Understanding Adoption of Livestock Health Management Practices: The Case of Bovine Leukosis Virus

Benjamin M. Gramig,[1] Christopher A. Wolf[2] and Frank Lupi[3]

[1]*Assistant Professor, Department of Agricultural Economics, Purdue University, 564 Krannert Bldg, West Lafayette, IN 47907 (corresponding author: phone: 765-494-4324; fax: 765-494-9176; e-mail: bgramig@purdue.edu).*
[2]*Professor, Department of Agricultural, Food, and Resource Economics, Michigan State University, 317A Agricultural Hall, East Lansing, MI 48824-1039 (phone: 517-353-3974; fax: 517 432-1800; e-mail: wolfch@msu.edu).*
[3]*Professor, Department of Agricultural, Food, and Resource Economics, Michigan State University, 301B Agricultural Hall, East Lansing, MI 48824 (phone: 517-432-3883; fax: 517 432-1800; e-mail: lupi@msu.edu).*

Herd-level livestock health management decisions have implications for farm profitability and the potential public impact of a livestock disease outbreak. Thus, adoption of health management practices is of interest to government officials concerned with managing the risk of disease outbreak and controlling the spread of infection. This paper uses a fractional logit model to estimate the disease risk reduction for livestock health management practices on farms, and then uses the economic benefits of these risk reductions as explanatory variables in an econometric model of adoption of these practices. We find that the economic damages from disease associated with a particular practice are statistically significant but ultimately of little practical economic importance in adoption decisions. Implications for policy and relation to prior research findings are discussed.

Les décisions entourant la gestion sanitaire du troupeau ont des répercussions sur la rentabilité des fermes et sur l'impact qu'une éclosion de maladies animales pourrait avoir sur la population. Par conséquent, l'adoption de pratiques de gestion sanitaire intéresse les représentants du gouvernement soucieux de gérer le risque d'éclosion de maladies et de maîtriser la propagation d'une infection. Dans le présent article, nous avons utilisé un modèle logit fractionnaire pour estimer la diminution du risque de maladies lorsque des pratiques de gestion sanitaire du troupeau sont adoptées à la ferme et nous avons ensuite utilisé les avantages économiques de cette diminution du risque comme variables explicatives dans un modèle économétrique d'adoption de ces pratiques. Les résultats ont montré que les dommages économiques liés aux maladies associées à une pratique en particulier sont statistiquement significatifs, mais qu'ils sont finalement sans importance économique dans les décisions d'adoption. Nous avons examiné les répercussions sur la politique agricole et avons fait le lien avec des résultats de recherche antérieurs.

INTRODUCTION

Herd-level livestock health management decisions have implications for farm profitability and have the potential to impact livestock disease outbreaks. Thus, adoption of health management practices is of interest to both farm managers and government officials concerned with managing disease outbreak risk and controlling the spread of infection. Making informed private economic decisions about adoption of disease management

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practices requires information about the production effects of disease, the impact of the management practices on the level of infection, and the market prices for inputs and outputs. This paper estimates the disease prevalence reduction associated with various livestock health management practices, and then uses the economic benefits of these reductions to explain adoption of effective practices.

The prior economic literature on livestock disease management has largely focused on either the efficient use of resources at the farm level (McInerney et al 1992; McInerney 1996; Chi et al 2002a, 2002b) or the costs of disease at the level of a country or economic sector (Buhr et al 1993; Bennett et al 1999; Bennett 2003; Bennett and Ijpelaar 2005). Our research is related to the former of these, but is distinct in its focus on understanding private disease management choices. Previous research on private disease management decisions has established a sound conceptual foundation for calculation of the total private economic cost of disease (McInerney et al 1992) and the effect of disease on the livestock production function (McInerney 1996). Although our research complements these efforts, we do not take the prescriptive approach that has been the focus of the aforementioned work. Instead, we make a contribution by investigating the factors that influence biosecurity and health management practice adoption. This information is of interest to policy makers and researchers alike because it provides evidence about how output losses from disease and other factors influence observed management choices.

Despite the broad attention given to adoption of innovations, technology, and conservation practices by agricultural economists to date (see, e.g., Feder et al 1985; Besley and Case 1993; Zepeda 1994; Zepeda et al 2003; Pannell et al 2006; Amsalu and de Graff 2007; Marenya and Barrett 2007), our focus on adoption behavior is unique in the literature dealing with livestock disease management. Within the context of the larger literature on adoption, this article focuses on one of the two key drivers of adoption or nonadoption identified by Pannell et al (2006): the relative advantage of a practice defined as "the degree to which an innovation is perceived as being better than the [practice] it supersedes" (Rogers 2003, p. 229 cited in Pannell et al 2006). Distinct from temporal studies of agricultural technology adoption that are found in the literature, this research fits into the cross-sectional category (e.g., Shapiro et al 1992 and Smale et al 1994) identified by Marra et al (2003).

Our empirical application is to dairy herd disease management, which has previously been the focus of prescriptive economic research by McInerney et al (1992) dealing with mastitis in the United Kingdom and by Chi et al (2002a, 2002b) studying four different diseases in the Canadian maritime provinces. One distinction between our work and Chi et al (2002a, 2002b) is that the data used in our empirical application represents a more diverse and commercially significant segment of the dairy industry in North America. This article makes three principal contributions to the economics of livestock health management literature: (1) it is the first work the authors are aware of that empirically examines the determinants of health management practice adoption; (2) it investigates the association between disease prevalence and veterinarian recommended disease-specific management practices, as opposed to general biosecurity and health management practices considered previously (Chi et al 2002b); and (3) it proposes the fractional logit model as an alternative econometric method for the estimation of herd-level disease control functions to quantify the effect of individual management practices on disease.

McInerney et al (1992) provided a conceptual foundation for the economic analysis of farm-level livestock disease based on economic efficiency. Their concept of the "loss-expenditure frontier" identifies the level of disease loss achievable at the lowest possible cost and was subsequently integrated with a model of the effects of disease on the livestock production function by McInerney (1996). Chi et al (2002b) utilized this theoretical framework to examine the relationship between management practices and disease on dairy farms in the Canadian Maritime Provinces and to determine the cost minimizing allocation of resources to control disease. This thread of research activity is inherently prescriptive in nature; based on what is economically efficient, it prescribes the optimal employment of animal health inputs. The current article draws on the same theoretical developments but extends this framework to model farmers' adoption behavior for specific management practices. Because the prior literature forms the basis for our theoretical framework, we begin by briefly reviewing the basic model of livestock disease control via the production function following the development in Chi et al (2002b). We then depart from the familiar marginal conditions for continuous input use and provide a discrete model of adoption based on the profit from adopting a binary practice relative to not adopting.

McInerney et al (1992) described the economic cost of disease as the sum of output losses from infection and disease control expenditures. Control expenditures include prevention (*ex ante*) and treatment (*ex post*) costs of disease. Their framework illustrates two key concepts: first, that there exists a trade-off between prevention and control expenditures, and second, that there are diminishing returns to control expenditures. One implication of diminishing returns is that it will not generally be economically optimal to prevent all expected losses from disease (Dijkhuizen et al 1995; Wolf 2005).

The primary objective of this research is to demonstrate a novel empirical approach that can be used to gain a better understanding of the determinants of livestock health management practice adoption. We proceed by first presenting a theoretical model of health management practice adoption that links the theoretical formulations in the literature that precede it (McInerney et al 1992; Chi et al 2002b) to farmer adoption of individual health management practices. The article continues by presenting the empirical methods for the two-stage econometric procedure to estimate a disease control function followed by an adoption equation. An empirical application section describes the U.S. Department of Agriculture (USDA) National Animal Health Monitoring System (NAHMS) data used to investigate bovine leukosis virus (BLV) on dairy farms. BLV is a blood borne disease that causes some cows to develop tumors in the uterus or other vital organs (New York State Cattle Health Assurance Program (2002) denoted NYSCHAP). BLV is spread by transferring blood or other body fluids through, for example, contaminated needles. BLV can have a serious economic impact on infected herds and many best management practices to control or prevent the disease have been developed for farm managers (NYSCHAP). The next section describes the empirical models followed by the estimation results for each of the two stages.

THEORETICAL MODEL OF ADOPTION BEHAVIOR

Given our objective of understanding the determinants of the adoption of health management practices, we consider herd-level economic decision making based on the profit function

$$\pi = P_Q Q(\mathbf{R}, \mathbf{K}, D) - \mathbf{P_V V_p} = P_Q\{Q_0[1 - F(D(\mathbf{V_p}))]\} - \mathbf{P_V V_p} \tag{1}$$

where P_Q is the market price of livestock output Q (e.g., kilograms of milk, live animal weight), which is a function of variable inputs $\mathbf{R}$, fixed inputs $\mathbf{K}$, and the level of disease D. Disease level $D \in [0,1]$ is the within-herd prevalence of disease and is denoted by the function $D(\mathbf{V_p}, \mathbf{R})$, where variable inputs and a $K \times 1$ vector of disease prevention inputs, $\mathbf{V_p}$, determine the level of infection. Disease is such that $D(0) \geq D(\mathbf{V_p})$ whenever $\mathbf{V_p}$ contains at least one nonzero element. The K individual elements of $\mathbf{V_p}$ are denoted v_k and operate as "damage control inputs" to the production function, as discussed in Chi et al (2002b). In general, disease control inputs may be continuous (e.g., $v_k \in [0,\infty]$), but a majority of these inputs are binary (e.g., $v_k \in \{0,1\}$) in nature, and this is the case in our empirical application. We will refer to such inputs as health management practices and suppress the variable and fixed inputs in the livestock production process in what follows because of our focus on disease outcomes and adoption of v_k. $\mathbf{P_V}$ is a $1 \times K$ vector of disease control input prices that correspond to the disease control inputs in $\mathbf{V_p}$.

The damage control relationship between $\mathbf{V_p}$ and D influences the livestock production function Q through the "damage function" (Chi et al 2002b) $Q = Q_0\{1 - F[D(\mathbf{V_p})]\}$, where Q_0 is the disease-free output level and $F(D) \in [0,1]$ is the proportion of disease-free output lost as a function of prevalence, such that $Q = Q_0$ ($Q < Q_0$) in the disease-free (diseased) state because $F(0) = 0$ ($0 < F(D) \leq 1 \forall\ D \in (0,1]$). The function $F(D)$ maps disease prevalence to the production outcome.

The decision to adopt an individual binary practice v_k hinges on the relative magnitude of profits when a farm adopts practice k, $\pi(v_k) = \pi_k^A$ and when it does not adopt, $\pi(0) = \pi_k^{NA}$, holding all other practices in $\mathbf{V_P}$ constant. A farmer will adopt v_k whenever

$$\pi_k^A \geq \pi_k^{NA} \tag{2}$$

For binary practice v_k, Equation (2) can be rewritten using Equation (1), $D(v_k = 1) = D(1)$, and $D(v_k = 0) = D(0)$ as

$$P_Q\{Q_0[1 - F(D(1))]\} - P_k v_k \geq P_Q\{Q_0[1 - F(D(0))]\} \tag{3}$$

which can be rearranged and written as

$$P_Q Q_0[F(D(0)) - F(D(v_k))] \geq P_k \quad \forall\ v_k = 1 \tag{4}$$

Only when the difference in the return from adoption of binary preventive health management practice v_k is greater than its cost will farmers adopt the practice. Note that when examining a single practice v_k, all other practices in $\mathbf{V_P}$ are evaluated at the same level (a *ceteris paribus* condition) in Equation (4). This description of the decision to adopt a single binary practice is consistent with the marginal criterion for economically optimal employment of health management practices (Chi et al 2002b).

Because disease control effectiveness of individual health management practices is clearly at the core of the adoption decision that follows from Equation (4), farmers are assumed to have knowledge about the effectiveness of the K damage control inputs implied by $F(D(v_k))$ in the "damage function" (Chi et al 2002b) at the core of livestock production. Implicit in Equation (4) is the assumption that farmers are economically rational and only adopt practices that effectively yield disease prevention that avoids costly output losses. Suppressing the argument in D and taking the function $F(D)$ as given, this means that adoption of binary v_k is fundamentally dependent on the prevalence of disease D. Therefore, the empirical relationship between management practice adoption and herd disease prevalence is required in order to assess the "relative advantage" of an individual practice (given by Equation (4) in our theoretical model) which has previously been identified as a key driver of adoption of management practices by farmers (Rogers 2003, p. 229 cited in Pannell et al 2006).

EMPIRICAL METHODS

In the context of our theoretical model, understanding health management practice adoption by livestock farmers requires an empirical approach capable of explaining the decision in Equation (4), which is based on knowledge of the underlying disease control relationship between v_k and D. We therefore require empirical methods capable of estimating (i) the disease control relationship between individual practices and herd prevalence, and (ii) the binary decision to adopt a practice that is a function of disease control effectiveness and other factors. Because adoption is a function of disease control, the disease control relationship must be established before the adoption decision can be modeled.

Disease Control Function

To estimate the effect of individual management practices on disease, we take as our dependent variable within-herd prevalence of disease $D_h \in [0,1]$, where $h = 1 \ldots H$ indexes herds. In prior economic research focused on selecting optimal control strategies, a disease control function was estimated according to the Tobit model (Chi et al 2002b). Shapiro et al (1992) also used the Tobit model to investigate the rate of adoption of double-cropping of soybeans and wheat. The ability of the Tobit model to handle excess zero observations seems appropriate, but because the range of the dependent variable is limited to the unit interval and the standard Tobit model does not ensure such fitted values, an alternative model is desirable (Wooldridge 2002).

We adopt the fractional logit model as an econometric procedure for analysis of limited-dependent variables that are continuous in the unit interval, which ensures non-negative estimates within the unit interval, and can handle a large number of zero observations (Papke and Wooldridge 1996; Wooldridge 2002). This model is identical to the familiar logit model for binary outcomes, except that it allows for the dependent variable to take on any value in the unit interval and not just the boundary values 0 and 1. The fractional response model takes the form,

$$E(D_h|\mathbf{z}) = G(\mathbf{z}\boldsymbol{\gamma}) \tag{5}$$

where $G(\,)$ is the c.d.f. of the logistic distribution, $\mathbf{z}$ is a vector of explanatory variables that influence the level of disease, and $\boldsymbol{\gamma}$ is a vector of coefficients.

Fractional logit regression (Papke and Wooldridge 1996) is a quasi-maximum likelihood method based on the work of Gourieroux et al (1984) and McCullagh and Nelder (1989), which utilizes the Bernoulli log-likelihood function

$$L(\boldsymbol{\gamma}) = \sum_{h=1}^{H} \{D_h \ln[G(\mathbf{z}\boldsymbol{\gamma})] + (1 - D_h) \ln[1 - G(\mathbf{z}\boldsymbol{\gamma})]\} \tag{6}$$

for sample size H, which is well defined for $0 < G() < 1$. This log-likelihood function is identical to that used in standard maximum likelihood estimation of binary response index models except for the fractional nature of the dependent variable. Because Equation (6) is a member of the linear exponential family of distributions, the quasi-maximum likelihood estimator $\hat{\boldsymbol{\gamma}}$ is consistent for $\boldsymbol{\gamma}$ when Equation (5) holds regardless of the true conditional distribution of D_h (Gourieroux et al 1984). The normal R^2, calculated as the square of the correlation coefficient between the estimated and observed prevalence, is the recommended goodness-of-fit measure to report for the fractional logit method (Papke and Wooldridge 1996).

A disease control function can be estimated according to the model in Equation (5). When the model regressors, $\mathbf{z}$, include K management practices $\mathbf{V_p} = [v_1, \ldots, v_k, \ldots, v_K]$ recommended by veterinarians, the model can be used to derive estimates of the marginal effect of adopting a single practice v_k on herd disease prevalence D_h. Knowledge about the relationship between disease level and output, embodied in $F(D)$ from the damage function, comes from production analysis or animal health research. The change in revenue associated with adopting a particular practice is derived by combining a known production relationship, market prices, and the estimated marginal effect (the fractional response of prevalence to adoption of v_k) from Equation (5). Thus, our theoretical model of adoption suggests a two-stage estimation procedure: first, estimate a disease control function to obtain information about the effectiveness of recommended disease management practices, and second, estimate adoption based on the revenue implications of the practice as derived from its estimated effectiveness.

Health Management Practice Adoption

For the second stage adoption behavior, consider a binary practice $v_k \in \{0,1\}$,

$$v_k = \begin{cases} 1 & \text{if } P_Q Q_0[F(D(0)) - F(D(1))] - P_k > 0 \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

Empirical analysis of the determinants of adoption according to Equation (7) requires data on market prices for inputs and outputs, as well as production functions for individual farms. These data are not often readily available or observable, thus we propose estimating adoption equations for binary practices using a latent variable approach (Wooldridge 2002), where the underlying latent variable of interest is

$$y^* = P_Q Q_0[F(D(0)) - F(D(1))] - P_k + e \tag{8}$$

and e is a continuously distributed variable independent of the other right-hand side terms, the distribution of which is symmetric about zero. Generally we are able to observe adoption of practice v_k but not the values of all the individual variables that determine y^*. Instead, observations on v_k indicate the sign of y^* according to

$$v_k = \begin{cases} 1 & \text{if } y^* > 0 \\ 0 & \text{if } y^* \leq 0 \end{cases} \tag{9}$$

The formulation in Equation (9) leads to the familiar binary response modeling framework, where we seek to explain the relationship between a vector of herd-specific explanatory variables $\mathbf{x}$ and the probability of adoption.

The fact that y^* may not be observable or have a well-defined unit of measurement means that other observable explanatory variables must populate $\mathbf{x}$ if we are to estimate an adoption equation according to Equation (9). Equation (7) indicates that adoption is a function of output losses, $P_Q Q_0[F(D(0)) - F(D(1))]$. In many situations, including our own, data collected for the purposes of animal health monitoring will contain herd-level data on disease prevalence and management practice adoption. These kind of data allow for the estimation of a disease control function, $D(\mathbf{V_p})$, that can be used with information about the production effects of disease, $Q_0F(D)$, and market prices for livestock products, $P_{Q,}$ to estimate the economic damages avoided by adopting an individual practice. With such data, we are able to compute the $P_Q Q_0[F(D(0)) - F(D(1))]$ component of the latent variable in Equation (8), which is a key determinant of the economic decision to adopt in our theoretical model. The information necessary to construct an economic estimate of benefits from adoption is likely available from price data and animal science or veterinary health professionals, so that the economic researcher need only estimate the relationship between adoption and herd-level prevalence in order to obtain an estimate of disease damages avoided to include as an explanatory variable in the adoption index in Equation (8).[1]

EMPIRICAL APPLICATION TO BLV IN DAIRY CATTLE

Data for our empirical application come from the 1996 NAHMS survey of dairy cattle conducted by the USDA's National Agricultural Statistics Service and Animal and Plant Health Inspection Service (APHIS).[2] The sample includes 973 observations selected from the top 20 dairy producing states and represents over 75,000 herds nationwide. Among the objectives that motivate the NAHMS survey is the estimation of prevalence for a given disease and species at the level of the national herd. Survey data include extensive farm-level behavioral information, such as animal inventory and operational characteristics, health management and biosecurity practices, feeding and manure management practices, and livestock morbidity, mortality, and culling details. The details of the NAHMS survey design are enumerated elsewhere (Ott et al 2003). Statistical analysis must take the complex random stratified sampling procedure into account for correct statistical inference when working with NAHMS data (Dargatz and Hill 1996; Lohr 1999; Lee and Forthofer 2006). We account for survey design effects throughout the statistical analysis that follows with the Stata statistical package's (StataCorp 2007) suite of survey commands that facilitate use of survey weights and finite population corrections that accompany NAHMS data.

To demonstrate our two-stage estimation procedure we focus on the production disease BLV, also referred to as bovine leukemia or enzootic bovine leucosis, which has previously been studied both in veterinary epidemiology (see, e.g., DiGiacomo et al 1985; DiGiacomo et al 1986; Heald et al 1992; Rhodes et al 2003b) and economic decision-making studies (Pelzer 1997; Chi et al 2002a, 2002b; Ott et al 2003; Rhodes et al 2003a). BLV is a retrovirus that primarily affects lymphoid tissue of cattle and causes malignant lymphoma and lymphosarcoma (LS), although leukemia is not a common finding, occurring in only 2–5% of BLV infected cows (Kirk 2000). BLV is horizontally transferred within blood lymphocytes, but it is uncertain whether or not it is transmitted vertically *in utero*. Economic losses to dairy farmers associated with BLV result from reduced milk production, increased replacement costs, and increased veterinary costs (Pelzer 1997). Because it is transmissible, the only way to eliminate losses from a herd is to cull all infected animals and routinely test new animals introduced to the herd to ensure the farm remains BLV free. Pelzer (1997) and Rhodes et al (2003b) have pointed out the important difference between the economic effect of clinical LS and subclinical level infection (BLV seropositive status). Our data examine BLV seropositive animals (those found to have antibodies to BLV in their blood), for which one estimate found that "a basic BLV control program may be economically beneficial in herds in which the prevalence of BLV infection is (greater than or equal to) 12.5%" (Rhodes et al 2003a, p. 346).

Summary statistics for the continuous and binary variables from the 1996 NAHMS dairy survey are reported in Table 1. The survey design effect illustrates the importance of accounting for the complex survey design when working with NAHMS data. The mean within-herd BLV prevalence was 40%, and 88% of all dairy herds had at least one seropositive cow (not reported in Table 1). A majority of farms sampled are in the Midwest (61%), which is reflective of the dairy industry. Only 13% of farms participate in the Milk and Dairy Beef Quality Assurance (MDBQA) program that involves implementation of a Hazard Analysis of Critical Control Points (HACCP) program for food safety, while 51% of farms are members of the Dairy Herd Improvement Association (DHIA), which tests and records cow milk production performance to facilitate management decisions. Additional binary variables reported in Table 1 are recommended health management practices for the control of BLV and are adopted by a percentage of farms that varies widely across practices from 7% to 98% in the sample.

Empirical Model of Disease Control Function and Estimation Results

In our application, livestock disease D in herd h, is the within-herd BLV prevalence and $\mathbf{z}$ includes disease-specific management practices recommended by veterinarians (Kirk 2000; Rhodes et al 2003a), herd size, and state-level dummy variables to control for spatial heterogeneity in the cross-sectional data. Management practices include the use of a dehorning method that minimizes the opportunity for exposure of uninfected animals to BLV (*dehorn_safe*), using milk replacer instead of natural nursing until weaning (*nonurse*), quarantining any new animals introduced to the herd (coded as *noquarantine* for when this practice is not followed), single use or sterilization of needles to administer injections (*cleaninject*), using different obstetrical sleeves on each individual animal (*new_sleeve*), insect control to reduce possibility of transmission between animals via an arthropod vector (*fly_control*), and tattooing (*tattoo*) that is discouraged for animal identification purposes because of the possibility of transmitting infected blood lymphocytes. In order to control for history of disease on the farm (which may or may not have been BLV), we included a binary variable indicating whether or not animals were culled from the herd because of disease (*cull_disease*).[3] Wisconsin was used as the reference or base for the

Table 1. Weighted NAHMS dairy 1996 sample statistics for BLV

	Mean	Std. err.	Design effect[a]
CONTINUOUS VARIABLES			
Within-herd BLV prevalence (seropositive animals)	0.399	0.011	1.55
Herd size	201	5.889	0.14
Average annual milk production (kilograms/cow)	7933	62.221	1.54
BINARY VARIABLES			
Midwest region	0.61	0.004	0.07
Southeast region	0.08	0.002	0.04
Northeast region	0.26	0.004	0.09
West region	0.04	0.002	0.07
Safe dehorning method	0.45	0.020	1.57
Colostrum not received via natural nurse	0.55	0.019	1.40
Cattle introduced to herd not quarantined	0.44	0.021	1.79
Clean injection of heifers (<24 months old)	0.07	0.009	1.40
Individual use obstetrical sleeves	0.16	0.015	1.66
Fly control practiced on farm	0.98	0.005	1.07
Tattooing for animal ID	0.08	0.010	1.31
Animals culled from herd because of disease (>0)	0.17	0.015	1.55
MDBQA (HACCP) participation	0.13	0.011	1.07
DHIA	0.51	0.019	1.49

Notes: n = 973 herds drawn from the top 20 dairy producing states, represent 75,309 herds or 80% of sector. Sample summary statistics calculated using Stata svymean procedure (StataCorp 2007) to account for complex survey design.
[a]Statistic = (Variance taking survey design into account/variance assuming a simple random sample).

location dummy variable, as it accounted for the largest number of observations among the 20 states represented in the NAHMS data.

The disease control function we estimated according to the model in Equation (5) took the form

$$\begin{aligned} E(BLV_h|\mathbf{z}) = \Lambda(&\gamma_0 + \gamma_1\, dehorn\_safe + \gamma_2\, nonurse + \gamma_3\, noquarantine \\ &+ \gamma_4\, cleaninject + \gamma_5\, new\_sleeve + \gamma_6\, fly\_control + \gamma_7\, tattoo, \\ &+ \gamma_8\, cull\_disease + \gamma_9\, herdsize + \gamma_{10}\, state1 + \cdots + \gamma_{28}\, state19) \end{aligned} \tag{10}$$

where $\Lambda()$ is the c.d.f. of the logistic distribution in the fractional logit model and maps $\mathbf{z\gamma}$ into the fractional outcome BLV_h.[4] We hypothesized that the sign of the veterinarian recommended practices *dehorn_safe, nonurse, cleaninject, new_sleeve*, and *fly_control* would be negative based on veterinary recommendations, and that the sign on *noquarantine, tattoo*, *cull_disease,* and *herdsize* would be positive because the two former are discouraged by veterinarians, a history of disease likely increases the chance that other animals in the herd are infected, and the larger the herd size the easier it is for infection to

Table 2. Fractional logit estimation results for the BLV disease control function

Explanatory variable	Coefficient	Std. error	Marginal effect[a]
Safe dehorning method	−0.47***	0.100	−0.11***
No natural nursing/separate calves from mothers	−0.09	0.101	−0.02
Cattle introduced to herd not quarantined	0.05	0.092	0.01
Clean injection of heifers (<24 months old)	−0.07	0.169	−0.02
Individual use obstetrical sleeves	0.16	0.142	0.04
Insect control practiced on farm	0.07	0.170	0.02
Tattooing for animal ID	−0.32*	0.190	−0.08*
Animals culled from herd because of disease (>0)	0.03	0.128	0.01
Herd size (1,000)	0.058	0.042	0.013
CA	0.64***	0.176	0.16***
FL	1.56***	0.228	0.36***
ID	0.12	0.212	0.03
IL	1.07***	0.251	0.26***
IN	0.44	0.400	0.12
IA	−0.34	0.249	−0.08
KY	0.84**	0.442	0.21**
MI	0.14	0.204	0.04
MN	−0.02	0.170	−0.01
MO	1.04***	0.319	0.25***
NM	−0.19	0.219	−0.04
NY	0.40**	0.161	0.09**
OH	0.89***	0.209	0.22***
OR	−1.08***	0.279	−0.21***
PA	0.22	0.187	0.05
TN	0.87**	0.433	0.21**
TX	1.43***	0.243	0.34***
VT	−0.04	0.249	−0.01
WA	−0.83***	0.262	−0.17***
Intercept	−0.49**	0.212	
Log likelihood		−37007.587	
R^2		0.186	
N		973	

Notes: Standard errors calculated by delta method, account for complex survey design.
Asterisks denote level of statistical significance: *10%, **5%, ***1%.
[a]Marginal effects evaluated at means for all variables with 0 to 1 changes for dummies.

spread. Practices that are explicitly recommended or discouraged by veterinarians were expected to be significant.

Estimation results for Equation (10) are reported in Table 2. The prevalence of BLV predicted by empirical model in Equation (10) is 0.395 compared with the observed weighted mean prevalence of 0.399 reported in Table 1. State-level heterogeneity not captured by other explanatory variables was significantly associated with herd prevalence as evidenced by the fact that the state dummies are jointly significant ($\chi^2(18) = 176.07$) at the 1% level. Higher BLV prevalence was found to be associated with some states (CA, FL, IL, KY, MO, NY, OH, TN, and TX) while lower prevalence was associated with others (OR and WA) relative to the reference state Wisconsin. Animals culled because of disease were not found to be significant. While herd size was not found to have a significant association with the level of infection, it was significantly ($p = 0.040$) associated with an alternative binary dependent variable indicating infection status ($y_h \in \{0,1\} = 1[D_h > 0]$, where 1[ ] is the indicator function). These regression results were not reported in Table 2 but are worth noting because it is generally thought that the number of animals (as a proxy for animal concentration/density) is positively associated with the binary occurrence of illness, and this is the case for the NAHMS data.

The regression results for the individual management practices revealed two practices with a statistically significant association with disease prevalence. The safe dehorning variable indicates that the herd either uses caustic paste, which prevents horn growth, or an electric dehorner instead of using a gouge dehorner or other "unsafe" practice to remove horns. The estimated marginal effect on within-herd BLV prevalence from adopting a safe dehorning method was an 11 percentage point reduction in prevalence. This result is consistent with veterinary studies that have previously identified electric dehorning as reducing the likelihood of BLV infection (DiGiacomo et al 1985; DiGiacomo et al 1986). Unsafe dehorning practices were observed on 456 farms in our sample compared with 524 farms adopting a safe dehorning method.

Though only marginally significant ($p = 0.072$), estimation results indicated that the use of tattoos for animal identification had a −8 percentage point marginal effect on within-herd BLV prevalence. This was not the expected sign; tattooing is a discouraged practice because of the risk of blood transfer on tattoo instruments between BLV-positive and BLV-negative animals. It is possible that the tattoo variable acts to some extent as a proxy for registered herds (an unobserved variable) in the data and that the sign of this estimate reflects this. Tattooing is not commonly used on dairy farms unless the animals are registered and being sold largely on the basis of highly valued genetics. It is plausible that the tattoo dummy is capturing this, and it is intuitive that registered herds were associated with lower expected disease prevalence because these animals must remain disease free to retain their value as breeding stock.

History of animals culled because of disease has the expected sign but is not significant. Further examination of the disease control practices reveals that dehorning, nursing, quarantine, and clean injection had the expected signs, while obstetrical sleeves, insect control and tattooing had unexpected signs in the estimated disease control function. A joint hypothesis test of the entire group of management practices in disease control function in Equation (10) resulted in a rejection ($p = 0.0008$) of the null $H_0{:}\gamma_2 = \gamma_3 = \gamma_4 = \gamma_5 = \gamma_6 = \gamma_7 = 0$. A joint test of the significance of the group of practices in Equation (10) that excluded safe dehorning ($H_0{:}\gamma_3 = \gamma_4 = \gamma_5 = \gamma_6 = \gamma_7 = 0$) resulted in a failure to reject ($p = 0.2621$) the null. This was interpreted as evidence against the importance of tattooing (along with the other practices) as a determinant of the level of infection when controlling for farm state, herd size, and use of a safe dehorning method.

The disease control function estimated for BLV indicated that the single practice with a statistically significant effect on the level of infection, when considered alone or as part of a group of practices, was the use of a safe dehorning method. As a result of this finding, we focused the second stage of our analysis solely on the adoption of a safe dehorning practice. This follows from our theoretical model of adoption because when adoption of a practice has no effect on the level of infection, $D(0) = D(1)$ for binary practice $v_k = 1$ and $[F(D(0)) - F(D(1))] = 0$. When this is the case, the latent variable underlying the adoption decision in Equation (8) is $y^* = -P_k < 0$ given that $E[e] = 0$, implying $v_k = 0$ in Equation (9); that is, there is no clear economic incentive to adopt when an individual practice has no significant measured effect on BLV prevalence.

This was precisely the case in our empirical application for all health management practices in **z** except *dehorn_safe* in Equation (10). The negative sign of the estimated coefficient for safe dehorning in the disease control function indicates that $\partial\Lambda(\mathbf{z}\boldsymbol{\gamma})/\partial \mathit{dehorn\_safe} < 0$ and farm-specific marginal effects of safe dehorning on BLV are estimated for herd h by (Wooldridge 2002, p. 459)

$$\begin{aligned} ME_h^{BLV} = & \\ & \Lambda(\gamma_0 + \gamma_1 1 + \gamma_2\, \mathit{nonurse} + \gamma_3\, \mathit{noquarantine} + \gamma_4\, \mathit{cleaninject} + \gamma_5\, \mathit{new\_sleeve} \\ & \quad + \gamma_6\, \mathit{fly\_control} + \gamma_7\, \mathit{tattoo} + \gamma_8\, \mathit{herdsize} + \gamma_9\, \mathit{state}1 + \cdots + \gamma_{27}\, \mathit{state}19) - \\ & \Lambda(\gamma_0 + \gamma_1 0 + \gamma_2\, \mathit{nonurse} + \gamma_3\, \mathit{noquarantine} + \gamma_4\, \mathit{cleaninject} + \gamma_5\, \mathit{new\_sleeve} \\ & \quad + \gamma_6\, \mathit{fly\_control} + \gamma_7\, \mathit{tattoo} + \gamma_8\, \mathit{herdsize} + \gamma_9\, \mathit{state}1 + \cdots + \gamma_{27}\, \mathit{state}19) \end{aligned} \tag{11}$$

where herd subscripts on the RHS variables are suppressed for notational compactness. The calculation of marginal effects by Equation (11) is easily transformed to provide an estimate of $BLV_h(0) - BLV_h(\mathit{dehorn\_safe})$ as $-ME_h^{BLV}$. The effect safe dehorning has on the BLV prevalence rate will be used in the computation of the estimated output losses avoided by adoption, which is an explanatory variable in our adoption model.

To arrive at an estimate of BLV output losses avoided by adopting a safe dehorning practice, we employ an empirical estimate from the veterinary literature based on the 1996 NAHMS dairy survey data to construct variables that are equivalent to $P_Q Q_0[F(BLV_h(0)) - F(BLV_h(\mathit{dehorn\_safe}))]$. Ott et al (2003) estimated that a 1 percentage point increase in BLV prevalence cost \$1.28 per cow/year (\$1.73 in 2009 US dollars) in terms of reduced milk output, lost calves, and net replacement costs.[5] Using the estimated marginal effect from Equation (11) in tandem with the output loss estimate from Ott et al (2003), we calculate an estimate for herd h of $P_Q Q_0[F(BLV_h(0)) - F(BLV_h(\mathit{dehorn\_safe}))]$ for inclusion in the second stage adoption equation as

$$\mathit{output\_loss}_h^{BLV} = \left(-ME_h^{BLV} * 100\right) * \mathit{herdsize}_h * \$1.28 \tag{12}$$

We convert ME_h^{BLV} to a positive percentage value and multiply by herd size and the estimated cost per animal/year/percentage point of BLV prevalence from Ott et al (2003).

Empirical Model of Disease Management Practice Adoption and Estimation Results

We can now estimate an adoption equation according to Equation (9) using the empirical model

Table 3. Binary response adoption equation for safe dehorning methods

Variable	Coefficient[a]	Std. error	Marginal effect[b]
Damages from BLV avoided if adopt ($1,000)	0.04	1.60e-05	0.01
Herd average milk production/cow (100 kg)	0.01	2.99e-05	0.0016
MDBQA (HACCP) participation	−1.00	0.214	−0.23
DHIA	0.67	0.182	0.16
Intercept	−3.06	0.514	
% Yes correctly predicted		63.5	
% No correctly predicted		62.3	
% Overall correctly predicted		63.0	
Pseudo-R^2		0.114	
F-statistic (4, 893)		19.25	
N		980	

Note: Standard errors calculated by delta method, account for complex survey design.
[a]All parameter estimates and F-test of overall significance, significant at 99% level.
[b]Marginal effects evaluated at means for all variables and 0 to 1 changes for dummies.

$$\begin{aligned}&\text{Prob}(\mathit{dehorn\_safe} = 1|\mathbf{x})\\&\quad = \Lambda\big(\beta_0 + \beta_1\, \mathit{output\_loss}_h^{BLV} + \beta_2\, \mathit{rolling\_avg} + \beta_3\, \mathit{MDBQA} + \beta_4\, \mathit{DHIA}\big) \qquad (13)\end{aligned}$$

Our available survey data do not provide any information for the calculation of $P_k v_k$ in a manner that would allow it to vary by farm. Hence, this term is subsumed in the constant, β_0. There is heterogeneity across observations in the explanatory variable $\mathit{output\_loss}_h^{BLV}$ as a result of herd size differences and because farm-specific marginal effects reflect the fact that individual farms adopt different combinations of management practices.

We hypothesize that the cost of production losses from BLV is positively associated with adoption; that is, the probability of adoption is expected to be increasing in the economic damages from BLV attributed to not adopting a safe dehorning method. In order to control for other farm characteristics that may affect adoption, our explanatory variables include the rolling average milk production per cow (*rolling_avg*) that serves as a herd productivity measure, along with dummies for participation in the MDBQA program and DHIA membership. Intuition suggests that farms that voluntarily participate in programs like DHIA or MDBQA, and are more productive, are likely to invest in veterinarian recommended practices. Thus, the hypothesized signs for all three are positive.

The estimation results for adoption Equation (13) are reported in Table 3. The entire group of explanatory variables is highly significant and correctly predicts 63% of all adoption choices observed in the data. This can be compared with a naïve prediction that "all adopt" ("none adopt") that would correctly predict the outcome just 45% (55%) of the time. The estimated parameter on damages from BLV suggests that an additional $1,000 of output losses avoided leads to an increase in the probability of adoption by 1 percentage point. While highly statistically significant, BLV damages avoided do not

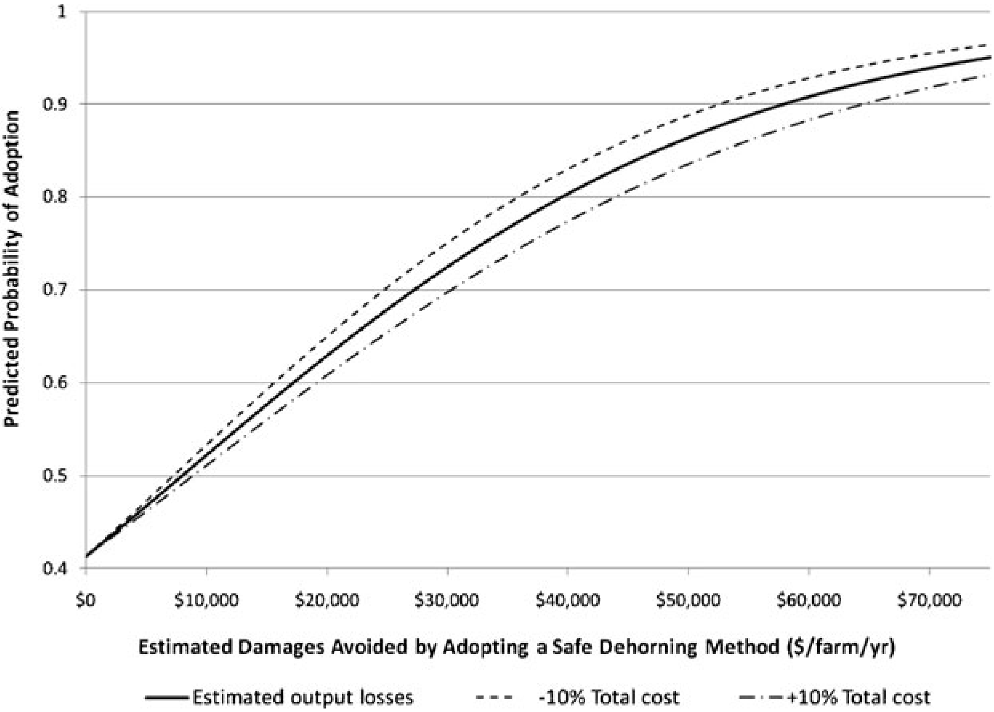

Figure 1. Predicted probability of adopting a safe dehorning method, given annual damages avoided

appear to be of great economic significance as a determinant of adoption. Similarly, an additional 1,000 kilograms of average milk production per cow is estimated to increase the probability of adoption by 1.6 percentage points. Participants in the MDBQA program are 23 percentage points less likely to adopt, while DHIA members are 16 percentage points more likely to adopt, according to our model.

The explanatory variable of greatest economic interest is the role of damages from BLV attributable to the adoption of safe dehorning methods. The estimated parameter on the variable $output\_loss_h^{BLV}$ has the hypothesized sign and is the focus of Figure 1. In this graph, the predicted probability of adoption (the solid line) is evaluated over the range of estimated output losses for the 1996 NAHMS data (all other variables evaluated at their survey-weighted sample means). The shape of the graph is reflective of the logistic distribution that underlies our econometric model of adoption and accords with the expected economic relationship—the probability of adoption is increasing (at a decreasing rate) in the damages from BLV avoided, all else constant. The graph also illustrates the fact that even with no damages from BLV, the predicted probability of adopting a safe dehorning practice is 41.3%. This suggests that there are likely other important determinants of the decision to adopt that we have not captured in our model and provides some fodder for discussion of the connection between our descriptive findings and the prescriptive literature on efficient allocation of resources that has preceded this work.

Previous research that has investigated the most efficient allocation of farm resources to biosecurity typically centers on the notion of the total economic cost of disease to a herd decision maker (McInerney et al 1992; Chi et al 2002b). Recall that total economic cost includes output losses, which we have included as an explanatory variable, as well as preventive (*ex ante* infection) and treatment (*ex post* infection) costs, which are not explanatory variables in our empirical model.[6]

To demonstrate this effect on the predicted probability, we graphed a 10% increase in the total economic cost of infection when control costs that are proportional to herd size are incorporated (the long-short dashed line) and a 10% decrease in total economic cost (the short dashed line). Note that larger total economic cost would indicate that preventive costs exceed any reductions in treatment cost achieved as a result of adoption, while smaller total costs would mean preventive costs are more than offset by the reductions in *ex post* cost of treatment achieved. A larger total economic cost from the prescriptive literature on herd-level livestock disease management therefore translates into a lower level of damages avoided from adoption, as depicted in Figure 1.

SUMMARY AND DISCUSSION

We adapted a theoretical model from the prescriptive literature on efficient herd-level livestock health management (McInerney et al 1992; McInerney 1996; Chi et al 2002b) to descriptively examine the decision to adopt disease management practices. Based on our theoretical model of adoption behavior we proposed a two-stage econometric procedure to estimate (i) a disease control function and (ii) an adoption equation so that we might shed light on the determinants of observed behavioral choices. Our focus on adoption of disease management practices is unique in the disease management literature. We also propose the use of the fractional logit model (Papke and Wooldridge 1996) as an alternative to the Tobit model used to estimate herd disease control functions (Chi et al 2002b) and other fractional dependent variables (Shapiro et al 1992) in the agricultural economics literature previously.

We demonstrated the proposed estimation procedure using 1996 dairy herd data from the USDA/APHIS NAHMS. Estimation of a disease control function for BLV using the fractional logit model found that the use of a safe dehorning method recommended by veterinarians for the control of BLV had a statistically significant and negative effect on the prevalence of infection. The estimated marginal effect from the first stage is the fractional response of BLV to use of a safe dehorning method, which was estimated to result in an 11 percentage point reduction in herd seroprevalence (see Table 2).

We then constructed a herd-specific variable for the estimated output losses from BLV that could be avoided by adopting the safe dehorning methods. These avoided output losses were calculated using the estimated marginal effect from the fractional logit and a value from the literature for the reduction in the "annual value of production" per cow per year per percentage point of BLV (Ott et al 2003). The constructed output loss variable was used as an explanatory variable in the second-stage adoption equation. Estimation of the adoption equation by the familiar logit binary response model found that economic damages from output losses are a statistically significant determinant of safe dehorning practice adoption (Table 3). The economic importance of the corresponding estimated marginal effect was found to be minimal: an additional $1,000 in damages is associated with a 1 percentage point increase in the probability of adoption. Our finding that the estimated probability of adoption would be 41.3% when there are no output losses from BLV that would be avoided by adopting (see Figure 1) suggests that other factors may play a larger role in determining whether farmers adopt safe dehorning methods.

On the basis of our descriptive model, the total economic cost of BLV likely did not play an economically important role in the adoption decision despite being at the core of optimal allocation of resources to disease management. However, it is not possible to make a direct comparison between our finding and those of researchers who identified the most efficient allocation of resources because the data are not sufficient. Also, the structure of our adoption model is not capable of considering multiple practices simultaneously, the role of spillovers to multiple diseases, or the opportunity cost of a farmer's time.

Typical models of economic decision making endow economic agents with rationality and assume that farmers have all of the information required to allocate resources in the most efficient manner possible. While it is not possible to know whether farmers had such information at the time they made the adoption decision observed in the NAHMS data, this is one dimension of the current problem that provides an opportunity for government intervention. It is possible for the government to invest in information dissemination about suggested management practices and the costs of infection, with the objective of improving economic decision making while simultaneously meeting government disease risk management objectives.

NOTES

[1]It may be important to take into account more general health benefits or preventive spillovers to multiple diseases from dehorning, but this research is outside the scope of the present study. We are grateful to an anonymous reviewer for making this point.

[2]Using survey data collected in 1995 may limit the degree to which the data are representative of the current BLV prevalence and management practice adoption rates on U.S. dairy farms. Data of this kind are not widely available and there is no other data set of this size and scope with such detail about farmer management behavior and BLV serology. When compared to the data used in Chi et al (2002b) from the Canadian Maritimes, this data represents a much more diverse and commercially significant segment of the dairy industry in North America.

[3]The authors are grateful to an anonymous reviewer for suggesting this as a potentially important explanatory variable in the disease control function.

[4]It is possible to implement the fractional logit method in Stata (StataCorp 2007) by using the generalized linear model command which allows the researcher to specify the binomial family of distributions and the logit link function without treating fractional dependent variables as binary.

[5]It is worth noting that the $1.28/cow/year/percentage point of BLV prevalence cost to herd managers of BLV seroprevalence does not take into account any additional management costs associated with providing extra care to sick animals. The authors are grateful to an anonymous reviewer for pointing this out.

[6]Data on these additional dimensions of total economic cost were not available in the 1996 NAHMS dairy survey. The decision was made not to attempt to calculate estimates of the total economic cost of disease because the effect on parameter estimates would only be to shift the level of the coefficients and should not affect the significance of economic cost as an explanatory variable.

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