

Using Genetic Marker Selection to Reduce Asymmetric Information in the U.S. Beef Supply Chain

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Overview

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Results and Discussion

Background

Bovine Respiratory Disease (BRD)

- Multi-factorial disease
- Largest cause of morbidity and mortality
- \$54.12 million estimated feedlot treatment costs
 - Underestimates total costs from BRD incidence
- Metaphylaxis treatment programs not significantly effective
- Calf stress and environment are important factors

Background

Genetic Marker Selection

- Neiberger, H. et al. (2014) have shown that calf genetics determine BRD susceptibility
- Select breeding stock with BRD resistant markers
- Effectively reduces BRD susceptibility compared to other treatment/prevention programs
- Calf stress and environment still important factors

Background

Production Environment

- Begins with cow-calf producers
 - calves raised alongside birthing cows
 - weaned and pre-weaned separation occurs
- Feedlots ultimately source calves from cow-calf producers
- Livestock health risk shifts to feedlots after purchase

Background

Agricultural Asymmetric Information

- Literature focused on crop production
 - input control and scheduled planting decisions assumed by crop contractors
 - commodity cooperatives
 - crop insurance

U.S. Beef Supply Setting

- Feedlots are *uninformed* about calf health during lot purchase
- Cow-calf producers hold *private information* about calf health

Objective

1. Show there exists a theoretical price premium mechanism that provides incentive for cow-calf producers to reveal calf health type.
2. Show empirical support for theoretical results.

How are objectives accomplished?

- Develop feedlot's problem in an adverse selection environment
- Evaluate profit-maximizing model outcomes
- Specify functional forms and empirically analyze model outcomes
- Use a stochastic data generating process to test empirical results

Contribution

New Markets

- Call attention to beef supply chains

Theoretical

- Show profit-maximizing conditions that support price premiums

Empirical

- Provide representative price premium values

Theoretical Environment

Feedlot costs

Feedlot cost function $C[q(\theta_i), r, t]$

Where

$q(\theta_i)$: calf q of health type θ for $i = \{\text{MS}, \text{N}\}$

r : per unit production price

t : weekly time period following calf intake

Assumptions

$$\theta_{MS} > \theta_N$$

$$C_t[q(\theta_N), r, t] > 0 \text{ and } C_{tt}[q(\theta_N), r, t] > 0$$

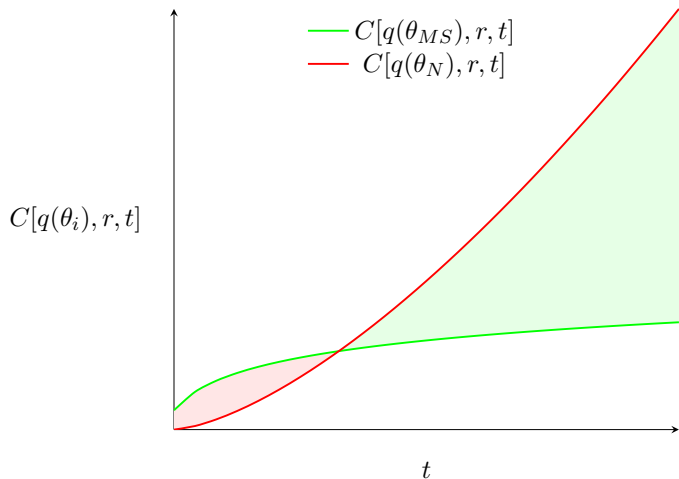
$$C_t[q(\theta_{MS}), r, t] > 0 \text{ and } C_{tt}[q(\theta_{MS}), r, t] < 0$$

$$\lim_{t \rightarrow \bar{t}} C_t[q(\theta_{MS}), r, t] = 0$$

Theoretical Environment

Feedlot costs

Figure 1: Feedlot calf health type costs over time



Theoretical Environment

Feedlot problem

Feedlot provides price schedule (T_{MS}, T_N) to cow-calf producers

Expected profit maximization provides optimal (T_{MS}^*, T_N^*)

Let

$\gamma \in (0, 1)$ be the probability of calf type $q(\theta_N)$

$f[q(\theta_i)]$ be the weight production function for $i = \{\text{MS}, \text{N}\}$

p be dressed beef price received

β be the discount factor

Theoretical Environment

Feedlot problem

$$\begin{aligned} \max_{q(\theta_{MS}), q(\theta_N)} \quad & \sum_{t=0}^T \beta^t (1 - \gamma) \{pf[q(\theta_{MS})] - C[q(\theta_{MS}), r, t] - T_{MS}\} \\ & + \beta^t \gamma \{pf[q(\theta_N)] - C[q(\theta_N), r, t] - T_N\} \end{aligned}$$

$$\text{s.t. } T_{MS} - c[q(\theta_{MS}), Z_{MS}] \geq 0 \quad (PC_{MS})$$

$$T_N - c[q(\theta_N), Z_N] \geq 0 \quad (PC_N)$$

$$T_{MS} - c[q(\theta_{MS}), Z_{MS}] \geq T_N - c[q(\theta_{MS}), Z_N] \quad (IC_{MS})$$

$$T_N - c[q(\theta_N), Z_N] \geq T_{MS} - c[q(\theta_N), Z_{MS}] \quad (IC_N)$$

Theoretical Environment

Feedlot problem

Recall $\theta_{MS} > \theta_N$

Participation Constraints

(PC_{MS}) binds at the optimum

(PC_N) nonbinding at the optimum

Incentive Compatibility

(IC_{MS}) nonbinding at the optimum

(IC_N) binds at the optimum

Theoretical Environment

Feedlot problem

Constraints become

$$\text{s.t. } T_{MS} - c[q(\theta_{MS}), Z_{MS}] = 0 \quad (PC_{MS})$$

$$T_N - c[q(\theta_N), Z_N] = T_{MS} - c[q(\theta_N), Z_{MS}] \quad (IC_N)$$

With **substitution** $(PC_{MS}) \rightarrow (IC_N)$

$$T_{MS} = c[q(\theta_{MS}), Z_{MS}] \quad (PC_{MS})$$

$$T_N = c[q(\theta_{MS}), Z_{MS}] + \{c[q(\theta_N), Z_N] - c[q(\theta_N), Z_{MS}]\} \quad (IC_N)$$

Theoretical Environment

Feedlot problem

$$\begin{aligned} \max_{q(\theta_{MS}), q(\theta_N)} \sum_{t=0}^T & \beta^t (1 - \gamma) \{ pf[q(\theta_{MS})] - C[q(\theta_{MS}), r, t] - c[q(\theta_{MS}), Z_{MS}] \} \\ & + \beta^t \gamma \{ pf[q(\theta_N)] - C[q(\theta_N), r, t] \} \\ & - \beta^t \gamma \{ c[q(\theta_{MS}), Z_{MS}] + (c[q(\theta_N), Z_N] - c[q(\theta_N), Z_{MS}]) \} \end{aligned}$$

q_{MS}^* and q_N^* solve FOC optimality conditions

$$pf[q_{\theta_{MS}}^*] = C[q_{\theta_{MS}}^*, r, t] + \frac{1}{(1 - \gamma)} c[q_{\theta_{MS}}^*, Z_{MS}] \quad (1^*)$$

$$pf[q_{\theta_N}^*] = C[q_{\theta_N}^*, r, t] + c[q_{\theta_N}^*, Z_N] - c[q_{\theta_N}^*, Z_{MS}] \quad (2^*)$$

Theoretical Environment

Feedlot problem

Constructing **optimal price schedule** (T_{MS}^* , T_N^*) from

$$T_{MS} = c[q(\theta_{MS}), Z_{MS}]$$

$$T_N = c[q(\theta_{MS}), Z_{MS}] + \{c[q(\theta_N), Z_N] - c[q(\theta_N), Z_{MS}]\}$$

From (1*) for T_{MS}^*

$$T_{MS}^* = c[q_{\theta_{MS}}^*, Z_{MS}] = (1 - \gamma) (pf[q_{\theta_{MS}}^*] - C[q_{\theta_{MS}}^*, r, t]) \quad (3^*)$$

From (2*) and (3*) for T_N^*

$$\begin{aligned} T_N^* &= (1 - \gamma) \{pf[q_{\theta_{MS}}^*] - C[q_{\theta_{MS}}^*, r, t]\} & (4^*) \\ &\quad - \{C[q_{\theta_N}^*, r, t] - pf[q_{\theta_N}^*]\} \\ &\geq 0 \end{aligned}$$

Theoretical Environment

Feedlot problem

(3*) and (4*) admit **price premium** expression for $q(\theta_{MS})$

$$\begin{aligned} T_{MS}^* - T_N^* &= (1 - \gamma) \{pf[q_{\theta_{MS}}^*] - C[q_{\theta_{MS}}^*, r, t]\} \\ &\quad - [(1 - \gamma) \{pf[q_{\theta_{MS}}^*] - C[q_{\theta_{MS}}^*, r, t]\} - \{C[q_{\theta_N}^*, r, t] - pf[q_{\theta_N}^*]\}] \\ &= C[q_{\theta_N}^*, r, t] - pf[q_{\theta_N}^*] \geq 0 \end{aligned} \tag{5*}$$

Data

Sourced from a large-scale U.S. commercial feedlot in Colorado

Sample includes 952 observations on

- Cattle health and treatment
- Arrival and processing dates
- Processing weight

Representative price and production cost data sourced from
USDA AMS and LMIC

Data

BRD categorization

BRD categorization for feedlot data (Shaefer et al., 2012)

0-5 categorical scale for calf presentation

- 0: normal respiratory function
- 3: $\geq 103^{\circ}\text{F}$ rectal temp, not tachypnic or dyspnic, with nasal discharge
- 5: $\geq 103^{\circ}\text{F}$ rectal temp and tachypnic or dyspnic

Figure 2: Proportion Statistics for Calf Respiratory Health Characterization ($n = 927$)

	Normal Respiratory Health	Morbidity Scale 3	Morbidity Scale 5	BRD
Proportion	0.525	0.263	0.183	0.446

Note: Each value is a proportional representation of the calf respiratory health characterization based on morbidity scale rankings within the data set

Empirical Methodology

Calf level

Representative calf profit (loss) for $i = \{\text{MS}, \text{N}\}$

- Data

$$E[\pi(q(\theta_i))] = \frac{1}{N} \sum_{n=1}^N (p_{t,n} f_n[q(\theta_i)] - C_n[q(\theta_i), r, t])$$

- Simulation

$$E[S_{(M)}\{\pi(q(\theta_i))\}] = \frac{1}{M} \sum_{m=1}^M (E[S_{(l)}\{\pi(q(\theta_i))\}])$$

for

M sampling iterations

l number of random $\pi(q(\theta_i))$ draws

Empirical Methodology

Aggregate level

Simulated aggregate profit (loss)

$$\Pi_{(S)}(q(\theta_{MS}), q(\theta_N)) = E[S_{(M)}\{\pi(q(\theta_{MS}))\}] + E[S_{(M)}\{\pi(q(\theta_N))\}]$$

Probability of non-genetic marker selection calf $q(\theta_N)$

$$\gamma = \frac{1}{M} \sum_{m=1}^M \left(\frac{\sum_{l=1}^L I[s^{(l)}(q(\theta_N))]}{L} \right)$$

Results

Data - calf level

Figure 3: Representative Per-Calf Revenue, Cost, and Profit Outcomes (\$/head)

	Healthy Calf	BRD Calf
Mean Per-Calf Revenue	1786.820	1789.904
Mean Per-Calf Cost	1755.227	1799.619
Mean Per-Calf Profit	31.039	-11.359

Note: Representative revenue, cost, and profit for a normal respiratory health and BRD calf are computed as the means of per-calf costs, revenues, and profits. The means for mean cost, mean revenue, and mean profit of morbidity scale three and five calves are computed to represent a BRD calf.

Results

Simulated - calf level

Figure 4: Summary Statistics for Monte Carlo Representative Per-Calf Profit (-Loss) Outcomes (\$/head)

	Healthy Calf	BRD
Mean	31.654	-15.719
Std. Dev	19.553	20.127
Min	-34.673	-75.951
Max	95.816	57.106

Note: Per-calf profit (-loss) summary statistics are computed for Monte Carlo simulation profit outcomes of normal respiratory health calves and calves considered to have contracted BRD

Results

Simulated - aggregate level

Figure 5: Monte Carlo simulation profit (\$) outcomes

	Healthy Calf	BRD	Total Profits
Mean	1718.38	-714.461	1003.922
Std. Dev	1066.25	905.943	1416.553
Min	-1698.99	-3949.47	-3353.120
Max	5142.72	2284.23	5674.469
$Pr(\text{loss})$			0.236
γ			0.456

Note: Total profits (losses) are computed as the sum of per-calf profit outcomes of normal respiratory health calves and calves considered to have contracted BRD. The probability of feedlot total loss, where total loss from BRD calves is greater than total profits from normal respiratory health calves, is the number of simulated observations resulting in loss over the simulation sample space

Discussion

How do we **link** BRD categorization to **genetic marker selection**?

Interpret data as

$q(\theta_{MS}) \equiv$ morbidity scale 0 ranking

$q(\theta_N) \equiv$ morbidity scale 3 and 5 ranking

Genetic marker selection **fee**, **price premium**, and **profits**

$$T_{MS}^* = (1 - \gamma)(pf[q_{\theta_{MS}}^*] - C[q_{\theta_{MS}}^*, r, t]) = \$17.22$$

$$T_{MS}^* - T_N^* = \$15.72$$

$$\pi(q(\theta_{MS})) > 0$$

Discussion

Asymmetric information

- Optimal price premium mechanism exists
- Empirical results support theoretical outcomes
- Simulation validates mechanism

Limitations

- Production data
- Cost assumptions
- BRD binary categorization in data

Questions?

Thank you

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