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**A Real Options Approach with Learning Spillovers:  
Investment in Anaerobic Digester Technology**

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## Abstract

This article modifies the real options approach (ROA) framework to technology investment valuation by introducing learning spillover effects. With uncertainty about future outcomes, investment values calculated using ROA include the value of waiting for more information, in contrast to net present value (NPV). When learning spillovers are present, firms that wait can learn from firms that invest in earlier periods. We examine green technology adoption that generates returns composed of net monetary revenue and non-monetary environmental valuation. Using distributional data from a recent anaerobic digester (AD) survey of US dairies, we find that parameters that impact individual firms' trigger values also generate industry-wide effects on adoption curves that can be magnified due to learning spillovers. Because learning spillovers can reduce the waiting value for later adopters, information sharing requirements for early adopters who receive government incentives should be a requirement if the program goal is widespread adoption.

**Keywords:** anaerobic digester, green technology, technology adoption, capital investment, irreversible investment, learning spillovers, real options

**JEL classification:** D83; O33; Q16; Q42; Q55

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## Introduction

Throughout the world, environmental policy is increasingly implemented with the goal of reducing the amount of pollution caused by production processes, and green technology adoption has become an integral part of environmental regulation. A United Nations Framework Convention on Climate Change report indicates that “many governments are also involved at the final stage of the technological cycle – adoption and diffusion – trying to remove barriers to the use of new [climate-friendly] technology” (2004). More recently at the Rio +20 Earth Summit, signatory countries agreed that “we must establish effective modalities for multi-stakeholder cooperation and sharing of the costs for the research, development... and diffusion of new technologies.... Such urgency is particularly great in the case of low-carbon technologies” (United Nations, 2014). Governments are often confronted with the choice of which green technologies to support before firms’ experience validates the technology’s viability; thus, more accurate predictive tools are necessary to make efficient policy decisions.

This article develops an extension to the real options approach (ROA) to account for learning spillovers which can be used to model firms’ investment decisions in green technologies. Previous literature has modeled decisions affected by learning spillovers using real options, but only in a game theoretic context. Our extension to the ROA accounts for the effect learning spillovers have on firms’ uncertainty about the true variance of option value they face. After extending the standard ROA framework to include learning spillovers, we examine an empirical application of the adoption of anaerobic digestion (AD) technology by US dairy producers. Using an *ex ante* approach to simulate industry-wide adoption over time, we construct a dynamic model of AD adoption to account for learning spillovers in the adoption decision using data from a recent survey of dairies. We map the adoption results for a parameter space

that includes a range of environmental valuations, capital cost, uncertainty (noise) about the option value variance, discount rate, benefits of learning, and whether learning spillovers are present. We then examine the comparative statics of changes in parameter values on adoption rates and compare them with adoption rates given by net present value (NPV) and ROA without learning spillovers. Our chosen parameter space is sufficiently wide to consider the range of adoption patterns spanning constant full adoption to constant zero adoption over the entire time horizon. Our analysis focuses on dairies large enough for AD technology to be potentially viable, which currently is at least 500 cows (U.S. Environmental Protection Agency 2006). We do not model the effects of size differences among large dairies.

The results indicate that capital cost and returns drive the decision to invest and that learning spillovers can affect adoption patterns in the presence of heterogeneous firms. With learning spillovers present and other parameters held constant, estimated adoption rates decrease from 100 percent to 25 percent when capital cost increases from \$2,800 per head to \$5,000 per head and increase from 44 percent to 100 percent when expected environmental valuation increases from \$0 per head to \$254 per head per year. We demonstrate dynamic adoption patterns that exhibit cascading adoption effects under the learning scenario. We also find evidence for a high value of waiting – on the order of 12-26 percent of the net present value. This implies that government programs subsidizing environmental technology adoption should include information sharing requirements if the program goal is widespread adoption.

## Technology Adoption

A variety of factors influence a firm's decision to adopt a new technology. Although an investment is often defined as profitable when net present value exceeds zero, a firm may delay investment even when the discounted expected returns exceed the cost of investment. In addition to the NPV of an investment, a firm considers the opportunity cost of investing today against the value of waiting to invest. The value of waiting increases with the irreversibility of the investment and, for a risk-averse firm, with the uncertainty of returns. Using the ROA allows one to model irreversibility of investment and return uncertainty when valuing investment decisions. Additionally, previous research has demonstrated the importance of learning spillovers in the context of technology adoption (e.g., Conley and Udry 2010; Foster and Rosenzweig 1995).

Although the ROA assigns value to waiting under irreversibility and return uncertainty, applied economic researchers commonly use NPV to estimate the value of investment opportunities and to predict adoption. Several recent studies used NPV to evaluate investment in AD in US agricultural settings (Manning and Hadrich 2015; Klavon *et al.* 2013; DeVuyst *et al.* 2011; Key and Sneeringer 2011, 2012; Bishop and Shumway 2009; Leuer, Hyde, and Richard 2008). Two have examined AD investment decisions using the ROA (Anderson and Weersink 2014; Stokes, Rajagopalan, and Stefanou 2008). ROA has also been used to examine other agricultural investment decisions (e.g., Maart-Noelck and Musshoff 2013; Feil, Musshoff, and Balmann 2012; Baerenklau and Knapp 2007; Tauer 2006; Isik, Hudson, and Coble 2005; Isik and Yang 2004; Diederer, Van Tongeren, and Van Der Veen 2003) as well as rural land use and forest management decisions (Regan *et al.* 2015; Miao, Hennessy, and Feng 2014; Tee, Scarpa, Marsh, and Guthrie 2014; Behan, McQuinn, and Roche 2006; Schatzki 2003; Insley 2002). They generally find that the ROA more accurately predicts actual investment decisions than the NPV.

Learning spillovers have been used to help explain the stylized S-shaped adoption curve initially identified in the sociology literature (Bohlen and Beal 1957) but have previously only been incorporated into the ROA framework using game theoretic models. Early research by Mariotti (1992) and Chamley and Gale (1994) examine investment equilibria that arise from different information diffusion processes that include learning spillovers and conclude that underinvestment may occur when there is a strategic value of waiting. More recently Lewis, Barham, and Robinson (2011) implicitly use the concept of real options to evaluate a reduced-form organic conversion model for Wisconsin dairies.

In the case of a green technology investment, environmental benefits accompany the economic benefits. The characteristics of agricultural producers who choose to adopt environmentally beneficial practices has been widely studied. In his review of literature, Burton (2014) notes that many, but not all, studies have found that education enhances participation in agri-environmental schemes, environmental attitudes of farmers, and investment in environmentally sustainable measures. Experience with agri-environmental schemes has also been commonly observed to contribute to engagement in new schemes.

In this study, we consider a firm-level measure of environmental valuation as a proxy for the heterogeneous characteristics that could contribute to the decision to adopt an environmentally beneficial technology. Addressing firms' uncertainty about the variance of option value to invest in the emerging technology, we develop a model that incorporates learning into ROA. If firms initially assume the variance to be large due to their ignorance, investment triggers estimated using the ROA will be higher than they would be if firms' beliefs were closer to the true variance. We also explicitly model the joint impacts of learning and capital cost,

environmental valuation, noise on option values, discount rate, and returns to learning in the adoption decision.

### **Theoretical Model**

The intuition of the ROA is that firms may benefit from delaying investment, especially if investment becomes a sunk cost or future returns are uncertain. If the firm delays investment today, it can often invest tomorrow; but if it invests today, it may not be able to liquidate or recover its investment tomorrow. In this section we compare ROA to NPV, after which we develop an ROA framework that includes learning spillovers.

To compare ROA and NPV investment implications, we use the approach of Dixit (1992), one of the first expositions to relate asset pricing methods to technology investment. The NPV approach has been widely used to model investment decisions, and it predicts that a firm will invest if the cost today is less than the discounted stream of expected returns in the future. If the investment cost is given by  $K > 0$ , the discount rate is given by  $0 \leq \rho \leq 1$ , and the returns per unit of time into perpetuity is given by  $R > 0$ , then a firm will invest if  $R \geq \rho K$ .

The point at which  $R$  equals  $\rho K$  is commonly referred to as the trigger value, or the threshold that must be exceeded to induce adoption. Dixit (1992) calls this the Marshallian trigger:<sup>1</sup>

$$(1) \quad M = \rho K.$$

Referring to Figure 1, the linear invest curve,  $i$ , shows the NPV of an investment with cost,  $K$ , facing a constant discount rate,  $\rho$ . Return per unit time,  $R$ , is measured on the x-axis, and

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<sup>1</sup> Dixit (1992) chooses this name based on Marshall's theory of firm entry and exit in a competitive market. It states that new firms will enter the market when output price exceeds long run average cost.

the value of the option to invest,  $V$ , is measured on the y-axis.<sup>2</sup> We see the Marshallian trigger value,  $M$ , occurs at the point where the value of investing is zero.

Under NPV,  $R$  is known for all time periods, while the ROA allows for a probability distribution of returns. The value of waiting comes from the flexibility the firm retains in where and how to invest and is shown by the curve  $w$  in Figure 1. The downside risk of investing increases as the variance of returns increases, which increases the value of waiting. The firm should invest at the point where the return that will be derived from investing exceeds the value of waiting for more information with the option of adopting in a later period, noted on the graph by the adjusted trigger,  $H$ . We derive  $H$  below.

If a firm's expected return,  $R$ , is less than the Marshallian trigger,  $M$ , both NPV and the ROA predict that the firm will wait to invest. If  $R$  exceeds  $M$  but is less than the adjusted trigger,  $H$ , NPV predicts investment while the ROA predicts waiting to invest. Finally, if  $R$  exceeds  $H$  then both NPV and the ROA predict investment.

The functional form of the wait curve,  $w$ , presented in equation (2) below, is derived by Dixit (1992) using differential equations. The value function depends on the choice to invest now or wait to invest and is composed of segments of the two curves:

$$(2) \quad V(R) = \begin{cases} BR^\beta & \text{if wait } (w), \\ R/\rho - K & \text{if invest } (i). \end{cases}$$

Before proceeding further, note that the curves in Figure 1 are used to visualize how to determine the optimal trigger,  $H$ , but cannot be used to directly compare  $V$  between choices. To

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<sup>2</sup> In financial economics, an option refers to the right to purchase an asset at a designated future time under specified conditions. The class of assets that can be structured into options is quite broad and is based on Black and Scholes' (1973) work on option pricing (Purvis *et al.* 1995). The procedure used to calculate investment option value is the same whether the discount rate is risk-free or risk-adjusted. If firms are risk-neutral, the risk-free rate produces option values that exceed the NPV due to the value of waiting. Risk-averse firms face even higher option values due to a higher, risk-adjusted discount rate.

the right of  $R = H$  the wait curve cannot be interpreted as producing a higher value than the invest curve for  $R > H$ . The bolded line shows the optimal choice values corresponding to an optimal  $H$ . For a more detailed explanation of this caveat, see Dixit (1992, p. 114).

Graphically, the parameter  $B$  scales the wait curve while the parameter  $\beta$  adjusts its exponential curvature. The point of tangency between the two curves  $w$  and  $i$  characterizes the indifference of the firm between waiting and investing and determines the adjusted trigger,  $H \geq M$ . The two conditions used to derive the optimal  $H$  simultaneously equate both  $V(R/R=H)$  and the slope of  $V(R/R=H)$  for both function components of (2). Dixit calls these the “value-matching” and “smooth-pasting” conditions, respectively.

We first examine the parameter  $\beta$ . It is a function of the variance of option value,  $\sigma^2$ , and the discount rate,  $\rho$ :

$$(3) \quad \beta = \frac{1}{2} \left[ 1 + \sqrt{1 + \frac{8\rho}{\sigma^2}} \right] > 1.$$

The requirement that  $\beta$  be larger than one is due to the sufficient, smooth-pasting condition. The scaling parameter,  $B$ , is determined by the necessary, value-matching condition which states that at  $R = H$ , the option value of waiting must equal the option value of investing. Using the value-matching condition, equating the two right-hand components of (2), and setting  $R = H$  gives  $H/\rho - K = BH^\beta$ . Rearranging gives an equation that can be compared to (1):

$$(4) \quad H = \rho K + \rho BH^\beta.$$

The second term in (4) captures the value of waiting.

The requirement of the smooth-pasting condition, that the slopes of the wait and invest curves be equal at the optimal  $H$ , allows differentiation of the two function components in (2) with respect to  $R$ . Setting the results equal to each other with  $R = H$  gives:

$$(5) \quad 1/\rho = \beta BH^{\beta-1}.$$

Solving for optimal  $H$  using (4) and (5) gives a result in terms of  $\beta$ ,  $\rho$ , and  $K$  only:

$$(6) \quad H = \frac{\beta}{\beta - 1} \rho K.$$

Comparing (6) to (1) shows that  $H$  is proportionally larger than  $M$  by a discount rate scaling factor,  $\beta/(\beta-1) > 1$ . Referring back to the discussion of equation (3), note that as variance decreases toward zero,  $\beta$  tends towards infinity and the adjusted trigger,  $H$ , approaches the Marshallian trigger,  $M$ . Derivations for equations (1) through (6) are contained in Dixit (1992).

### ***Ex ante* Estimation**

If the analyst has data to approximate the discount rate, average return, variance of option value, and investment cost, s/he is able to perform a simple *ex post* calculation of the adjusted trigger,  $H$ , using equations (3) and (6). When technology adoption behavior is examined *ex ante*, it may be possible to reasonably estimate the discount rate, the expected return, and the investment cost, but the variance of option value is more difficult to estimate accurately.

However, if a reasonable estimate of the distribution of expected returns can be obtained, then the variance of option value can be estimated. Purvis *et al.* (1995) propose generating a plausible distribution by modeling the value of the opportunity to invest as a geometric Brownian motion process:

$$(7) \quad \frac{dV}{V} = \mu dt + \sigma dz.$$

Using a first-order Taylor series expansion of the derivative, they show that:

$$(8) \quad \frac{dV}{V} \approx \frac{\Delta V / \Delta t}{V} = \frac{1}{V} * \frac{\Delta V}{\Delta t} = \frac{\Delta(\ln V)}{\Delta t} = \frac{\ln(V_t) - \ln(V_{t+1})}{\Delta t},$$

which compares the value of investment today to the value of investment tomorrow. Using  $v$  Monte Carlo iterations, the researcher can generate a series of values for  $dV/V$  and calculate the variance.

We calculate (8) using the following method. We take  $n+1$  random draws from the distribution of expected returns which gives us a vector of returns across time,  $\{R_t\}$  for  $t=\{0, \dots, n+1\}$ , where  $n$  is the number of years the investment generates returns. From the vector of returns we calculate a present value of investment at time  $t = 0$  and a present value of investment at time  $t = 1$ :

$$(9) \quad PV_t = \sum_{t=0}^n \frac{R_t}{(1 + \rho)^t}, \quad PV_{t+1} = \sum_{t=1}^{n+1} \frac{R_t}{(1 + \rho)^{t-1}}.$$

To convert present values into equivalent values,  $V$ , for investments in perpetuity, we assume that the firm can reinvest at the same cost,  $K$ , after  $n$  years:

$$(10)^3 \quad V_t = \frac{\left[ \frac{\rho}{1 - \left( \frac{1}{(1 + \rho)^n} \right)} PV_t \right]}{\rho}, \quad V_{t+1} = \frac{\left[ \frac{\rho}{1 - \left( \frac{1}{(1 + \rho)^n} \right)} PV_{t+1} \right]}{\rho}.$$

For each Monte Carlo iteration, equations (10) can be substituted into an estimate of the Brownian motion trend:

$$(11) \quad \mu_v = \frac{1}{v} \sum_{m=1}^v [\Delta \ln V_m].$$

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<sup>3</sup> The scaling factors on the present values in equations (10) are equal. Purvis *et al.* use slightly different notation that explicitly accounts for the effect of the adoption period. With  $t = 0$ , the specification simplifies.

Using the result of equation (11), we estimate the variance of the Brownian motion from (7), which corresponds to the variance of the value of the option to invest:

$$(12) \quad \sigma^2 \approx \sigma_v^2 = \frac{1}{v} \sum_{m=1}^v [\Delta \ln V_m - \mu_v]^2.$$

When we calculate  $\sigma_v^2$  using Monte Carlo iterations, we expect that as the number of iterations becomes large,  $\mu_v$  should approach 0. In the empirical application we use the sum of net monetary revenue and a firm-specific, non-monetary environmental valuation as the return and calculate  $\sigma_v^2$  for each firm in each period for each set of parameter values.

### **Learning Spillovers**

The success or failure of early technology adopters may impact adoption decisions of observing firms. We anticipate that these learning spillover effects reduce firms' uncertainty about the value of the option to invest. The theoretical structure of learning spillovers begins with two assumptions: (a) each firm initially has a belief about the variance of the option value that is larger than the true variance, and (b) firms' beliefs about the variance of option value converge to the true variance as they learn from a larger number of adopters.

Allowing for  $J$  firms, we create a dynamic adoption model, where in each period firm  $j$  decides whether to adopt the technology or not by using the adjusted trigger,  $H$ , as a decision rule. Firms face uncertainty on the variance of option value, but that uncertainty decreases as more firms adopt in subsequent periods. To model this uncertainty, noise is added to a firm-specific variance estimator,  $\sigma_{jt}^2$ , defined in (12).

All firms begin with no technology adoption which is defined by  $a_j = 0$ . If a firm adopts,  $a_j$  becomes 1. The industry-wide adoption rate is characterized by  $\bar{a}_t = 1/J \sum_{j \in J} a_j$ . The firm's true variance of option value,  $\sigma_{jt}^2$ , is unknown *ex ante*, and as the industry's collective experience

increases, the accuracy of the firm's belief about variance increases. Beginning in period one, firms will be uncertain about the true variance and will believe the variance to be large. Each firm that adopts will contribute to a decrease in noise that will drive the belief about variance towards the true variance. This effect can be modeled by scaling the true variance of option value defined in (12) by a noise parameter,  $\varepsilon$ , weighted by the industry-wide adoption rate:

$$(13) \quad \sigma_{jt\alpha}^2 = \sigma_{jt}^2 + (1 - \bar{a}_t^\gamma \alpha) \varepsilon \sigma_{jt}^2.$$

If we do not allow firms to learn in the model, the binary learning parameter,  $\alpha$  is set to zero, and the noise term obscures the true variance through all time periods by a factor of  $1 + \varepsilon$ . If we allow firms to learn,  $\alpha$  is set to one. The parameter  $\gamma$ ,  $0 < \gamma \leq 1$ , captures marginal benefits to learning spillovers: constant when  $\gamma = 1$  and diminishing when  $\gamma < 1$ . Because  $\bar{a}_t$  is bounded between 0 and 1, learning spillover effects drive beliefs about variance toward the true variance more under diminishing than under constant marginal benefits at each point,  $\bar{a}_t$ , i.e. the first firms to adopt have a greater impact on learning spillovers than the last firms who adopt.

### **Empirical Model**

We use the ROA with learning spillovers to analyze AD technology investment by US dairy producers. An AD is any enclosed vessel that allows bacteria to break down nutrients in organic waste and convert them to biogas (Wellinger 2007).<sup>4</sup> The main benefit of an AD is capturing methane that would otherwise be emitted into the atmosphere as a greenhouse gas. Thus, ADs can generate energy while reducing environmental harm. Anaerobic digesters are used on 1,270 municipal waste water treatment facilities in the US to capture methane (Water Environment Federation, 2015), but adoption among livestock producers has been less extensive. AD

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<sup>4</sup> See Wilkinson (2011) for an overview of the history, engineering, chemistry, and economics of AD.

technology is emerging, has wide expansion potential, and requires significant sunk costs to implement (AgSTAR 2010). Long-term return uncertainty exists for producers considering adopting this technology.

The first AD built on a US dairy occurred in 1979 (AgSTAR, 2015). By 2005 one percent of US dairies with at least 500 cows had adopted AD technology, and by 2015 that number had increased to six percent (U.S. Department of Agriculture, 2012; AgSTAR, 2015). Because manure management in US agriculture contributes 4.7% of total carbon dioxide equivalent emissions and because increasing use of liquid manure handling systems has increased methane emissions by 68 percent from 1990 to 2012 (U.S. Environmental Protection Agency 2014), AD adoption by US animal producers has the potential to mitigate a significant portion of greenhouse gas emissions. Technical innovation, such as AD adoption, has been found to be an important strategy for dairies seeking to comply with government-enforced greenhouse gas emission reduction targets and efficiency requirements (Njuki and Bravo-Ureta, 2015).

The data for this analysis are from a survey of US dairy firms carried out in cooperation with the USDA National Agricultural Statistics Service by Cowley (2014). Fifty-six respondents owned or had previously owned ADs on dairies at the time of the survey; that is one quarter of all dairies that own ADs. Firms reported the total amount paid for the digester by grants and by themselves which provides a measure of capital cost. They also reported annual operating costs of the digester and revenue received from electricity generation, non-electricity generation, and coproducts, which provides a measure of annual net revenue. All cost and revenue data are converted to dollars per head. All data other than capital cost are measured per year. Data are presented in Table 1.

Survey respondents also ranked the importance of various factors in their adoption decision. We use the ratio of their rankings of “environmental stewardship and ecological sustainability” and “sell surplus methane, electricity, and/or other digestion co-products” to construct a proxy of the heterogeneous, firm-level characteristics that could contribute to adopting an environmentally beneficial technology which we refer to as environmental valuation.

There are two limitations of this data set that affect the analysis we perform. The first is that, due to privacy restrictions on the survey data, we are unable to access the individual observations. Instead, we use sample distributions of the data, characterized by values for the 25<sup>th</sup> percentile, median, 75<sup>th</sup> percentile, and maximum as presented in Table 1. While we lack information about possible correlation among the data, the distributions accurately reflect the variation in costs and benefits that firms face and are sufficient to examine comparative statics and perform the adoption simulation. The second limitation is due to sample selection. Our survey data only contains responses of firms that have adopted AD technology.

In light of these two limitations, we produce a set of adoption scenarios using baseline values from the survey data along with a range of perturbations to the baseline in order to approximate dairies that considered adopting but did not. We simulate firms excluded from our survey sample, i.e. those that considered adopting but chose not to, by scaling the capital cost distribution and the environmental valuation distribution towards non-adoption conditions.

Using the distribution quantiles of the survey reported in Table 1, we bootstrap empirical distributions for capital cost (Figure 2), revenue sources and operating cost (Figure 3), net revenue (Figure 4), and environmental valuation (Figure 5) using 15,000 samples.

Data from each of the four quantiles is drawn with 25 percent probability. Capital cost is simply drawn from the descriptive statistics according to their quantile probabilities whereas net

revenue and environmental valuation are constructed from multiple distributions. We take the mean of the bootstrapped capital cost distribution for baseline capital cost,  $E(K) = \$2,800$  per head, presented in Figure 2.<sup>5</sup> We scale capital cost by a factor  $a_K \geq 1$  in order to perturb  $E(K)$  towards non-adopters across model simulations. The capital cost scale values of 1.0 to 2.0 presented in Table 3 correspond to capital cost values of \$2,800 to \$5,600 per head.

To construct the net revenue distribution, we randomly draw one observation with 25 percent probability for each quantile for each component and then calculate net revenue as the sum of electricity revenue ( $E$ ), non-electricity methane gas revenue ( $G$ ), and coproduct revenue (most commonly organic fiber,  $F$ ) minus operating cost ( $C$ ) all measured in per head per year:

$$(14) \quad R = E + G + F - C.$$

Electricity revenue is calculated using the following equation:

$$(15) \quad E = P_w * kWh * 0.8 * 24 * 365,$$

where the wholesale price of electricity is  $P_w$ ,  $kWh$  is electricity generator capacity in kilowatt hours and the generator is assumed to operate at 80 percent capacity over one year.

The distributions of components used to compute net revenue in equation (14) are presented in the top four graphs in Figure 3, and the distributions of generator capacity and electricity wholesale price used in equation (15) are shown in the bottom two graphs in Figure 3. The distribution of net revenue calculated in equation (14) is presented in Figure 4. This empirical distribution is highly skewed to the right, meaning some firms receive high net revenues. It has a dominant peak near \$100 per head per year, and the distribution is not smooth. The mean of the net revenue distribution,  $E(R)$ , is \$337 (see Table 2).

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<sup>5</sup> Note that the mean of capital cost is considerably higher than the median due to skewness toward high values in the survey data. The distributions for other parameters are similarly skewed.

Using survey data, Bishop, Shumway, and Wandschneider (2010) find that there is a range of values that dairy firms place on environmental and social benefits of adopting AD technology in Washington State. We model this firm heterogeneity by generating a distribution of environmental valuations that scale the net revenues.<sup>6</sup> In the Cowley survey, dairy firms rank nine factors that influenced their decision to adopt AD technology from most important to least important (1 to 9). The factors include “environmental stewardship and ecological sustainability” and “sell surplus methane, electricity and/or other digestion co-products”.

To construct an environmental valuation distribution from these factors, we assume truncated normal distributions for firms’ valuation of monetary benefits,  $V(R)$ , and of environmental benefits,  $V(\eta)$ , of AD using the means and standard deviations reported by Cowley (2014), respectively  $V(R) \sim N_{[1,9]}(2.8, 2.07)$ ,  $V(\eta) \sim N_{[1,9]}(3.82, 1.45)$ . Randomly drawing from these two distributions, we scale the net revenues,  $R$ , by the inverse ratio of the valuation ranks to give a baseline estimate of environmental valuations,  $\eta$ .

The distribution of environmental valuations is presented in Figure 5. This empirical distribution is highly skewed to the right, peaks at zero, and is fairly smooth. While the distribution peaks at zero, less than 15 percent of firms are estimated to place no value on the non-monetary environmental benefits of AD. The mean of the environmental valuation distribution,  $E(\eta)$ , is \$318 per head per year (see Table 2). To analyze different levels of environmental valuation, we allow the scale parameter,  $a_n$ , to vary from 0 to 1.2 in increments of

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<sup>6</sup> Available data do not allow us to measure environmental valuation by credits such as carbon offsetland or renewable energy credits. They also do not separate out other non-market benefits of AD adoption like reduced risk of being sued by neighboring land owners for water pollution or odor. We treat firms’ reported ranking of environmental impacts in their AD adoption decision as a proxy for all non-market benefits that contribute to firm heterogeneity.

0.2.<sup>7</sup> These scale values presented in Table 3 correspond to environmental valuation distributions with means ranging from \$0 to \$381 per head per year.

When modeling the investment decision and the trigger value, the return in each year includes net monetary revenue plus non-monetary environmental valuation:

$$(16) \quad R_{\eta_j} = R + a_{\eta} * \eta_j$$

In each simulation we hold the net revenue distribution constant across firms and time, while we hold scaled environmental valuation,  $a_{\eta} * \eta_j$ , for each firm constant across time. All scaling of returns occurs through scaling environmental valuation. This is to simplify our examination of the comparative statics of the adoption curves.

In addition to capital cost,  $E(K)$ , and the environmental valuation distribution, we also perturb the noise term  $\varepsilon$ , the discount rate  $\rho$ , and the marginal benefits of learning term  $\gamma$  as presented in Table 3. We perturb the noise parameter,  $\varepsilon$  (the multiple of true variance), from zero to six, attempting to model a wide range in the amount of information firms can learn from each other. We use Erickson, Moss, and Mishra's (2004) estimation of average return in the US agricultural sector from 1960-2001 of  $\rho = 0.05$  and perturb it towards lower opportunity cost of technology investment, with  $\rho = 0.04$ . We use two values of benefits of learning – decreasing returns,  $\gamma = 0.2$ , and constant returns,  $\gamma = 1.0$ . We compare all scenarios without and with learning,  $\alpha = 0$  and  $\alpha = 1$ , respectively.

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<sup>7</sup> We include one instance of a larger environmental valuation,  $a_{\eta} = 1.2$ , to allow for the possibility that the ordinal rankings from which the parameter was constructed underestimated environmental valuation.

Following this procedure, we perform 20,000 Monte Carlo iterations,  $v$ , for each of 100 firms,  $J$ , assuming a 20-year investment lifetime,  $n$ , over six time periods,  $T$ .<sup>8</sup> Holding parameters from Table 2 constant, we randomly draw a 20-year stream of returns from the probability distribution of returns in each iteration and, discounting them, estimate the variance of option value,  $\sigma_{jt}^2$ . As predicted by the theory, the Brownian motion drift term,  $\mu_v$ , converges to 0. To adjust firms' beliefs about the variance, we scale it by  $\varepsilon$  according to equation (13). In the case of learning, the scaled variance approaches the unscaled variance as more firms adopt the technology.

We simulate scaled variance of option value,  $\sigma_{jta}^2$ , for each firm in each time period which is then used to calculate the wait curve parameter,  $\beta_{jt}$ , using equation (3). We use  $\beta_{jt}$  in a modification of equation (6) for finite return streams:

$$(17) \quad H_{jt} = K \sum_{i=1}^{20} 1/(1 + \rho\beta_{jt}/(\beta_{jt} - 1))^i$$

and solve for  $H_{jt}$ , each firms' adjusted trigger.<sup>9</sup> Comparing the solution of equation (17) to that of equation (16) in each period, each firm decides to adopt if its expected return exceeds its adjusted trigger value:

$$(18) \quad E(R_{\eta_j}) > H_{jt}$$

## Results

Among the 3,341 US dairies with more than 500 cows (USDA, 2012), the current AD adoption rate is six percent. The actual AD adoption curve we have observed over the past 35 years is dynamic but has not reached a very high level of adoption. Without sufficient data to calibrate

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<sup>8</sup> We limit the simulation length to  $T = 6$  periods because in all cases, firms exhibit no dynamic behavior beyond six periods.

<sup>9</sup> We follow an equivalent procedure to modify (1) when we solve for  $M$ .

the model to the actual AD adoption curve, we examine the comparative statics of a range of model parameters that bracket the historical adoption patterns and allow us to assess their implications on AD adoption.

Adoption curves are categorized into four types: (a) all firms adopt in the first period (i.e., constant, full adoption), (b) some firms adopt in the first period and no additional firms adopt in later periods (constant, non-zero, non-full adoption), (c) no firms adopt in any period (constant, zero adoption), and (d) some firms adopt in later periods (dynamic adoption). Of the 1,008 scenarios examined, 28 percent have constant, full adoption over the entire period, 42 percent have constant, non-zero, non-full adoption, 7 percent have constant, zero adoption, and 23 percent have dynamic adoption.

In Figure 6, we present 298 of the adoption curves. Each square represents one adoption curve and corresponds to a set of unique parameter values with no learning, i.e.,  $\alpha = 0$ . Each diamond represents one adoption curve corresponding to the same set of unique parameter values with learning, i.e.,  $\alpha = 1$ .

An extreme case of constant, zero adoption occurs only when the environment is not valued and capital cost is high. The other extreme case of constant, full adoption occurs only when capital cost is low or there is no noise (or uncertainty) about the true value of adopting. These extreme cases apply whether or not there is learning and document that our simulations bound the set of possible technology adoption patterns.

There is no instance of dynamic adoption when there is no learning. When there are constant marginal benefits from learning, three quarters of the simulations result in dynamic adoption. A mix of adoption curve types is visible in most graphs and demonstrates that adoption curves transition types as parameters are adjusted over the domain. The only exception to this

transition is when learning occurs; the qualitative nature of adoption is the same whether learning provides constant or diminishing marginal benefits. Even when the categorical type defined in Figure 6 is the same, details of the adoption curves generally differ between the learning and the no-learning cases, as will be demonstrated below.

We are particularly interested in the instances of dynamic adoption, and especially in those where learning spillovers affect adoption curves. Adoption curves are the aggregate result of the behavior of individual firms in response to their unique trigger values. If a firm's expected return,  $E(R\eta_j)$  from adoption exceeds its adjusted trigger value,  $H_{jt}$ , it will adopt the technology. If trigger values are calculated using the NPV approach, as in the Marshallian trigger,  $M$ , they have the potential to be too low and predict adoption when firms are observed not to adopt. Average trigger values across firms and time are presented in Table 4 for four cases.

The first case assumes that there is no uncertainty in returns, i.e.,  $\text{Var}(R\eta_j) = 0$ , which implies that the learning case parameter,  $\alpha$ , and the noise scaling factor,  $\varepsilon$ , from equation (13) have no impact on the scaled variance of option value, so  $\sigma_{j\alpha}^2 = 0$ . With no uncertainty in returns, we get the Marshallian trigger value as implied by the NPV approach,  $M = \$287$  per head. The second case also assumes there is no learning, i.e.,  $\alpha = 0$ , but that noise contributes to high variance of returns, i.e.,  $\text{Var}(R\eta_j) = \$123,810$ . These assumptions lead to a scaled variance of option value,  $E(\sigma_{j\alpha}^2) = 0.0217$ , and to an average adjusted trigger value,  $H = \$361$  per head which is 26 percent greater than the Marshallian trigger and implies a \$74 per head value of waiting.

The third case assumes learning,  $\alpha = 1$ , constant marginal benefits of learning,  $\gamma = 1.0$ , with the same high variance of returns. These assumptions lead to smaller scaled variance of option value,  $E(\sigma_{j\alpha}^2) = 0.0090$ , which corresponds to a lower, average adjusted trigger value,  $H$

= \$329 per head, which is 15 percent greater than the Marshallian trigger and implies a \$42 per head value of waiting. The fourth case also assumes learning,  $\alpha = 1$ , with the same high variance of returns, but with diminishing marginal benefits of learning,  $\gamma = 0.2$ , as more firms adopt. Scaled variance of option value decreases even more,  $E(\sigma_{jta}^2) = 0.0066$ , which leads to a lower, average adjusted trigger value,  $H = \$322$  per head, 12 percent greater than the Marshallian trigger and implies a \$35 per head value of waiting.

Industry adoption curves change shape depending on how near some firms' expected return,  $E(R_{jt})$ , are to their adjusted trigger values,  $H_{jt}$ . First-period adopters all have an expected return,  $E(R_{jt})$ , that exceeds their adjusted trigger value,  $H_{jt}$ . In cases where learning induces greater adoption than no learning, the decrease in option value uncertainty caused by firms who adopted in previous periods is enough to decrease some non-adopters' adjusted trigger values,  $H_{jt}$ , to be less than their expected return,  $E(R_{jt})$ , in subsequent periods.

In Figure 7 through Figure 11 we examine both the shape and the magnitudes of industry adoption curves that correspond to a subset of squares and diamonds in Figure 6. We choose these cases to visualize the comparative statics of parameter changes. They do not necessarily reflect empirical estimates of actual adoption curves. Rather, they provide a framework for examining the effects of alternative parameter values.

In Figure 7, we examine adoption curves with three alternative capital costs with and without constant marginal benefits of learning. As capital cost,  $a_K * E(K)$ , increases, rates of adoption decrease. For non-scaled capital cost,  $E(K) = \$2,800$ , the simulation produces constant, full adoption, and there is no difference between the no-learning and learning cases. On the other end of the parameter range considered in this figure, capital cost is scaled to be large,  $a_K * E(K) = \$5,000$ , and results in a lower, constant, non-zero, non-full adoption rate of 23 percent for the no-

learning case. The learning case starts at 23 percent in the first period and rises to 25 percent over the next two periods.

An intermediate capital cost of  $a_K * E(K) = \$3,900$  results in a constant, non-zero, non-full adoption rate of 56 percent in the no-learning case. A cascading adoption pattern emerges in the learning case; each set of previous-period adopters reduces the scaled variance of option value  $E(\sigma_{jta}^2)$  and the adjusted trigger values,  $H_{jt}$ , enough to induce non-adopters to adopt. This curve looks like the top half of a classic S-shaped technology adoption curve, and the difference in this case may come from the homogeneity of risk preferences among firms.<sup>10</sup> Under learning the adoption rate increases from 56 percent in the first period to 76, 87, 95, and 100 percent in the following four periods. Under learning, if capital cost increases less than a third (in this case, from the intermediate to the high level), adoption decreases by three-fourths.

Figure 8 reveals adoption curves with three scaled environmental valuations,  $a_\eta * E(\eta)$ . When firms place no value on the environmental benefits of AD, 28 percent of firms adopt in the first period, and no additional adoption occurs in the remaining periods for the no-learning case, while adoption increases to 44 percent for the learning case by the fourth period. When scaled environmental valuation,  $a_\eta * E(\eta) = \$127$  per head per year, 66 percent of firms adopt in the first period. Without learning, no other firms adopt in the remaining periods. With learning, dynamic adoption occurs and the adoption rate increases to 87 percent in period two, 95 percent in period three and reaches 100 percent in period four. The adoption curve for the scaled environmental valuation,  $a_\eta * E(\eta) = \$254$  attains a constant 77 percent adoption rate for the no-learning case and reaches full adoption in the third period for the learning case.

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<sup>10</sup> We allow for heterogeneity across firms in environmental valuation but not in risk preference. In the classical technology diffusion literature, firms that adopt in different periods have different risk preferences and other characteristics such as community position, education, and formal association memberships (Bohlen and Beal 1957).

Note that all three adoption curves in Figure 8 are categorized into the same type of constant, non-zero, non-full adoption under no-learning and dynamic adoption under learning in Figure 6. Dynamic adoption curves emerge when the effect of one parameter does not dominate the effects of all other parameters. For learning spillovers to induce investment in subsequent periods, some firms' expected return,  $E(R_{ij})$ , must be reasonably close to adjusted triggers,  $H_{jt}$ , that learning spillovers nudge their trigger value below the firms' expected returns.

The scaled variance of option value,  $\sigma_{jta}^2$ , is a function of the noise parameter  $\varepsilon$ , the effect of which is diminished as more firms adopt. As shown in Figure 9, constant, full adoption occurs when no noise obscures the true variance,  $\sigma_{jta}^2 = \sigma_{jt}^2$ . In this instance, there is no difference between the no-learning and learning cases. As  $\varepsilon$  increases, adoption rates decrease to 74 and 56 percent for  $\varepsilon = 3$  and 6, respectively, in the no-learning cases. Dynamic adoption patterns emerge for the learning cases when first period adoption is less than 100 percent, and higher values of  $\varepsilon$  correspond to more dynamic adoption patterns.

Increasing the discount rate,  $\rho$ , from 0.04 to 0.05 decreases the rate of adoption by increasing the opportunity cost of investing in the technology (see Figure 10). The effects of learning spillovers diminish as the discount rate,  $\rho$ , increases, and the effect of increasing the discount rate from  $\rho = 0.04$  to  $\rho = 0.05$  is quite large. Adoption decreases 16 percentage points under the no-learning case and 53 percentage points under the learning case. If we consider this one percentage point difference in the discount rate as a risk adjustment for risk-averse firms, it is clear that risk-aversion greatly impacts investment option values and firms' adoption decisions.

Figure 11 depicts the effect of differences in the marginal benefits of learning from other adopters. The no-learning case results in a constant, non-zero, non-full adoption rate of 56

percent for both cases. In the learning case, the adoption curve is steeper under diminishing marginal benefits of learning than under constant benefits of learning. Under diminishing marginal benefits of learning, when early adopters have a larger impact than later adopters on reducing the scaled variance of option value,  $\sigma^2_{jta}$ , towards its true value, the adjusted trigger values,  $H_{jt}$ , fall faster and more firms' expected return,  $E(R_{nj})$ , exceed them.<sup>11</sup> All firms ultimately adopt under both diminishing marginal benefits of learning and constant benefits of learning. The difference between the two learning effects occurs in the rapidity of adoption, and both cases result in a final rate nearly double the no-learning adoption rate.

## Conclusions

We develop a method to incorporate learning spillovers into a real options framework. We then use the newly developed method to simulate dynamic adoption for AD technology in the US dairy industry. After initializing the model using data from a recent survey, we examine a series of adoption scenarios using perturbations of key parameters, focusing on likely omissions due to sample selection bias. We find evidence of sample selection bias by the extremely high adoption rates predicted by the model using baseline (mainly survey mean) parameters. With perturbations to the parameters in the direction of omitted non-adopters, we develop adoption curves that are much closer to the current adoption situation in the US.

We find that all model parameters have important impacts on the decision to invest. They include capital cost, environmental valuation, noise surrounding the variance of option value, discount rate, and learning. Trends are consistent: decreases in capital cost, discount rate, or noise or increases in the stream of returns lead to lower trigger values for investing in AD

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<sup>11</sup> Adoption rates in the first period are the same for constant and diminishing marginal benefits of learning cases because the same firms adopt when learning has yet to take place. In subsequent periods, adoption rates are higher for diminishing marginal benefits of learning because early adopters provide more information than later adopters while the total amount of information available to learners remains constant across cases.

technology; learning spillovers lead to lower trigger values after early adopters implement the new technology. Although not specifically calibrated to the current dairy AD adoption rate of six percent of dairies with more than 500 cows, the model scenario that would approach the observed adoption rate would have high capital cost, low environmental valuation, and learning spillovers.

With other parameters held constant, increasing capital cost from \$2,800 per head to \$5,000 per head leads to a decrease in adoption rates from 100 percent to 25 percent in the case of learning. Of particular importance is the effect of the farmer's subjective valuation of environmental benefits of AD. With other parameters held constant, increasing scaled expected environmental valuation from \$0 per head to \$254 per head per year, both of which values are within the range of the survey data, leads to an increase from 44 percent to 100 percent adoption in the case of learning.

A key finding is the importance of determining the value of learning spillovers when considering adoption of new technologies. Learning spillovers consistently induce adoption by causing decreases in the adjusted trigger value. The impact of learning on adoption rates can be quite large, increasing adopters by as much as an additional two-thirds compared to the no-learning case. Learning spillovers also generally lead to cascading adoption, where adopters in one period produce an effect large enough to induce another set of adopters in later periods. Without learning, adoption is static – those who adopt do so in the first period.

This study also confirms what other studies have found regarding the inadequacy of NPV in signaling adoption when investment is irreversible and returns are uncertain. The average value of waiting to invest is \$35 to \$74 per head per year in the learning with diminishing marginal benefits and no-learning cases, respectively, or 12 to 26 percent of the Marshallian

trigger value,  $M$ . We demonstrate that under conditions where learning takes place, the adjusted trigger is reduced toward the Marshallian trigger through the information that early adopters share.

These results inform policy makers' consideration of conditions under which green technology will be adopted by firms as well as where policy instruments can best be applied to induce adoption. Capital cost subsidies, more reliable markets for energy obtained from recovered methane, and development of carbon markets all appear to contribute to AD adoption. Additionally, government support of education concerning the benefits of AD or strengthening environmental policy may be important to inducing higher adoption among firms by increasing their environmental valuations. Importantly, programs used to encourage AD adoption should include requirements to share information if policy makers are interested in widespread adoption, because without learning spillovers from early adopters, there are few later adopters.

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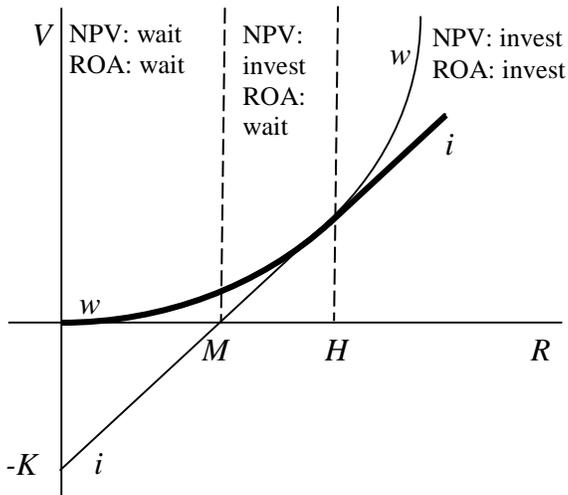
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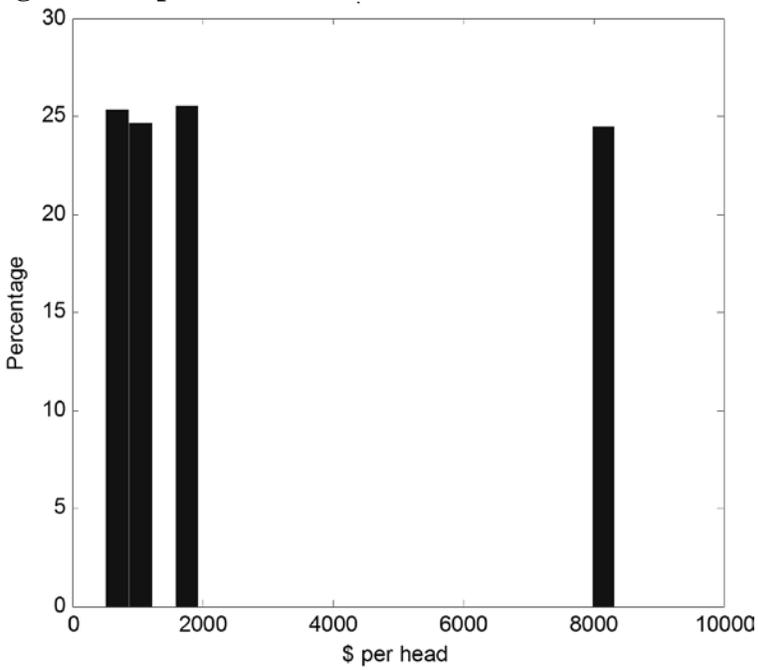
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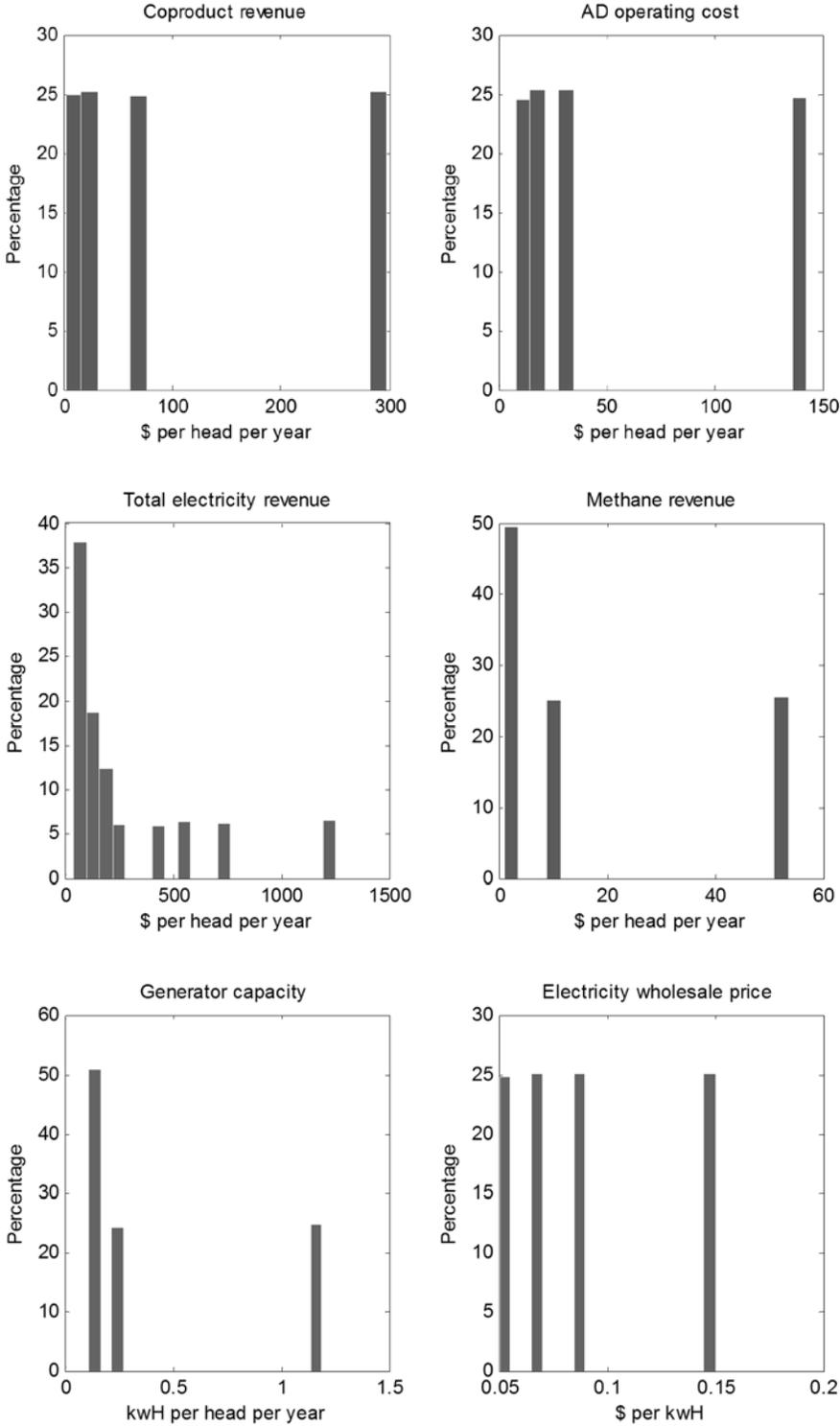
**Figure 1. Firm choice curves: wait ( $w$ ) or invest ( $i$ ).**



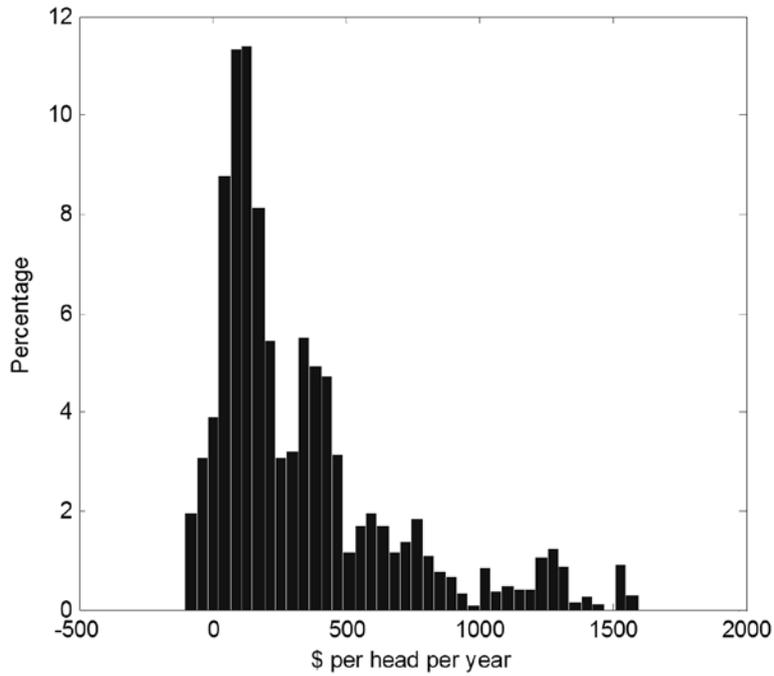
**Figure 2. Capital cost distribution.**



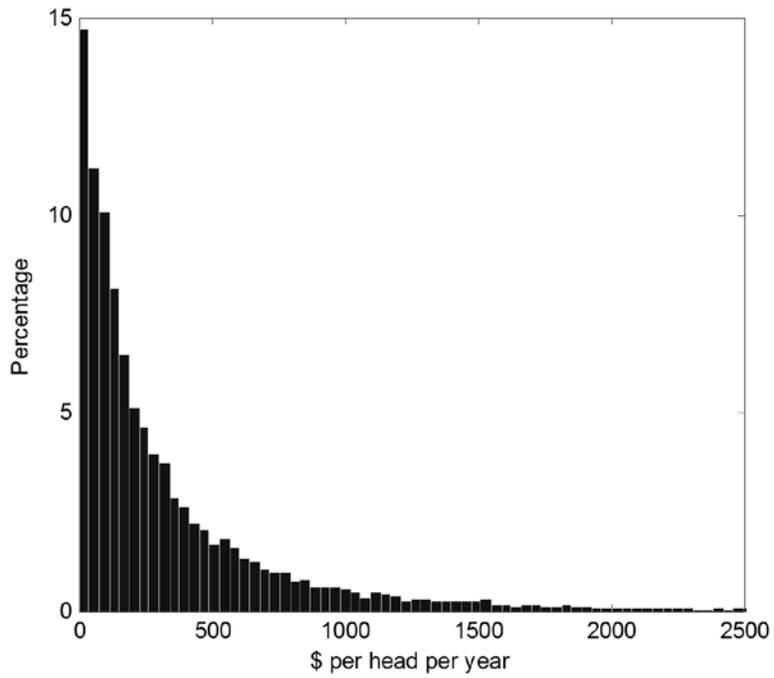
**Figure 3. Components of the net revenue distribution.**



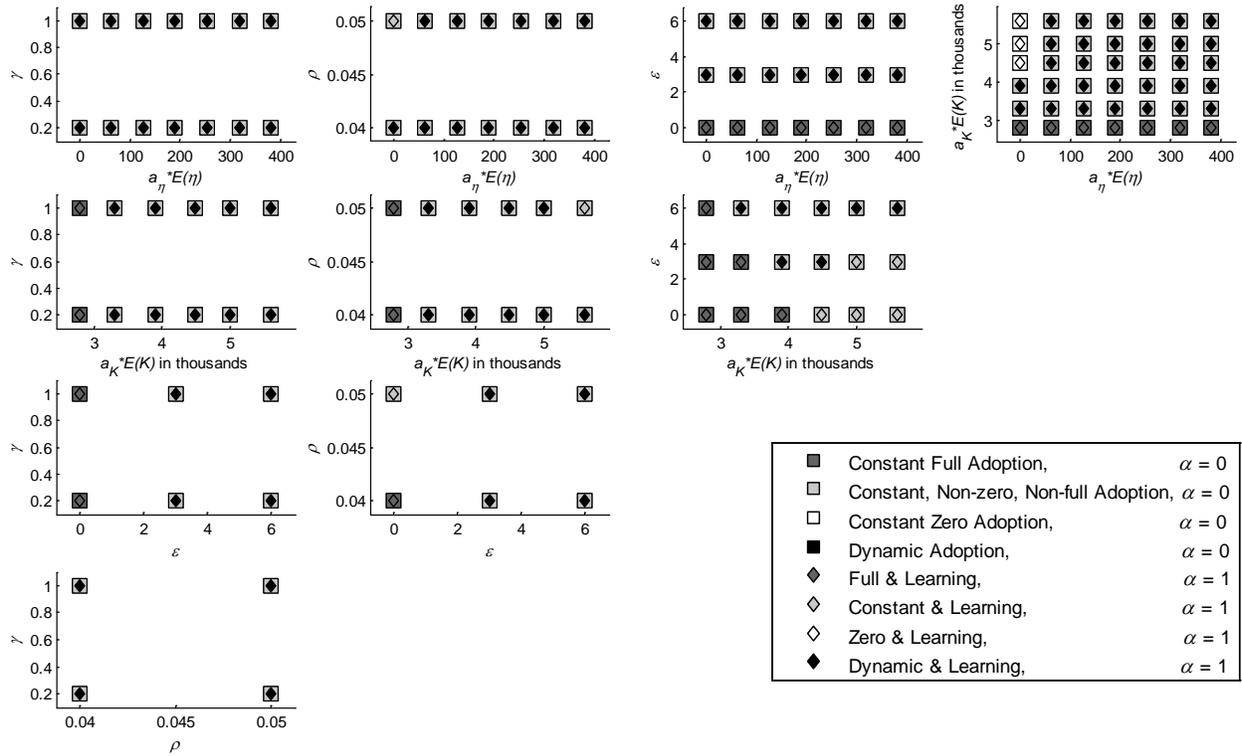
**Figure 4. Net revenue distribution.**



**Figure 5. Environmental valuation distribution.**

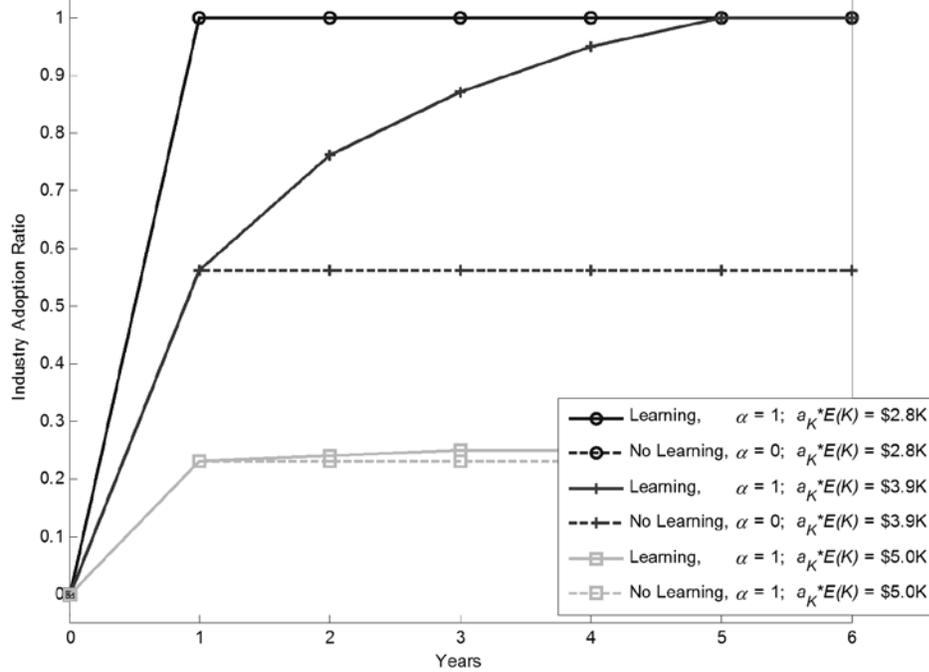


**Figure 6. Categorized adoption patterns.<sup>a</sup>**



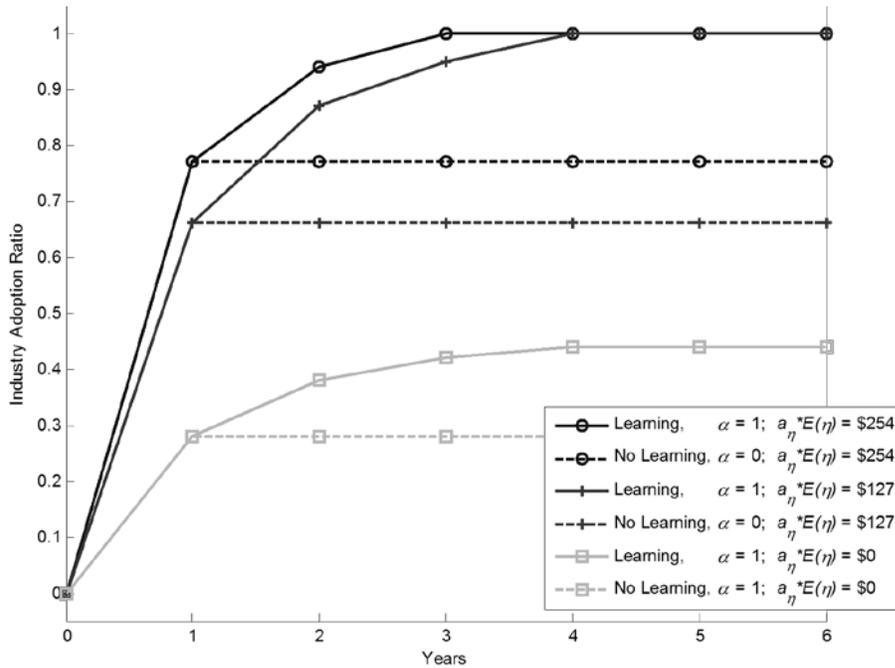
<sup>a</sup> Parameters not shown on the axes are held constant with scaled capital cost,  $a_K * E(K) = \$3,900$  per head; scaled expected environmental valuation,  $a_\eta * E(\eta) = \$63$  per head per year; noise,  $\varepsilon = 6$ ; discount rate,  $\rho = 0.04$ ; and constant marginal benefits of learning,  $\gamma = 1.0$ .

**Figure 7. Adoption curves for different capital costs,  $a_K * E(K)$ .<sup>a</sup>**



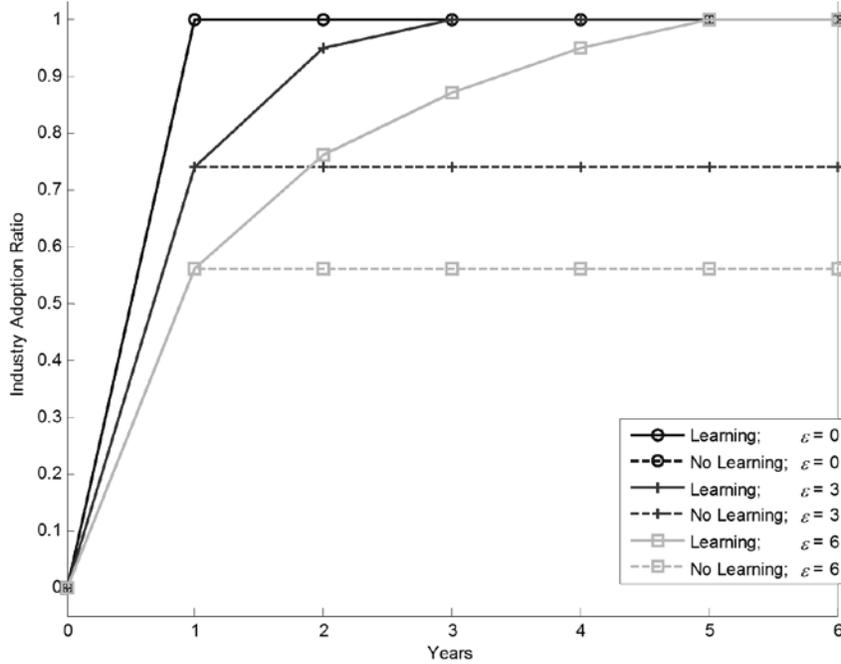
<sup>a</sup> Parameters held constant with scaled expected environmental valuation,  $a_\eta * E(\eta) = \$63$  per head per year; noise,  $\varepsilon = 6$ ; discount rate,  $\rho = 0.04$ ; and constant marginal benefits of learning,  $\gamma = 1.0$ .

**Figure 8. Adoption curves for different environmental valuations per head per year,  $a_\eta * E(\eta)$ .<sup>a</sup>**



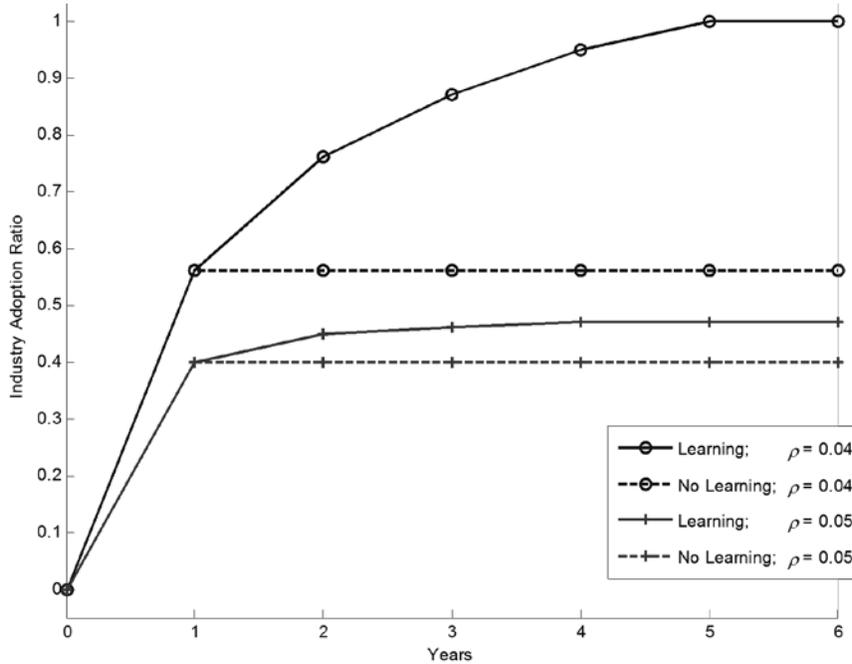
<sup>a</sup> Parameters held constant with scaled capital cost,  $a_K * E(K) = \$3,900$  per head; noise,  $\varepsilon = 6$ ; discount rate,  $\rho = 0.04$ ; and constant marginal benefits of learning,  $\gamma = 1.0$ .

**Figure 9. Adoption curves for different noise values,  $\varepsilon$ .<sup>a</sup>**



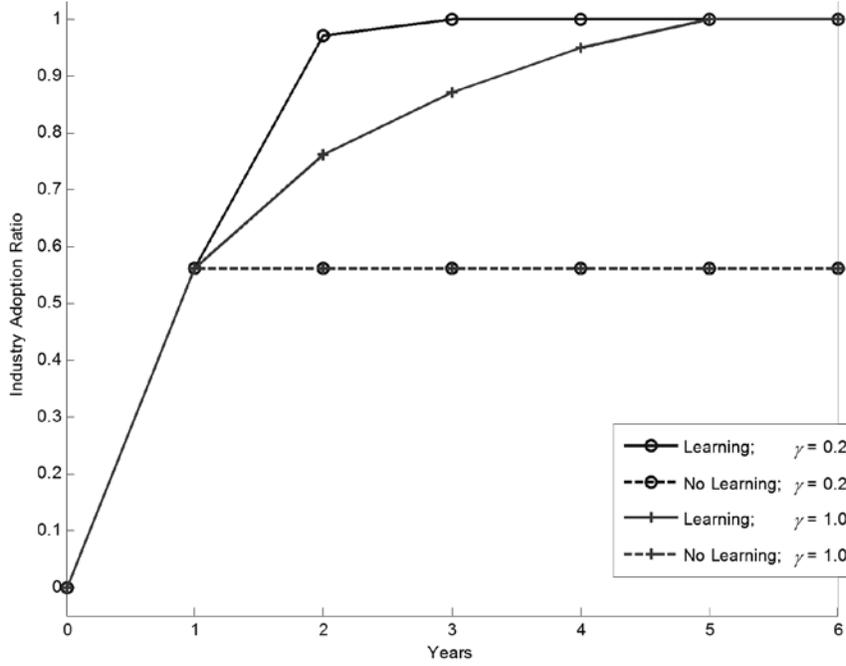
<sup>a</sup> Parameters held constant with scaled capital cost,  $a_K * E(K) = \$3,900$  per head; scaled expected environmental valuation,  $a_\eta * E(\eta) = \$63$  per head per year; discount rate,  $\rho = 0.04$ ; and constant marginal benefits of learning,  $\gamma = 1.0$ .

**Figure 10. Adoption curves for different discount rates,  $\rho$ .<sup>a</sup>**



<sup>a</sup> Parameters held constant with scaled capital cost,  $a_K * E(K) = \$3,900$  per head; scaled expected environmental valuation,  $a_\eta * E(\eta) = \$63$  per head per year; noise,  $\varepsilon = 6$ ; and constant marginal benefits of learning,  $\gamma = 1.0$ .

**Figure 11. Adoption curves for constant and marginal benefits of learning,  $\gamma$ .<sup>a</sup>**



<sup>a</sup> Parameters held constant with scaled capital cost,  $a_K * E(K) = \$3,900$  per head; scaled expected environmental valuation,  $a_\eta * E(\eta) = \$63$  per head per year; noise,  $\varepsilon = 6$ ; and discount rate,  $\rho = 0.04$ .

**Table 1. Distributional data from anaerobic digester survey.**

Name	Units	25 <sup>th</sup> Percentile	Median	75 <sup>th</sup> Percentile	Maximum	N
Total capital cost	\$ per head	\$523	\$912	\$1671	\$8333	56
Generator capacity	kWH	0.11	0.16	0.26	1.19	56
Sell electricity to grid?	Yes = 1, no = 0	1	1	1	1	47
Electricity retail price	\$ per kWh	\$0.07	\$0.09	\$0.11	\$0.17	44
Revenue from methane (excluding electricity)	\$ per head per year	\$0.89	\$3.19	\$10.98	\$53.57	56
Coproduct net value	\$ per head per year	\$1.82	\$25.89	\$63.14	\$297.62	56
Operating cost	\$ per head per year	\$7.81	\$17.66	\$29.67	\$142.86	56
Scale: 1 = most important, 9 = least important				Mean	Variance	N
Importance of “environmental stewardship and sustainability”				3.82	1.45	50
Importance of “sell surplus methane and other co-products”				2.8	2.07	50

*Source:* Cowley (2014).

**Table 2. Parameter values held constant across simulations.**

Constant	Name	Constant across all scenarios
$E(K)$	Capital cost per head	\$2,800
$E(R)$	Expected net revenue per head per year	\$337
$E(\eta)$	Expected environmental valuation per head per year	\$318
$J$	Number of firms	100
$n$	Investment lifetime, years	20
$T$	Periods in simulation	6
$v$	Monte Carlo iterations	20,000

**Table 3. Parameters that vary across simulations.**

Parameter	Name	Values across scenarios (1,008 combinations)						
$a_K$	Capital cost scale	1.0	1.2	1.4	1.6	1.8	2.0	
$a_\eta$	Environmental valuation scale	0	0.2	0.4	0.6	0.8	1.0	1.2
$\varepsilon$	Noise scale	0	3	6				
$\rho$	Discount rate	0.04	0.05					
$\alpha$	Learning case	0	1					
$\gamma$	Benefits of learning	0.2	1.0					

**Table 4. Average trigger values across firms and time.<sup>a</sup>**

Parameter	Name	Equation	Marshallian			
			$\alpha$ is N/A,	$\alpha = 0,$	$\alpha = 1,$	$\alpha = 1,$
					$\gamma = 1.0,$	$\gamma = 0.2,$
			$Var(R_{\eta_j})$ →\$0	$Var(R_{\eta_j}) =$ \$123,810	$Var(R_{\eta_j}) =$ \$123,810	$Var(R_{\eta_j}) =$ \$123,810
$E(\sigma_{jta}^2)$	Variance of option value	(13)	→0	0.0217	0.0090	0.0066
$\beta/(\beta-1)$	Discount rate scale	(6)	→1	1.67	1.40	1.33
	Trigger value	(17)	\$287	\$361	\$329	\$322
	Trigger name		M	H	H	H

<sup>a</sup> For scenarios with scaled capital cost,  $a_K * E(K) = \$3,900$  per head; expected net revenue,  $E(R_{\eta_j}) = \$337$  per head per year; scaled expected environmental valuation,  $a_{\eta} * E(\eta) = \$63$  per head per year; discount rate,  $\rho = 0.04$ ; and noise scale  $\varepsilon = 6$ .