Biotechnology Adoption Over Time In the Presence of Non-Pecuniary Characteristics that Directly Affect Utility: A Derived Demand Approach

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Generally, new production technologies are adopted because they will increase profits, mostly due to lower production costs *ceteris paribus*. In the case of the first-generation crop biotechnologies, however, additional factors play a role. These factors affect the utility functions of individual producers *directly*, as well as possibly affecting their utility functions *indirectly* through profits. This article considers the effect that embodied non-pecuniary factors have on the derived demand for a new, first-generation crop biotechnology over time. We show that the derived demand for the biotechnology will increase (shift out) at first and then begin to become more inelastic to price increases as adopters get accustomed to, and value more highly, the non-pecuniary benefits. We consider the convenience embodied in the Roundup Ready® soybean system as an example. Then, as empirical support for the transformation of the elasticity of derived demand, we examine Roundup Ready® soybean system costs and adoption over the period 1996-2007. The data suggest that, despite recent increases in the system costs of the technology, adoption continued to increase, signaling a relatively inelastic demand response.

Key words: biotechnology, non-pecuniary, derived demand, technology adoption, demand elasticity.

Introduction

Generally, when we think of new production technology, we think of a new product or technique that will increase profits, mostly due to lower production costs *ceteris paribus*. In the case of the first-generation crop biotechnologies (the so-called "agronomic" traits), however, additional factors are in play which are, at least in part, non-pecuniary in nature. Consider the convenience factor, for example. Adopters have long touted the convenience provided by biotech crops. Studies have found that producers place a value on the additional convenience afforded by some of the first generation biotech crops above and beyond the time savings. These studies are summarized in Marra and Piggott (2006). For example, consider the convenience aspects of Roundup Ready® soybeans. Adoption of this biotech technology allows over-the-top herbicide applications that consist of using a spray boom that can spray up to 20 rows at a time, and at a much higher ground speed, when compared to a post-directed application, which is the only post-emergence option for conventional soybeans. Spraying over the top as opposed to a post-directed application is less costly, simpler, and reduces the worry of applying the herbicide within a narrow window of time. The post emergence, over-the-top spray is more convenient than any other weed control option in the soybean production system. The value of the producer's

time saved is part of the story and enters his utility function through increases in profits. However, features such as having a simpler system to operate and less worry about timing and precision of pesticide treatments are components of convenience that affect the producer's utility function directly.

An Everyday Illustration

To illustrate what we mean by the effect of components of convenience that enter one's utility function directly, consider the mobile phone. The proliferation of mobile phones in the past few years and the convenience this technology bestows on users is unquestionable. The consumption of mobile minutes continues to increase today because of the utility that a consumer derives from the freedom of being able to place a call using this technology from almost anywhere, compared with placing the call using non-mobile technology that has a limited geography (less convenient) but is often substantially cheaper. Furthermore, consumers have become so accustomed to having access to the world on their mobile phones that it is commonplace to keep these phones on or near one's person at all times. For seasoned mobile phone users, ask yourself the following question: How responsive would your demand for an additional mobile minute (or set of mobile minutes) be *now* if the cost increased compared to how you would

respond when you were considering adopting this technology (acquiring your first phone)? For most mobile phone consumers we expect the answer to be that their demand response has become more inelastic to price increases.

Purpose of the Article

This article shows the effects non-pecuniary factors embodied in new technologies have on the derived demand for these technologies *over time*. Our hypothesis is that, with the embodied non-pecuniary factors, such as increased convenience, in play, the derived demand for these technologies will increase (shift out) at first and then begin to become more inelastic to price increases as adopters get "used to" and value the additional convenience more highly. The specific argument we develop in the remainder of the article is that, as adopters get accustomed to the convenience a biotech technology affords them, their demand responsiveness to price *increases* becomes more inelastic, leading to a kinked derived demand curve for this technology. A key insight into the ideas developed in this article is to view the biotech technology as a factor of production, with the conventional technology being the alternate factor, and the demand for an additional acre of the biotech technology as a derived demand. The remainder of the article is organized as follows. After a brief review of previous research, we present a theoretical model with some comparative statics, followed by a graphical representation of technology adoption in this setting. Empirical support for the theoretical results is presented, and then the conclusion follows.

Background

Several approaches have been taken to analyze agricultural technology adoption. The first was the seminal work of Griliches (1957) in which he modeled the technology diffusion curve (adoption path) of hybrid corn as a function of economic variables, such as the factors affecting the innovation's profitability. He found that as such factors differ across space and time, the slope and ceiling of the adoption path will differ as well. His modeling approach was to fit a logistic curve to the adoption data for hybrid corn over time, making the slope and the adoption ceiling functions of the economic variables. Others have modeled the probability that an individual decision-maker will adopt the new technology using a random utility framework (sometimes directly and sometimes implied), which results in the probability of adoption as a function of economic variables, including

farm and producer characteristics (Bosch, Cook & Fuglie, 1995; Rahm & Huffman, 1984; Shapiro, Brorsen, & Doster, 1992). These studies used cross-sectional survey data. Still others focused on the timing of adoption in a temporal framework (Feder & Slade, 1984; Lindner, Pardey, & Jarrett, 1982; McWilliams, Tsur, Hochman, & Zilberman, 1998; O'Mara, 1971). The goal of these studies was to determine why some producers are early adopters and some are laggards.

Another line of research has focused on the role of information and learning in technology adoption. These studies followed Griliches' approach of modeling a logistic diffusion curve as a function of the variables of interest (e.g., Lindner & Pardey, 1979; Warner, 1974) or as the probability that an individual will adopt (Fischer, Arnold, & Gibbs, 1996; Goodwin & Kastens, 1996; Marra, Hubbell, & Carlson, 2001). Substantial literature also exists that examines the role of risk in the adoption of a new technology (e.g., Foster & Rosenzweig, 1995; Goodwin & Kastens, 1996; Just & Zilberman, 1983; Shapiro et al., 1992). These studies modeled the decision to adopt in an expected utility framework, assuming output price, output revenue, or input price is uncertain. The role of characteristics of the innovation that can affect utility directly has been examined in only a few studies (see Batz, Peters, & Janssen, 1999, for an example and a review of this literature). These studies have taken the probability-of-adoption approach to analyze the effect of such non-pecuniary characteristics as the relative flexibility or the risk characteristics of the innovation. The Batz et al. article also uses cross-sectional data collected in two time periods, introducing some of the dynamic aspects of the adoption decision.

This article is an extension of the technology adoption literature in that we consider in a derived demand framework the characteristics of the innovation as factors in the decision-maker's adoption decision, while also incorporating the role of learning and developing skills with the innovation into the adoption model. We derive theoretical results in this framework and examine specifically the role of the non-pecuniary characteristics of the innovation. We then consider changes in the derived demand for the biotech technology over time. Specifically, we examine how the price elasticity of demand transforms over time in the presence of an embodied non-pecuniary characteristic of a new technology.

A Model of Biotech Technology Adoption Over Time, Accounting for Characteristics that Directly Affect Utility

This section presents the theoretical results derived from our modeling framework. In order to develop a model of biotech technology adoption over time and derive the results in this section, we rely on the following assumptions:

1. Producers are utility maximizers whose optimization problem involves a sequence of independent static optimization problems. Thus the decision of how many acres are allocated to each technology in any given period is dependent only on the circumstances and economic conditions of that period. At any time, a producer can disadopt the technology or a non-adopter can adopt. That is, there is no systematic link between past, present, and future decisions regarding consumption or adoption levels.

2. Perfect competition exists in the factor markets.

3. Both technologies, conventional and biotech, are scale-neutral. This assumption holds for both technologies when the decision is to plant one more acre using either technology, and holds globally for the biotech technology. All other variable inputs (types and levels) are predetermined, once the choice of total acres (A_t) is allocated to each technology (A_t^B for a biotech acre and A_t^C for a conventional acre; $A_t^B + A_t^B = A_t$) is made. That is, a producer chooses a production "system" with each acre allocated to one of the two technologies in a given period t. Thus, the cost of allocating an additional acre (A_t^B or A_t^C) out of the total acres to be planted to the crop, A_t, to either technology is constant at a particular point in time t and equal to r_t^B for the biotech technology and to r_t^C for the conventional technology.

4. The biotech technology has an additional non-pecuniary characteristic (e.g., convenience), q, associated with its adoption that enters the producer's utility function directly and not through profits (i.e., $q = q(A_t^B, t)$, while the conventional technology does not. Because q is associated with each acre of the biotech technology (A_t^B), as adoption increases, higher levels of q are achieved (i.e., $\frac{\partial q}{\partial A_t^B} > 0$). The utility value of each unit of q is also increasing over time (i.e., $\frac{\partial q}{\partial t} \geq 0$). The utility function exhibits positive marginal utility with respect to q (i.e., $U_q = \frac{\partial U}{\partial q} > 0$). The marginal utility of the consumption good (U_{x_t}) with respect to q is zero (i.e., $U_{x_t} = \frac{\partial U_x}{\partial q} = 0$) because q is a non-pecuniary component of utility and so, therefore, does not affect consumption. The marginal utility of the consumption good (U_{x_t}) is assumed to be diminishing (i.e., $U_{x_t x_t} = \frac{\partial U_x}{\partial x_t} < 0$) and this diminishing marginal utility is constant with respect to time (i.e., $\frac{\partial U_{x_t x_t}}{\partial t} = 0$).

5. We assume that the adoption costs (r_t^B) per unit of output associated with the biotech technology declines at first due to endogenous factors, such as increasing skill levels with the technology through learning. This decline continues for a few seasons (say, up to t^r) and then these costs may increase due to exogenous factors such as input price increases or the advent of some loss of productivity due to some other external factor. These assumptions can be captured by imposing a structure on r_t^B over time of $r_t^B = r_t^B (r_0^B, t)$, where r_0^B is the initial adoption cost at time period t^0, $\frac{\partial r_t^B}{\partial t} < 0$ for $t < t^r$, and $\frac{\partial r_t^B}{\partial t} > 0$ for $t > t^r$.

6. For clarity of exposition and without loss of generality, we further assume producers are risk-neutral and that their discount rate is zero.

Under these assumptions, the producer's utility maximization problem for each period, t, can be written as:

$$\max_{x_t, A_t^B} \ U_t\left(x_t, \ q\left(A_t^B, t\right)\right)$$

$$st$$

$$p_t^x x_t = p_t^y f\left(A_t^B, \ A_t^c\right) - r_t^B (r_0^B, t) A_t^B - r_t^C A_t^C$$

$$A_t^B + A_t^C = A_t \tag{1}$$

where $U_t(\ )$ is a producer's utility function defined over consumption of market goods (x_t) and the non-pecuniary characteristic affecting utility directly that is associated with an acre of biotechnology and period of time $q(A_t^B, t)$ for time period t. The utility function is subject to a budget constraint whereby the amount spent on market goods ($p_t^x x_t$) is equal to the profit from the total acres available (A_t) in any given period t. Profit is equal to the value of production $p_t^y f\left(A_t^B, A_t^C\right)$, where p_t^y is the market price of the output produced according to the production function $f(A_t^B, A_t^C)$, less the cost associated with choice of acres $r_t^B (r_0^B, t) A_t^B + r_t^C A_t^C$. The optimization problem can be restated more simply by forming the following Lagrangean equation:

$$\max_{x_t, \ A_t^B} \ \Im = U_t\left(x_t, \ q\left(A_t^B, t\right)\right)$$

$$+ \lambda_t [\, p_t^y f(A_t^B, A_t) - \ r_t^B (r_0^B, t)\, A_t^B$$

$$- r_t^C [A_t - A_t^B] - p_t^x x_t]. \tag{2}$$

The first-order necessary conditions (FONC) for this maximization problem can be written as

$$\frac{\partial \Im}{\partial x_t} = U_{x_t} - \lambda_t p_t^x = 0 \tag{3a}$$

$$\frac{\partial \Im}{\partial A_t^B} = U_q q_{A_t^B} + \lambda_t \left[p_t^y f_{A_t^B} - r_t^B (r_0^B, t) + r_t^C \right] = 0 \tag{3b}$$

$$\frac{\partial \Im}{\partial \lambda_t} = p_t^y f\left(A_t^B, A_t\right) - r_t^B (r_0^B, t) A_t^B$$

$$- r_t^C \left[A_t - A_t^B \right] - p_t^x x_t = 0. \tag{3c}$$

The sufficient second-order conditions for a constrained maximum is that the bordered Hessian determinant of the second partials of $\Im$ be positive, which can be written as

$$0 < D = \begin{vmatrix} \Im_{x_t x_t} & \Im_{x_t A_t^B} & \Im_{x_t \lambda_t} \\ \Im_{A_t^B x_t} & \Im_{A_t^B A_t^B} & \Im_{A_t^B \lambda_t} \\ \Im_{\lambda_t x_t} & \Im_{\lambda_t A_t^B} & \Im_{\lambda_t \lambda_t} \end{vmatrix}$$

$$= \begin{vmatrix} U_{x_t x_t} & 0 & -p_t^x \\ 0 & U_{A_t^B A_t^B} + \lambda_t p_t^y f_{A_t^B A_t^B} & p_t^y f_{A_t^B} - r_t^B (r_0^B, t) + r_t^C \\ -p_t^x & p_t^y f_{A_t^B} - r_t^B (r_0^B, t) + r_t^C & 0 \end{vmatrix}. \tag{4}$$

Condition 3a is the standard result, which shows that the optimal level of x_t is chosen where the marginal benefits $\left(U_{x_t}\right)$ equals the marginal cost $\left(\lambda_t p_t^x\right)$ of an additional unit of x_t. The same is true for the optimal level of A_t^B in Condition 3b but it takes some rearranging to make this transparent. Rearranging Condition 3b we can write

$$U_q q_{A_t^B} + \lambda_t p_t^y f_{A_t^B} = \lambda_t \left[r_t^B (r_0^B, t) - r_t^C \right], \tag{5}$$

where the left-hand side (LHS) of Equation 5 represents the marginal benefit and the right-hand side (RHS) of Equation 5 represents the marginal cost of adopting one more acre of the biotech technology (A_t^B). Noteworthy of the LHS is that it is comprised of two components: (1) a *direct utility component*, the marginal utility from an additional acre of biotech technology through the non-pecuniary factor, $q\left(U_q q_{A_t^B}\right)$; and (2) an *indirect utility component*, the value of the marginal product of an additional acre of the biotechnology $\left(p_t^y f_{A_t^B}\right)$ which, when multiplied by the marginal utility of an additional dollar (λ_t), converts this component measured in dollars to utils. Therefore, we also have the standard result for the optimal level of A_t^B that the marginal benefits must equal the marginal costs of an additional unit of A_t^B.

We are interested in solving for the demand functions for market goods (x_t) and an acre of biotechnology (A_t^B) implied by the system of Equation 3. These three equations contain the terms x_t, A_t^B, λ_t, p_t^y, A_t, r_0^B, r_t^C, p_t^x, t. Under the terms of the implicit function theorem, this system can be solved for the variables x_t, A_t^B, and λ_t in terms of the remaining terms p_t^y, A_t, r_0^B, r_t^C, p_t^x, and t. The simultaneous solution of the FONC in Equation 3 reveals the following results:

$$x_t = x_t \ (p_t^y, A_t, r_0^B, r_t^C, p_t^x, t) \tag{6a}$$

$$A_t^B = A_t^B \ (p_t^y, A_t, r_0^B, r_t^C, p_t^x, t) \tag{6b}$$

$$\lambda_t = \lambda_t (p_t^y, A_t, r_0^B, r_t^C, p_t^x, t). \tag{6c}$$

Equations 6a, 6b, and 6c indicate the chosen levels of market goods (x_t) and acres of biotechnology (A_t^B) for any given level of prices (p_t^y, r_0^B, r_t^C, p_t^x) and the amount of total acreage available (A_t) at a given period of time (t).

The Maximum Utility Function Over Time

Given that the focus of the article pertains to the impact of learning and the non-pecuniary factor *over time*, it is of interest to understand how the *maximum* value of utility is affected by time t. If the optimal solutions for the choice variables are substituted into $U_t (x_t, q(A_t^B, t))$ we obtain the following *maximum* utility function defined over the exogenous parameters of the problem p_t^y, A_t, r_0^B, r_t^C, p_t^x, t as

$$U^* \left(p_t^y, A_t, r_0^B, r_t^C, p_t^x, t \right)$$

$$= U \left(x_t \left(p_t^y, A_t, r_0^B, r_t^C, p_t^x, t \right), q \left(A_t^B \left(p_t^y, A_t, r_0^B, r_t^C, p_t^x, t \right), t \right) \right)$$

$$= U \left(x_t (\alpha), q \left(A_t^B (\alpha), t \right) \right), \tag{7}$$

where $\alpha = (p_t^y, A_t, r_0^B, r_t^C, p_t^x, t)$. The function $U^*(\alpha)$ gives the *maximum* value of utility for any given level of prices (p_t^y, r_0^B, r_t^C, p_t^x) and amount of total acreage

available (A_t) at a given period of time (t), because it is precisely the optimal levels of x_t and A_t^B that maximize utility subject to the two constraints spelled out in Equation 1. Using the envelope theorem (Silberberg, 1990), we can derive the following condition:

$$\frac{\partial U^*(\alpha)}{\partial t} = \frac{\partial \Im}{\partial t} = U_q(\alpha) \frac{\partial q}{\partial t} - \lambda_t(\alpha) \frac{\partial r_t^B}{\partial t} A_t^B(\alpha). \tag{8}$$

From Equation 8 and using Assumption #4, we can denote the following refutable hypothesis concerning the sign of the *maximum* value of utility function for any given level of prices (p_t^y, r_0^B, r_t^C, p_t^x) and amount of total acreage available (A_t) over time as

For $t < t^r$:

$$\frac{\partial U^*(\alpha)}{\partial t} = U_q(\alpha) \frac{\partial q}{\partial t} - \lambda_t(\alpha) \frac{\partial r_t^B}{\partial t} A_t^B(\alpha) > 0. \tag{9a}$$

For $t > t^r$:

$$\frac{\partial U^*(\alpha)}{\partial t} = U_q(\alpha) \frac{\partial q}{\partial t} - \lambda_t(\alpha) \frac{\partial r_t^B}{\partial t} A_t^B(\alpha) > 0$$

$$\text{if } U_q \frac{\partial q}{\partial t} > \lambda_t \frac{\partial r_t^B}{\partial t} A_t^B. \tag{9b}$$

For $t = t^* > t^r$:

$$\frac{\partial U^*(\alpha)}{\partial t} = U_q(\alpha) \frac{\partial q}{\partial t} - \lambda_t(\alpha) \frac{\partial r_t^B}{\partial t} A_t^B(\alpha) = 0$$

$$\text{if } U_q \frac{\partial q}{\partial t} = \lambda_t \frac{\partial r_t^B}{\partial t} A_t^B. \tag{9c}$$

For $t > t^*$:

$$\frac{\partial U^*(\alpha)}{\partial t} = U_q(\alpha) \frac{\partial q}{\partial t} - \lambda_t(\alpha) \frac{\partial r_t^B}{\partial t} A_t^B(\alpha) < 0. \tag{9d}$$
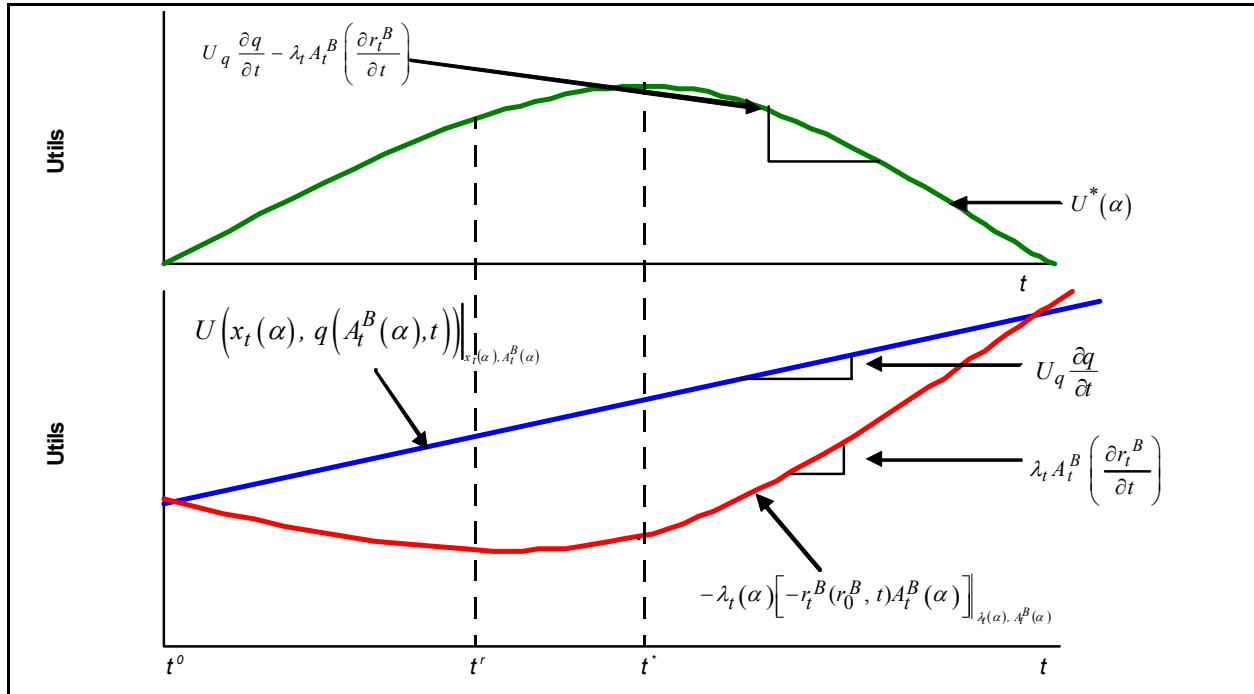
Figure 1. The maximum value of utility over time.

Equation 9a states that during the interim $t < t^r$ when adoption costs (r_t^B) per unit of output associated with the biotech technology decline (i.e., $\frac{\partial r_t^B}{\partial t} < 0$) due to endogenous factors, such as increasing skill levels with the technology through learning or through system cost decreases, the maximum value of the utility function is increasing with respect to time. Equation 9b states that during the interim $t > t^r$ when adoption costs (r_t^B) per unit of output associated with the biotech technology begins to increase (i.e., $\frac{\partial r_t^B}{\partial t} > 0$), due to exogenous factors such as system cost increases or the advent of some loss of productivity due to the development of pest resistance, the maximum value of the utility function is still increasing with respect to time during subsequent periods as long as the marginal benefit of the non-pecuniary characteristic $U_q \frac{\partial q}{\partial t}$ more than offsets (exceeds) the marginal cost associated with the additional cost of the biotechnology $\frac{\partial r_t^B}{\partial t} A_t^B$. When this is multiplied by the marginal utility of an additional dollar (λ_t), this additional cost measured in dollars converts to utils (i.e.,

$U_q \frac{\partial q}{\partial t} > \lambda_t \frac{\partial r_t^B}{\partial t} A_t^B$). Equation 9c states that during the interim $t > t^r$, at some time period $t = t^*$, the rate of change of the maximum value of utility function will become zero when the marginal cost in utils associated with the additional cost of the biotechnology $\lambda_t \frac{\partial r_t^B}{\partial t} A_t^B$ equals the marginal benefit in utils of the non-pecuniary characteristic $U_q \frac{\partial q}{\partial t}$. Equation 9d states that when $t > t^*$, the marginal benefit is less than the marginal cost, meaning $U^*(\alpha)$ is decreasing with respect to time. Figure 1 provides an illustration of the relationships shown in Equation 9.

The Price Elasticity for the Derived Demand for Biotechnology Over Time

The focus of this article is to understand how the derived demand function for the biotech technology is affected by changes in the cost of this system in the presence of learning and non-pecuniary factors at play. In particular, we are interested in whether there are any refutable hypotheses with respect to the elasticity of derived demand and how it changes over time. To do so, we first must investigate whether there are any refutable
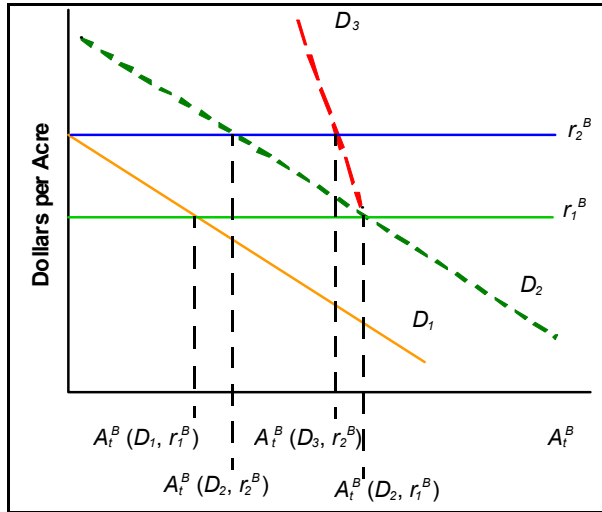
Figure 2. Changes in the demand for the biotech technology (A_t^B) as adoption increases.

hypotheses with respect to $\dfrac{\partial A_t^B(\alpha)}{\partial r_t^B}$, since the elasticity

of derived demand is equal to $\eta_{A_t^B r_t^B} = \dfrac{\partial A_t^B(\alpha)}{\partial r_t^B} \dfrac{r_t^B}{A_t^B(\alpha)}$. Inspection of Lagrangean

function in Equation 2 reveals that r_t^B only enters the first constraint, meaning no refutable hypotheses are implied by the maximization hypothesis alone (Silberberg, 1990). This fact is reinforced by deriving this comparative static result (see the Appendix for details) which can be shown to be equal to

$$\frac{\partial A_t^B(\alpha)}{\partial r_t^B} = \frac{U_{x_t x_t}\left[-\left(p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C\right)A_t^B\right] - p_t^x \lambda_t p_t^x}{D}. \tag{10}$$

Assuming diminishing marginal utility of consumption goods ($U_{xx} < 0$) (see Assumption #4) the demand function for the biotech technology is, indeed, down-

ward sloping (i.e., $\dfrac{\partial A_t^B}{\partial r_t^B} < 0$). Using this result we can

write the following expression for the elasticity of demand for the biotech technology:

$$0 > \eta_{A_t^B r_t^B}(\alpha) = \frac{\partial A_t^B(\alpha)}{\partial r_t^B} \frac{r_t^B}{A_t^B(\alpha)}$$

$$= \frac{\left[U_{x_t x_t}\left[-\left(p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C\right)A_t^B\right] - p_t^x \lambda_t p_t^x\right]}{D} \frac{r_t^B}{A_t^B(\alpha)}. \tag{11}$$

Differentiating Equation 11 with respect to t reveals the following result (see the Appendix for details):

see footnote below for equation 12[1] (12)

where $z(\alpha) = \left(p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C\right)A_t^B < 0$.

Using Equation 12 we can further establish (see the Appendix for details) the following conditional refut-

able hypothesis concerning $\left|\dfrac{\partial \eta_{A_t^B r_t^B}(\alpha)}{\partial t}\right|$ of

$$\left|\frac{\partial \eta_{A_t^B r_t^B}(\alpha)}{\partial t}\right| < 0 \text{ for } t > t^r. \tag{13}$$

The result in Equation 13 states that for the interim $t > t^r$, which occurs when adoption costs increase (i.e.,

$\dfrac{\partial r_t^B}{\partial t} > 0$ for $t > t^r$), the elasticity of derived demand

becomes more *inelastic* to price increases. This results in a kinked derived demand curve after t^r.

A Graphical Representation

Figure 2 illustrates the results derived in the foregoing section as they relate to the derived demand for acres of

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1. Equation 12:

$$\left|\frac{\partial \eta_{A_t^B r_t^B}(\alpha)}{\partial t}\right| = \frac{\left[r_t^B U_{x_t x_t} \frac{\partial z}{\partial t} + \left(U_{x_t x_t} z(\alpha) + \left(p_t^x\right)^2 \lambda_t\right)\frac{\partial r_t^B}{\partial t}\right]\left(-D A_t^B(\alpha)\right) - \left(U_{x_t x_t} z(\alpha) + \left(p_t^x\right)^2 \lambda_t\right)\left[-\frac{\partial D}{\partial t} A_t^B(\alpha) - D \frac{\partial A_t^B(\alpha)}{\partial t}\right]}{\left[-D A_t^B(\alpha)\right]^2} \lessgtr 0$$
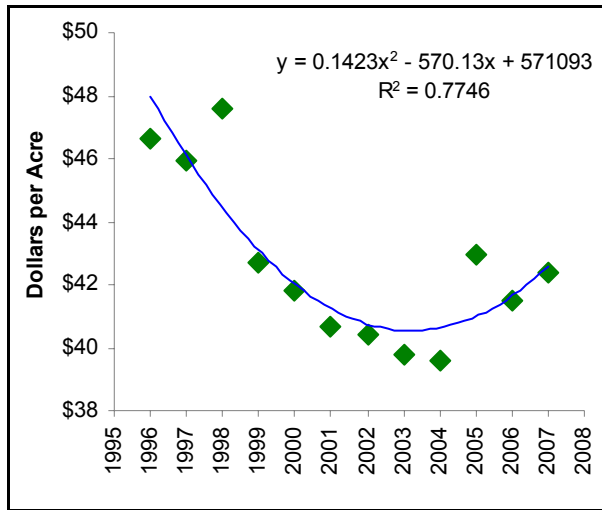
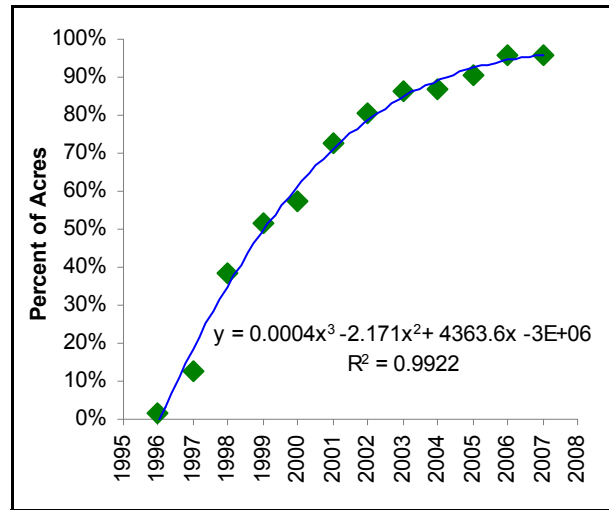**Figure 3. United States Roundup Ready® soybean system costs, 1996-2007. (Source: dmrkynetec, Inc.)**

Figure 4. United States adoption of Roundup Ready® soybeans, 1996-2007. (Source: dmrkynetec, Inc.)

the biotech technology, A_t^B. The initial demand function for A_t^B is designated as D_1 in Figure 2. The intersection of D_1 and r_1^B indicates the quantity of A_t^B demanded at time t^r, just before r_t^B begins to rise $A_t^B (D_1, r_1^B)$. As the value of the non-pecuniary factor, q, is realized (see Figure 1) the demand for A_t^B shifts outward to D_2, resulting in an increase in the demand for A_t^B at every price and at r_1^B the quantity demanded is $A_t^B (D_2, r_1^B)$. Then, the demand for A_t^B becomes less elastic so that, as r_t^B increases, the response to the price increase is not as great as it would have been. The difference is the response with the original demand elasticity compared to the new lower demand elasticity, and is shown in Figure 2 as $A_t^B (D_3, r_2^B) - A_t^B (D_2, r_2^B)$. Therefore, as the cost of the biotech technology increases, coupled with the non-pecuniary factor's effect, we would expect the producer's rate of adoption to slow or even reverse slightly, depending on the relative magnitude of the changes in both cost and the non-pecuniary factor. The key point is that the demand response in the presence of the non-pecuniary factor is significantly dampened when compared to the case where a non-pecuniary factor is not present, due to the kinked demand curve after $t > t^r$ when r_t^B increases.

Empirical Evidence

As empirical support for the relationships above, consider the cost of herbicide and seed expenditures,

including technology or royalty fees, for Roundup Ready® soybeans over the period 1996-2007, shown in Figure 3. As the fitted second-order polynomial trend line reveals, during the period of 1996 through 2004, these system costs declined and then began to rise over the period 2005-2007. This second-order polynomial trend line mimics our theoretical path for r_t^B described in Assumption #5 with t^r corresponding with 2005, the period that system costs began to rise. Figure 4 illustrates the adoption of Roundup Ready® soybeans over this same period with a fitted third-order polynomial trend line depicting the adoption path over time. Notable is the rapid adoption over the period 1996-2004 when the cost per acre was declining. As evidence of the elasticity of derived demand for biotechnology having become quite inelastic to price increases, Figure 4 also reveals that, despite the increase in costs shown in Figure 3, aggregate adoption of the technology in 2005-2007 continued to increase, but at a much slower rate. This illustrates that the demand response to the price increase appears to be relatively inelastic.

Additional factors are probably affecting the curves in Figures 3 and 4. The first is the development of technical skills with the biotech technology that come with practice. This learning over time, discussed earlier, would have increased the rate of decline of the total user cost (Figure 3) and make the adoption path steeper in the time period up to 2004 (Figure 4). The second is the increasing value of the non-pecuniary factors, such as convenience, as adopters get "used to" having them. That adopters place a value on these non-pecuniary factors has been demonstrated in various studies, summa-

rized in Marra and Piggott (2006). For example, it was estimated that, in 2001, five years after the initial commercial introduction of Roundup Ready® soybeans, the convenience factor was worth on average from $3.33 to $4.18 *per acre per year* to producers who adopted Roundup Ready® soybeans. Although we do not have empirical evidence that would verify that this value is increasing over time, it is intuitively plausible, as was illustrated by the cell phone adoption example earlier. The increasing value of the non-pecuniary factors also tends to make the demand for the biotech technology less elastic to price increases over time, further enhancing the result in Equation 13.

Conclusion

This article has illustrated the effects that non-pecuniary factors embodied in new technologies have on the derived demand for these technologies as the adopter gains experience with them. A simple model where producers are utility maximizers whose optimization problem involves a sequence of independent, static optimization problems is developed. The technology adoption process is modeled by recognizing that the innovation is a factor of production in final output and incorporates the role of learning and developing skills with the innovation into our framework. The model establishes the refutable hypothesis that, with embodied non-pecuniary factors in play, the derived demand for the new biotech technologies over time will increase (shift out) at first and then begin to become more inelastic to price increases as adopters get "used to" and value the additional non-pecuniary factors more highly. This leads to a kinked derived demand curve.

The implications of this analysis are two-fold. The first is that as the biotech technology is adopted on more and more acres, the prices of the unique components of the technology system will increase due to increased aggregate demand for them and the system cost will rise, but the demand response to the higher cost will become smaller. This effect is, of course, self-limiting due to competition from other technology sellers. The second is that producers may be more reluctant to switch away from a new biotech technology, such as Roundup Ready® soybeans, and the reluctance becomes stronger over time, even if continued use of the new technology results in an effect such as weed resistance build-up (an implicit increase in the cost of the system due to additional spraying costs associated with weed resistance and perhaps a negative externality if the resistance spreads off-farm).

References

Batz, F.J., Peters, K.J., & Janssen, W. (1999). The influence of technology characteristics on the rate and speed of adoption. *Agricultural Economics*, *21*, 121-130.

Bosch, D.J., Cook, Z.L., & Fuglie, K.O. (1995). Voluntary versus mandatory agricultural policies to protect water quality: Adoption of nitrogen testing in Nebraska. *Review of Agricultural Economics*, *17*, 13-24.

Feder, G., & Slade, R. (1984). The acquisition of information and the adoption of new technology. *American Journal of Agricultural Economics*, *66*, 312-320.

Fischer, A.J., Arnold, A.J., & Gibbs, M. (1996). Information and the speed of innovation adoption. *American Journal of Agricultural Economics*, *78*, 1073-1081.

Foster, A.D., & Rosenzweig, M.R. (1995). Learning by doing and learning from others: Human capital and technological change in agriculture. *Journal of Political Economy*, *103*, 1176-1209.

Goodwin, B.K., & Kastens, T.L. (1996). An analysis of marketing frequency by Kansas crop producers. *Review of Agricultural Economics*, *18*, 575-584.

Griliches, Z. (1957). Hybrid corn: An exploration in the economics of technological change. *Econometrica*, *25*, 501-523.

Just, R.E., & Zilberman, D. (1983). Stochastic structure, farm size and technology adoption in developing agriculture. *Oxford Economic Papers*, *35*, 307-328.

Lindner, R.K., & Pardey, P.G. (1979, January). The micro processes of adoption—A model. Paper presented at the 9th Congress of the Australian and New Zealand Association for the Advancement of Science, Auckland, New Zealand.

Lindner, R.K., Pardey, P.G., & Jarrett, F.G. (1982). Distance to information source and the time lag to early adoption of trace element fertilizers. *Australian Journal of Agricultural Economics*, *26*, 98-113.

Marra, M., Hubbell, B., & Carlson, G. (2001). Information quality, technology depreciation, and Bt cotton adoption in the southeast. *Journal of Agricultural and Resource Economics*, *26*(1), 158-175.

Marra, M.C., & Piggott, N.E. (2006). The value of non-pecuniary characteristics of crop biotechnologies: A new look at the evidence. In R. Just, J. Alston, & D. Zilberman (Eds.), *Regulating Agricultural Biotechnology: Economics and Policy* (pp.145-178). New York: Springer-Verlag Publishers.

McWilliams, B., Tsur, Y., Hochman, E., & Zilberman, D. (1998). Count-data regression models of the time to adopt new technologies. *Applied Economics Letters*, *5*, 369-373.

O'Mara, G. (1971). *A decision theoretic view of technique diffusion in a developing country*. Unpublished doctoral thesis, Stanford University, Palo Alto, California.

Rahm, M.R., & Huffman, W.E. (1984). The adoption of reduced tillage: The role of human capital and other variables. *American Journal of Agricultural Economics*, *66*, 405-413.

Shapiro, B.I., Brorsen, B.W., & Doster, D.H. (1992). Adoption of double-cropping soybeans and wheat. *Southern Journal of Agricultural Economics*, *24*, 33-40.

Silberberg, E. (1990). *The structure of economics: A mathematical analysis* (2nd ed.). New York: McGraw-Hill.

Warner, K.E. (1974). The need for some innovative concepts of innovation: An examination of research on the diffusion of innovations. *Policy Sciences*, *5*, 433-451.

NOTE: Appendix is in a one-column format to allow for longer equations.

Appendix

Substituting Equation 6 into Equation 3 results in the following FONC:

$$U_{x_t}\left(x_t(\alpha),\, q\left(A_t^B(\alpha),\, t\right)\right) - \lambda_t(\alpha)\, p_t^x = 0 \tag{A1a}$$

$$U_{A_t^B}\left(x_t(\alpha),\, q\left(A_t^B(\alpha), t\right)\right) + \lambda_t(\alpha)\left[p_t^y f_{A_t^B}(\alpha) - r_t^B(r_0^B, t) + r_t^C \right] = 0 \tag{A1b}$$

$$p_t^y f\left(A_t^B(\alpha),\, A_t\right) - r_t^B(r_0^B, t)A_t^B(\alpha) - r_t^C\left[A_t - A_t^B(\alpha)\right] - p_t^x x_t(\alpha) = 0. \tag{A1c}$$

Derivation of $\dfrac{\partial A_t^B}{\partial r_t^B}$

To derive $\dfrac{\partial A_t^B}{\partial r_t^B}$, differentiate Equation A1 with respect to r_t^B, which can be written in matrix form as

$$\begin{bmatrix} U_{x_t x_t} & 0 & -p_t^x \\ 0 & U_{A_t^B A_t^B} + \lambda_t p_t^y f_{A_t^B A_t^B} & p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \\ -p_t^x & p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C & 0 \end{bmatrix} \begin{bmatrix} \dfrac{\partial x_t}{\partial r_t^B} \\[2ex] \dfrac{\partial A_t^B}{\partial r_t^B} \\[2ex] \dfrac{\partial \lambda_t}{\partial r_t^B} \end{bmatrix} = \begin{bmatrix} 0 \\ \lambda_t \\ A_t^B \end{bmatrix} \tag{A2}$$

Applying Cramer's rule to solve for $\dfrac{\partial A_t^B}{\partial r_t^B}$ results in the following expression:

$$\frac{\partial A_t^B}{\partial r_t^B} = \frac{\begin{vmatrix} U_{x_t x_t} & 0 & -p_t^x \\ 0 & \lambda_t & p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \\ -p_t^x & A_t^B & 0 \end{vmatrix}}{D} = \frac{U_{x_t x_t} \begin{vmatrix} \lambda_t & p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \\ A_t^B & 0 \end{vmatrix} - p_t^x \begin{vmatrix} 0 & \lambda_t \\ -p_t^x & A_t^B \end{vmatrix}}{D}$$

$$= \frac{U_{x_t x_t} \left[-\left(p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \right) A_t^B \right] - p_t^x \lambda_t p_t^x}{D}. \tag{A3}$$

Derivation of $\left| \dfrac{\partial \eta_{A_t^B r_t^B}(\alpha)}{\partial t} \right|$

To derive $\left| \dfrac{\partial \eta_{A_t^B r_t^B}(\alpha)}{\partial t} \right|$ it is useful to first write $\eta_{A_t^B r_t^B}(\alpha)$ as follows:

$$\eta_{A_t^B r_t^B}(\alpha) = \frac{U_{x_t x_t} \left[-\left(p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \right) A_t^B \right] - \left(p_t^x \right)^2 \lambda_t}{D} \frac{r_t^B}{A_t^B(\alpha)} = \frac{\left[-U_{x_t x_t} z(\alpha) - \left(p_t^x \right)^2 \lambda_t \right] r_t^B}{D A_t^B(\alpha)} < 0, \tag{A4}$$

where $z(\alpha) = \left(p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \right) A_t^B < 0$.

In addition, since $\eta_{A_t^B r_t^B}(\alpha) < 0$ it is also convenient to first multiply both sides of Equation A4 by (-1) which results in

$$\left| \eta_{A_t^B r_t^B}(\alpha) \right| = (-1) \left(\frac{\left[-U_{x_t x_t} z(\alpha) - \left(p_t^x \right)^2 \lambda_t \right] r_t^B}{D A_t^B(\alpha)} \right) = \frac{\left[U_{x_t x_t} z(\alpha) + \left(p_t^x \right)^2 \lambda_t \right] r_t^B}{-D A_t^B(\alpha)}. \tag{A5}$$

Differentiating Equation A5 by *t* results in the following:

$$\left|\frac{\partial \eta_{A_t^B r_t^B}(\alpha)}{\partial t}\right| = \frac{\left[\frac{\partial\left[U_{x,x_t}z(\alpha)+\left(p_t^x\right)^2\lambda_t\right]r_t^B}{\partial t} + \left[U_{x,x_t}z(\alpha)+\left(p_t^x\right)^2\lambda_t\right]\frac{\partial r_t^B}{\partial t}\right]\left(-DA_t^B(\alpha)\right) - \left[U_{x,x_t}z(\alpha)+\left(p_t^x\right)^2\lambda_t\right]r_t^B\left[\frac{\partial\left(-DA_t^B(\alpha)\right)}{\partial t}\right]}{\left[DA_t^B(\alpha)\right]^2}$$

$$= \frac{\left[r_t^B U_{x,x_t}\frac{\partial z(\alpha)}{\partial t}+\left(U_{x,x_t}z(\alpha)+\left(p_t^x\right)^2\lambda_t\right)\frac{\partial r_t^B}{\partial t}\right]\left(-DA_t^B(\alpha)\right) - \left[U_{x,x_t}z(\alpha)+\left(p_t^x\right)^2\lambda_t\right]\left[-\frac{\partial D}{\partial t}A_t^B(\alpha)-D\frac{\partial A_t^B(\alpha)}{\partial t}\right]}{\left[-DA_t^B(\alpha)\right]^2}$$

$$= \frac{\left[r_t^B U_{x,x_t}\frac{\partial z(\alpha)}{\partial t}+\left(U_{x,x_t}z(\alpha)+\left(p_t^x\right)^2\lambda_t\right)\frac{\partial r_t^B}{\partial t}\right]\left(-DA_t^B(\alpha)\right) - \left[U_{x,x_t}z(\alpha)+\left(p_t^x\right)^2\lambda_t\right]\left[-\frac{\partial D}{\partial t}A_t^B(\alpha)-D\frac{\partial A_t^B(\alpha)}{\partial t}\right]}{\left[-DA_t^B(\alpha)\right]^2}.$$

(A6)

Differentiation of the FONC Equations 3b and 3c with respect to *t* results in following two expressions:

$$\left[p_t^y\frac{\partial f_{A_t^B}}{\partial t}-\frac{\partial r_t^B}{\partial t}\right] = -\left[\frac{1}{\lambda_t}\right]\frac{\partial U_q q_{A_t^B}}{\partial t}$$

$$\frac{\partial A_t^B(\alpha)}{\partial t}\left[p_t^y f_{A_t^B}-r_t^B(r_0^B,t)+r_t^C\right] = \frac{\partial r_t^B}{\partial t}A_t^B(\alpha).$$

(A7)

Using Equation A7 we can establish the result for $\dfrac{\partial z(\alpha)}{\partial t}$ as

$$\frac{\partial z(\alpha)}{\partial t} = \left(p_t^y\frac{\partial f_{A_t^B}}{\partial t}-\frac{\partial r_t^B}{\partial t}\right)A_t^B(\alpha) - \left(p_t^y f_{A_t^B}-r_t^B(r_0^B,t)+r_t^C\right)\frac{\partial A_t^B(\alpha)}{\partial t}$$

$$= -\left[\frac{1}{\lambda_t}\right]\frac{\partial U_q q_{A_t^B}}{\partial t}A_t^B(\alpha) - \frac{\partial r_t^B}{\partial t}A_t^B(\alpha)$$

$$= \left[-\left[\frac{1}{\lambda_t}\right]\frac{\partial U_q q_{A_t^B}}{\partial t}-\frac{\partial r_t^B}{\partial t}\right]A_t^B(\alpha) < 0 \text{ for } t > t^r.$$

(A8)

Evaluating *D* reveals

$$
D = \begin{vmatrix} U_{x_t x_t} & 0 & -p_t^x \\ 0 & U_{A_t^B A_t^B} + \lambda_t p_t^y f_{A_t^B A_t^B} & p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \\ -p_t^x & p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C & 0 \end{vmatrix}
$$

$$
= U_{x_t x_t} \begin{vmatrix} U_{A_t^B A_t^B} + \lambda_t p_t^y f_{A_t^B A_t^B} & p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \\ p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C & 0 \end{vmatrix} - p_t^x \begin{vmatrix} 0 & U_{A_t^B A_t^B} + \lambda_t p_t^y f_{A_t^B A_t^B} \\ -p_t^x & p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \end{vmatrix}
$$

$$
= -U_{x_t x_t} \left(p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \right)^2 + \left(p_t^x \right)^2 \left(U_{A_t^B A_t^B} + \lambda_t p_t^y f_{A_t^B A_t^B} \right) > 0. \tag{A9}
$$

Differentiating Equation A9 with respect to *t*

$$
\frac{\partial D}{\partial t} = U_{x_t x_t} 2 \left(p_t^y f_{A_t^B} - r_t^B(r_0^B, t) + r_t^C \right) \left(\frac{\partial r_t^B}{\partial t} \right) > 0 \text{ for } t > t^r. \tag{A10}
$$

Using Equations A8, A9, and A10 we can make the refutable hypothesis for Equation A6 as

$$
\left| \frac{\partial \eta_{A_t^B r_t^B}(\alpha)}{\partial t} \right| = \frac{[+](-)-(+)[-]}{[+]} < 0 \quad \text{for } t > t^r. \tag{A11}
$$