frac{\rho_i}{\rho_i-1}}$, $E_{t-k}(w_{ijt})$ denotes expectation for price of input x_{ijt} at *t* given information at *t-k,* and $\hat{a}_{ijt}$ is defined in the text. A tilde is given to input levels to denote that those values are "*conceived*" at time *t-k* and thus are distinguished from the values that are actually chosen by the firm at time *t*.

The Lagrangian is given by $L = \sum_i \sum_j E_{t-k}(w_{ijt})\tilde{x}_{ijt} + \lambda_Y \left(\bar{Y}_t - A_t^{\frac{\rho}{\rho-1}} \right) + \lambda_R \left(\bar{R}_t - R_{1t} - R_{2t} \right)$.

First order conditions for $\tilde{x}_{11t}$ and $\tilde{x}_{12t}$ are

(A-5) $$\frac{\partial L}{\partial \tilde{x}_{11t}} = E_{t-k}(w_{11t}) - \lambda_Y A_t^{\frac{1}{\rho-1}} \delta X_{1t}^{\frac{-1}{\rho}} A_{1t}^{\frac{1}{\rho_1-1}} \delta_1 \left(\hat{a}_{11t}\tilde{x}_{11t} \right)^{\frac{-1}{\rho_1}} \hat{a}_{11t} = 0$$

(A-6) $$\frac{\partial L}{\partial \tilde{x}_{12t}} = E_{t-k}(w_{12t}) - \lambda_Y A_t^{\frac{1}{\rho-1}} \delta X_{1t}^{\frac{-1}{\rho}} A_{1t}^{\frac{1}{\rho_1-1}} (1-\delta_1) \left(\hat{a}_{12t}\tilde{x}_{12t} \right)^{\frac{-1}{\rho_1}} \hat{a}_{12t} = 0$$

First order conditions for $\hat{a}_{11t}$ and $\hat{a}_{12t}$ are

(A-7) $$\frac{\partial L}{\partial \hat{a}_{11t}} = -\lambda_Y A_t^{\frac{1}{\rho-1}} \delta X_{1t}^{\frac{-1}{\rho}} A_{1t}^{\frac{1}{\rho_1-1}} \delta_1 \left(\hat{a}_{11t}\tilde{x}_{11t}\right)^{\frac{-1}{\rho_1}} \tilde{x}_{11t} - \lambda_R \theta_1 \left(c_{11(t-k)}\hat{a}_{11t}\right)^{\theta_1 - 1} c_{11(t-k)} = 0$$

(A-8) $$\frac{\partial L}{\partial \hat{a}_{12t}} = -\lambda_Y A_t^{\frac{1}{\rho-1}} \delta X_{1t}^{\frac{-1}{\rho}} A_{1t}^{\frac{1}{\rho_1-1}} (1-\delta_1) \left(\hat{a}_{12t}\tilde{x}_{12t}\right)^{\frac{-1}{\rho_1}} \tilde{x}_{12t} - \lambda_R \theta_1 \left(c_{12(t-k)}\hat{a}_{12t}\right)^{\theta_1 - 1} c_{12(t-k)} = 0$$

Dividing (A-5) by (A-6) yields

(A-9) $$\frac{E_{t-k}(w_{11t})}{E_{t-k}(w_{12t})} = \frac{\delta_1}{1-\delta_1}\left(\frac{\hat{a}_{11t}\tilde{x}_{11t}}{\hat{a}_{12t}\tilde{x}_{12t}}\right)^{\frac{-1}{\rho_1}}\left(\frac{\hat{a}_{11t}}{\hat{a}_{12t}}\right)$$

Dividing (A-7) by (A-8) yields

(A-10) $$\left(\frac{c_{11(t-k)}\hat{a}_{11t}}{c_{12(t-k)}\hat{a}_{12t}}\right)^{\theta_1-1} \frac{c_{11(t-k)}}{c_{12(t-k)}} = \frac{\delta_1}{1-\delta_1}\left(\frac{\hat{a}_{11t}\tilde{x}_{11t}}{\hat{a}_{12t}\tilde{x}_{12t}}\right)^{\frac{-1}{\rho_1}}\left(\frac{\tilde{x}_{11t}}{\tilde{x}_{12t}}\right)$$

Dividing (A-9) by (A-10) and solving for $\frac{\tilde{x}_{11t}}{\tilde{x}_{12t}}$, we obtain

(A-11) $$\frac{\tilde{x}_{11t}}{\tilde{x}_{12t}} = \left(\frac{E_{t-k}(w_{11t})}{E_{t-k}(w_{12t})}\right)^{-1}\left(\frac{c_{11(t-k)}\hat{a}_{11t}}{c_{12(t-k)}\hat{a}_{12t}}\right)^{\theta_1}$$

Substituting (A-11) into (A-9) and solving for $\frac{\hat{a}_{11t}}{\hat{a}_{12t}}$ we obtain

(A-12) $$\frac{\hat{a}^*_{11t}}{\hat{a}^*_{12t}} = \left(\frac{\delta_1}{1-\delta_1}\right)^{\frac{\rho_1}{1+\theta_1-\rho_1}}\left(\frac{E_{t-k}(w_{11t})}{E_{t-k}(w_{12t})}\right)^{\frac{1-\rho_1}{1+\theta_1-\rho_1}}\left(\frac{c_{11(t-k)}}{c_{12(t-k)}}\right)^{\frac{-\theta_1}{1+\theta_1-\rho_1}}$$

which is equation (6). Asterisks are given to the factor-augmenting parameter to denote that they are optimal values. Substituting (A-12) into (A-11) yields

(A-13) $$\frac{\tilde{x}^*_{11t}}{\tilde{x}^*_{12t}} = \left(\frac{\delta_1}{1-\delta_1}\right)^{\frac{\rho_1\theta_1}{1+\theta_1-\rho_1}}\left(\frac{E_{t-k}(w_{11t})}{E_{t-k}(w_{12t})}\right)^{\frac{\rho_1-\rho_1\theta_1-1}{1+\theta_1-\rho_1}}\left(\frac{c_{11(t-k)}}{c_{12(t-k)}}\right)^{\frac{(1-\rho_1)\theta_1}{1+\theta_1-\rho_1}}$$

which is equation (7). By substituting (A-12) into the optimal condition for period t (A-4) with $\hat{a}^*_{1jt}$ replacing a_{1jt}, and rearranging, we get

(A-14)
$$\frac{x^*_{11t}}{x^*_{12t}} = \left(\frac{\delta_1}{1-\delta_1}\right)^{\frac{\theta_1\rho_1}{1-\theta_1-\rho_1}} \left(\frac{w_{11t}}{w_{12t}}\right)^{-\rho_1} \left(\frac{E_{t-k}(w_{11t})}{E_{t-k}(w_{12t})}\right)^{\frac{-(1-\rho_1)^2}{1+\theta_1-\rho_1}} \left(\frac{c_{11(t-k)}}{c_{12(t-k)}}\right)^{\frac{(1-\rho_1)\theta_1}{1+\theta_1-\rho_1}}$$

which is equation (8). The condition for $\frac{x^*_{21t}}{x^*_{22t}}$ can be analogously found as (A-14):

(A-15)
$$\frac{x^*_{21t}}{x^*_{22t}} = \left(\frac{\delta_2}{1-\delta_2}\right)^{\frac{\theta_2\rho_2}{1-\theta_2-\rho_2}} \left(\frac{w_{21t}}{w_{22t}}\right)^{-\rho_2} \left(\frac{E_{t-k}(w_{21t})}{E_{t-k}(w_{22t})}\right)^{\frac{-(1-\rho_2)^2}{1+\theta_2-\rho_2}} \left(\frac{c_{21(t-k)}}{c_{22(t-k)}}\right)^{\frac{(1-\rho_2)\theta_2}{1+\theta_2-\rho_2}}.$$

Appendix II.

In this appendix, we demonstrate that the condition $\theta_i > 1$ ensures that $\frac{\partial \hat{a}_{i2}}{\partial \hat{a}_{i1}} < 0$ and $\frac{\partial^2 \hat{a}_{i2}}{\partial \hat{a}_{i1}^2} < 0$

on the innovation function, equation (4),

$$R_{i(t-k)} = \left(c_{i1(t-k)}\hat{a}_{i1t}\right)^{\theta_i} + \left(c_{i2(t-k)}\hat{a}_{i2t}\right)^{\theta_i},$$

for $c_{ij(t-k)} > 0$, $\hat{a}_{ij} > 0$, $j = \{1,2\}$. At a given research budget, differentiating both sides of the

innovation function with respect to $\hat{a}_{i1}$ yields

$$0 = \theta_i c_{i1(t-k)}^{\theta_i} \hat{a}_{i1}^{\theta_i - 1} + \theta_i c_{i2(t-k)}^{\theta_i} \hat{a}_{i2}^{\theta_i - 1} \frac{\partial \hat{a}_{i2}}{\partial \hat{a}_{i1}}.$$

Solving for $\frac{\partial \hat{a}_{i2}}{\partial \hat{a}_{i1}}$ yields

$$\frac{\partial \hat{a}_{i2}}{\partial \hat{a}_{i1}} = -\frac{c_{i1(t-k)}}{c_{i2(t-k)}} \left(\frac{c_{i1(t-k)}\hat{a}_{i1}}{c_{i2(t-k)}\hat{a}_{i2}}\right)^{\theta_i - 1} < 0.$$

Differentiating both sides of the innovation function’s first-derivative equation again with

respect to $\hat{a}_{i1}$ gives

$$0 = \theta_i(\theta_i - 1)c_{i1}^{\theta_i}\hat{a}_{i1}^{\theta_i - 2} + \theta_i(\theta_i - 1)c_{i2}^{\theta_i}\hat{a}_{i2}^{\theta_i - 2}\left(\frac{\partial \hat{a}_{i2}}{\partial \hat{a}_{i1}}\right)^2 + \theta_i c_{i2}^{\theta_i}\hat{a}_{i2}^{\theta_i - 1}\frac{\partial^2 \hat{a}_{i2}}{\partial \hat{a}_{i1}^2}.$$

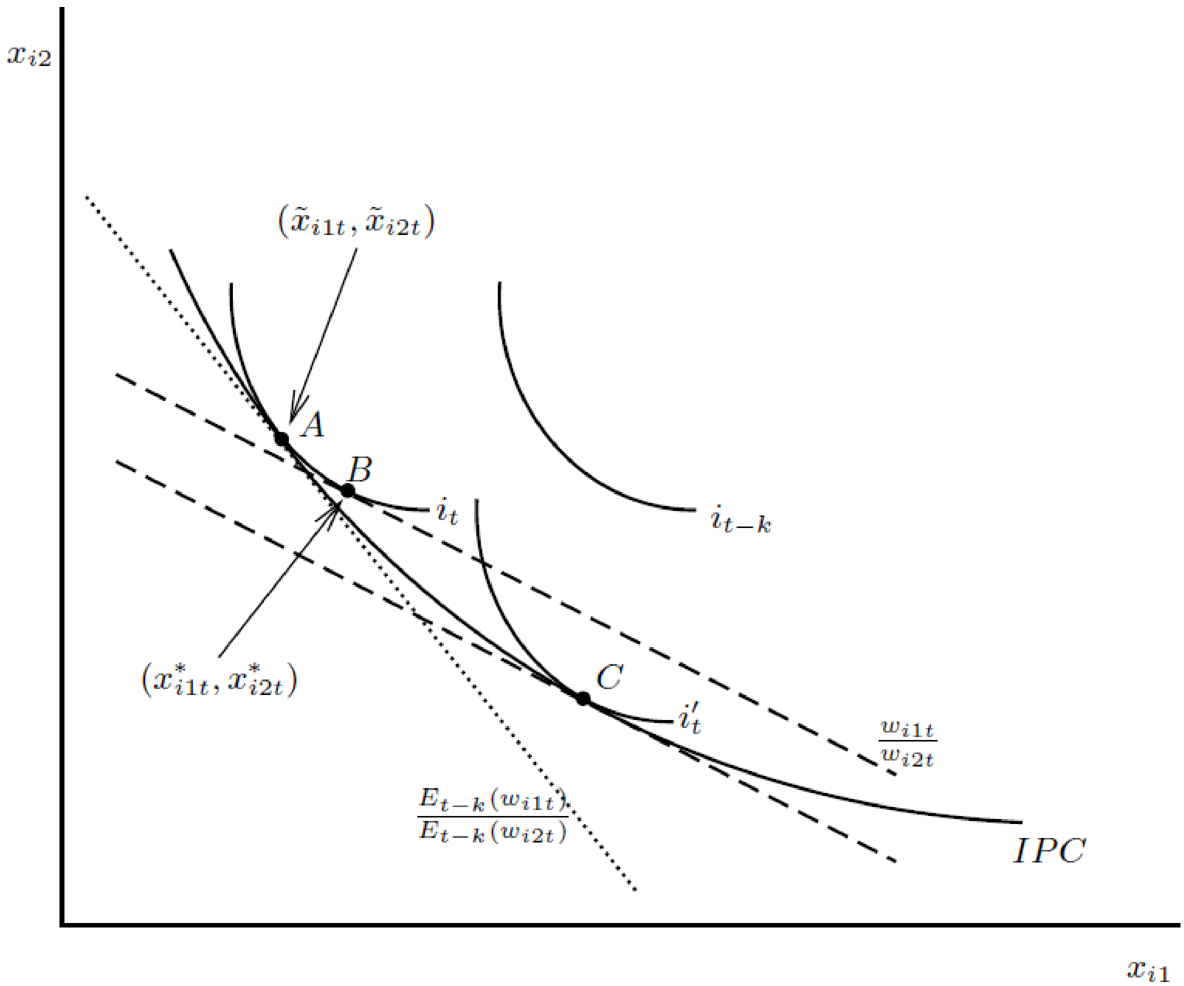
Solving for $\frac{\partial^2 \hat{a}_{i2}}{\partial \hat{a}_{i1}^2}$ yields

$$\frac{\partial^2 \hat{a}_{i2}}{\partial \hat{a}_{i1}^2} = -\frac{\theta_i(\theta_i - 1)c_{i1}^{\theta_i}\hat{a}_{i1}^{\theta_i - 2} + \theta_i(\theta_i - 1)c_{i2}^{\theta_i}\hat{a}_{i2}^{\theta_i - 2}\left(\frac{\partial \hat{a}_{i2}}{\partial \hat{a}_{i1}}\right)^2}{\theta_i c_{i2}^{\theta_i}\hat{a}_{i2}^{\theta_i - 1}} < 0.$$

Appendix III.

In Figure III.1, we describe a firm's optimization process when a gap between expected prices and realized prices exists. We make use of the Innovation Possibilities Curve (IPC) (Ahmad 1966). The state subscript is suppressed for simplicity. At time *t-k*, the firm contemplates R&D with existing production technology represented by the isoquant i_{t-k}. Given the research budget in time *t-k*, the envelope of all possible isoquants in time *t* is illustrated by the IPC. Based on the expected price ratio $\frac{E_{t-k}(w_{i1t})}{E_{t-k}(w_{i2t})}$, which is denoted by the dotted line, the optimizing pair of technical change and input coordinates is represented by the point *A*. The point corresponds to the research outcome generating isoquant i_t with conceived cost-minimizing input levels $\tilde{x}_{i1t}$ and $\tilde{x}_{i2t}$. Now let us assume that the ratio of input prices $\frac{w_{i1t}}{w_{i2t}}$ is realized at time *t* as denoted by the dashed lines and that they do not coincide with the expected relative price. Even though the firm is constrained by the isoquant i_t generated as a research outcome, it is not constrained to operate at a particular point on the isoquant. Given the actual price ratio, the conceived production plan $(\tilde{x}_{i1t}, \tilde{x}_{i2t})$ is no longer optimal, and instead, the optimizing input coordinates occur at point *B* $(\tilde{x}^*_{i1t}, \tilde{x}^*_{i2t})$ where the realized isoquant is tangent to the realized relative price. Had the firm had perfect foresight, the research plan contemplated and invested in would have been the technology represented by isoquant $i_t^{'}$ with optimizing input coordinates at point *C*, in which case no adjustment of input coordinates would have taken place from the conceived production plan.

Figure III.1. Optimization Process



Source: Adapted from Ahmad (1966)