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An Analysis of Dairy Farm Financial Efficiency and Price Expectations in Seedstock Bull Markets

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To the Graduate Council:

I am submitting herewith a thesis written by Seth H. Ingram entitled "An Analysis of Dairy Farm Financial Efficiency and Price Expectations in Seedstock Bull Markets." I have examined the final electronic copy of this thesis for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Master of Science, with a major in Agricultural Economics.

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An Analysis of Dairy Farm Financial Efficiency and Price Expectations in Seedstock Bull Markets

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Abstract

The first thesis chapter employs two single-stage data envelopment analysis (**DEA**) models under varying returns to scale assumptions to provide technical efficiency estimates for 26 dairy farms in Tennessee, Kentucky, and North Carolina participating in the UT Dairy Gauge program. These analyses reveal how efficiently farms utilize inputs (cows, feed, labor, forage) to generate farm income relative to other sample farms. Under the assumption of constant returns to scale (**CRS**) 7 farms are estimated to be technically efficient, while 13 farms display comparative efficiency under an assumption of variable returns to scale (**VRS**). No significant difference existed between dairy farms in Tennessee relative to farms in neighboring states. This study advances the literature on dairy farm efficiency as the first of its kind to utilize DEA in the analysis of Southeast region dairy farms in the US.

The second thesis chapter investigates optimism bias in bull price expectations using incentivized lab-in-the-field experiments with Alabama and Tennessee cattle producers. Price prediction tasks based on past market transactions for 18 bulls from the Angus, Charolais, and Simmental breeds are utilized for this analysis. The tasks provide EPDs to facilitate accurate price expectations and reduce uncertainties stemming from bull characteristics. The results reveal that the EPD information provision prevents optimism bias from contaminating price expectations in the whole sample. However, the study also determines that, unlike buyers, sellers are prone to unrealistic optimistic expectations and show reduced accuracy prediction levels. These results reveal that optimism bias can be moderated by the type of EPD information utilized, breed characteristics, and regional differences in cattle operations. This chapter contributes to the literature by documenting the role of behavioral biases in the formation of

cattle price expectations and suggesting potential channels that transmit this effect to real cattle operations.

Table of Contents

List of Tables

List of Figures

CHAPTER 1: MEASURING THE EFFICIENCY OF DAIRY FARMS IN THE SOUTHEAST US USING A DATA ENVELOPMENT ANALYSIS MODEL

Abstract

This study employs two single-stage, input-oriented, data envelopment analysis (**DEA**) models under varying returns to scale assumptions to provide technical efficiency estimates for 26 dairy farms in Tennessee, Kentucky, and North Carolina. This analysis reveal how efficiently farms are utilizing inputs (cows, feed, labor, forage) to generate farm income relative to other farms in the sample. Under the assumption of constant returns to scale (**CRS**) 7 farms are estimated to be technically efficient, while 13 farms display comparative efficiency under an assumption of variable returns to scale (**VRS**). No significant difference is found to exist between dairy farms in Tennessee relative to farms in neighboring states. Although, the efficient farms were relatively larger than the inefficient farms, on average, no conclusion regarding economies of scale can be drawn from this analysis due to the exclusion of fixed input costs from consideration. This study advances the literature on dairy farm efficiency as the first of its kind to utilize DEA in the analysis of dairy farms in the Southeast region of the US.

Introduction

In any farm enterprise, input cost and production management are critical components of the enterprise's financial efficiency. This is especially true within the US dairy industry due to the recent volatility in feed and labor markets. Research on the financial efficiency of dairies in the Southeast region of the US is limited but needed, as hundreds of these dairy farms have proven unviable and shut down operations in the last decade. In 2010, Tennessee, Kentucky, and North Carolina contained 490, 940, and 450 licensed dairy herds, respectively. By 2020, Tennessee, Kentucky, and North Carolina contained only 180, 450, and 145 licensed herds, respectively (USDA-ESMIS, 2022). This equates to a greater than fifty percent decline in dairy farms licensed to sell milk in each of these three states. Consolidation in the dairy industry is a nationwide trend that has resulted in American consumers relying on far fewer, but increasingly larger, dairy enterprises to supply a greater volume of milk products (MacDonald et al., 2020). The apparent struggle of so many dairy farm operators in the Southeast region of the US to maintain efficient operations warrants further analysis.

This study utilizes financial records for the 2020 calendar year provided by 26 dairy farms across TN, KY, and NC to provide an analysis of the relative technical efficiency of these operations and demographic factors influencing farm efficiency. Technical efficiency differs from economic efficiency in that it specifically refers to the efficient utilization of inputs by firms or farms to produce an output. The farms in this dataset vary widely in size, predominate cow breed, and management strategies. The variety among the farms in this subset of the population ensures that this analysis is not too narrowly focused and allows for comparison between subgroups in the sample.

Data envelopment analysis **(DEA)** is the method utilized to measure farm efficiency. This is a non-parametric linear programming technique first outlined by Charnes et al. (1978) that measures the efficient use of inputs to produce one or more outputs and assigns an estimate of efficiency on a scale of 1 (most efficient) to 0 (least efficient) to each decision-making unit (**DMU**). The DEA method has been used in several previous studies measuring the technical efficiency of dairy farms (Aldeseit, 2013; Barnes, 2006; Murova and Chidmi, 2013; Stokes et al., 2007). However, no analysis of this kind has focused on dairy farms in the Southeastern region of the US.

The primary inputs for production on dairy farms in the Southeast are generally consistent across operations. First, the optimal number of milk cows in a herd is an important input consideration for dairy producers. It is well established in the existing literature that economies of scale are present in the US dairy industry (MacDonald et al. 2016; MacDonald et al., 2020; Mosheim and Lovell, 2009). Average production costs per cow are consistently lower on large dairy farms relative to smaller farms. Wolf et al. (2016) find this to be especially true during "good years," when the larger herds in their dataset of dairies in the North-Central region of the US achieved significantly higher profitability than smaller herds. Wolf et al. (2020) study of Midwest dairy farm profitability finds that the average return on assets (**ROA**) for herds containing 500 cows or more is more than double the average ROA for herds containing less than 100 cow herds. Additionally, a recent study conducted by USDA's Economic Research Service reveals that annual milk output per cow across dairy farms with > 1,000 cows was 10,990 kg from 2000 to 2016, while the output per cow across dairy farms with ≤ 100 cows was only 9,321 kg during this same period (Njuki, 2022). The same study also found that milk productivity on dairy farms with > 1,000 cows increased at an annual rate more than four times the rate of farms with 100 cows or less. The literature is unambiguous in conveying that dairy enterprises with larger herds tend to be the most efficient.

The US dairy industry is labor intensive. Several studies have examined the impact of labor efficiency and costs on dairy farm efficiency (El-Osta and Johnson, 1998; Kauffman and Tauer, 1986; MacDonald et al., 2016; Yi and Ifft, 2019). Labor costs, on the average dairy farm, are the second largest variable input costs incurred behind feed costs (Yi and Ifft, 2019). Moreover, wage rates in the US are rising, and it is becoming increasingly difficult for dairy operations to source high-quality labor (Salfer et al, 2017). This was the case even before the vast labor shortages caused by the COVID-19 pandemic. Yi and Ifft (2019) highlight current labor challenges in the US dairy industry in their study of labor-use efficiency on more than 300 dairy farms in New York. They find that the tightening labor supply, increasing labor costs, and potential immigration policy amendments makes efficient labor management a critical aspect of any successful dairy operation. Additionally, their study finds that labor use efficiency has a significant positive relationship with farm financial performance. Higher labor costs do not necessarily indicate inefficiency. Studies by Yi and Ifft (2019) and MacDonald et al. (2016) find that larger, more profitable dairy farms spend more on labor per hundredweight (cwt) of milk produced, and credit this to better performing farms typically hiring more highly skilled workers. Labor is certainly one of the most important and costly inputs in the US dairy industry. Optimizing labor productivity is a core strategy for dairy producers to improve the technical efficiency of their operations.

Feed costs are consistently the highest variable input cost for US dairy enterprises. Approximately 70 to 80 percent of total operating costs for the average US dairy are feed expenses (MacDonald et al. 2020). Feed costs in the US have varied widely and unpredictably over the past 20 years (Bozic et al, 2012**;** MacDonald et al. 2016; MacDonald et al. 2020; Nicholson and Stephenson, 2015). There is consensus in the literature that purchased feed costs has a negative relationship with farm financial performance (Kauffman and Tauer, 1986; Yi and Ifft, 2019; El-Osta and Johnson, 1998). Kaufman and Tauer (1986) analyze farm records from 112 dairy farms in New York in the ten-year period from 1974 through 1983 and conclude that purchased feed per cow is an important factor in explaining differences in farm efficiency. El-Osta and Johnson (1998) utilize data from the 1993 USDA Farm Costs and Returns Survey to perform weighted least squares regression on a net farm income model and determine that purchase feed costs were one of the most important factors in explaining the variation in net returns per cwt of milk sold.

Another considerable input cost for dairy farms in the Southeast is the cost of forage. Current research on the impact of forage costs on farm efficiency is limited. Although, a recent USDA report finds that smaller dairy herds tend to be more reliant on forage than larger herds (MacDonald et al. 2020). Two studies completed prior to the turn of the century find that forage costs per cow have a significantly negative impact on the financial performance of US dairy farms (El-Osta and Johnson, 1998; Haden and Johnson, 1989). However, the dynamics of the dairy industry at the time of these studies were very different than today. The average dairy farm in the US was much smaller and more reliant on forage than the average farm today. An updated analysis of efficient forage cost management is needed.

The primary objective of this study is to determine the most efficient use of inputs (cows, feed, labor, forage) to produce farm income for the dairy farms in the sample. To accomplish this objective, I employ the single stage DEA method to estimate farm efficiency across the 26 dairy farms in our sample. Two scenarios with differing returns to scale assumptions are considered.

This analysis is the first of its kind to provide an analysis of dairy farm efficiency in the Southeast using DEA. An additional objective of this study is to determine if Tennessee farms show increased efficiency relative to farms in neighboring states. The University of Tennessee's Master Dairy program is an exclusive extension education program intended to enhance the efficiency Tennessee dairy producers, and funding from the USDA Dairy Business Innovation Initiative (**DBII**) program was also provided in Tennessee beginning in 2019 for this purpose. The results of this study will provide information and recommendations to help dairy farmers in the Southeast attain relative efficiency by adjusting input levels and certain production practices for their operations.

Data

The data utilized in this study was provided by 26 dairy farms participating in the Dairy Gauge Benchmark Program. Dairy Gauge enables producers to compare their farm financial performance with those of their peers through financial benchmarking. One of these farms inaccurately reported the labor costs of its operation and is not included in the dataset used for analysis in this study. This dataset consists of 13 farms located in Tennessee, 11 farms in Kentucky, and 2 farms in North Carolina. The information collected from each of these farms includes the annual milk marketing statements, income report, balance sheet and mean number of milk cows in production.

This full sample of dairies accounted for 13 percent of the total milk production in these three states in 2021. Moreover, the 13 farms located in Tennessee account for 42 percent of the milk production in the state (Bilderback et al., 2022). Holstein is the predominate breed of cow used by 20, or 77 percent, of the farms in the sample. Holstein cows produce the highest milk yield of the dairy cow breeds and is the most common dairy breed in the Southeast. In fact, 86 percent of dairy cows in the United States are Holstein (Njuki, 2022). The remaining 6 farms in the dataset run Jersey cows or a mix of the two breeds. Table 1 displays the input and output data that will be used in the DEA models as well as the data summary statistics for each DMU. The 26 DMU represent the dairy farms in the sample.

Farm income, the output in the DEA models, represents the gross farm revenue of each operation minus its income from dividends gained from membership in cooperatives. Dividend income is excluded due to this revenue being unrelated to any of the inputs examined in this analysis. Consequently, dividend income should not be considered when measuring the technical efficiency of the farms. All other sources of farm revenue, including milk income, government payments, cull income, and calf and heifer income, are included in this composite measure of farm income. The number of cows in production on dairy farms fluctuates throughout the year. However, an average number of cows figure is necessary to serve as an input in this DEA analysis. This cow number was calculated by taking the mean number of lactating and dry cows in the herd during the 2020 calendar year. Heifers that have not calved are not included in this head count, since these animals have not yet contributed milk production for the dairy enterprise. The feed input in the model simply represents the dollar amount spent by the farm to purchase feed. The forage input denotes the total cost of forage production on each farm. This cost is a combination of labor, seed, fertilizer, chemicals, equipment, and other costs solely incurred for the production of forage. The labor input value represents each farm’s total labor costs, including the operator management fee, minus the cost of labor associated with forage production that is already accounted for in the forage cost input value.

Table 1. Outputs and Inputs Used in Data Envelopment Analysis Models

DMU[1]	Breed	Farm income	Cows	Forage	Labor	Feed
1	Holstein	$5,560,873	940	$596,819	$750,215	$2,048,348
2	Holstein	$11,393,340	1,750	$1,497,947	$1,534,830	$4,148,186
3	Holstein	$17,729,231	2,340	$2,171,218	$2,034,569	$6,158,557
4	Holstein	$3,109,122	427	$418,435	$231,261	$878,594
5	Jersey	$1,166,676	290	$137,367	$114,435	$393,150
6	Holstein	$4,777,593	875	$454,298	$611,758	$1,605,010
7	Holstein	$4,348,890	672	$328,971	$612,149	$1,535,422
8	Holstein	$776,420	114	$98,754	$104,965	$172,623
9	Holstein	$1,819,000	346	$123,818	$207,709	$739,587
10	Jersey	$547,542	114	$87,964	$63,534	$164,031
12	Jersey	$399,623	90	$86,478	$16,420	$174,083
13	Mixed	$1,199,350	250	$132,064	$174,884	$492,893
14	Holstein	$683,988	128	$100,828	$148,877	$211,245
15	Holstein	$1,584,027	249	$185,605	$256,982	$608,029
16	Holstein	$913,869	165	$53,221	$117,490	$284,458
17	Holstein	$1,451,374	213	$228,798	$188,279	$655,254
18	Holstein	$1,265,543	233	$147,619	$192,977	$410,993
19	Holstein	$1,763,871	350	$226,637	$293,523	$726,693
20	Holstein	$539,870	103	$89,874	$115,758	$209,740
21	Jersey	$264,458	97	$31,817	$50,178	$72,440
22	Jersey	$1,897,795	339	$73,727	$199,297	$674,842
23	Holstein	$679,180	96	$83,300	$102,444	$91,833
24	Holstein	$4,543,168	705	$534,947	$379,574	$1,417,306
25	Holstein	$1,999,215	277	$295,680	$235,708	$515,420
26	Holstein	$1,366,266	305	$194,095	$73,485	$387,439
27	Holstein	$6,326,859	998	$992,856	$507,142	$1,815,213
Mean	–	$3,004,121	479	$360,505	$358,402	$1,022,745
SD	–	$3,901,683	539	$493,677	$465,277	$1,367,128
Min	–	$264,458	90	$31,817	$16,420	$72,440
Max	–	$17,729,231	2340	$2,171,218	$2,034,569	$6,158,557

[1]DMU (decision-making unit) represents dairy farms

Methods

A single-stage DEA model is utilized to produce an estimate of technical efficiency for each dairy farm (DMU) relative to the other farms in the sample. DEA models can be categorized by orientation type as either input-oriented or output-oriented models. An input-oriented DEA model estimates the minimal input levels necessary for DMUs to achieve a given level of output. Output-oriented DEA models maximize the output levels of DMU's while maintaining the current input levels. Model selection between an input- or output-oriented model is based on the objective of the evaluation, whether DMUs are aiming to be more efficient by reducing inputs levels or increasing outputs levels. Choosing between these two models also depends on which aspect, inputs or outputs, DMUs have more control over. In this analysis, the focus is on the input levels of dairy farms, so an input-oriented DEA model is employed.

Various return to scale assumptions can be imposed on DEA models. Constant returns to scale (CRS) and variable returns to scale (VRS) are assumed according to their frontiers (Charnes et al., 1978; Banker et al., 1984). For frontiers in which inputs and outputs change proportionally, a CRS model is the best fit. However, a VRS model is assumed when a constant proportional relationship is lacking between inputs and outputs and there is great variability in the data. In this study, two separate DEA models, one assuming CRS and another assuming VRS, are utilized.

In the input-oriented DEA models employed in this study, number of cows, feed, forage, and labor are used as inputs, while farm income is used as the output. The DEA model is setup as follows:

- **Decision variables:** v_{ik} and u_{jk} are weights for the i_{th} input and j_{th} output, for DMU k
- **Objective:** Maximize $\Sigma_{j=1}^{n} y_{jk} u_{jk}$, where y_{jk} refers to the j_{th} output for DMU k

- **Subject to constraints:**

  1) $\Sigma_{i=1}^{m} x_{ik} v_{ik} - \Sigma_{j=1}^{n} y_{jk} u_{jk} \geq 0,\ k = 1,2, \dots, K$

  2) $\Sigma_{i=1}^{m} x_{ik} v_{ik} = 1$

  3) $v_{ik}, u_{jk} \geq 0$

Where *K* refers to the number of DMU, *m* and *n* refers to the number of inputs and outputs, respectively, and x_{ik} refers to the i_{th} inputs for DMU *k*. These constraints serve to ensure (1) the efficiency of any one DMU does not exceed 100%, (2) the sum of weighted inputs for each DMU *k* is equal to 1, and (3) the weights are never a negative value. The efficiency of the k_{th} DMU is calculated as follows:

$$Efficiency = \frac{\Sigma_{j=1}^{n} y_{jk} u_{jk}}{\Sigma_{i=1}^{m} x_{ik} v_{ik}}$$

To solve this DEA model, Solver from Excel (Ragsdale, 2020) is used to analyze the model. First, the solver tool is utilized to solve for the maximum output for each farm under the constraints and obtain the efficiency scores. Then, the shadow price of the corresponding constraints in the sensitivity report are utilized as weights to multiply the output and input values and produce the target output and input values for each farm to attain technical efficiency. Finally, a measure of input overuse is obtained by taking the difference between the target input and the actual input levels for each DMU.

After the efficiency estimates are generated, a one-way analysis of variance (**ANOVA**) model is used in each scenario to estimate differences in efficiency between farms located in Tennessee and all other farms in the sample. The framework of the ANOVA model utilized is presented below.

$$y = \alpha + \sum_{i=1}^{K-1} B_i \, Xi + \varepsilon$$

In this equation, y is the dependent variable (technical efficiency), α represents the intercept, Xi is an indicator variable, B_i is the parameter estimate for each indicator variable, K represents the total number of indicator variables, and ε is the standard error term.

Results and Discussion

Scenario 1: Constant Returns to Scale Assumption

The initial scenario provides an analysis of the relative efficiency of all 26 dairy farms in the sample under the assumption of constant returns to scale**.** Table 2 summarizes the efficiency and overuse of inputs for all 26 farms and ranks the farms by efficiency. The DEA model finds 7 of these 26 dairy farms to be technically efficient. These efficient farms use varying breed types. Holstein is the predominate breed of cow for 5 of the efficient farms, while the other two efficient farms primarily use Jersey cows. In addition, 4 of the efficient farms are located in Tennessee, while 3 are located in Kentucky. No efficient farms are located in North Carolina; however, this should not be considered a reliable indication that farms in North Carolina are less efficient, since only two farms from the state are included in the sample.

The income level for every farm in the analysis is equal to its target value as a result of the selection of the input-oriented model. This DEA model is employed to minimize inputs for a given level of output. Each of the efficient farms are found to be efficiently utilizing inputs to produce farm income with no overuse. This result is consistent with the definition of efficiency in the DEA model. However, for every inefficient farm, an overuse of all four inputs is realized. These operations are overusing inputs relative to the farms on the efficient frontier. In other

Table 2. CRS Data Envelopment Analysis Results

DMU	Efficiency	Income	Overuse Cows	Overuse Forage	Overuse Labor	Overuse Feed
26	1	$1,366,266	0	0	0	0
23	1	$679,180	0	0	0	0
3	1	$17,729,231	0	0	0	0
7	1	$4,348,890	0	0	0	0
22	1	$1,897,795	0	0	0	0
12	1	$399,623	0	0	0	0
4	1	$3,109,122	0	0	0	0
25	0.987	$1,999,215	4	$44,037	$3,034	$6,634
16	0.986	$913,869	9	$764	$12,249	$4,082
24	0.964	$4,543,168	26	$19,493	$13,831	$59,212
8	0.954	$776,420	5	$4,504	$4,788	$7,873
27	0.952	$6,326,859	48	$139,299	$24,311	$87,016
17	0.899	$1,451,374	21	$51,055	$21,722	$151,094
15	0.895	$1,584,027	26	$19,463	$58,142	$63,759
2	0.887	$11,393,340	198	$169,370	$173,541	$469,028
9	0.885	$1,819,000	40	$14,189	$23,803	$114,334
1	0.879	$5,560,873	114	$72,378	$90,981	$248,409
6	0.866	$4,777,593	117	$60,811	$81,888	$214,840
5	0.864	$1,166,676	61	$18,625	$15,515	$53,304
18	0.819	$1,265,543	42	$26,766	$34,990	$74,519
10	0.802	$547,542	23	$17,384	$12,556	$32,416
21	0.775	$264,458	56	$7,145	$14,533	$16,267
14	0.759	$683,988	31	$24,252	$53,083	$50,810
13	0.754	$1,199,350	62	$32,543	$43,095	$121,458
19	0.746	$1,763,871	89	$57,504	$74,474	$184,380
20	0.717	$539,870	29	$25,465	$46,472	$59,429

words, the efficient farms in this scenario could attain the same level of farm income using fewer inputs than the inefficient farms utilize.

Table 2 displays the farms ranked by efficiency score and details each inefficient farms overuse of inputs relative to the relatively efficient farms. Feed is the largest contributor to technical inefficiency in terms of dollar amounts for 17 of 19 inefficient farms. This is an unsurprising result, considering that feed costs are known to makeup the majority of total input costs for dairy operations (MacDonald et al. 2020). Improving feed efficiency is key for improving overall farm technical efficiency. Our results indicate that this should be the primary focus of the farms not on the efficient frontier in our sample.

The order of overuse amounts for forage and labor varies by DMU. For example, DMU 25 reflects only a slight overuse of labor, but a relatively large overuse of forage. This farm needs to thoroughly examine its forage process. This inefficiency could be a result of poor forage quality not adequate nutrients to maximize milk productivity or insufficient quantity as a result of the previous year's weather conditions on the farm (i.e., drought). On the contrary, the DMUs at the bottom of the efficiency rankings consistently show a greater overuse of funds on labor compared to forage. These farms could benefit from evaluating labor productivity and distribution for their operations. Adjustments to the size of the labor force or labor assignments on the farm may be necessary to improve labor efficiency.

The table also reflect a broad range in the overuse of cows. While it may be reasonable for DMU 25 to reduce its herd size by 4, a reduction nearly 200 cows for DMU 2 is not realistic. This overuse estimate should not necessarily be interpreted as recommending a number of cows for farms to cull, but rather as an indication of inferior cow performance relative to cows on the efficient farms. This could be the result of genetic inferiority in areas like residual feed intake and milk productivity. Operator mismanagement could also be to blame for some operations. This measure needs to be examined on a farm-by-farm basis to determine the appropriate application for each operation.

For further comparison between efficient farms and inefficient farms, farms are grouped by efficiency rating. Table 3 displays the average value of income and inputs for each group. These results reveal that the average income and input levels of efficient farms are higher than those of inefficient farms. However, this does not necessarily mean that the size of the farms is directly related to efficiency. In fact, when sorting the farms by the number of cows, only one of the 5 largest farms is found to be technically efficient. Having a larger operation does not always lead to greater efficiency.

Following this estimation of efficiency scores for each farm, a one-way ANOVA test is utilized to determine if there is statistical evidence that the mean efficiency score of farms in Tennessee is significantly different from farms operating in the other states in the sample. Although initiatives like the UT Master Dairy program are available and DBII grant funds had been received to support Tennessee farmers for an extended period, the results displayed in the appendix do not reveal any significant difference between the mean efficiency estimates for farms in Tennessee relative to the farms in the neighboring states.

Scenario 2: Variable Returns to Scale Assumption

The second scenario considered is an analysis of the relative efficiency of the same 26 farms under the assumption of variable returns to scale. The results from this scenario are displayed in Table 4. This model shows 13, or half of the farms in the sample, to be technically efficient. Each of the seven farms found to be efficient in the previous scenario under the CRS assumption remain efficient in this VRS scenario. Holstein is the predominate breed of cow for 10 of these

Table 3. CRS Efficiency Subgroup Average Values for All Farms

Efficiency	Farms	Avg Income	Avg Cows	Avg Feed	Avg Labor	Avg forage
Efficient (=1)	7	$4,218,586	610	$1,414,396	$467,089	$478,461
Inefficient (<1)	19	$2,556,686	431	$878,454	$282,741	$316,680

Table 4. VRS Data Envelopment Analysis Results

DMU	Efficiency	Income	Overuse Cows	Overuse Forage	Overuse Labor	Overuse Feed
3	1	$17,729,231	0	0	0	0
4	1	$3,109,122	0	0	0	0
6	1	$4,777,593	0	0	0	0
7	1	$4,348,890	0	0	0	0
12	1	$399,623	0	0	0	0
16	1	$913,868	0	0	0	0
21	1	$264,458	0	0	0	0
22	1	$1,897,795	0	0	0	0
23	1	$679,180	0	0	0	0
24	1	$4,543,168	0	0	0	0
25	1	$1,999,215	0	0	0	0
26	1	$1,366,266	0	0	0	0
27	1	$6,326,859	0	0	0	0
8	0.985	$776,420	2	$1,502	$1,596	$35,783
17	0.933	$1,451,374	14	$47,272	$12,621	$296,254
2	0.932	$11,393,340	193	$101,904	$301,125	$282,196
1	0.924	$5,560,873	71	$45,118	$74,088	$154,850
10	0.916	$547,542	10	$7,362	$5,318	$13,729
15	0.910	$1,584,027	22	$16,700	$40,390	$177,183
20	0.909	$539,870	9	$8,160	$51,931	$84,897
9	0.892	$1,819,000	273	$13,429	$22,527	$532,379
5	0.877	$1,166,676	49	$16,873	$14,056	$48,292
18	0.820	$1,265,543	42	$26,626	$34,807	$78,935
14	0.789	$683,988	27	$21,236	$46,883	$105,979
13	0.773	$1,199,350	57	$29,986	$39,708	$161,244
19	0.749	$1,763,871	88	$56,844	$73,620	$207,723

efficient farms, while the other three efficient farms primarily use Jersey cows. Six of the efficient farms are located in Tennessee, while 7 are located in Kentucky. Both farms located in North Carolina remain inefficient in this scenario. Each of the inefficient farms are found to be overusing all four inputs relative to the use of inputs by farms on the efficient frontier. It's also important to note that the order of farms ranked by efficiency is generally consistent across both scenarios. For instance, the three most inefficient farms in this scenario—DMU 13, 14, and 19—are also three of the most inefficient farms in Scenario 1. Regardless of the assumption of returns to scale, the same collection of farms is found at the top and bottom of the efficiency rankings. Feed remains the largest contributor to technical inefficiency in terms of dollar amounts for the inefficient farms. Additionally, the farms at the bottom of the efficiency rankings are still consistently show a greater overuse of funds on labor compared to forage. In fact, only DMUs 17, 10, and 5 reflect a greater need for focus on forage efficiency. These findings are consistent with the results in Scenario 1. The returns to scale assumption is not found to impact the primary area of focus for farm operators to improve technical efficiency.

Table 5 separates efficient and inefficient farms and displays the average value of income and inputs of each subgroup. The results show that the average income and inputs of efficient farms are higher than those of ineffective farms, which is consistent with the results of Scenario 1. However, the gap between efficient an inefficient farm output and input averages is narrower for every variable in this scenario. Finally, a one-way ANOVA model is utilized to determine there is still no significant difference between the mean efficiency estimates for farms in Tennessee and the other farms in this scenario. The ANOVA test results are displayed in the appendix.

Table 5. VRS Efficiency Subgroup Average Values

Efficiency	Farms	Avg Income	Avg Cows	Avg Feed	Avg Labor	Avg forage
Efficient (=1)	13	$3,719,636	568	$1,200,816	$397,806	$439,926
Inefficient (<1)	13	$2,288,606	390	$844,675	$318,998	$281,084

Conclusion

This analysis of the technical efficiency of 26 dairy farms in the Southeast region of the US using an input-oriented DEA model finds 7 of the 26 farms in the sample to be technically efficient when constant returns to scale is assumed, while exactly half of the farms are estimated to be technically efficient under an assumption of variable returns to scale. In each case, these efficient farms lie on the efficient frontier for the sample, meaning they operate at the optimal utilization of inputs to produce their respective levels of farm income. However, the inefficient farms, those not on the efficient frontier, are found to be overusing each of the farm inputs considered in the analysis (cows, feed, labor, forage) relative to the levels at which the farms on the efficient frontier use them to produce farm income. These inefficient farms need to examine their use of inputs and adjust accordingly in order to attain relative efficiency. Feed costs were found to be the largest contributor to technical inefficiency in terms of dollar amounts for the inefficient farms in both scenarios. Feed efficiency is a key determinate of technical efficiency in the dairy industry and should be a primary focus for farm operators to attain relative efficiency. The magnitude of forage and labor overuse varies by DMU. However, the most inefficient farms in both scenarios showed a greater need for focus on improving labor use efficiency.

No significant difference in efficiency is recorded for farms operating in Tennessee relative to farms in Kentucky and North Carolina. Although programs intended to increase dairy farm efficiency exist in Tennessee, participation in the UT Master Dairy program by the farms in our sample was low. Only 6 of the 13 farms in Tennessee completed the program. In addition, funds received from the DBII program were only made directly available to farmers in late 2020. The impact of this funding on farm efficiency will be realized if this analysis is updated for the years following.

This analysis of the technical efficiency of dairy farms in the Southeast using DEA models is insufficient to determine the presence or absence of economies of scale. Both scenarios do find larger farms to have a higher average technical efficiency. However, only one of the five largest farms in the sample is found to be efficient under the assumption of CRS in scenario 1. Additionally, it is important to note that this analysis only considers the use of variable inputs to produce farm income. The basis of realizing economies of scale is the spread of fixed costs over many units of output leading to reduced per-unit fixed costs. This analysis would need to include fixed input costs such as building expenses, principal payments, land, and equipment costs to provide a reliable analysis of scale economies in the industry. These inputs often account for a large proportion of farming costs, that need to be recovered through long-term profitability. Therefore, the overall long-term efficiency of the farm cannot be obtained without proper treatment of fixed inputs. The exclusion of fixed costs from the analysis prevents the formation of conclusions regarding economies of scales from this study. The recommendations to inefficient farms focus on improving input-use efficiency rather than adjusting farm size to reach the efficient frontier.

This study is not without limitations. The mechanism of the DEA model itself is important to note. As a non-parametric model, the DEA model can perform efficient analysis on the data without estimating parameters. However, due to the lack of regression analysis on the parameters, the results cannot be tested with statistic inference. This reduces the guarantee of the reliability of the analysis results to some extent. Another limitation stems from the availability of data. The data utilized in this study only covers the 2020 calendar year, so the conclusions obtained are static, lacking the analysis of dynamic changes in farm efficiency. This dataset does not allow for the impact of time trends to be considered. Consequently, it is impossible to evaluate the dynamic performance of the farms. Further analysis of the efficiency of these farms using additional data from subsequent years will be helpful to improve the reliability of analysis and could also allow for the incorporation of financial indicators (i.e. ROA).

CHAPTER 2: PREDICTING SEEDSTOCK BULL PRICES: DOES INFORMATION MATTER?

Abstract

This chapter investigates the role of optimism bias in bull price expectations using incentivized lab-in-the-field experiments with Alabama and Tennessee cattle producers. Price prediction tasks based on past market transactions 18 bulls from the Angus, Charolais, and Simmental breeds are utilized for this analysis. The tasks provide expected progeny differences (EPDs) to facilitate accurate price expectations and reduce uncertainties stemming from bull characteristics. Per the between-subject study design, participants are randomly assigned to Seller or Buyer roles to causally investigate the impact of optimism bias and confidence on accurate price predictions. The results reveal that the EPD information provision prevents optimism bias from contaminating price expectations in the whole sample. However, the study also determines that, unlike Buyers, Sellers are prone to unrealistic optimistic expectations, and they show a reduced accuracy level in their predictions. Additionally, cattle producers with higher risk tolerance and confidence are shown to be less likely to accurately predict bull prices. These results reveal that optimism bias can be moderated by the type of EPD information utilized, breed characteristics, and regional differences in cattle operations. This study contributes to the literature by documenting the role of behavioral biases in the formation of cattle price expectations and suggesting potential channels that transmit this effect to real cattle operations.

Introduction

Buying a bull can be a complicated decision that has major implications for a cattle operation's long-term profitability (Clary, Jordan, and Thompson, 1984; Worley, Dorfman, and Russell, 2021). The ideal bull will vary across operations depending on breed composition, marketing plan, average herd cow age, number of heifers, and other factors. Typically, bull buyers have information about the animal's expected progeny differences (EPDs), performance, and physical traits. EPDs are estimates of the expected performance of future progeny of an animal relative to the progeny of other animals within the same breed for given traits. EPD measures can be a valuable tool for producers to compare the predicted genetic merit of bulls within a breed to produce progeny with desired traits. Bull EPD values are calculated based on the performance data of the individual bull, its offspring, and its relatives. When using EPDs, producers are able to make more accurate selection decisions and accelerate genetic progress.

Numerous studies have utilized auction sale data to provide an analysis of the information utilized by producers when selecting a bull for breeding, albeit with mixed evidence regarding the extent to which producers incorporate EPD measures into their cattle market operations (Dhuyvetter et al., 1996; Chvosta, Rucker, and Watts, 2001; Irsik et al., 2008; Jones et al., 2008; Vanek et al., 2008; McDonald et al., 2010; Bekkerman, Brester, and McDonald, 2013; Vestal et al., 2013; Brimlow and Doyle, 2014; Kessler, Pendell, and Enns, 2017; Boyer et al. 2019; Tang et al. 2020). The literature shows that producers placed low importance on EPD values in bull selection decisions when EPD measures were first introduced (Dhuyvetter et al., 1996; Chvosta, Rucker, and Watts, 2001; Irsik et al., 2008). That is, EPDs were not found to significantly impact the price of a bull in a sale. However, more recent research reveals that EPDs impact the market price of bulls (Jones et al., 2008; Vanek et al., 2008; McDonald et al., 2010; Vestal et al., 2013; Brimlow and Doyle, 2014; Kessler, Pendell, and Enns, 2017; Boyer et al., 2019; Tang et al., 2020).

Recently, EPDs have evolved to also include genomic data, or DNA information, in the calculation of EPDs, referred to as genomically-enhanced EPDs (GE-EPDs) (Meuwissen et al., 2001; Matukumalli et al., 2009). These new GE-EPD indicators provide a more reliable prediction of a bull's genetic merit relative to standard EPDs, due to measuring actual genetic relatedness as opposed to a pedigree estimate (Van Eenennaam and Drake, 2012; Rolf et al., 2014). This information is especially valuable for the evaluation of young, unproven animals that have yet to sire many calves in the genetic evaluation. GE-EPDs allow bulls without progeny to receive substantial boosts in accuracy at a young age.

The utilization of GE-EPDs in the process of bull selection in commercial operations is low (Vestal et al., 2013; Smith, 2021). Vestal et al. (2013) used data from three Oklahoma Beef Inc. Performance-Tested bull sales in 2009-2010 in a revealed preference study and found that genomic data had no relation with buyers' preferences. Smith (2021) employed a survey of bull buyers in Tennessee and determined that producers do not significantly value GE-EPD measurements when evaluating bulls for purchase. As previously stated, GE-EPDs are intended to serve as a more accurate source of genetic information for producers, but no study has found these values to impact the sale price of a bull. This might suggest a lack of understanding from producers regarding the purpose and value of this relatively new selection tool. Smith (2021) also reports that the education level of bull buyers does not statistically explain the variation in elicited WTP values, indicating that the lack of incorporating EPD measures in buying decisions might stem from behavioral biases.

If carefully utilizing the available information is the best profit-maximizing strategy, why do producers sub-optimally behave when buying or selling cattle? Since education does not appear to be a good predictor of WTP values, can behavioral biases better explain the documented inefficiencies in the cattle market? Recent findings in the behavioral economics literature show that buying and selling decisions are prone to optimism bias triggered by the endowment effect (Drouvelis and Sonnemans, 2017). Optimism bias leads to unreasonably high (low) price expectation if economic agents are selling (buying) goods in the market. It has also been shown that optimism bias and attention are causally related and can mutually enforce each other (Kress and Aue, 2017). Studies have tried to measure optimism bias— sometimes referred to as self-serving bias, cognitive dissonance, over-confidence, or over-optimism—using various experiments (Mayraz, 2011). This bias is displayed when decision makers underestimate the probability of negative events or overestimate the likelihood of positive events simply due to the impact of these events on their utility (Bénabou and Tirole, 2016). Mayraz (2011) presented an experiment to test wishful thinking, or optimism bias, using the wheat market as an example. Participants who were randomly assigned the role of Farmer (i.e., seller) displayed higher average price expectations relative to participants assigned the role of Baker (i.e., buyer). The presence of this bias also has implications for decision making that could lead to the sellers or buyers increasing their risk exposure or returns (Deaton and Laroque, 1996; Woolverton and Sykuta, 2009). That is, making a wrong decision in the short-term because of bias, could lead to unintentional long-term issues. For instance, holding unrealistic price expectations can also lead to substantial financial losses and bankruptcies. Recent decision theory models link upward price expectations to optimism bias when the decision-maker has a relevant stake (Bénabou and Tirole, 2016). However, the optimism bias and its potential negative consequences have not been studied in the cattle market. Attempting to measure if optimism exists would be a unique contribution to the bull buying literature and would give insights if educational programs need to address this bias in making a bull purchase.

Therefore, the primary objectives of this study are to provide an analysis of variables influencing price prediction accuracy in seedstock bull markets, determine if optimism bias exists, and examine factors affecting producers' valuation of various information, like EPDs when predicting bull prices. We develop a novel preference elicitation experimental procedure for the seedstock bull market by building on Mayraz's (2011). Additionally, most of the literature on this topic is using hedonic pricing models on actual bull sales data and two studies have used survey data to elicit stated values for bulls (Vestal et al., 2013; Smith, 2021). No study, to our knowledge, has used a field experiment setting with actual producers to study the determinants of price expectations in the cattle market and to identify behavioral biases affecting price formation. Our study enriches the existing literature with a new perspective on price formation channels and will be useful in developing debiasing tools and methods in helping cattle buyers and seedstock bull producers avoid overvaluations and properly estimate bulls' market values.

Data

The data utilized in our study was collected through incentivized lab-in-the-field experiments conducted at the 2022 annual cattlemen conventions in Tennessee and Alabama during the months of January and March, respectively. Each of these conventions are heavily attended by cattle producers in these states and draw a representative sample of producers for each state. We invited 69 participants in Tennessee and 95 participants in Alabama to participate in our experiment on voluntary basis. Every respondent was compensated with $15 for participating in our study and was informed of the potential to earn an additional $10 reward for accurately predicting the bull's price in a randomly selected experimental task. This potential additional payoff serves as an incentive for accuracy by the participants in our study. At the beginning of the experiment, each participant was randomly assigned a role as either a seller or buyer in the seedstock bull market. Assigned roles were intended to create a market framing mimicking real cattle markets. Moreover, the role assignment allowed us to trigger different decision-making channels sellers and buyers utilize when operating in an actual market. Following the role assignment, each participant underwent three training exercises (one for each breed used in the experiment). Then, participants were asked to predict the market price of bulls in 18 tasks.

We prepared 18 price prediction tasks based on past real cattle market transactions including bulls from three breeds: Angus, Charolais, and Simmental. Angus, Charolais, and Simmental bulls sold during 2021 at seedstock bull sales in Tennessee, Kansas, and Alabama, respectively were selected for use in our study. These are three commonly utilized breeds in the herds of Tennessee and Alabama cattle producers. Six bulls from each breed were selected to form the 18 incentivized tasks in our experiment. The six bulls from each breed were strategically selected such that a balanced number of bulls with high, average, and low EPD values were presented. In each task, participants were provided with a scenario and EPD information of the bull before they were asked to predict its market price. The scenarios were intended to establish a common baseline for all participants in their evaluations, as the bulls' value might otherwise be affected by the characteristics of the respondent's herd. In addition, participants were provided with a brief five to seven second looping video of the bull walking from left to right in each task to provide opportunity for visual examination (Figure 1).

Figure 1. Screenshot from a Bull Video Provided to Participants

When asked to predict the market value of the bull in each task, participants were made aware that an accurate price prediction had to be within the range of $500 above to $500 below the true market price. Participants were also asked to indicate their confidence level in their price prediction on a slider scale of one to 100 at the end of each task before they concluded their price predictions. Finally, at the conclusion of the experiment, participants completed a survey composed of herd composition, decision-making, and demographic characteristic questions related to their own cattle operations.

Methods

We employ multiple Probit regression analyses to model the probability of accurate price predictions in the entire sample of our data and in sub-samples separated by breed and risk preference for a total of 10 equations. Equations 1-5 model the probability for the full sample. Equations 6-8 and 9-10 model the probability for the three breeds in our experiment and risk preference groups, respectively. The equations are written as follows:

$$\Pr\,(Y = 1|X) = \Phi(\beta_0 + \beta_1 S) \tag{1}$$

$$\Pr\,(Y = 1|X) = \Phi(\beta_0 + \beta_2 TN) \tag{2}$$

$$\Pr\,(Y = 1|X) = \Phi(\beta_0 + \beta_1 S + \beta_2 TN + \beta_3 STN) \tag{3}$$

$$\Pr\,(Y = 1|X) = \Phi(\beta_0 + \beta_1 S + \beta_2 TN + \beta_3 STN + \beta_4 C) \tag{4}$$

$$\Pr\,(Y = 1|X) = \Phi(\beta_0 + \beta_1 S + \beta_2 TN + \beta_3 C + \beta_4 RP + \beta_5 E + \beta_6 GE + \beta_7 ER + \beta_8 P + \beta_9 A + \beta_{10} C + \beta_{11} SM + \beta_{12} STN) \tag{5-8}$$

$$\Pr\,(Y = 1|X) = \Phi(\beta_0 + \beta_1 S + \beta_2 TN + \beta_3 C + \beta_5 E + \beta_6 GE + \beta_7 ER + \beta_8 P + \beta_9 A + \beta_{10} C + \beta_{11} SM + \beta_{12} STN) \tag{9-10}$$

where *Y* is the probability of an accurate price prediction with one being the case where the participant's price prediction was within the accurate price range and zero otherwise; Φ is the standard normal cumulative distribution function; *S* is a binary variable indicating if a participant was assigned the Seller role in the study; *TN* is a binary variable for participants in the Tennessee sample; *C* the is indicated confidence level in price predictions; *RP* denotes the subject's risk tolerance level measured with a slider scale of 0 to 10 indicating the decision-maker's risk-tolerance level (Falk et al., 2018); *EPD* is a binary variable showing if EPDs are utilized by participants; *GE* is a binary variable for participants utilizing GE-EPDs; *ER* is a binary variable for participants utilizing EPD ranks; *P* is a binary variable for participants utilizing physical characteristics; *A* is a binary variable for participants with Angus cattle in their operation; *C* is a binary variable for participants with Charolais cattle in their operation; *SM* is a binary variable for participants with Simmental cattle in their operation; and *STN* is a binary interaction variable for participants assigned the Seller role and if they are in the Tennessee. Table 6 provides the definitions of dependent and independent variables examined.

Hypothesized Variable Signs

Based on previous studies and experimental results, we expect to observe behavioral differences in price predictions between sellers and buyers in lab-in-the field experiments (Mayraz, 2011). The existing research shows that decision-makers usually are prone to optimism bias, and they form their price expectations aligning with their stakes. In our study design, this means sellers will be more likely to overpredict bull prices in 18 tasks compared to the true market prices. Contrarily, optimism bias predicts that buyers will be more likely to underpredict cattle prices in the experiment.

Table 6. Definitions Of Dependent and Independent Variables Examined

Variable	Definition
Accurate Price	=1 if the price prediction is accurate; otherwise zero
Seller	=1 if subject was assigned the Seller role in the market; otherwise zero
Tennessee	=1 if subject is in the Tennessee sample; otherwise zero
Confidence	= confidence level indicated for price prediction (from 1 to 100)
Risk Preference	= the subject's risk tolerance level (from 1 to 10)
EPD	=1 if the subject utilizes EPDs for bull evaluation; otherwise zero
GEEPD	=1 if the subject utilizes GE-EPDs for bull evaluation; otherwise zero
EPDRank	=1 if the subject utilizes EPD % ranks for evaluation; otherwise zero
Phenotype	=1 if the subject utilizes physical traits for evaluation; otherwise zero
Angus	=1 if the subject utilizes Angus cattle; otherwise zero
Charolais	=1 if the subject utilizes Charolais cattle; otherwise zero
Simmental	=1 if the subject utilizes Simmental cattle; otherwise zero
Seller*Tennessee	=1 if the subject is a Seller and in Tennessee; otherwise zero

Moreover, we also expect that price expectations and accurate price predictions are the function of producer characteristics. Producers are more likely to accurately predict cattle prices when they are more informed about EPD and/or GE-EPD measures. In that regard, we expect producers to demonstrate a higher degree of prediction accuracy if they apply greater utilization of EPDs, GE-EPDs, and physical characteristics in the process of bull evaluation.

We expect that participants' confidence in their price predictions will have an impact on the price prediction accuracy. There is evidence that decision-makers with increased confidence are more biased, increasingly overpredict, and therefore less likely to achieve accurate predictions (Mayraz, 2011).

However, we are uncertain regarding the impact producer utilization of certain breeds in their operation will have on prediction accuracy. It seems logical to expect participants to be more confident and accurate in tasks involving breeds they are most familiar with. However, it is established that confidence is associated with bias, and breed familiarity may not translate to accurate price predictions.

Previous studies reveal that EPD measures and physical characteristics are primary determinants of the market value of bulls (Jones et al., 2008; Vanek et al., 2008; McDonald et al., 2010; Vestal et al., 2013; Brimlow and Doyle, 2014; Kessler, Pendell, and Enns, 2017; Boyer et al. 2019; Tang et al. 2020). Accordingly, we anticipate that the utilization of EPD, EPD percentage rank, and phenotype information in our experiment will result in an increased proportion of accurate price predictions. Additionally, the literature supports an expectation that consideration of GE-EPDs will result in increased accuracy because of more complete and reliable bull evaluations (Van Eenennaam and Drake, 2012; Rolf et al., 2014). Furthermore, risk tolerance is expected to have a negative relationship with prediction accuracy.

Results

Table 7 provides the summary statistics for our experimental study sample across the two states. In both Tennessee and Alabama, the producers in our study were far more likely to have Angus cattle in the herd than Charolais or Simmental. Approximately 80% of all producers in our sample utilize Angus cattle in their herd, while approximately 30% utilize Simmental. Producers in Tennessee indicated that only 22% utilized Charolais, while Alabama producers indicated that 29% utilized Charolais. An additional question in our survey asked participants to indicate whether they use certain information in their evaluation and valuation of cattle. Participants in Tennessee indicated that 78% utilized EPDs and 51% utilized GE-EPDs, which are 13% and 16% higher rates than those in Alabama, respectively. Our discussion on general producer characteristics of our sample yields results consistent with previous studies and indicate a knowledge gap among our participants regarding the value and availability of GE-EPDs for the evaluation of bulls (Smith, 2021). Most participants in both states primarily utilize physical characteristics in their examination of bulls. Surprisingly, 9% more producers in Tennessee utilized physical characteristics in their evaluations of bulls than Alabama producers. Interestingly, the only information used at a higher rate by Alabama producers relative to Tennessee producers is EPD percentile rank values of bulls within the breed. The survey results also find the average producer in both states to be slightly risk seeking.

The mean price predictions made by Buyers and Sellers in Alabama and Tennessee are displayed in Figure 2**.** When EPD information is provided, we find no significant difference between the average price prediction made by Buyers and Sellers within either sample. However, when comparing Buyers and Seller groups across states, we find a significant difference in average price predictions for both treatments **(**Figure 3). The mean price prediction made by

Table 7. Sample Summary Statistics for Alabama and Tennessee Participants

Variable	N	Alabama, N = 95[1]	Tennessee, N = 69[1]	p-value[2]
Has Angus in herd	164	75 (79%)	57 (83%)	0.56
Has Simmental in herd	164	28 (29%)	21 (30%)	0.89
Has Charolais in herd	164	28 (29%)	15 (22%)	0.27
Uses EPD	164	62 (65%)	54 (78%)	0.07
Uses GEEPD	164	33 (35%)	35 (51%)	0.04
Uses Phenotype	164	84 (88%)	67 (97%)	0.04
Uses EPDRank	164	56 (59%)	37 (54%)	0.50
General Confidence [0,100]	163	77 (19)	78 (17)	0.98
Financial Confidence [0,100]	163	77 (17)	77 (19)	1.00
Risk Tolerance [1,10]	163	6.27 (2.01)	6.59 (1.86)	0.32
Tolerance to Delay gratification [1,10]	163	7.12 (1.81)	7.23 (1.73)	0.75
General trust of others [1,10]	163	6.52 (2.14)	6.34 (2.04)	0.46
Proportion of income from cattle operation	163	30 (30)	34 (29)	0.09
Age	163	47 (17)	51 (15)	0.10
Male	164	72 (76%)	46 (67%)	0.20
Cattle business is full-time job	164	38 (40%)	26 (38%)	0.76

[1]n (%); Mean (SD)

[2]Pearson's Chi-squared test; Wilcoxon rank sum test

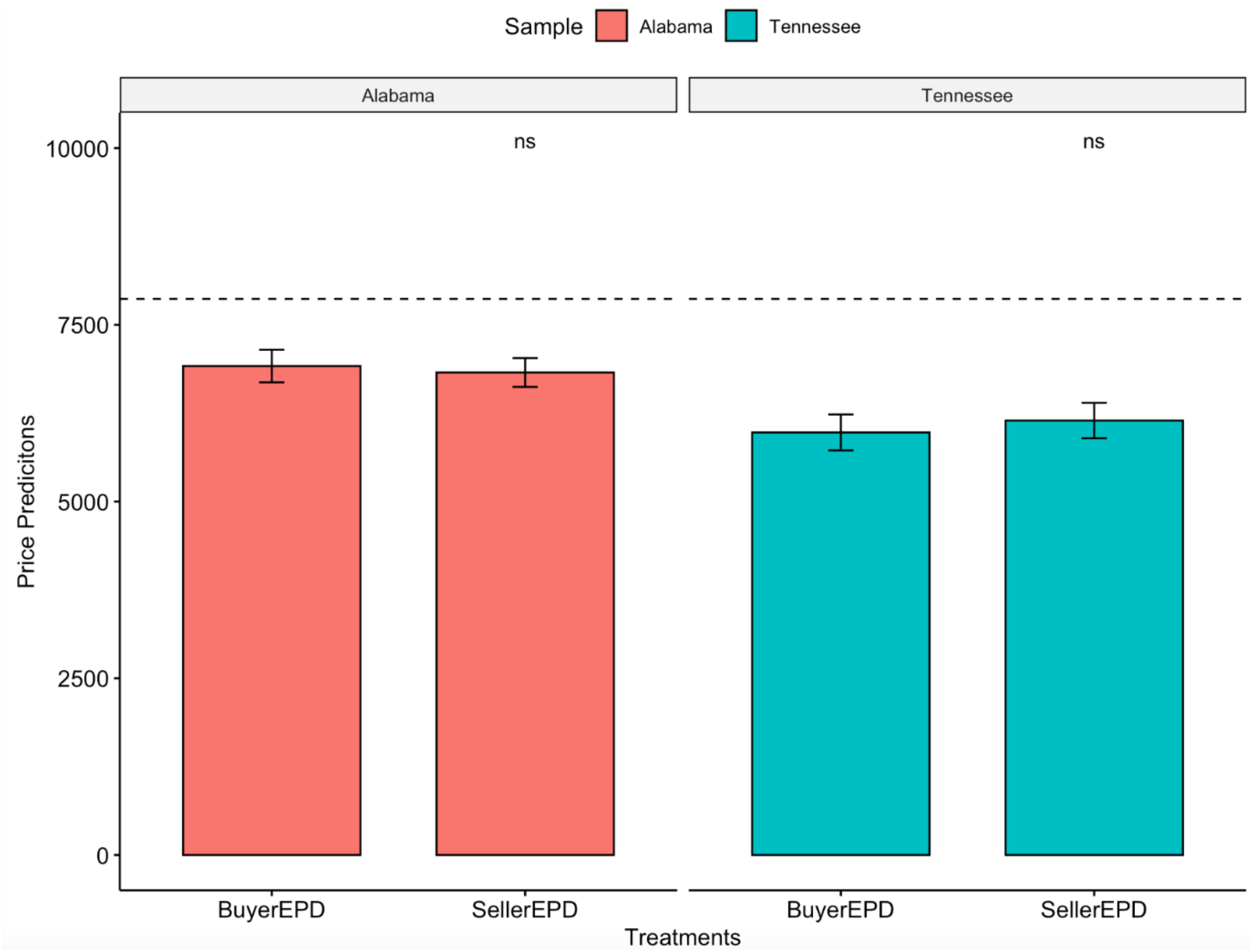

Figure 2. Mean Price Predictions Across States
Note: The dashed line is the average of true, NS represents not significant

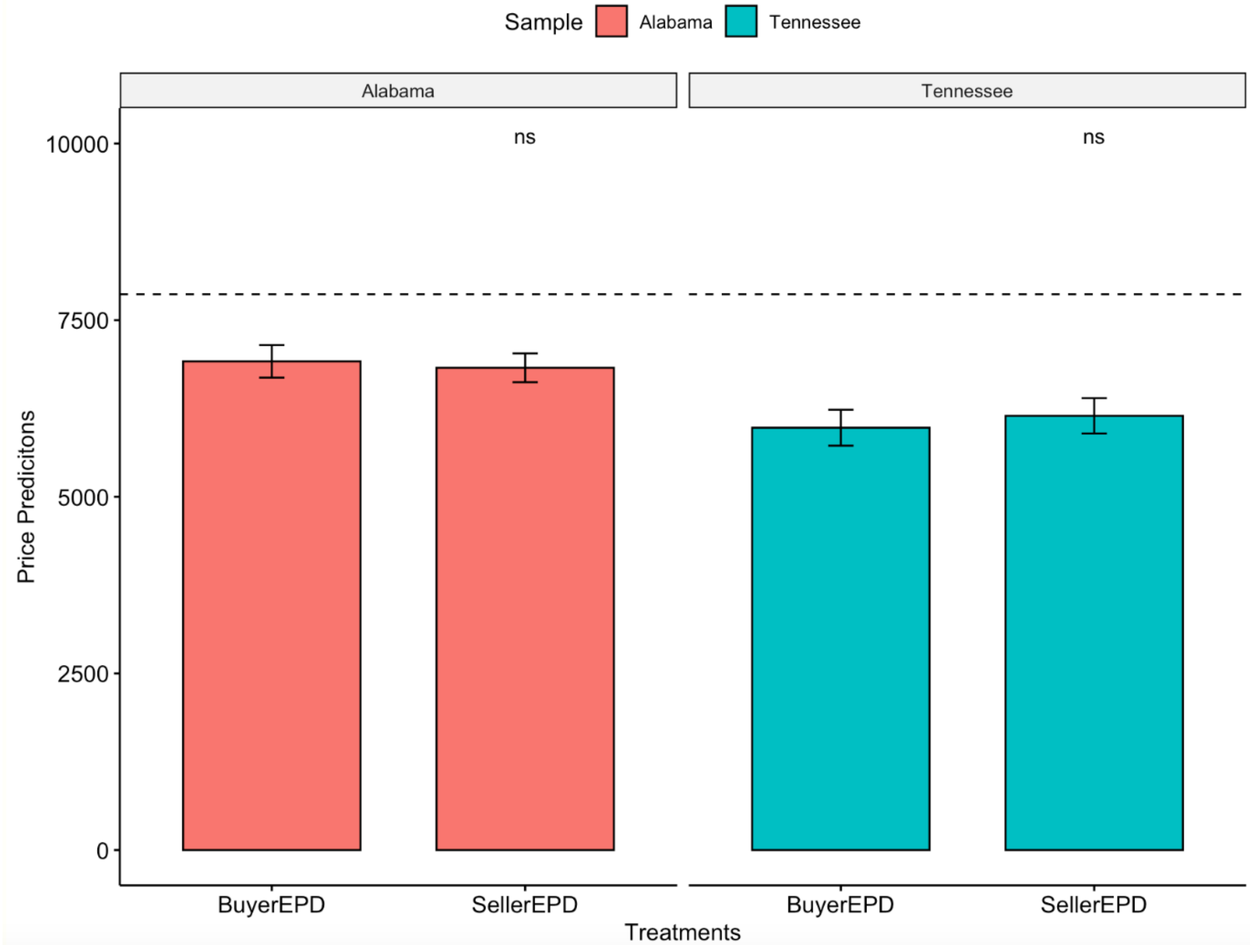

Figure 3. Mean Price Predictions Across Treatments
Note: The dashed line is the average of true prices. *** and ** represent significance at the 1% and 5% level, respectively.

both Buyers and Sellers in Alabama was significantly higher than the mean prediction made by Tennessee producers with the same market roles in our experiment.

However, the mean price prediction in both states was lower than the $7,867 average of true prices for the 18 bulls used in our study. This is likely explained, in part, by the prevalence of small cow-calf enterprises in both Alabama and Tennessee that do not normally purchase expensive seedstock bulls. Many of the participants in our sample are likely not accustomed to paying or receiving this much for bulls used in their operations. Although, the Alabama sample has a mean price prediction closer to the true average of prices in both treatment groups, this does not directly translate to increased price prediction accuracy across treatments for the Alabama sample. Figure 4 reveals that Sellers in Tennessee had a significantly higher proportion of correct price predictions than Sellers in Alabama.

Figure 5 shows the average price prediction accuracy of all participants in Alabama and Tennessee. There is no significant difference between the proportion of accurate predictions by the participants in the two states. Figure 6 compares the proportion of accurate price predictions by all Buyers and Sellers in our experiment. The role assigned to participants is not found to have a significant impact on price prediction accuracy in the full sample, which confirms that the optimism bias disappears when decision-makers are provided with more information.

Probit Regression Results

The results from our Probit analyses of accurate price prediction probabilities of all participants in our experiment (equations 1-5) are displayed in Table 8. We find that participants, assigned the role of Seller in seedstock bull markets, were less likely to make accurate price predictions

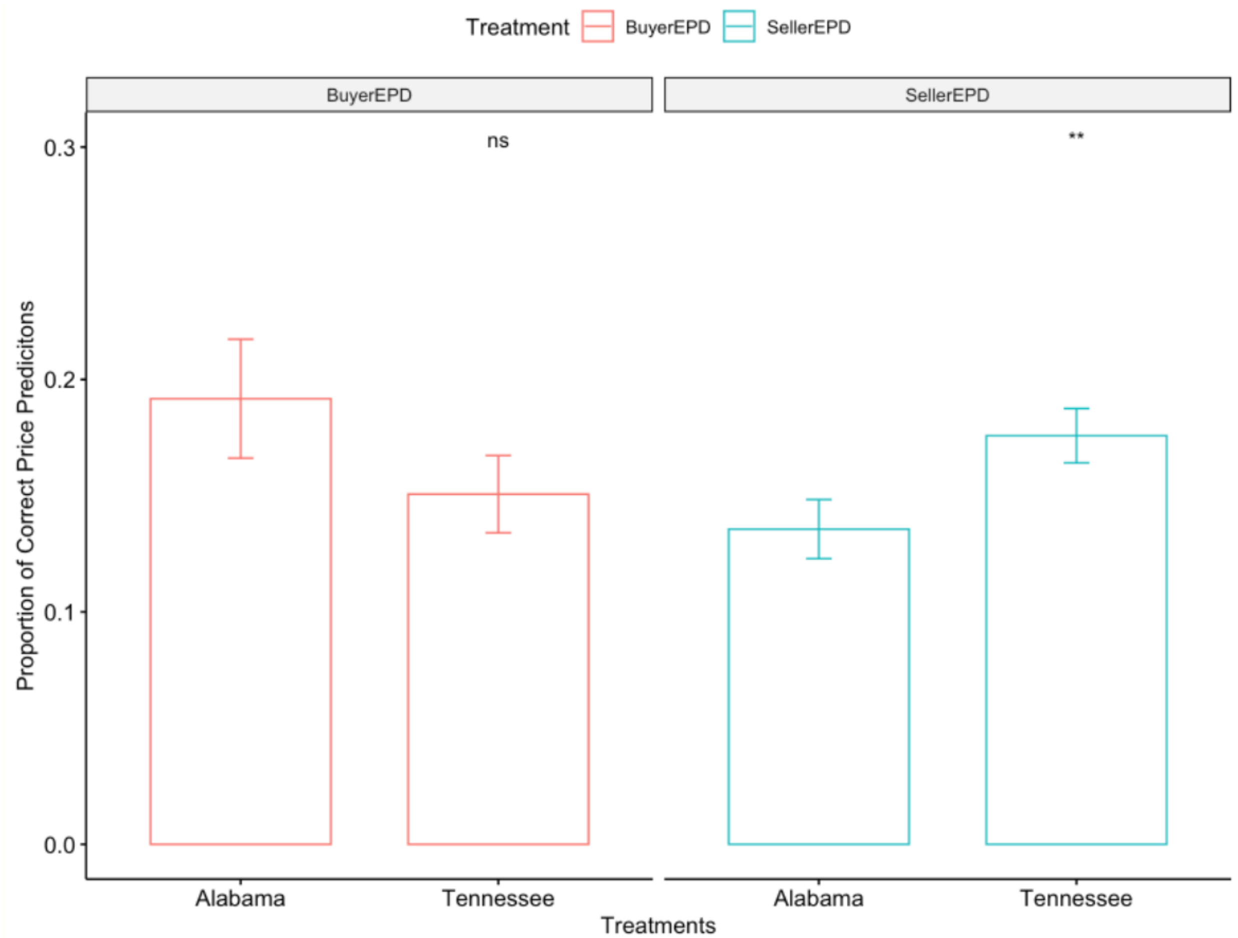

Figure 4. Proportion of Accurate Price Predictions Across Treatments by Sample
Note: ** represent significance at the 5% level and NS represents not significant.

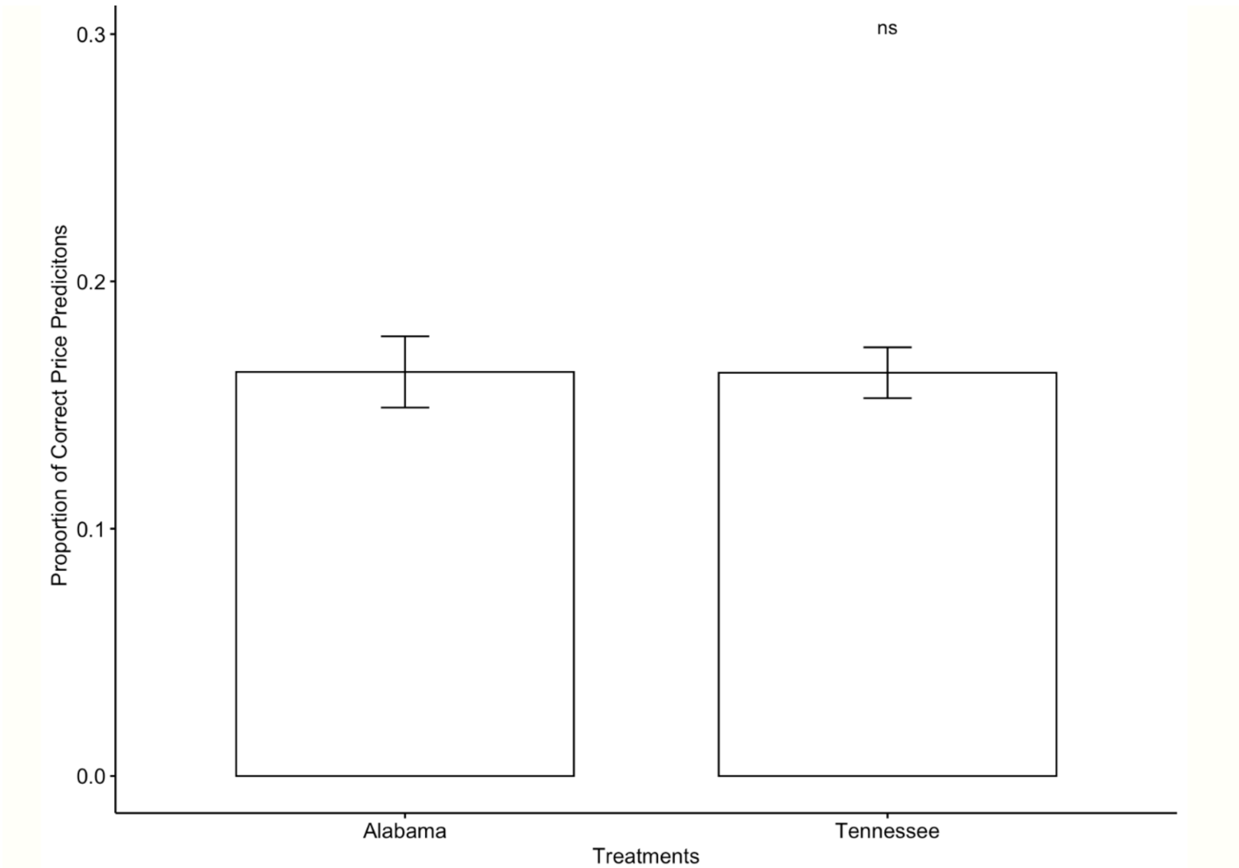

Figure 5. Proportion of Accurate Price Predictions Across States
Note: NS represents not significant.

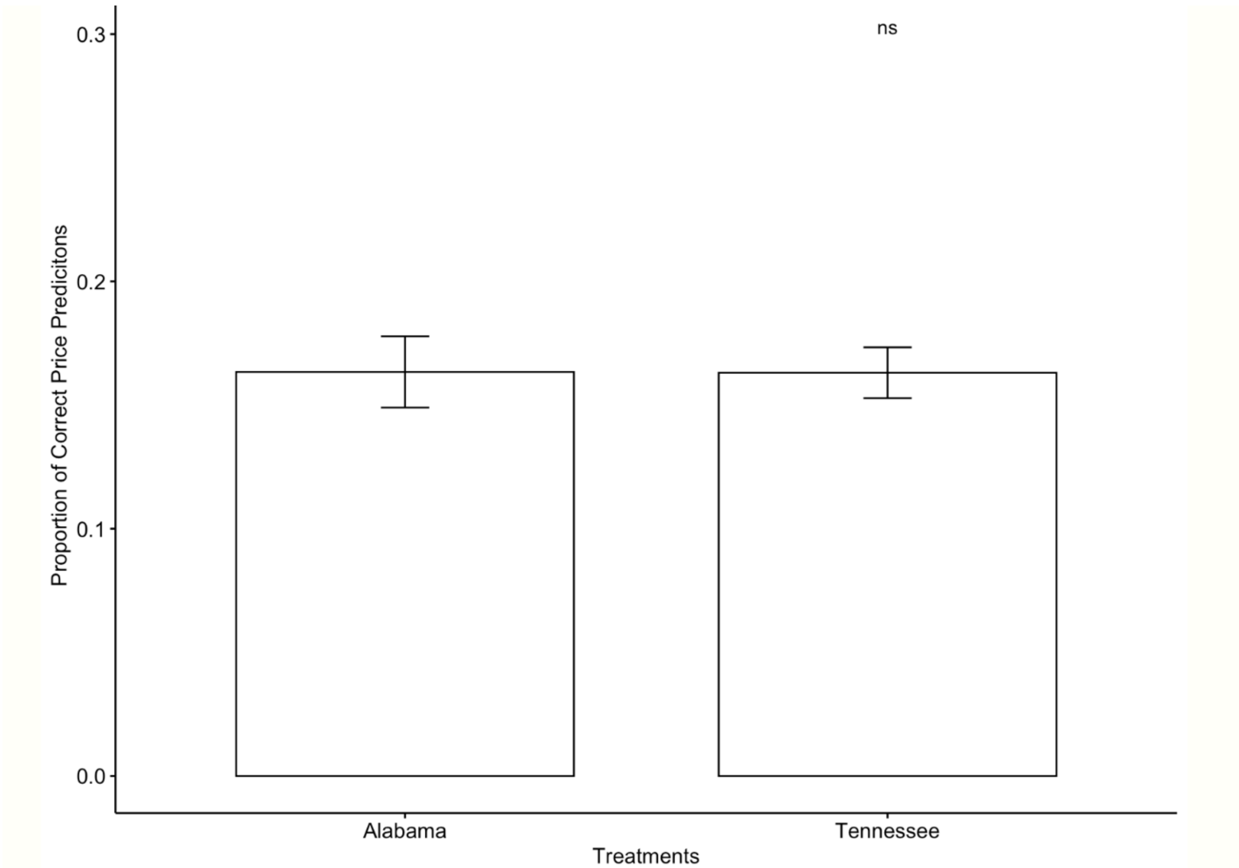

Figure 6. Proportion of Accurate Price Predictions Across Market Roles
Note: NS represents not significant.

Table 8. Probit Results of Successful Prediction Probabilities for All Participants

Variable	All (1)	All (2)	All (3)	All (4)	All (5)
Seller	-0.1		-0.2**	-0.2**	-0.2**
	(0.1)		(0.1)	(0.1)	(0.1)
Tennessee		-0.005	-0.2	-0.2	-0.2*
		(0.1)	(0.1)	(0.1)	(0.1)
Seller*Tennessee			0.3**	0.3**	0.4***
			(0.1)	(0.1)	(0.1)
Confidence				0.001	-0.001
				(0.002)	(0.001)
Risk Preference					-0.003
					(0.02)
EPD					-0.02
					(0.1)
GEEPD					0.2*
					(0.1)
EPDRank					0.1*
					(0.1)
Phenotype					0.1
					(0.1)
Angus					0.1
					(0.1)
Charolais					0.1
					(0.1)
Simmental					0.1
					(0.1)
Constant	-0.9***	-1.0***	-0.9***	-0.9***	-1.1***
	(0.1)	(0.1)	(0.1)	(0.1)	(0.1)
N	2945	2945	2945	2945	2945

Note: Model 5 regression controls for subject fixed effects. Standard errors are clustered at subject level. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

relative to those assigned the role of buyer when we control for other variables. These results also reveal that participants in Tennessee were less probable to make accurate price predictions relative to those in Alabama. Furthermore, we find that only participants utilizing GE-EPDs and EPD percentile rank measurements were significantly more likely to make successful predictions. This finding supports our hypothesis that participants using advanced selection tools would be more likely to provide accurate valuations for the bulls in our experiment. Additionally, the subset of Sellers in Tennessee were found to be more likely to make accurate predictions compared to sellers in Alabama.

Table 9 shows the results of three separate probit regression models utilized to provide an analysis of successful price prediction probabilities for each breed of bull included in our experiment (equations 6-8). In the Charolais and Simmental tasks, we again find that Sellers were less probable to make accurate price predictions relative to buyers. We also find that confidence has a significantly negative impact on the probability of accurate price predictions in our Angus tasks, yet no significant impact in tasks involving the other two breeds. This may be a result of a much higher proportion of producers in our experiment utilizing Angus cattle in their operation relative to other breeds. Participants being more familiar with the Angus breed may have led to overconfidence when making price predictions in these tasks. Again, only utilization of GE-EPDs and EPD percentile ranks were shown to significantly impact the probability of successful price predictions. Utilization of GE-EPDs and EPD percentile ranks increased the probability of accurate price predictions in Simmental tasks and Angus tasks, respectively. Interestingly, participants utilizing a cattle breed in their operation did not significantly impact the probability of successful predictions in the tasks in our experiment focusing on this same breed of bull. Sellers in Tennessee were found to be more likely to make an accurate price

Table 9. Probit Results of Successful Prediction Probabilities Across Breeds

Variable	Angus Tasks (6)	Charolais Tasks (7)	Simmental Tasks (8)
Seller	-0.2	-0.1*	-0.3*
	(0.1)	(0.04)	(0.2)
Tennessee	-0.2	-0.1	-0.2
	(0.1)	(0.04)	(0.2)
Seller*Tennessee	0.4**	0.1	0.5**
	(0.2)	(0.1)	(0.2)
Confidence	-0.01***	0.000	0.001
	(0.002)	(0.001)	(0.002)
Risk Preference	-0.001	-0.001	-0.004
	(0.02)	(0.01)	(0.03)
EPD	-0.2	0.03	-0.01
	(0.1)	(0.03)	(0.2)
GEEPD	0.1	0.03	0.3**
	(0.1)	(0.03)	(0.1)
EPDRank	0.3***	0.001	0.1
	(0.1)	(0.03)	(0.1)
Phenotype	0.3	-0.02	0.1
	(0.2)	(0.04)	(0.2)
Angus	-0.03	0.02	0.2
	(0.1)	(0.03)	(0.1)
Charolais	0.3**	0.01	-0.1
	(0.1)	(0.03)	(0.1)
Simmental	0.1	0.02	0.05
	(0.1)	(0.03)	(0.1)
Constant	-1.0***	0.2***	-1.4***
	(0.2)	(0.1)	(0.3)
N	978	978	978

Note: Regressions control for subject fixed effects. Standard errors are clustered at subject level. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

prediction in Angus and Simmental tasks but not in tasks with Charolais bulls. This may be a result of Charolais cattle being the least utilized breed in our Tennessee sample.

We performed additional analyses of accurate price predictions among low- and high-risk participants (equations 9-10). The results are displayed in Table 10. The demographic survey in our experiment reveals the median risk preference of participants to be 6.8. Consequently, we classified all participants with a risk preference higher than 6.8 as high-risk and all participants with a selected risk preference below 6.8 as low risk. The analysis of these subgroups reveals that high-risk participants assigned the role of Seller in the market were significantly less likely to make an accurate price prediction than Buyers with a similar risk preference. However, the assignment of market roles among relatively low-risk participants did not significantly impact the probability of successful predictions. This indicates that Sellers with a high-risk tolerance are more likely to display optimism bias in price expectations and overshoot the true market price of bulls. Among relatively low-risk participants, the Tennessee sample remains significantly less likely to make successful price predictions relative to the Alabama sample. However, no significant regional difference in probability is displayed among high-risk participants. Furthermore, Sellers in Tennessee were found to have an increased probability of accuracy in both risk preference groups

Confidence is shown to be negatively correlated with the probability of price prediction accuracy among high-risk participants, but no impact on accuracy among low-risk participants. Confident individuals tend to be more risk seeking, and therefore more prone to have a bias in price expectations (Möbius et al., 2022). This increased bias likely contributed to the negative relationship between confidence and accuracy in the relatively high-risk group (Arkes, 2001). We also find that only low-risk participants utilizing GE-EPDs in their evaluation of bulls are

Table 10. Probit Results of Successful Prediction Probabilities Across Risk Preference Groups

Variable	Low-Risk (9)	High-Risk (10)
Seller	-0.3	-0.2**
	(0.2)	(0.1)
Tennessee	-0.3*	-0.1
	(0.2)	(0.1)
Seller*Tennessee	0.5**	0.2*
	(0.2)	(0.1)
Confidence	0.000	-0.003*
	(0.003)	(0.002)
EPD	0.01	0.002
	(0.1)	(0.1)
GEEPD	0.3**	-0.03
	(0.1)	(0.1)
EPDRank	0.1	0.1
	(0.1)	(0.2)
Phenotype	0.1	0.1
	(0.2)	(0.1)
Angus	0.04	0.03
	(0.1)	(0.1)
Charolais	0.1	0.1
	(0.2)	(0.1)
Simmental	0.1	0.04
	(0.2)	(0.1)
Constant	-1.3***	-1.0**
	(0.2)	(0.2)
N	1458	1476

Note: Regressions control for subject fixed effects. Standard errors are clustered at subject level. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

more likely to make accurate price predictions. It is logical to expect low-risk individuals to consider the information provided when predicting market prices. Results from the additional analyses examining regional differences are included in the appendix.

Discussion

The primary objectives of this article were to provide an analysis of the factors influencing the probability of accurate price predictions in seedstock bull markets and to determine if optimism bias influences price expectations in these markets. This study adds to the existing literature by drawing analysis from a lab-in-the-field experiment with actual producers, who were provided with information and assigned to Seller or Buyer roles, predicting the actual selling price of bulls. Optimism bias is not found to exist when information is provided in seedstock bull markets.

This result supports the notion that the existence of bias depends, at least in part, on the degree of a decision maker's subjective uncertainty (Mayraz, 2011). However, Sellers are found to be consistently less likely to make accurate predictions relative to Buyers. This finding may be due to an underlying endowment effect in seedstock bull markets. In addition, confidence is determined to have a negative impact on the probability of accuracy in the Angus tasks and among relatively high-risk participants. The negative correlation between accuracy and confidence in Angus tasks suggests overconfidence from participants when valuing bulls within breeds they are most familiar with. Furthermore, our study reveals that high-risk participants have a lower probability of making accurate price predictions relative to low-risk participants. It is also interesting to report that only participants utilizing GE-EPDs and EPD percentile rank measures are found to have an increased probability of making accurate price predictions.

Additionally, our study advances the literature by its comparison of information use among producers in multiple states. Considerable variation in the rate of utilization of decision relevant information across the Alabama and Tennessee samples are found to exist. Tennessee participants utilize EPDs, GE-EPDs, and physical characteristics at higher rates than those in Alabama when evaluating cattle, while Alabama participants are found to utilize EPD percentile rank measures more commonly than those in Tennessee. However, GE-EPDs are utilized at the lowest rate of the information options. This indicates the existence of a knowledge gap regarding the increased reliability presented by GE-EPDs in the evaluation of cattle among producers in these two states. Interestingly, although the Tennessee sample reported a greater utilization of most information and physical traits, participants in Alabama were more likely to be accurate in predicting the market price of the bulls in our experiment. Future research utilizing biometric technology, such as eye tracking, could help further understand the information used during evaluation of a bull.

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Appendix

Table 11. CRS Efficiency ANOVA Results

Variable	Coefficient	Std. Error	t	P > t	95% Conf. Interval	
Non-TN farms (base)	0	--	--	--	--	--
Tennessee farms	-0.0030	0.0387	-0.08	0.94	-0.0828	0.0769
Constant	0.9014	0.0294	30.68	0	0.8407	0.9620

Table 12. VRS Efficiency ANOVA Results

Variable	Coefficient	Std. Error	t	P > t	95% Conf. Interval	
Non-TN farms (base)	0	--	--	--	--	--
Tennessee farms	-0.0396	0.0313	-1.26	0.22	-0.1042	0.0251
Constant	0.9616	0.0238	40.42	0	0.9125	1.0107

Table 13. Probit Results of Successful Prediction Probabilities Across States

Variable	Alabama, N = 95	Tennessee, N = 69
Seller	-0.2**	0.1*
	(0.1)	(0.1)
Confidence	0.002	-0.005***
	(0.002)	(0.002)
Risk Preference	-0.01	-0.002
	(0.02)	(0.02)
EPD	-0.05	-0.03
	(0.1)	(0.1)
GEEPD	0.2**	0.1
	(0.1)	(0.1)
EPDRank	0.2**	0.1
	(0.1)	(0.1)
Phenotype	-0.1	0.9**
	(0.1)	(0.4)
Angus	-0.02	0.2*
	(0.1)	(0.1)
Charolais	0.1	0.1
	(0.2)	(0.1)
Simmental	0.1	0.03
	(0.1)	(0.1)
Constant	-1.1***	-2.0***
	(0.2)	(0.4)
N	1710	1224

Note: Regressions control for subject fixed effects. Standard errors are clustered at subject level. ***, **, and * represent significance at the 1%, 5%, and 10% level, respectively.

Vita

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