The World's Largest Open Access Agricultural & Applied Economics Digital Library

This document is discoverable and free to researchers across the globe due to the work of AgEcon Search.

Help ensure our sustainability.

Give to AgEcon Search

AgEcon Search
http://ageconsearch.umn.edu
aesearch@umn.edu

*Papers downloaded from **AgEcon Search** may be used for non-commercial purposes and personal study only. No other use, including posting to another Internet site, is permitted without permission from the copyright owner (not AgEcon Search), or as allowed under the provisions of Fair Use, U.S. Copyright Act, Title 17 U.S.C.*

Staff Paper

The Value of Genetic Information in Selection of Replacement Holstein Heifers

Brian R. Radke
James W. Lloyd
J. Roy Black
Stephen Harsh

Staff Paper 2000-50 **December, 2000**

Department of Agricultural Economics
MICHIGAN STATE UNIVERSITY
East Lansing, Michigan 48824

MSU is an Affirmative Action/Equal Opportunity Institution

The Value of Genetic Information in Selection of Replacement Holstein Heifers

Brian R. Radke, James W. Lloyd, J. Roy Black and Stephen Harsh

brian.radke@gov.ab.ca, lloydj@cvm.msu.edu, blackj@msu.edu, harsh@msu.edu

30 pages

Abstract

Genetic information is valuable to livestock producers because its incorporation into their selection decisions results in improved animals. Hedonic models have been developed to value bulls' genetic traits to form a pricing mechanism for semen (Schroeder et al.; Richards and Jeffrey). Harris and Freeman estimated the economic weights of genetic traits that maximize producer income. These examples are representative of studies which valued genetic traits, but we are not aware of any research valuing the information on the underlying genetic traits.

Copyright © **2000 by Brian R. Radke; James W. Lloyd; J. Roy Black; Stephen Harsh.** All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies

The Value of Genetic Information in Selection of Replacement Holstein Heifers

Brian R. Radke*, James W. Lloyd, J. Roy Black, Stephen Harsh

Department of Agricultural Economics, 202 Agriculture Hall, Michigan State University, East Lansing, MI 48824-1039, USA

* Corresponding author, current affiliation:

Alberta Agriculture, Food and Rural Development

#905 6909 116 Street, Edmonton, Alberta, Canada T6H 4P2

Tel: 780/422-0723; Fax: 780/427-1439

brian.radke@gov.ab.ca

Submitted November 1, 2000

The Value of Genetic Information in Selection of Replacement Holstein Heifers

Introduction

Genetic information is valuable to livestock producers because its incorporation into their selection decisions results in improved animals. Hedonic models have been developed to value bulls' genetic traits to form a pricing mechanism for semen (Schroeder et al.; Richards and Jeffrey). Harris and Freeman estimated the economic weights of genetic traits that maximize producer income. These examples are representative of studies which valued genetic traits, but we are not aware of any research valuing the information on the underlying genetic traits.

The value of information framework has been applied to two broad categories of producer decisions in the agricultural economics literature: the value of pricing messages in marketing decisions (cf. Eidman, Dean and Carter); and the value of weather forecasts (cf. Baquet, Halter and Conklin), soil tests (cf. Babcock, Carriquiry and Stern) and pest scouting (cf. Swinton and King) in agronomic decisions. The value of information framework was originally posed in the context of comparing multiple competing information systems (IS) that each map their own set of noisy messages to the same set of outcomes of an underlying random variable or event (Marschak and Miyasawa). Based on a message, the IS user makes a decision and observes a consequence that affects his welfare. The value of an IS is represented by the increase in the decision-maker's welfare by using the IS versus not using the IS in the decision. The typology adopted in this manuscript is information consists of the set of possible competing IS, and an IS is defined as set of messages and associated decision rule. Then the value of information can be defined as the value of the most valuable competing IS.

This framework can be applied to assess the value of genetic information in livestock producer decision making. Genetic evaluations provide information of animals' true genetic merit for the respective biological traits, with the various evaluations potentially forming different IS. The value of genetic information is specific to the decision; we focus on the value of genetic information in the selection of replacement Holstein heifers in dairy herds.

The need for a method of heifer selection is predicated on the optimal dairy herd culling rate[1] literature because, for a given herd size, the number of replacement heifers entering a cow herd determines the number of cows culled from the herd. The consensus among the literature is selecting only a portion of the replacement heifers to enter the cow herd (and selling the remainder of the replacements) to result in cow culling rates of 20% to 30% maximizes producer profit. This consensus is compelling because the studies employed different assumptions, different analytical techniques, and different economic conditions representative of a number of countries (i.e., U.S.A, England, Ireland, Netherlands, Canada). Assumptions of random (i.e., no use of genetic information) selection of replacement heifers, constant herd size, no seasonal effects on reproduction and production, and risk neutrality were typical in the dynamic optimization (McCullough and DeLorenzo; Rogers et al.; Congleton and King; Van Arendonk and Dijkhuizen; Killen and Kearney; Bauer, Mumey and Lohr) and simulation (Allaire; Allaire and Cunningham; Kuipers; Korver and Renkema; Pearson and Freeman) studies of culling rates.

The existence of an IS for replacement heifer selection that is more profitable than the benchmark of random selection would be more intuitively acceptable to producers and further increase producer profit. Some simulation studies selected replacement heifers based on the simulated genetic IS of estimated breeding value (EBV) for milk. Milk EBV is the average of the parents' predicted transmitting abilities (PTAs) for milk production. PTAs, which are estimated

[1] Culling rate, annually defined as, the number of animals leaving the herd due to sale or death divided by the average herd size.

by the U.S. Department of Agriculture, predict the genetic merit the parents are expected to transmit to offspring. While selection based on the milk EBV genetic IS has theoretical justification (Henderson), empirical support for heifer selection on this basis is lacking.

That genetic information, or at least the milk EBV IS, may be of little value in replacement Holstein heifer selection is implied through applying standard optimal replacement theory to the culling literature. The optimal culling rates of the studies which used random selection of replacement heifers did not systematically differ from those studies which based selection on the milk EBV IS. A standard result of replacement theory is that as the expected profitability of the potential replacements rises relative to the existing assets, the optimal length of the utilized assets' lives decrease (Perrin) which is equivalent to an increase in the culling rate. One possible explanation for the similarity among the most profitable culling rates, despite the differences in information used for selection, is that the biologically orientated EBV genetic IS produces messages of future profitability that are so noisy that they have little value in replacement heifer selection. In the classical Bayesian approach to decision theory framework, this corresponds to no effective revision of the posterior probability distribution from the flat prior. An alternative explanation for the similarity in the optimal culling rates in the face of information differences is that differences among the studies may preclude the recognition of the value of EBV in heifer selection.

The objective of this study is to determine the economic value of genetic information in the selection of replacement Holstein heifers, and assess whether this value is sufficient to prompt producers to select heifers on this basis. In addition to the subject matter contribution, this empirical application of the value of information advances the current literature in two respects.

The first contribution is an empirical application of Epstein's theoretical decision-making framework of potential message updating over the decision time horizon. This is not to be confused with the value of information literature in a dynamic setting. The current literature consists of messages, often assumed perfect, for different decisions at various stages of a sequential multistage production process. In contrast, in this research the updated messages (of replacement heifers' profitability) all pertain to the same decision – the selection of the most profitable heifers. Notice that in our context, receipt of perfect message results in subsequent messages being superfluous.

Second, we evaluate the optimality of a simple IS that is static, heuristic and representative of the IS conventionally used by agricultural decision-makers and valued in the literature. The issue of whether decision-makers have chosen the IS that maximizes their welfare (i.e., is optimal), from among the universe of potential IS, is a natural extension of Marschak and Miyasawa's concept of competing IS. The optimality of the static simple heuristic IS is evaluated by comparison with a complex IS that incorporates message updating and quasi-maximizes the value of the information.

Theoretical framework for the value of genetic information in replacement heifer selection

In order to establish the framework for the value of genetic information in replacement heifer selection, the objective function of the decision-maker must be established. The profit maximizing dairy producer desires selection of the most profitable animals. Van Arendonk showed that lifetime profit corrected for the opportunity cost of postponed replacement (LPCOC) is the correct method of ranking animals for profitability. This measure of an animal's lifetime profit explicitly recognizes that, in retaining the animal in the herd, the average potential replacement's profit is foregone.

Animal selection decisions among a cohort of heifers are similar to what is commonly referred to as the optimal stopping problem (Dixit and Pindyck) except the state variable is a portfolio of nonidentical assets (heifers). With perfect information, heifer selection is a two step procedure for producers. The heifers are ranked by LPCOC and the top are *N* selected, where *N* is determined by the targeted culling rate in the cow herd. The remaining heifers will be sold. The second decision is when in the rearing period these remaining heifers are sold. The profit maximizing producer will sell the animals when the gross sale price less the cumulative average variable rearing cost is the greatest. This can be represented as

(1) $$\max_{s_{at}} \Pi_h^{perfect} = \sum_a \left[\left(1 - \sum_t s_{at} \right) \pi_a + \sum_t s_{at} r_t \right], a = 1, \ldots, A_h; t = 1, \ldots, T.$$

subject to

$$\sum_t s_{at} \in (0,1)$$
$$\sum_a s_{at} = n_h$$

Where

Π_h is the profit of herd h from heifer selection;

$$s_{at} = \begin{cases} 1 & \text{if animal } a \text{ is not selected (i.e. is culled) in period } t; \\ 0 & \text{otherwise;} \end{cases}$$

π_a is the lifetime profit of animal a corrected for opportunity cost;

r_t is the gross sale price less the cumulative average variable rearing cost in period t;

n_h is the number of heifers, in herd h, to be sold;

A_h is, for herd h, the total number of heifers which form a cohort for selection purposes;

T is the total number of periods in the rearing process.

Uncertainty in predicting a heifer's subsequent profitability is incorporated into (2) by noting that $L(G_{at})$ is a noisy message of LPCOC. Where L is first lactation milk production which is a function of the heifer's estimated genetic information (G_{at}).

(2) $$\max_{s_{at}} \Pi_h = \sum_a \left[\left(1 - \sum_t s_{at} \right) \pi_a \left(L_a \left(G_{at} \right) \right) + \sum_t s_{at} r_t \right], a = 1, \ldots, A_h; t = 1, \ldots, T.$$

The profit associated with random selection benchmark can be represented as

(3) $$\max_{s_{at}} \Pi_h^{random} = \sum_a \left[\left(1 - \sum_t s_{at} \right) \mathrm{E}\left[\pi_a \left(L_a \left(G_{at} \right) \right) \right] + \sum_t s_{at} r_t \right], a = 1, \ldots, A_h; t = 1, \ldots, T.$$

The LPCOC is the expectation (E) of the heifer cohort, and the only selection decision is with respect to which period to sell the excess heifers.

The *ex ante* value of genetic information in heifer selection can then be assessed by Π_h - Π_h^{random}. If genetic information is of no value in heifer selection then $\Pi_h = \Pi_h^{random}$. The *ex post* value of perfect information in heifer selection is represented by $\Pi_h^{pefect} - \Pi_h^{random}$.

Assuming sale of the heifers occurs in the period k when the selection decision is made, the profit from heifer selection in rearing period k using genetic information is

(4) $$\max_{s_{ak}} {}^k\Pi_h = \sum_a \left[\left(1 - s_{ak} \right) \pi_a \left(L_a \left(G_{ak} \right) \right) + s_{ak} r_k \right], a = 1, \ldots, A_h; t = 1, \ldots, k.$$

The increased value of genetic information in rearing period T versus rearing period k is

(5) $$({}^T\Pi_h - {}^T\Pi_h^{random}) - ({}^k\Pi_h - {}^k\Pi_h^{random}).$$

Theoretical genetic IS for replacement heifer selection

To assess the value of genetic information in Holstein replacement heifer selection, an IS comprised of a decision rule, s_{at}, that transforms a set of messages, $\mathbf{M}$, into action by the decision-maker is required. Let an IS for replacement heifer selection be $s_{at}(\mathbf{M}, \mathbf{p})$

subject to

$$0 \le p_t \le 1$$

$$S = \prod_{t=1}^{T} p_t$$

Where

M is a partitioned matrix of dimension A_h by T, composed of elements $\mathbf{g_{at}w_t}$, where $\mathbf{g_{at}}$ is a 1 x B vector, containing the B genetic evaluations for animal a available at time t; $\mathbf{w_t}$ is a B x 1 vector of weights for the B genetic evaluations in time period. $\mathbf{g_{at}w_t}$ then is a message of animal a's composite genetic evaluations at time t.

p is a 1 x T vector whose elements, p_t, are the proportions of animals to be selected in period t.

S is the overall proportion of animals to be selected.

The decision rule begins with the first period (t =1) in which the heifers are ranked by $\mathbf{g_{a1}w_1}$ and the top $p_1 \cdot A_h$ are selected, and the remaining $(1-p_1) \cdot A_h$ are sold. The number of animals to be selected, $p_1 \cdot A_h$, is rounded to the nearest integer. The remaining animals are then re-ranked in the second period (t =2) by the second period messages, with $p_2 \cdot (p_1 \cdot A_h)$ selected and the remaining sold. This process continues to the T^{th} period when the number of animals selected is equal to S, so the number sold in the final period is $p_1 * p_2 * p_3 * A_h - S * A_h$, if positive. These selected heifers will then initiate their first lactation and associated profit. Heifer selection can then be considered a dynamic value of information issue, weighing the value of the more informative message versus the cost of its attainment.

Theoretical message evaluation

Given the lack of research on messages of heifers' LPCOC, genetics is one of the few sources of information for heifer selection that is available industry wide. However, any genetic message of heifer profitability is noisy for two reasons. The first is genetic evaluations predict biological performance (i.e., milk production), which only explains a portion of the variation in animal profitability. For example, first lactation mature equivalent milk production (actual milk production standardized for effect of age and season of calving), which is one of the best early indicators of LPCOC, has a 0.51 correlation with the profit measure (Weigel et al.).

The second reason genetic messages of heifer profitability are noisy is the genetic evaluations result in imperfect estimation of biological performance. Although genetics is responsible for 25% of the variation in milk production (environmental effects account for the remaining 75%), heifers' parents' PTAs explained less than 7% of the within herd variation in heifers' subsequent first lactation milk production (Radke). This discrepancy is due to uncertainties about the heifers' true genetic merit. A genetic evaluation produced by the USDA is the mean of the animal's true genetic merit probability distribution. The variance of this distribution is inversely related to the reliability of the genetic evaluation, which the USDA also estimates, and is the squared correlation of an animal's estimated genetic value and its true genetic value. At a maximum, a heifer's parents' PTAs will have a reliability of 0.10 in predicting the daughter's subsequent milk production. Mendelian sampling, in which a parent transmits a distribution of genetic merit to offspring with random chance determining the merit transmitted to any given offspring, contributes to the low reliability. Although genetic IS of biological performance will be noisy, the 0.3 Pearson rank correlation between heifers' parents' PTAs and the heifers' subsequent first lactation milk production suggests they may have value in heifer selection (Radke).

Three messages of heifer profitability are evaluated. The genetic evaluations (i.e., $\mathbf{g}_{\mathbf{at}}$) are the same for all three messages, however the $\mathbf{w}_{\mathbf{t}}$ vary between messages. The benchmark random message of heifer profitability trivially uses no genetic information (i.e., **w** = 0). The simple genetic message is milk EBV, which was used in the culling simulation studies that did not assume random heifer selection. In addition to its simplicity, this heuristic IS is easily implementable as heifers' milk EBVs are currently provided to dairy producers for selection and breeding decisions. Due to the positive correlation between fat and protein PTAs and milk production, genetic selection index theory and statistical theory suggest the message will be improved by incorporating information on these two PTAs of the parents. In addition, the milk-fat and protein reliabilities, which can be considered measures of the informativeness of the respective PTAs, may be valuable in heifer selection. A complex genetic message composed of all available and potentially valuable genetic evaluations (i.e., the parents' PTAs for milk, fat and protein and associated reliabilities) is also evaluated. Because the simple genetic message is a condensed version of the complex message the latter must be more informative and cannot be less valuable (Marschak and Miyasawa).

The genetic messages are also dynamic. The messages will improve in informativeness over the course of the heifers' rearing as the USDA periodically re-estimates the genetic evaluations as more information on the heifers' relatives are collected. However, the rate of improvement in informativeness will vary among the messages and among animals.

Deriving and testing the quasi-optimal IS - Empirical methods

A heifer selection IS consists of, for each period, the genetic messages (i.e., $\mathbf{g_{at}w_t}$) that are a method of ranking the heifers, and the proportion of heifers to be selected (i.e., p_t). The random IS and simple genetic IS are static, ignoring the dynamic nature of the decision and the updating of their respective messages. These static IS conduct all heifer selection in the period in which r_t is the greatest. While theoretically, a complex genetic IS that incorporates message updating should be more informative and at least as valuable as the other IS, it is unclear what values of **w** and **p** would result in the realization of this potential. Confronted with the varying reliabilities of the PTAs and the dynamic environment of heifer selection, genetic theory could not contribute values for the two vectors.

The complex genetic IS of how and when to select heifers with updating messages is not amenable to standard optimization techniques such as dynamic programming. Genetic theory is silent on the required transition probabilities among the genetic evaluations and on the relationship between the genetic information and LPCOC (i.e., the posterior probability distribution of classical Bayesian decision theory is unknown). Furthermore, while the structure of the problem appears amenable to an optimal stopping framework, the context of dynamically selecting individuals among a cohort leaves it unworkable. Specifically the cohort context implies that a state variable is a multivariate distribution of the heifers' parents' PTAs. Further complicating the problem is the realization that because the cohort consists of nonidentical animals *a priori* there is no reason to expect all stopping (i.e., selection) decisions will occur in a single period, rather the decisions may themselves be dynamic. Instead Modified Box-Complex, a derivative free non-linear search technique, is used to produce the complex genetic IS that quasi-maximizes the value of updated genetic information in the selection of replacement heifers.

This method of sequential searching has been found useful in globally optimizing nonlinear multivariable objective functions subject to constraints (Harris). Based on Harris' description, Kuester and Mize's procedure for Box's original Complex algorithm was modified to include Nelder-Mead's flexible polyhedral procedures. Briefly, a number of vectors of search variables are created, often randomly. Each vector forms a vertex of an *s* dimension geometric figure or complex, where *s* is the number of elements of the search vector. An iteration of the algorithm begins with ensuring all constraints have been met and then calculating the objective value associated with each vertex. The centroid, or center of mass of the complex, is calculated using all the vectors except the one with the lowest objective function value. Generally, the vertex with the lowest objective value function is moved in *s* dimensional space, using the centroid as a reference point, until the new vertex no longer has the lowest objective value. The iterations continue until all the objective values are within a given parameter for a defined number of iterations.

The USDA genetic evaluations are overwritten when re-estimated; thus an extended time frame would be required to collect multiple heifer cohorts for each herd in order to generate a quasi-optimal genetic IS for each herd. Rather a cross-sectional approach to generate a IS, which maximizes the average profit of the individual herds was opted for. The advantage of this method, besides the decreased data requirements, is greater ease of industry-wide IS implementation. The new objective function associated with the cross-sectional approach can then be represented as

(6) $$\Psi = \max_{s_{at}} \frac{1}{H} \sum_{h=1}^{H} \frac{\Pi_h}{A_h}.$$

The use of psi, the average herd profit per heifer, imposes equal weighting of each herd, regardless of its size, in the objective function.

The per heifer herd average *ex ante* value of genetic information in Holstein replacement heifer selection, Ω, is calculated as

(7) $$\Omega = \Psi - \frac{1}{H} \sum_{h=1}^{H} \frac{\Pi_h^{random}}{A_h}$$

Sample size calculations determined the requisite number of herds for one-tailed analysis of paired *t* tests to detect a $20 difference in profit per heifer between the benchmark of random selection and that associated with the selection using the two genetic IS. Based on the calculations, to detect a $20 difference the 115 herds are randomly divided in two groups following stratification on herd size. For the average herd in Michigan, a $20 difference would result in roughly a $1,000 annual increase in herd profit which we felt is sufficient to interest producers in collecting the necessary data and using a non-random IS. The 58 herds used with Complex to derive the quasi-optimal genetic IS, denoted as the IS-deriving sample, are comprised of 1,034 animals and range in size from ten to one-hundred and thirty-two heifers, average of 17.8 and median of 14. The remaining 948 heifers in 57 herds of ten to seventy-three heifers, average of 16.3 and median of 14, termed the IS-testing sample, are used to test the performance of the heifer selection IS. In comparing the value of the complex genetic IS that has message updating to the simple genetic IS that is static and heuristic, paired *t* tests are again employed, however, a zero difference is tested using a two-tailed distribution.

Modified Box-Complex is used to develop a quasi-optimal genetic heifer selection IS for each of three scenarios using the IS-deriving sample of 58 herds. Complex is used to generate twenty solutions for each scenario. The complex genetic IS for each scenario is the one of the twenty solutions with the highest value of the objective function. Using a simulation program and the IS-testing sample of 57 herds, the complex and simple genetic selection IS are compared with the benchmark random IS for each scenario. The simulation program simply calculates the average profit per heifer for each herd given A_h, $\mathbf{g_{at}}$, $\mathbf{w_t}$, $\mathbf{p}$, S, and r_t.

Data

The data set consists of Michigan Holstein heifers that were born between July 1, 1992 and December 31, 1992 and first calved between July 1, 1994 and December 31, 1994. Genetic evaluations collected consists of the heifers' parents' milk, fat and protein PTAs, along with the milk-fat reliability and protein reliability from the 1993 to 1994 semi-annual sire and dam animal model evaluations calculated by the Animal Improvement Programs Laboratory, USDA (Beltsville, MD); the one exception being the dam genetic evaluations from July 1993 which were unavailable (i.e., $\mathbf{g}_{\mathbf{a1}}$, $\mathbf{g}_{\mathbf{a3}}$, and $\mathbf{g}_{\mathbf{a4}}$ are 1 x 10 vectors, and $\mathbf{g}_{\mathbf{a2}}$ is 1 x 5). Heifer birth dates, calving dates and first lactation mature equivalent milk production were collected from Michigan Dairy Herd Improvement.

In effect, the sample consists of, for each herd, a cohort of heifers that were born within a six month window of time and calved within a six month window of time, with the two windows being separated by four six month rearing periods ($T = 4$). The end of a rearing period coincided with the release of new genetic evaluations by the USDA. Herds whose heifer cohort contained less than 10 heifers were deleted, leaving a sample consisting of 1,982 heifers in 115 herds which were divided into the IS-deriving and IS-testing samples.

Unfortunately, LPCOC is generally not available. So the LPCOC, associated with a given level of mature equivalent first lactation milk production, is deterministically estimated for each heifer based on information provided by Weigel et al. Generation of this profit measure likely misrepresented the true distribution of heifer profits in two ways. The use of a linear relationship between LPCOC and first lactation milk production assumed a constant marginal profit for milk, and as a result overestimated the profit of high producing animals. Secondly, Weigel et al. generated the relationship based on nonoptimal culling practices, which corresponded to lower heifer profits. The resulting distribution of LPCOC would be narrower than the true distribution due to compression of the upper tail of the distribution.

The milk PTAs are one to two orders of magnitude greater than the other genetic data.

The PTAs' coefficients of variation are at least triple that of the reliabilities. The respective means of the genetic evaluations rose consistently over the four periods. Within herd, π_a generally had a range of under $2,500.

To evaluate the effect of the input parameters S and r_t on rule performance the three different scenarios listed in Table 1 are considered. To make the transition from Michigan's 1996 average culling rate of 37% to a 30% culling rate suggests 80% of heifers need to be selected in base scenario A (Michigan Dairy Herd Improvement Association). The base net return per period from sale of a heifer is the 15% sunk portion of total cost (Karszes) to raise the animal to the respective period because capital costs are not assumed to be influenced by the heifer selection decision. The effect of selecting a lower percentage of heifers is evaluated in scenario B. Selecting 70% of heifers is appropriate for producers with minimal heifer death loss or desiring a cow culling rate lower than 30%. In scenario C the effect of the r_t are evaluated. Specifically, later sale of heifers incurs increasing losses and the absolute difference between r_1 and r_2, and r_2 and r_3 is less relative to the other scenarios.

Results

Unless otherwise stated, all results presented are evaluating the performance of the IS on the 57 herd IS-testing data that was not used in deriving Complex's quasi-optimal selection rules. Radke contains the $\mathbf{p}$ and $\mathbf{w_t}$ of the quasi-optimal rules for each scenario.

In conducting Complex's twenty runs of each scenario occasionally solutions, but never the solution with the highest objective value, generated the same value of the objective function but with different $\mathbf{p}$ and $\mathbf{w_t}$. Instances were found where a given herd's profit varied between the two solutions, suggesting IS that make different selection decisions for a considerable portion of the herds can result in the same value of (6).

More interestingly, under scenario A, a case also exists where the profit for each herd is identical for two Complex solutions suggesting more than a single vector of search variables exist which result in the same animal selection decisions, $\mathbf{w_4}$ for these rules are reported in Table 2 (each rule conducts all selection in period 4). A message created by the average of the weights results in the same profit as the original messages for each herd but one which experienced a relative loss of $1 per heifer. This suggests the search space between these two local optima is a shallow valley. The great similarity of the values of the elements of $\mathbf{w_4}$ which correspond to each parents' milk PTAs, and to a lesser extent sire protein reliability and dam milk-fat reliability suggest these pieces of information contain the majority of value contained in the complex genetic message.

Averaging the weights from the twenty scenario A solutions, which vary in objective values of (6) from $169 to $174, and applying it to the IS-deriving sample results in a value of (6) of $161 which is above random selection's objective value (3) (for the average herd) of $140 per heifer. This suggests the valley between the twenty local optima can be quite deep, extending almost half way down to the floor of random selection. This low value of the average would hinder Complex's quasi-optimization of the objective function because this average, or centroid, is used extensively as a reference point for movement of the vertices.

Perfect selection of each herd would have resulted in (1) (for the average herd) having a value of $272 per heifer, however focusing on even a single herd's genetic information it is unclear how to derive an IS to optimally rank the animals. So this estimate represents the maximum any IS could ever achieve, and it is highly unlikely that any cross-section IS would approach this level of performance. The complex genetic IS accounts for approximately 25% of the range in profit between perfect selection and random selection. This performance is consistent with the low positive rank correlations between predictions of first lactation production and actual production (Radke), and therefore LPCOC. For a given herd in the IS-deriving sample, Complex accounts for between -63% and 100% of the range in profit between perfect selection and random selection.

The complex genetic IS, and by definition the other two selection rules, conduct all selection in period 4 of scenario A. The difference in profit of the two genetic selection IS over random selection, presented in Figure 1, represents only the value of the two genetic messages because **p** is identical for all three rules. Specifically, Figure 1 presents, for each herd, the average heifer profit of each genetic IS less the profit from random selection.

Random selection is not dominated in the first nor second degree by either of the genetic IS. While for the majority of herds the random IS is inferior to at least one of the other two IS, random selection provides the highest profit of all three rules for ten of the 57 herds. Including ties, the complex IS has the highest objective value for 39 herds under scenario A, while for 33 herds the highest average profit per heifer is associated with the simple genetic IS.

Table 1 presents the value and standard errors of (7) (the increase in herd average profit per heifer for each of the two genetic heifer selection IS over the random IS) for the three scenarios. Using a one-tailed *t* test, the hypothesis that the complex genetic IS is not $20 more profitable than random selection under scenario A is rejected at P = 0.045 (*t* statistic = 1.73). The mean profit difference of $27.39 between selection based on the simple genetic IS and a random IS for this scenario is not significantly greater than $20 ($P$ = 0.12, *t* statistic = 1.20).

Figure 2 presents the difference in the value of the two genetic IS. For the majority of herds the difference in profit is minimal, although a few herds greatly benefit from use of one IS over the other. The less than $4 difference in mean profit of the IS is not significantly different statistically (P = 0.28 two-tailed, t statistic = 1.09) nor pragmatically.

For scenario B, Complex is used to generate a new quasi-optimal selection IS with the 58 herds in the IS-deriving sample. Again, this IS conducted all animal selection in the period 4. To assess whether the complex genetic IS generated under scenario B was sufficiently different to warrant the industry employing another IS for the different proportion to be selected, the IS were compared. The complex IS from the base scenario A was adapted to scenario B by specifying S = 0.7 rather than S = 0.8 when simulating the IS' performance on the 57 herd IS-testing sample. Although a few herds in the IS-testing sample greatly profit over the use of one IS over the other, the average loss per heifer by using the adapted scenario A complex genetic message for scenario B is \$2.46 per heifer as opposed to using the quasi-optimal message for scenario B. This small difference is not statistically different than zero (P = 0.45 two-tailed, t statistic = 0.76) and is not felt to be sufficient to warrant a complex genetic message for each scenario.

The adapted scenario A complex genetic IS is then tested against the simple genetic and random selection IS under the conditions of scenario B. The comparison of the selection IS' performances under scenario B is substantially similar to that presented in Figure 1 for scenario A. The distribution is slightly wider and flatter than that in Figure 1, with random selection being the most profitable method of heifer selection for 15 herds, 5 of which random selection is the most profitable method of selection under scenarios A and B. Neither the complex nor the simple genetic selection IS exhibit first or second degree stochastic dominance over random selection. Including ties, the complex genetic IS and the simple genetic IS represent the maximum profit for 32 and 33 herds, respectively.

The \$32.07 value of (7) associated with the complex IS is not statistically \$20 greater than random selection (P = 0.06, t statistic = 1.54). However, the mean herd \$35.21 increase in average profit per heifer as a result of selection based on the simple genetic message is statistically greater than \$20 (P = 0.03, t statistic = 1.96).

Again, while slightly flatter and wider, the histogram comparing the average profit per herd through use of the complex genetic IS versus the simple IS is very similar to that of Figure 2. Similar to the results under scenario A, the -\$3.14 difference in profits associated with the two IS which make use of the genetic information are not statistically (P = 0.45 two-tailed, t statistic = -0.76) nor practically different[2].

Under scenario C with the increasingly negative returns to heifer rearing, only one of the twenty solutions generated by Complex completes all the necessary heifer selling in the first period, and this rule has the third lowest value of (6). The remaining solutions generally select 83 to 93% of the heifers in period 1, the remaining majority of the selection occurs in period 2 in eleven of the solutions and in period 3 in three solutions. Commonly, a few herds sell animals in period 4. As the latter tends to occur primarily in the larger herds, the effect on the objective function is small as the loss in profit is averaged over the entire herd before entering the objective function. The quasi-optimal complex genetic IS selected 0.9, 0.91, 1.0 proportion of the heifers in periods 1 to 3 respectively, with a few herds selling heifers in period 4. Of the three scenarios, this one has the greatest range in objective values at 5.1%.

The variability of the periods in which selection occurs under the various r_t may reveal the factors that impact the simple appearing trade-offs made in heifer selection. Within a herd, the range in π_a is generally between \$1,000 to \$2,500, so the profit from making a better choice in terms of which animals are selected could potentially more than compensate for conducting some selection in periods which are nonoptimal in terms of maximizing the herd profit from r_t. Under scenarios A and B, with the improved information in period 4 and the $44 cost to total herd profit for each animal selected in period 3, all selection was conducted in period 4. However, under scenario C, the contention is whether Complex was routinely willing to pay $20 and occasionally $50 to attain the improved genetic information and/or to simply make sequential decisions to improve those selected.

Similar to the approach taken with scenario B, the complex IS from base scenario A is adapted to operate in scenario C by forcing all selection to occur in the first period based on $\mathbf{w_4}$ (i.e., $\mathbf{w_1} = \mathbf{w_4}$). The resulting IS is $9.72 more profitable per heifer for the average herd than using the complex genetic IS optimized under scenario C conditions[3].

The complex genetic IS from scenario A, modified for scenario C, is compared to selection based on the simple genetic message and the random message. The distributions for scenario C corresponding to Figure 1 are again substantially similar. The selection IS based on the genetic information are not first or second order stochastic dominant to random selection. The majority of herds profit from at least one selection IS using genetic messages versus random selection. Interestingly, of the 15 herds for whom random selection is the most profitable selection method under this scenario, for 5 of these herds random selection is the superior rule regardless of scenario. Under scenario C, the complex IS accounts for the highest profit per heifer in 35 herds, while selection based on the simple genetic message results in the highest

---

[2] The complex IS is less profitable than the simple heuristic IS due to sampling error in the quasi-optimal $\mathbf{w_4}$ and $\mathbf{p}$ such that they are not quasi-optimal for the IS-testing sample. See Radke for more discussion of the sampling error.

[3] The quasi-optimal complex IS for scenario C is less profitable than that adapted from scenario A due to sampling error in the quasi-optimal choice variables such that they are not quasi-optimal for the IS-testing sample.

profit for 34 herds.

The complex IS' \$32.04 (Equation 7) is statistically greater than \$20 more profitable per heifer than random selection (P = 0.04, t statistic = 1.76), while the \$25.09 difference between the simple genetic selection IS and random selection is not (P = 0.21, t statistic = 0.82). The \$6.95 difference in mean average profit per heifer between the two selection rules which use the genetic messages is not statistically different than zero (P = 0.12 two-tailed, t statistic = 1.58), and similar to previous scenarios a few herds profit greatly from use of one genetic IS over the other.

The values of (5), averaged across herds and on a per heifer basis, for the two genetic messages are elicited from Table 1 by subtracting the increased profit of an IS under scenario A from the IS' profit from scenario C. Scenarios A and C each select 80% of the heifers using the same weights; the only difference between the scenarios is that these weights are applied to the genetic information from rearing period 4 under scenario A and to the genetic information from rearing period 1 for scenario C. Comparing the profit of the complex genetic IS in Table 1 between scenarios A and C reveals the theoretically more informative message of parents' PTAs for milk, fat, protein and associated reliabilities from rearing period 4 are slightly less valuable than the same information from rearing period 1. Considering the simple genetic message, heifers' milk EBV message from rearing period 4 increase in value by \$2 per heifer over the period 1 milk EBV message. These changes are small and unimportant indicating updating of the genetic information over the course of the rearing interval, which should theoretically increase informativeness, is of little value in replacement heifer selection.

Summary and Conclusions

These results suggests genetic information is valuable in replacement heifer selection, and the average *ex ante* value is estimated at greater than $20 per heifer, realized over the course of the heifers' lives. The value of the genetic information is robust across the three scenarios. For the average Michigan producer this $1,000 profit increase from heifer selection represents approximately a 3% to 5% increase in farm income which should be sufficient to interest producers in selecting heifers based on genetics. Then a dairy producer that shifts from no heifer selection, and therefore an excessive culling rate, to the strategies of selecting heifers based on genetic information and an optimal culling rate among the cow herd would reap the profits of each strategy for a total 5% to 45% increase in farm net income.

While the relative profit distributions (i.e., Figures 1 and 2) are evaluated for a cross-section of herds, with each herd consisting of a single cohort of heifers, the profit distribution of a given herd for a number of cohorts is of primary interest to dairy producers. Variability among herds is composed of individual cohort effects and herd management effects. This latter effect is constant for cohorts within a given herd and will result in the profit distributions of a given herd having lower variances and possibly different means than Figures 1 and 2. However, using first lactation milk production to deterministically, rather than stochastically, estimate LPCOC results in an overly narrow distribution of profits. The net effect of these two opposing factors on the width of the profit distribution for a given herd is unclear.

The suggestion that for some herds random heifer selection would consistently be more profitable than selection based on the genetic information warrants reconsideration. While a priori it is plausible that genetic information may be of little value in heifer selection, it is difficult to understand how, for a given herd, this information could have negative value resulting in random selection consistently providing higher profits than selection based on genetic information. It is possible that the single cohorts of heifers that represented these five herds experienced a random event which led to poor performance of the heifers with the higher genetic estimates. The random event may have been due to Mendelian sampling, or an environmental effect that discriminated against the genetically superior heifers. In either situation, it is not surprising that selection based on genetic information consistently results in lower profits for this cohort of heifers regardless of scenario. In summary, the differences between herds in terms of profit per heifer are due to random noise and systematic herd effects.

It can be concluded that while the quasi-optimal complex genetic message of heifer profitability based on parents' PTAs of milk, fat and protein and associated reliabilities is technically more informative than the simple genetic message based solely on parents' milk PTAs (i.e., milk EBVs), the values of the two messages are pragmatically equivalent. Then heifer selection should use the simpler EBV milk IS, rather than the quasi-optimal complex IS. This similar performance of the two IS which utilize the genetic information suggests the value of the genetic information resides primarily in the parents' milk PTAs, while the other PTAs and the estimates of the PTAs' informativeness (i.e., the reliabilities) have relatively little value in replacement Holstein heifer selection. The commonality of the weights for the milk PTAs of the two selection rules (presented in Table 2) which resulted in identical selection decisions, support the relative importance of the milk PTA information. While it is likely that the fat and protein PTAs are not valuable in heifer selection due to high correlation with PTA milk, the limited value may also have sourced from limited variability in the information, this is likely more relevant for the reliabilities.

With the genetic information having no practical change in value during rearing, the decision of when to make the heifer selection decisions reduces to maximizing the profit from sale of the excess heifers. The incorporation of updated genetic messages during the rearing period is the first empirical value of information application of Epstein's framework of potential message updating. The finding that the value of the genetic information was static, negating the need for dynamic information management, is likely specific to the genetic heifer selection IS. This finding supports the contention that, even with static value of information, sequential decision-making may be more valuable than simultaneous. This warrants consideration in future value of information research in complex decision environments, whether static or dynamic.

Unique to the value of information literature is the comparison of a quasi-optimal IS to a heuristic IS. Due to the value of the information being static, this comparison of the two genetic IS reduces to comparing quasi-optimal complex messages versus simple heuristic messages. Then an appropriate inference from this research is, given static value of information, the simple appearing heuristic IS, conventionally used by decision-makers and evaluated in the value of information literature, have been implicitly optimally selected from the universe of IS that comprise information. It is unclear whether the decision-makers' use of a static IS in the presence of a potentially dynamic decision environment is serendipitous or purposeful. And it remains unclear whether the decision-maker could chose, or design, an IS to maximize his welfare in a truly dynamic decision environment.

While profitable, selection based on milk EBV is capturing only a portion of the profit potentially available through heifer selection. Recalling that LPCOC is estimated as a deterministic function of first lactation milk production, this low capture ratio is then consistent with the results presented by Radke revealing a diffuse distribution of within herd rank correlations between parent PTA based predictions of first lactation milk production and actual production. To capture this elusive profit the dairy industry needs to continue to explore potential information sources other than EBV on which to base methods of heifer selection.

New sources of information can easily be included in the theoretical framework and the quasi-optimal empirical method used here. Moreover, this approach is useful in solving applied problems in which it is difficult to model the theoretically valuable information. This difficulty may arise because insufficient data is available to model the theoretical decision or theory does not indicate how the information should be utilized by the decision-maker. This approach is also amenable to valuing unique attributes of a message, which in the present case includes information on the informativeness of the message. This approach should be particularly fruitful with dynamic decisions, including the valuation of different IS, or the evaluation of a given IS' change in value of over time.

Acknowledgments

The authors thank Al Thelen, Terry Speer and Lyle Smith at Michigan DHI, as well as, Leigh Walton and H. D. Norman at the Animal Improvement Laboratory, USDA for assistance with data collection. Jason Shelagowski's assistance in FORTRAN programming is acknowledged. The financial support of the first author by the Department of Agricultural Economics through the Animal Industry Initiative funds provided by the Agricultural Experiment Station at Michigan State University while this work was conducted is gratefully acknowledged.

References

Allaire, F.R. "Economic consequences of replacing cows with genetically improved heifers." *J. Dairy Sci.* 64(1981):1985-1995.

Allaire, F.R., and E.P. Cunningham. "Culling on low milk yield and its economic consequences for the dairy herd." *Livest. Prod. Sci.* 7(1980):349-359.

Baquet, A.E., A.N. Halter, and F.S. Conklin. "The value of frost forecasting: a Bayesian appraisal." *Amer. J. Agr. Econ.* 58(August 1976)511-520.

Bauer, L., G. Mumey, and W. Lohr. "Longevity and genetic improvement issues in replacing dairy cows. Can. J. Ag. Econ. 41(1993):71-80.

Box, M.J. "A new method of constrained optimization and a comparison with other methods." *Comput. J.* 8(1965):42-52.

Congleton, W.R., and L.W. King. "Culling cows on predicted future profitability with a variable planning horizon." *J. Dairy Sci.* 68(1985):2970-2983.

Dixit, A.K., and R.S. Pindyck. *Investment under uncertainty*, pp. 103-104. Princeton NJ: Princeton University Press, 1994.

Epstein, L.G. "Decision making and the temporal resolution of uncertainty." *Int. Econ. Rev.* 21(June 1980) 269-283.

Eidman, V.R., G.W. Dean, and H.O. Carter. "An application of statistical decision theory to commercial turkey production." *J. Farm Econ.* 49(1976):852-868.

Harris, B.L., and A.E. Freeman. "Economic weights for milk yield traits and herd life under various economic conditions and production quotas." *J. Dairy Sci.* 76(1993):868-879.

Harris, T.R. "Appendix A: The Modified Box-Complex." *Analysis of Irrigation Scheduling for Grain Sorghum in the Oklahoma Panhandle.* Oklahoma State University Ph.D. Dissertation, 1981.

Henderson, C.R. "Selection index and expected genetic advance." Page 141 in *Statistical Genetics and Plant Breeding ; a symposium and workshop*. W. D. Hanson and H. F. Robinson, ed. Natl. Acad. Sci.-NRC, Washington, DC, 1963.

Karszes, J. "Dairy replacement programs: costs and analysis Western New York, 1993." *1994 Heifer Management Symposium* Mimeograph Series Cornell Cooperative Extension,

Killen, L., and B. Kearney. "Optimal dairy cow replacement policy." *Ir. J. Agric. Econ.* Rur. Sociol. 7(1978):33-40.

Korver, S., and J.A. Renkema. "Economic evaluation of replacement rates in dairy herds II. Selection of cows during the first lactation." *Livest. Prod. Sci.* 6(1979):29-37.

Kuester, J.L., and J.H. Mize. *Optimization Techniques with FORTRAN.* pp 368-385. New York: McGRaw-Hill Book Co., 1973.

Kuipers, A. *Development and Comparison of Selection Criteria for Cows and Bulls with a Dairy Herd Simulation Model.* Univ. Wisconsin, Madison Ph.D. Thesis, 1980.

Marschak J., and K. Miyasawa. "Economic comparability of information systems." *Int. Econ. Rev.* 9(June 1968) 137-174.

McCullough, D.A., and M. DeLorenzo. "Effects of price and management level on optimal replacement and insemination decisions." *J. Dairy Sci.* 79(1996):242-253.

Michigan Dairy Herd Improvement Association. *Michigan Dairy Production Herd Evaluation Report*, 1996.

Nelder, J.A., and R. Mead. "A simplex method for function minimization." *Comput. J.* 7(1964):308-313.

Pearson, R.E., and A.E. Freeman. "Effect of female culling and age distribution of the dairy herd on profitability." *J. Dairy Sci.* 56(1973):1459-1471.

Perrin, R.K. “Asset replacement principles.” *Amer. J. Agr. Econ.* 54(February 1972):60-67.

Radke, B.R. *Prepartum Selection of Holstein Heifers to Maximize Profit of Michigan Producers.* Michigan State Univ. East Lansing Ph.D. Dissertation, 1998.

Richards, T.J., and S.R. Jeffrey. “Establishing indices of genetic merit using hedonic pricing: An application to dairy bulls in Alberta.” *Can. J. Ag. Econ.* 44(1996) 251-264.

Rogers, G.W., J.A.M. van Arendonk, and B.T. McDaniel. “Influence of production and prices on optimum culling rates and annualized net revenue.” *J. Dairy Sci.* 71(1988):3453-3462.

Schroeder, T.C., J.A. Espinosa, and B.K. Goodwin. “The value of genetic traits in purebred dairy bull services.” *Rev. Ag. Econ.* 14(1992):215-226.

Van Arendonk, J.A.M. “Use of profit equations to determine relative economic value of dairy herd life and production from field *data*.” *J. Dairy Sci.* 74(1991):1101-1107.

Van Arendonk, J.A.M. and A.A. Dijkhuizen. “Studies on the replacement policies in dairy cattle. III. Influence of variation in reproduction and production.” *Livest. Prod. Sci.* 13(1985):333-349.

Weigel, D.J., B.G. Cassel, I. Hoeschele, and R.E. Pearson. “Multiple trait prediction of transmitting abilities for herd life and estimation of economic weights using relative net income adjusted for opportunity cost.” *J. Dairy Sci.* 78(1995):639-647.

Table 1. The value of genetic information, measured as the increase in herd average heifer profit, in replacement heifer selection for three scenarios.

						Mean and (Standard Error) of Ω		
						Genetic IS		
Scenario	r_1	r_2	r_3	r_4	S	Complex	Simple	Difference
A	$45	$71	$114	$158	0.8	**$31***	**$27**	$4
						(6.5)	(6.1)	(3.6)
B	$45	$71	$114	$158	0.7	**$32**	**$35***	-$3
						(7.8)	(7.7)	(4.1)
C	-$10	-$30	-$60	-$140	0.8	**$32***	**$25**	$7
						(6.8)	(6.2)	(4.4)

*Significantly different ($P \leq 0.05$) than $20, using one-tailed *t* test.

Table 2. Period 4 weights, and their average, for two scenario A rules with identical selection decisions for the 58 IS-deriving herds.

	$\mathbf{w}_4$		
$\mathbf{g}_4$	Rule I	Rule II	Average
sire milk	0.69	0.70	0.70
sire fat	0.50	0.43	0.47
sire protein	0.52	0.43	0.48
sire reliability milk-fat	0.01	-0.06	-0.03
sire reliability protein	-0.24	-0.26	-0.25
dam milk	0.29	0.30	0.30
dam fat	-0.05	-0.03	-0.04
dam protein	0.41	0.23	0.32
dam reliability milk-fat	0.13	0.11	0.12
dam reliability protein	-0.14	0.25	0.06