ESSAYS ON HORN FLY CONTROL ECONOMICS IN STOCKER CATTLE, STOCKER CATTLE PRODUCER PURCHASING PREFERENCES, AND FOOD INSECURITY DURING COVID-19

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Submitted to the Faculty of the
Graduate College of the
Oklahoma State University
in partial fulfillment of
the requirements for
the Degree of
DOCTOR OF PHILOSOPHY
DECEMBER 2021

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ACKNOWLEDGEMENTS

During the last several years, countless people gave me the strength and motivation to complete my doctorate program, and I wish to express my heartfelt gratitude to them.

First of all, I wish to express my deepest and sincere gratitude to my former and current major advisors, Dr. Brian Adam and Dr. Kellie Raper. During my course study and academic research, I was encouraged by their great knowledge and plentiful experience. Dr. Brian Adam advised me until he retired in 2020. He opened the door of my doctorate program with helping me on courses and research with his kindness and unwavering support. Dr. Kellie Raper accepted and advised me after Dr. Brain Adam retired, her sunshine smile gives me a lot of confidence. One essay in my dissertation would not be accomplished without a unique data she gave me, as well as her enduring patience and encouragement. I also would like to thank Dr. Baily Norwood, whose expertise was invaluable in formulating the research questions and methodology for another essay in my dissertation. I appreciate his kindness and encouragement during the writing of the essay. I also wish to thank my committee members, Dr. Rodney Holcomb and Dr. Ravi Jadeja for their invaluable feedback, especially at the time I presented my proposal and during my dissertation defense. I would be failing in my acknowledgements if I did not thank Dr. Wade Brorsen and Dr. Chanjin Chung. The third essay in my dissertation would not be completed without Dr. Wade Brorsen's instruction. He offered me the original data and helped formulating the research question and methods, which is so priceless. Dr. Chanjin Chung served as my committee before Dr. Brian Adam retired, I appreciate his comments and support on my dissertation proposal. Let me also say enormous thanks to Ms. Anna Whitney, the graduate student specialist, for her efficient handling of all my administrative matters, and ensuring that my paperwork was always up to date and in order.

I appreciated so much for my family and friends during all my study, I couldn't get through without their encouragement and support. To my mom (Junying Liu), dad (Yaxin Yin), I try my best to always carry with me the virtues of life they taught me including honesty, hard work, and respect among many others. To my parents in laws, I am grateful to their love and care for my little kids. To my best friend Candi Ge, her company, encouragement, and friendship is invaluable in my life, especially during the hardest time in the previous years.

My special thanks go to my husband (Guangwei Yang), who has several roles in my life as a friend, a teamer, and a teacher. He has seen me at my strongest and weakest points and everything in between, and he support, encourage, and calm down me all the time. To our two beautiful kids Thomas and Mia, thank you for being our kids. I am guilty but grateful to them that there were countless times I could not be with them like other moms even when you were little, because I was either studying or working on my research. I hope to make it up to them some day.

Lastly, I would like to thank my fellow graduate students who in one way or the other contributed to my successful completion of the program. May God Almighty bless you.

Name: MENGYU YIN

Date of Degree: DECEMBER 2021

Title of Study: ESSAYS ON HORN FLY CONTROL ECONOMICS IN STOCKER CATTLE, STOCKER CATTLE PRODUCER PURCHASING PREFERENCES, AND FOOD INSECURITY DURING COVID-19

Major Field: AGRICULTURAL ECONOMICS

Abstract:

Horn flies cause extensive economic loss to cattle. The efficiency of two insecticides to controll horn flies, Corathon® and LongRange®, and the profitabilities that stocker cattle producer could expect to achieve were evaluated. A total of 302 stocker cattle records from Kansas were analyzed. Both treatments were effective compared to the control group, adding $17-$18 profit per head. The cattle treated with LongRange® had the fewest horn flies and best average daily gain, but LongRange®'s higher treatment cost made its net profit similar to Corathon®'s.

The stocker industry plays a critically important role in the cattle industry and is the most flexible and complicated segment of the beef supply chain. It is useful to analyze the factors affect Stocker producers' calf purchasing decisions. Selected data from a recent survey, the '2017 Oklahoma Beef Calf/Stocker Movement Survey'. was used to 1) test the independence of relationships between important demographic information and the nine factors reflecting stocker operator's purchasing preferences; and 2) applying a latent class model to the stocker producer population to classify producers into subgroups based on cattle purchasing preferences. Oklahoma stocker producers were divided into four latent classes according to purchasing preferences using latent class analysis.

With the pandemic of COVID-19 and lower employment rates and household income, food insecurity issue arises worldwide which should be considered and measured. Since the measurement of food insecurity by the United States Department of Agriculture (USDA) were not administered until December of 2020. The impact of pandemic on food insecurity cannot be monitored. some expedited internet surveys were administered by organizations to attempt to measure food insecurity in pandemic, such as the Covid Impact Survey that is conducted by National Opinion Research Center (NORC) at the University of Chicago. The food insecurity rates for three separate weeks in the spring of 2020 from the NORC survey that mimicked the screening procedure of CPS-FSS survey were reported. Meanwhile, food insecurity rates were compared across 2008 Crisis, Pre-COVID and COVID-19 with a same screening procedure.

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CHAPTER I

INTRODUCTION

This dissertation consists of two essays related to stocker cattle production and one essay on food security in COVID-19 pandemic period. The first essay analyzes the efficiency of certain insecticides for horn flies and determines the profitability that a stocker cattle producer could expect by using either of these insecticides relative to a control group. The study uses a field experiment data from the Riley County in northeast Kansas in 2016. The second essay focuses on understanding the purchasing behavior and preferences of Oklahoma stocker producers through latent class analysis using the 2017 Oklahoma Beef Calf/Stocker Movement Survey. Chi-square tests are used to test the independence of relationships between important demographic information and nine cattle purchase characteristics. The third essay uses the Current Population Survey Food Security Supplement conducted by the United States Department of Agriculture and the Covid Impact Survey that conducted by National Opinion Research Center (NORC) at the University of Chicago to compare the food insecurity situation in the COVID-19 pandemic period with the 2008 financial crisis and pre-COVID period.

Essay I

Essay I (Chapter II) focuses on whether either of two insecticides could help control the number of horn flies for stocker cattle and estimates the expected profitability from application of either of the insecticides. The horn fly, Haematobia irritans (L.), is an prevalent and normal pest of pastured cattle in the United States. Both genders of horn flies feed frequently every day on cattle, which causes decreased eating, resulting in weight loss and reduced milk production in cows.

Options for controlling horn flies in cattle include walk-through traps, insecticide-impregnated ear tags (Corathon®), sprays, pour-on chemicals, insecticide dust bags, insecticide feed additives, and LongRange (Butler and Okine 1999; Campbell et al. 2006 and Li et al. 2011). Corathon® is a very popular insecticide cattle ear tag used to control horn flies on stocker cattle, lasting up to 5 months with a small amount of insecticide released after they are attached to the ear of stocker cattle. LongRange® is used to shoot the cattle with an insecticide pellet by an air "gun". This is comparatively new method. When compared to applying the insecticide-impregnated tag to the cattle ears, shooting insecticide into the cattle could reduce stress on animals and minimize discomfort (Loftin and Corder, 2013). LongRange® can have lower labor cost than other methods because of the delivery method, while the cost per application is much higher than Corathon®, the ear tag method. Literature reports that calf growth could be improved with the population of horn fly controlled.

Different insecticide control methods have different levels of effectiveness on the control of horn flies, but rarely has research focused on the economic value of different controls. This study used experiment data and input cost information from Riley County in northeast Kansas in 2016 to help address the following two objectives: (1) determine the effectiveness of either insecticide controlling horn flies compare with the control group, and (2) determine the profitability for applying either of insecticides relative to a control group.

Essay II

The second essay (Chapter III) focuses on stocker cattle operators' purchase preferences. The United States has the world's largest beef cattle industry, producing beef for domestic and export use. The beef cattle industry is very complicated with diverse production systems. According to Peel (2003), typically beef production includes three stages 1) the cow-calf phase that produce weaned feeder calves for further feeding, 2) the background or stocker cattle phase where the weaned calves are intended to be sold as feeder cattle, but have not been sent to the feedlot, 3) the finishing phase where cattle are fattened in the feedlot for slaughter.

The stocker industry is critical and varied in the cattle industry and is the most flexible segment of the beef supply chain (Peel, 2017). The stocker industry is difficult to define, understand, or even identify given traditional data (Peel, 2017). Typically, the stocker industry has two possible operation styles. In one, cow-calf producers retain the ownership of the weaned calves in a post weaning growing program until they are suitable for placing in the feedlot. In the other, one is operating as a separate independent commercial enterprise that buy weaned calves from cow-calf producers and sells them later at heavier weights to feedlots.

The stocker segment is considered to be the most flexible and complicated part in the beef cattle supply chain. The decision of purchasing calves is obviously complex, partially because there are many factors of influence including beef cattle market changes, the cost of inputs such as forage price and availability, and weather conditions that affect grass quality. While a range of ideas exists on how stocker producers operate and some conceptual pictures of stocker behavior are suggested in previous literature, some of interesting variables may not be directly measurable.

In order to help understand stocker operations, it is necessary to analyze the factors might affect stocker producers' calf purchasing decisions. There is little data about stocker production and feeder cattle movement around the country. Of course, there is also very limited research attempting to understand the purchasing behavior of stocker producers. Any previous studies of the stocker industry have been limited by data availability. This paper makes use of selected data from a recent survey, the '2017 Oklahoma Beef Calf/Stocker Movement Survey'. In the survey, Oklahoma stocker operators were asked to rate the importance of each of nine characteristics when making decisions to buy cattle. The second essay has the following two objectives: 1) using chi-square tests to test the independence of relationships between important demographic information and the nine factors reflecting stocker operator's purchasing preferences; and 2) applying a latent class model to the stocker producer population to classify producers into subgroups based on cattle purchasing preferences.

Essay III

The third essay (Chapter IV) concentrates on a comparison of food insecurity during the COVID-19 period, the Great Recession period, and normal times. With a quarantine announced by Wuhan city of China on January 23rd, 2020, the COVID-19 virus started a pandemic from China to Europe, United States and eventually the whole world. Department stores, restaurants and most public locations required masks and social distancing. Schools went online and businesses that are not essential closed in United States. However, the virus kept spreading very fast, the United States became the leader of the world in confirmed COVID-19 cases and a national emergency on March 13th, 2020 was declared by the United States government after the first person dead from the virus. With the loss of job opportunities, household income decreases. The unemployment rate jumped to 14.7% in April 2020 from 4.4% in the previous months (USBLS,2020). The ability of people to access food was affected by changes in employment and household income. Feeding America reported on April 19th, 2020 that they expected people who seek for food assistance would rise by almost 50%, and in the previous six months combined, they had put more money on food (CBS, 2020).

Food insecurity is a very important issue for a country because it is related to the basic living requirements of people and the stability of the whole society. With the COVID-19 pandemic and lower employment rates and household income, food insecurity should be considered and measured. A household would be seemed as food secure if people have ability to acquire enough, safe, and nutritious food. On the contrast, a household is deemed to be food insecure if they have difficulty acquiring sufficient, safe, and nutritious food for an active, healthy life (Owens et al. 2020). Adverse macroeconomic events such as the COVID-19 pandemic and the Great Recession led to great impacts for the world, including economic environment, and the household's financial situation, physical and mental health. These impacts on different aspects of well-being are not independent but related to each other. Measuring the impact for the whole society and for households from adverse macroeconomic events is an important job of economic researchers.

In the United States, measuring food insecurity is done by the United States Department of Agriculture (USDA). USDA conducts a food security survey through the Current Population Survey Food Security Supplement (CPS-FSS) every December. This survey is highly representative because of the scientific and expensive sampling procedure. Since the CPS-FSS was not administered until December of 2020, it could not monitor the pandemic's impact on food insecurity in the spring and summer of 2020. As such, some expedited internet surveys were administered by organizations to attempt to measure food insecurity in pandemic, such as the Covid Impact Survey that is conducted by NORC at the University of Chicago.

While it is hard to compare with the CPS-FSS survey to the NORC survey because the expedited survey did not use the same method to measure food insecurity, measuring and comparing the rates of food insecurity is the main purpose of this paper. This study has the following objectives: 1) measure the state of food insecurity in the United States during the first few months of the COVID-19 outbreak. 2) analyze the results of the NORC survey and provide some adjustments to its food insecurity rate so that it can be compared to rates during the relatively normal year prior to the pandemic, during the Great Recession, and during the first few months of the Covid-19 pandemic.

CHAPTER II

ECONOMICS OF INSECTICIDES TO CONTROL HORN FLIES (DIPTERA: MUSCIDAE) IN STOCKER CATTLE

Introduction

Horn flies, *Haematobia irritans (L.),* are prevalence and normal pest of pastured cattle in the United States. Horn flies are approximately 1/8 inch long, about half the size of a house fly (Loftin and Corder 2013). Horn flies live on the head, back and shoulders of cattle (and occasionally horses) all the time, although they might move to the belly of the hosts when the weather is hot and wet. They usually leave their hosts only when they are going to lay eggs on the fresh manure of the hosts. In the southern United States, horn flies can be observed throughout the year, but have the most numbers from spring to early fall (DeRouen et al. 2009).

Both genders of horn flies feed on cattle with their stiff needle-like mouthparts and take 20 to 40 blood meals per day (Kunz et al. 1991). This annoys the cattle through dermal irritation which causes cattle eat less, resulting in weight gain and milk production reduction. Economic losses from horn flies in cattle were estimated by Kunz et al. (1991) to be US$876 million (US$1.764 billion in 2021 dollars). Control of horn flies significantly benefits beef productivity and profitability, especially for stockers (Hogsette et al. 1991).

The economic threshold of the number of horn flies is normally defined as 200 flies per animal (Schreiber et al. 1987 and Hogsette et al. 1991). Options for controlling horn flies in cattle include walk-through traps, insecticide-impregnated ear tags (Corathon®), sprays, pour-on chemicals, insecticide dust bags, insecticide feed additives, and LongRange® (Butler and Okine 1999; Campbell et al. 2006 and Li et al. 2011). Walk-through horn fly traps capture the flies when an animal passes through the trap. The trapped flies then die from starvation or dehydration (Loftin and Corder, 2013).

Insecticide-impregnated ear tags were first used in the late 1970s (Cocke et al. 1990). The tags distribute insecticide with a small amount over a long period of time after they are attached to the ears of stocker cattle. With the long-term use of insecticide-impregnated ear tags, the horn flies became resistant to those insecticides, reducing the use of those ear tags (Foil et al., 2010; Oyarzun et al., 2011; and Domingues et al., 2014). Sprays apply insecticide to stocker cattle with high volume and high pressure. Pour-ons are liquid insecticides poured directly onto the backs of cattle. The effectiveness of pour-ons and sprays can be compromised by under-estimating or over-estimating the amount to be applied. Insecticide dust bags are installed at an opening point such as a gateway so that insecticide is applied to the cattle when they pass through. LongRange® is a comparatively new method that shoots the cattle with an insecticide pellet using an air "gun." LongRange® could reduce stress on animals and minimize discomfort compared to other dosing methods (Loftin and Corder 2013) since it can be used in the field.

Previous literature concluded that controlling horn flies improved calf growth (DeRouen et al. 2009; Schreiber et. al. 1987), and those different insecticides, like macrocyclic lactone, organophosphate, and pyrethroids, have different levels of effectiveness on the control of horn flies (Swiger and Payne 2016). However, little research has focused on the economic value of those controls.

This paper reports on a study in which two different insecticides were applied to stocker cattle to reduce the number of horn flies. The objectives were to: (1) determine the effectiveness of either insecticide controlling horn flies compare with the control group, and (2) determine the profitability for applying either of insecticides relative to a control group.

Data

This study was conducted with 302 stocker cattle in Riley County in northeast Kansas in 2016. There were two treatment groups for testing efficacy of Corathon® and LongRange® in controlling horn flies, and a control group. Corathon® is a very popular insecticide cattle ear tag used to control horn flies on stocker cattle, lasting up to 5 months. Bayer® Corathon® Cattle Ear Tags were used in this experiment. Corathon® was applied with the Allflex® Universal Total Tagger with red pin and black clip. Only one application of Corathon® is needed if timed appropriately. Applying too early or too late would make Corathon® miss its best ability to control horn flies. Therefore, it is best to apply Corathon® to cattle after the number of horn flies reaches up to 50 or more per animal side (Loftin and Corder 2013). This would also help to limit the growth of insect resistance. LongRange® is a relatively new technology in delivering an insecticide to beef cattle. LongRange® can have lower labor cost than other methods. Shooting the insecticide onto cattle from a distance could avoid handling cattle for application of the insecticides, therefore reducing the chance of injury to people and animals, as well as reducing stress to the animals.

There were 15 pastures, with animals grouped in 5 blocks. There were three pastures in each block with each block including three groups: control group, Corathon® group and LongRange® group (Table 2.1).

The 15 pastures were grouped into five blocks as shown in Figure 2.1. Cattle were randomly assigned to each treatment and block with the numbers for each treatment shown in Table 2.1.

The average horn flies' numbers in two treatment groups were recorded weekly from the second week through the 11th week. There were 111 cattle in the control groups, 87 cattle in the Corathon® groups, and 104 cattle in the LongRange® groups. Average daily gain was calculated as total gain, the difference between the weights on the 90th day and the first day, divided by 90 days.

The data (Table 2.2) include the color of the animal (black or not black), implanted hormone treatment (Ralgro® or Revalorg®), the number of pens in each pasture, and whether the animal had pink eye. Pasture is a blocking factor (Block) and so pasture was treated as a random effect. The appropriateness of assuming a random effect was tested using a likelihood ratio (LR) test. Because of the proximity of the pastures, weather conditions, including temperature, humidity, and precipitation, were assumed to be the same for the 15 pastures.

Methods

Treatment effectiveness was measured as percent reduction in f horn fly numbers per animal. Percent reduction was calculated as follows

(2.1) $$\text{Percent reduction} = 100*(1-T/C)$$

where T and C is the average number of flies per cattle in the treated groups and control group (Swiger and Payne, 2016).

To determine the most profitable insecticide, the objective is to choose treatment i (where i = 0 is no treatment) to maximize marginal expected profit, or

(2.2) $$\max_{i=0,1,2} E(\pi_i) = E(P(Q) * MW_i) - C_i$$

where $E(P(Q) * MW)$ is the expected value of marginal weight gain, C_i is the cost of each treatment, $P(Q)$ is the value of gain per pound, which is a function of the weight of the animal, and MW_i is the marginal weight gained with each treatment. Partial budgeting is used to determine the optimal treatment.

Proc Mixed in SAS was used to measure the effects of the fixed effects treatments – control, Corathon® and LongRange®, cattle color (black or not), hormone implant (Ralgro® or Revalorg®), pink eye (yes or not) – a random block effect, and residual error on weight gain:

$$(2.3) \qquad ADG_{ijkb} = \alpha_0 + \sum_{j=1}^{2} \beta_j T_j + \sum_{k=1}^{2} \gamma_k H_k + \alpha_1 Color_i + \alpha_2 PinkEye_i + B_b + \varepsilon_{ijkb}$$

where ADG_{ijkb} is the average daily gain for the i^{th} cattle under the j^{th} treatment and k^{th} hormone in the B^{th} pasture block, $\alpha_1, \alpha_2,\ \beta_j$, and γ_k are parameters to be estimated, T_{ijkb} is a dummy variable for treatments, H_{ijkb} is a dummy variable for hormones, $Color_i$ is an indicator variable for cattle color ($Color$ = 1 for black cattle), $PinkEye_i$ is an indicator variable for pink eye ($PinkEye$ = 1 if the animal had pink eye), $B_b \sim N(0, \sigma_b^2)$ is the block random effect, and ε_{ijkB} is a random error term with $\varepsilon_{ijkb} \sim N(0, \sigma_\varepsilon^2)$.

A likelihood ratio test was used to estimate the significance of block random effect by using the Proc Mixed procedure in SAS. The likelihood ratio test was specified as

$$(2.4) \qquad -2\left(\ln L(\tilde{\theta}) - \ln L(\hat{\theta})\right) \xrightarrow{d} X_1^2$$

where $\ln L(\tilde{\theta})$ is the restricted log likelihood value and $\ln L(\hat{\theta})$ is the unrestricted log likelihood value. The value of $2 \ln L(\tilde{\theta})$ with the block variable was -556, and the value of $2 \ln L(\hat{\theta})$ without the block variable was -562, then $\lambda_{LR} = 562 - 556 = 6 > X_1^2 = 3.84$. This result shows that B (pasture block) has a random effect on average daily gain.

The coefficients for both insecticides are expected to be positive, indicating that compared to the control group, the insecticides increase average daily gain. Theoretically, LongRange® is expected to be more effective than Corathon®, because LongRange® technology was developed more recently than Corathon®. Black cattle are expected to have higher average daily gain than non-black cattle. The expected signs of both implanted hormone treatments are positive. Incidence of pink eye is expected to decrease average daily gain, because pink eye might annoy cattle and cause them to limit their food intake (Thrift and Overfield 1974).

Results

The effects of the treatments on the number of horn flies and the average daily gain are shown in Figure 2.2. Compare with the control group, the number of horn flies were on average 34% and 50% lower with applying Corathon® and LongRange® , respectively. (Table 2.2).

The statistically significant coefficients for T1 (Corathon®) and T2 (LongRange®) indicate that average daily gains for cattle treated with Corathon® were 0.2101 higher, and for cattle treated with LongRange® were 0.2506 higher, than those for cattle in the control group (Table 2.3). Whether the cattle were black or not was not statistically significant. Ralgro® was associated with an additional 0.1504 average daily gain with a statistical significance of $p = 0.0751$, and Revalorg® was associated with additional 0.2362 average daily gain with a statistical significance of $p = 0.0054$. The presence of pinkeye was not statistically associated with average daily gain.[1]

Discussion

The results show that the two insecticides evaluated here were effective in controlling horn flies in stocker cattle. To determine the economic effectiveness of each treatment, the marginal benefits of increases in average daily gain were compared with the marginal costs.

[1] Models including variables for interactions between the insecticide treatments and hormone applications were tested, but were insignificant and did not improve the estimates, so they were omitted.

The value of marginal weight gains (VMW) per head in the season-long period is estimated as

(2.5) $$E(VMW_j) = E\left(P * ADG_j * 90\right)$$

$$j = 1,2$$

where $E(VMW_j)$ is the expected value of marginal weight gains with different treatments per head, P is the value of weight gains, ADG_j is the average daily weight gain with the j^{th} treatment over the 90 days of the total trial. Because the price of beef per pound varies by the weight of the animal, with the per unit price typically lower for animals of heavier weight, a characteristic termed a "price slide" (Brorsen et al. 2001), the value of weight gain is calculated as

(2.6) $$P = \frac{R_{675} - R_{575}}{100} = \frac{\$1.6238/lb * 675lbs - \$1.7518/lb * 575lbs}{100lbs} = \$0.8877/lb \text{ (\$1.9570/kg)}$$

where R_{675} is the price per pound for animals that weigh 675 pounds (306kg) and R_{575} is the price per pound for animals that weigh 575 pounds (260 kg). The price for 675-lb. (575-lb.) animals is the average weekly price for 650-700lb. (550-600lb.) Medium to Large-Frame #1 feeder steers from January 2010 – June 2018 in Oklahoma from the LMIC.[2]

The values of marginal weight gain are:

Corathon®: $E(VMW) = \$0.8877 * \ 0.2101lb * \ 90days = \$16.79/head$

LongRange®: $E(VMW) = \$0.8877 * \ 0.2506lb * \ 90days = \$20.02/head$

The cost of Corathon® in the trial was $4.75 per head, and the cost of LongRange® was $10 per head. The cost of labor for applying Corothon® was $0.21 per head, and the cost of labor for applying LongRange® was $0.07 per head.

[2] LMIC is Livestock Marketing Information Center

Comparing the weight gains value with the costs, cattle with application of Corathon® gained 18.91 lbs/head (0.2101 lb. x 90 days) or 8.58 kg/head on average, then the additional net profit can be achieved to minus the treatment cost and labor cost: $\$16.79 - \$4.75 - \$0.21 = \$11.83$/head, for cattle in the group of appling Corathon ®. Cattle with application of the LongRange® treatment gained of 22.55 lbs/head (0.2506 x 90 days), or 10.23 kg/head on average, and additional profit from the application of LongRange® can be calculated: $\$20.02 - \$10.00 - \$0.07 = \$9.95$/head (Table 2.4). Although application of LongRange® produced a greater reduction of horn flies' numbers, and a greater increase in pounds of gain, its marginal profit is a little bit lower than that of Corathon® because the treatment and labor costs with application of LongRange® were much higher than that with application of Corathon®.

Table 2.5 shows similar measures, assuming that the price slide is 50% steeper than the price slide used in Table 2.4. A steeper price slide reduces the value of additional gain, reducing the profit from using the insecticides to $4.26/head for Corathon® and $0.93 for LongRange®. In contrast, Table 2.6 shows similar measures for a slide that is 50% less steep than that assumed in Table 2.4. With a less steep slide (meaning that the value of additional pounds of gain is increased), the profit of each insecticide is higher relative to the control group ($19.39/head for Corathon® and $18.97/head for LongRange®). For both insecticides, the flatter price slide allows the weight gains to achieve greater profit because of smaller price reductions. LongRange®'s greater weight gains increase its profit more when those gains are not as severely discounted by the price slide. The results of this study suggest that use of both insecticides increased profitability, although under typical assumptions Corathon® achieved a slightly higher profitability than LongRange®.

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Table 2. 1 Experimental Design

Block	Pasture	No. of Sampled Cattle	Product
1	1	29	Control
	2	25	LongRange®
	5N	12	Corathon®
2	13	19	Control
	14	19	LongRange®
	12	19	Corathon®
3	18	25	Control
	17	31	LongRange®
	16	29	Corathon®
4	7	27	Control
	3N	14	LongRange®
	6N	13	Corathon®
5	3S	12	Control
	5S	14	LongRange®
	6S	14	Corathon®

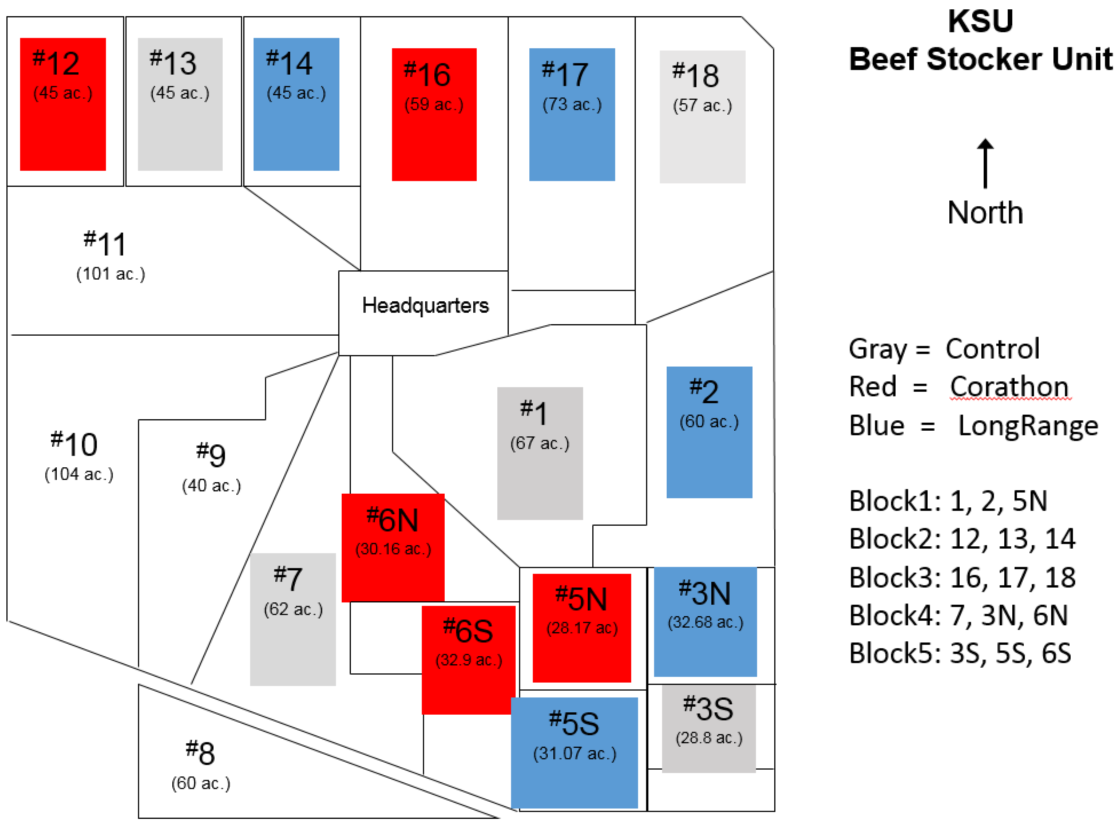

Figure 2. 1 Layout of Pastures

Table 2. 2 Average Number of Horn Flies Per Animal and Percent Reduction Under Two Insecticides Compared to Control Group

	Corathon®				LongRange®				Control		
Week	**Avg # horn flies**	**percent reduction**	**# of cattle**	**sd.**	**Avg # horn flies**	**Percent reduction**	**# of cattle**	**sd.**	**Avg # horn flies**	**# of cattle**	**sd.**
2	5	69	69	6	4	75	73	3	16	71	14
3	10	67	69	15	8	74	72	7	30	71	28
4	19	54	69	19	16	62	71	15	43	71	34
5	24	49	70	15	20	57	70	12	47	71	31
6	36	22	69	42	26	43	69	22	46	71	41
7	48	17	71	50	36	37	68	33	57	71	44
8	146	17	69	124	112	36	67	106	176	71	152
9	190	21	72	153	142	41	66	102	240	71	183
10	256	20	69	207	116	64	65	92	320	71	255
11	342	3	73	230	320	10	64	239	353	71	345
Avg./Tot	108	34	70.0	86.10	80	50	68.5	62.86	133	71.0	113

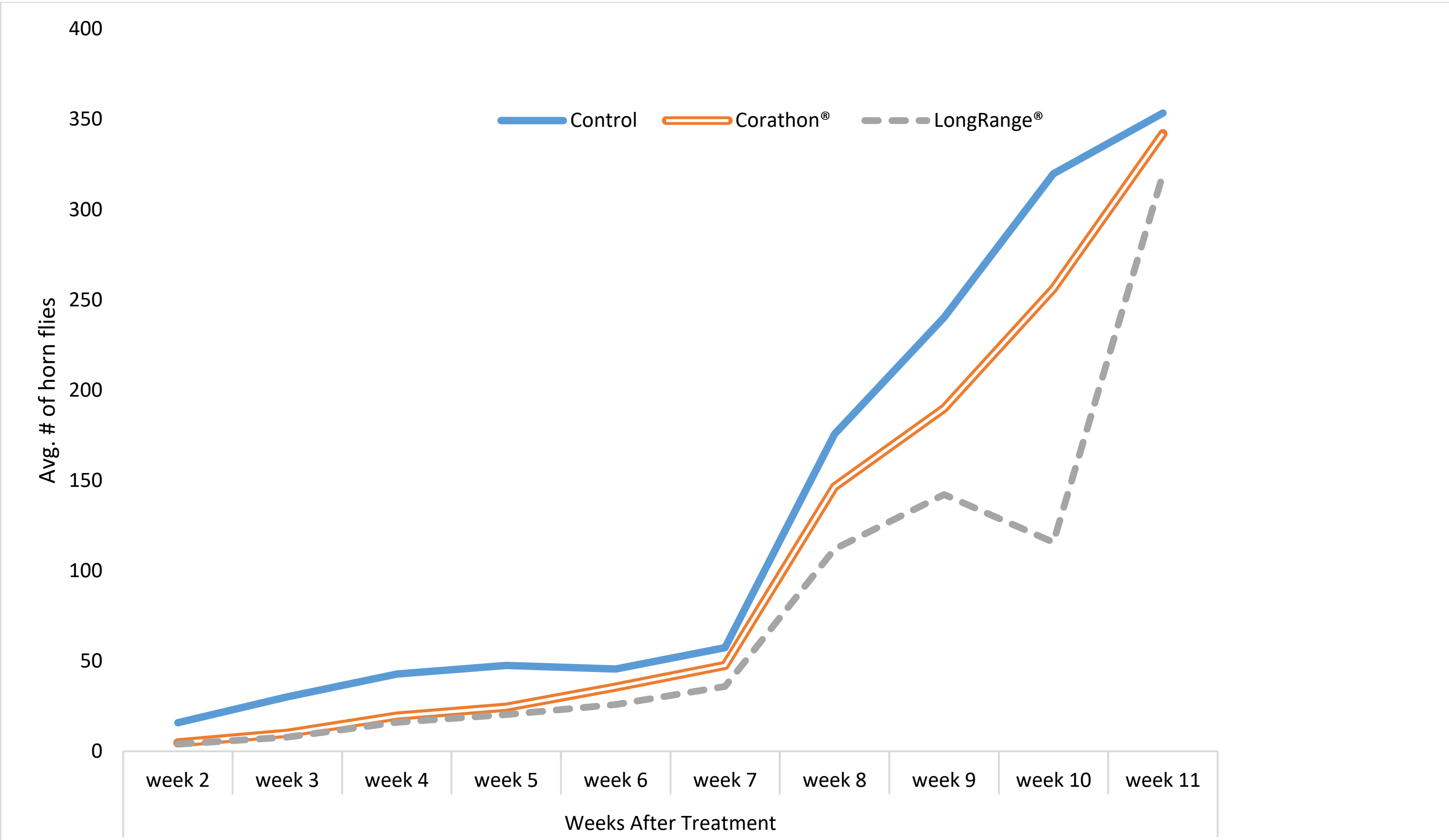

Figure 2. 2 Average Number of Horn Flies for Treatment Groups and Control, by Week

Table 2. 3 Effect of Horn fly Treatments on Average Daily Gain (lb/day) of Stocker Cattle

Effect	**Estimate**	**Standard Error**	**DF**	**t Value**	**Pr > |t|**
Intercept	1.1903	0.18	4	6.49	0.0029
***T_1* (Corathon®)**	0.2101	0.09	291	2.45	0.0149
***T_2* (LongRange®)**	0.2506	0.08	291	3.07	0.0023
Color	0.1026	0.08	291	1.34	0.1810
***H_1* (Ralgro)**	0.1504	0.08	291	1.79	0.0751
***H_2* (RevalorG)**	0.2362	0.08	291	2.81	0.0054
PinkEye	0.0444	0.18	291	0.25	0.8026
BLOCK	0.0015	0.00		0.25	0.4021
Residual	0.3491	0.03		12.01	<.0001

Table 2. 4 Additional Revenue and Net Profit from Treatments Compared to Control Group: Price Slide Calculated from Averages of Observed Prices from 2010-2018

P_{675} ($/lb)	P_{575} ($/lb)	Price Slide ($/lb)	VMG ($/lb)		Added Revenue ($/head)	Treatment Cost ($/head)	Labor Cost ($/head)	Net Profit ($/head)
1.6238	1.7518	-0.128	0.8877	Corathon®	$16.79	$4.75	$0.21	$11.83
				LongRange®	$20.02	$10.0	$0.07	$9.95

Table 2. 5 Additional Revenue and Net Profit from Treatments Compared to Control Group: Price Slide 50% Steeper than Table 2.4

P675 ($/lb)	P575 ($/lb)	Price Slide ($/lb)	VMG ($/lb)		Added Revenue ($/head)	Treatment Cost ($/head)	Labor Cost ($/head)	Net Profit ($/head)
1.5918	1.7838	-0.192	0.4878	Corathon®	$9.22	$4.75	$0.21	$4.26
				LongRange®	$11.00	$10.0	$0.07	$0.93

Table 2. 6 Additional Revenue and Net Profit from Treatments Compared to Control Group: Price Slide 50% Less Steep than Table 2.4

P675 ($/lb)	P575 ($/lb)	Price Slide ($/lb)	VMG ($/lb)		Added Revenue ($/head)	Treatment Cost ($/head)	Labor Cost ($/head)	Net Profit ($/head)
1.6558	1.7198	-0.064	1.2878	Corathon®	$24.35	$4.75	$0.21	$19.39
				LongRange®	$29.04	$10.0	$0.07	$18.97

CHAPTER III

A LATENT CLASS ANALYSIS OF STOCKER CATTLE PRODUCER PURCHASING PREFERENCES

Introduction

The United States is the biggest producer of beef in the world, with the largest fed-cattle industry, producing high-quality and grain-fed beef for both domestic and export use (USDA-ERS 2019[a]). In 2017, the value of all U.S. cattle and calves was $103.90 billion, with 93.71 million head (USDA-NASS 2019[b]). The total value of all cattle and calves in Oklahoma was estimated be to $5.4 billion on January 1, 2017, ranking 5th among states in the value and quantity of production (USDA-NASS 2019[b]).

The U.S. beef cattle industry is complex and involves diverse production systems utilizing diverse resources around the country. Commercial beef cattle production can typically be classified to three stages: (1) the cow-calf segment which produces weaned feeder calves for further grazing and/or feeding, (2) the backgrounding or stocker phase of production which includes weaned calves intended for sale as feeder cattle, but not yet placed in the feedlot (Peel 2003), and (3) the finishing phase in which cattle are fattened for slaughter.

The second phase, stocker operations, is the focus of this article. A stocker operation may be most often defined as "the process of growing and developing calves from weaning weights (450 to 600 lb) to yearling weights (700 to 850 lb) when the cattle are ready to enter a feed yard" (Shane et al. 2015). Stocker cattle production associates value added from cow-calf to finishing phase of beef cattle (Johnson et al. 2011; Peel 2003). The stocker cattle phase of cattle production is focused on increasing calves' weights using forage-based production systems, and in many cases, quality, while sometimes adjusting stocker cattle feeding help to fit to the marketing price. Glynn, Hill and Basi (2015) found an average daily gain for stockers of 1.77 pounds and an average net return of approximately $76.57/head. Both measures exhibited notable variation across producers.

The stocker industry has two operation possibilities. It may be a component of a cow-calf operation where the producer retains ownership of weaned calves in a post-weaning growing program until they are suitable for feed lot placement. The other possibility is that the stocker operation is a separate commercial enterprise (Johnson et al. 2010). As an independent commercial enterprise, stocker operators buy calves after they were weaned, grow them on forage and sell them to cattle feeders at after gaining more weights for feedlot placement. Some operators may focus on purchasing poorly managed calves and work to upgrade cattle quality and performance after purchase to added value. Improved health of stocker cattle helps them appear more attractive to possible buyers. Sorting calves to be sold in more uniform groups adds value as well. Depending on regional differences in forage across the United States, stocker cattle can be grazed either seasonally or year-round. Cattle may be grazed all summer or placed in pastures at twice the stocking density. Winter production systems typically employ either perennial cool season forages or annual cool season forages, such as small grains pasture (Phillips et al. 2006).

The stocker industry is difficult to define, understand, or even identify and is considered to be the most flexible and complicated part in the beef cattle supply chain (Peel 2017). The decision of purchasing calves is obviously complex, partially because there are many factors that influence the decision of stocker operators, such as the factors of the selling calves from cow-calf industry, the whole beef cattle market changes, the cost of input such as the forage price, the weather condition that affect the quality of the grass and price of substitute goods. As it represents a range of purchase strategies, production strategies and risk tolerance.

In order to help understand stocker operations, it is useful to analyze factors that might affect stocker producers' purchasing decisions. Since little data exists about stocker production and feeder cattle movement around the country, there is very limited research regarding the purchasing behavior of stocker producers. This paper utilizes a recent, unique survey of Oklahoma stocker producers to analyze stocker producer purchasing preferences. Latent class analysis is used to categorize stocker producers according to those preferences.

Data

This paper uses data from the 2017 Oklahoma Beef Calf/Stocker Movement Survey, a comprehensive survey of Oklahoma cattle producers conducted by Oklahoma State University, in conjunction with USDA's Animal and Plant Health Inspection Service (APHIS) and the National Agricultural Statistics Service (NASS). The primary objective of the survey was to augment available data on stocker production, marketing, and movement. The survey was promoted heavily to stocker producers through existing Oklahoma Cooperative Extension Service newsletters (mail and email) and newspaper articles, radio spots, Oklahoma Cattlemen's Association publications, producer meetings, conferences and mailing pre-survey postcards to stocker producers. A total of 4,844 survey questionnaires were distributed, and 1,461 were completed and usable with a 30.2% survey response rate. There are 207 survey questionnaires were responded by stocker producers and other associated operators. As part of the survey, Oklahoma stocker operators were asked to rate the importance of nine characteristics of stocker cattle when making a purchase decision. This paper uses data regarding stocker purchase decisions, as well as producer demographic data from the survey.

Methods

Latent Class Analysis Model

Latent class analysis (LCA), introduced by Lazarsfeld (1950), is a statistical method used to identify and describe unobserved subgroups within a population, called latent classes, based on responses to a set of observed indicators, such as a questionnaire response (Collins and Lanza 2010; Magidson and Vermunt 2000; Lazarsfeld 1950; Clogg 1995). LCA results can be used to classify individuals into their most likely (latent) group, where groups are the based on a categorical latent variable (LV) (Agresti 2002). LCA is used to estimate class membership probabilities and item response probabilities (Porcu and Giambona 2017). Class membership probabilities represent the probability that an individual is a member of a specific class. Item response probabilities are conditional upon class membership and represent the probability that an individual gives a specific response given latent class membership. Following Porcu and Giambona (2017), the latent class model can be expressed as:

(3.1) $$\mathrm{P}(\mathrm{Y} = \mathrm{y}) = \sum_{c=1}^{C} \gamma_c \prod_{j=1}^{J} \prod_{k=1}^{R_j} \rho_{j,k|\mathrm{c}}^{I(y_j = k)}$$

where $\mathrm{I}(\mathrm{y}_j = \mathrm{k})$ is an indicator function that equals 1 when the response to item $\mathrm{y} =$ k and 0 otherwise. Let j = 1…, J be the observed categorical items with k = 1…, R_j the response categories. Y and y represent a vector and a particular response pattern; C is the number of latent classes, where c = 1, . . . C; γ_c is the probability of membership in latent class c (class membership probabilities) and ρ is the item-response probabilities conditional on latent class membership (item response probabilities).

For our data set, we have j =1 through 9 categorical items, which are the nine stocker purchase characteristics for which importance is evaluated. For each characteristic, we have 1 through 5 associated with importance rank, which reflects stocker producers' purchase behavior preference. For example, we could have a vector y = 2, 2,3,4,1,5,2,4,3. and Equation 3.1 expresses the probability of observing a particular responses pattern is a function of the probabilities of membership in each latent class (γ) and the item-response probabilities conditional on latent class membership (ρ). So, each individual (stocker producer) belongs to one and only one class, such that in each class, the sum of the membership probabilities is 1, $\sum_{c=1}^{C} \gamma_c = 1$.

The parameter ρ item response probabilities expresses the relationship between each factor and each latent class, indicate with response from individuals, how well each individual (stocker producer)can be classified into specific latent classes. Each individual (stocker producer) gives one response to each categorical item j, so, the item response probabilities vector for a particular categorical item conditional on a particular latent class sum to 1 (Collins and Lanza 2010). Ultimately, latent class parameters are estimated to characterize the probabilities for population belong to each class, and class es sizes.

The procedure of determining the number of classes in the LCM is called class enumeration. Multiple latent class models are estimated with different latent class numbers and fit statistics are collected from each fitted model. Finally, the most reasonable latent class model that best describe the data will be chosen. Several papers demonstrated the model fitting indices used to do class enumeration (Morgan 2015; Morovati 2014; Nylund, Asparouhov and Muthén, 2007; Yang 2006). Generally the fit indices values do not all point to oneoption, so fit indices are needed to be jointly considered during the procedure to decide the number of class, this help to illuminate how well the classes are classifying and differentiating among the individuals considered (Law and Harrington 2016; Muthén 2003; Nylund-Gibson and Choi 2018). While the "true" correct class number would not be known in any given data analysis, fit indices have been shown to often work well in simulation studies.

Latent class models use the maximum likelihood method for parameter estimation. In this paper, SAS 9.4 is used to estimate the latent class models. Multiple tests are used for class enumeration. There are four information criteria which are Bayesian Information Criterion (BIC), Sample-sized adjusted Bayesian Information Criterion (SBIC), Akaike information criterion (AIC) and Consistent Akaike information criterion (CAIC).

The four information evaluation criteria are widely used for class enumeration, where smaller criteria values point to a better fit. The BIC index is considered more reliable with samples large (Liu et al. 2017). However, according to Nylund et al. (2007), the BIC underestimates the number of classes when samples are small. Since our sample is relatively small, the BIC will not be relied on heavily in our class enumeration process. Two likelihood-based tests include Vuong-Lo-Mendell-Robin adjusted likelihood ratio test (VLAR-LRT) and Bootstrapped likelihood ratio test (BLRT). The two likelihood-based tests provide p-values to indicate an imporvement statistical significance with adding a class in model fit. If a p-value for a k class is not significant, the k-1 class is concluded to be better fit (Nylund, Asparouhov and Muthén 2007), while SAS 9.4 used in this paper does not give the results of the two likelihood-based tests.

Multiple-group Latent Class Analysis

Multiple-group latent class analysis tests whether there are item-response probability or class membership probability differences across different populations (Goodman 1974; Hagenaars and McCutcheon 2002; Collins and Lanza 2010). Differences in these probabilities can indicate that the latent structure is not the same across the populations tested. There may be interest in whether there exist differences of the latent class model result across production region, or producer age. For example, when a group variable is included, both latent class membership (γ_c) and item-response probabilities (ρ) will be conditioned on group. Suppose a group variable g is included, then the multiple-group latent Class analysis model can be expressed as:

(3.2) $$\mathrm{P}(\mathrm{Y} = \mathrm{y}|g) = \sum_{c=1}^{C} \gamma_{c|g} \prod_{j=1}^{J} \prod_{k=1}^{R_j} \rho_{j,k|cg}^{I(y_j=k)}$$

Lanza et al. (2007) advises establishment of whether item-response probabilities measurement invariance across groups holds before testing class membership probabilities across different groups. Comparing fit of two nested latent class models can establish whether item-response probabilities are invariant across groups. Model 1 allows ρ parameters vary across groups. Model 2 restricts the ρ parameters to be equal across groups. If the restricted model has a significantly poorer fit compared with the unrestricted model, then it is misspecified to restrict item-response probabilities to be equal across groups. In contrast, if the fit is similar between model 2 and model 1, this indicate that item-response probabilities do not differ across the groups. In other words, measurement invariance across groups holds.

Among the two nested models, the distribution of the likelihood-ratio difference test is asymptotically chi-square, model fit can be compared by $(G_2^2 - G_1^2) \sim \chi^2_{|DF_2 - DF_1|}$ and H_0: item-response probabilities hold across groups (Collins and Lanza 2010). If the *p* value is significant, the null hypothesis is suggested to be rejected. This implies that latent classes may differ across groups to some extent, and it needs to be cautious to interpret group differences in latent class membership probabilities. The ρ parameters in the unconstrained model give a benchmark to interpret the latent variables in the nature and extent of group differences. If the measurement of group differences is severe, it may have to model for group separately, providing group-specific interpretations of latent classes (Lanza et al. 2007).

Analysis Demographic Factor Independence

Descriptive analysis is used to determine if demographics impact the importance rankings of stocker producers. The chi-square test is used to statistically test independence between individual demographic characteristics shown in table 3.1 and the nine stocker purchase factors from table 3.2. For example, the chi-square test will indicate if the stocker producer region is independent from their importance ranking for each of the nine stocker characteristics.

Results

Table 3.1 shows the demographic characteristics of stocker producers including: production region, educational level, single or multiple counties, age, types of operation, and annual capacity. Respondents come from four regions, that 32.8%, 21.2%, 24.7% and 21.3% are located at Northwest, Northeast, Southwest, and Southeast respectively. Regarding education, 42.9% of respondents have bachelor’s degree, while 29.6%, 14.3% and 10.2% have high school diplomas, 2-year degrees or graduate degrees respectively. Approximately, 38.9% of respondents have operations on land in multiple counties. The majority of respondents are older with 63.3% at 55 and over. Stocker operations are evenly split, where 37.7% of respondents are cow/calf producers who retain the ownership of the weaned cattle before they are sold to feedlots, while 36.5% operate as a separate commercial stocker operation. The other respondents operate elsewhere on beef supply chain. Stocker operations size is distributed relatively evenly, where 26.6% have annual capacities of less than 100 head, 39.2% have annual capacities between 101 to 500 head and 34.2% have over 500 head.

This study examines nine characteristics related to stocker cattle purchases, including specific breed of the cattle, general cattle type (frame or muscling), cattle size/weight, certified preconditioned cattle, purchasing cattle from a specific geographic origin, avoiding cattle from a specific geographic origin, distance shipped, avoidance of ‘trader’ cattle, and the source/method of purchase (auction or direct). Certified preconditioned cattle are managed by producers in a specific protocol before they sell their calves to next stage, with practices such as castrating, dehorning, administering a health program and vaccinating (Schumacher et al. 2011). “Trader” cattle refer to cattle that are stale or being sold multiple times in a short period. Stocker producers were asked to rate the importance of each factor when they consider buying stocker cattle as very important, important, indifferent, slightly important, and not important, as reported in table 3.2. Nearly 69% of stocker producers chose specific breed to be important and very important, and 15% of them think it is not important at all. More than 90% of stocker producers think cattle type is important when they are purchasing. Similarly, about 83% of stocker producer chose cattle size and weight as important and very important in their purchasing. We can see that stocker producers emphasize the physical aspects of calves. Whether cattle are certified preconditioned is not as important as the physical characteristics in that only 27.5% of stocker producers think it is important, however, 35.75% rate it as not important at all. Rating of purchasing or avoiding from a specific origin are comparatively even. Distance shipped of cattle is a relatively important factor in stocker producers purchasing behavior as 63.41% of them consider it as important and very important. Stocker producers do not like the uncertainty as 85.5% rate avoiding “trader” cattle as important or very important. Source or method of purchase is important or very important to 61.6% of stocker producers. Mean and standard deviation of importance scores for the nine cattle purchase characteristics across all stocker producers are reported in table 3.3. In general, the factors that the stocker producers consider most important when they purchase cattle are avoiding “trader cattle”, animal type, and animal size and weight. The least important purchase characteristic is certified preconditioned cattle.

Independence Test between Demographic Information and Nine Factors

Chi-square testing was used to test whether demographic information in table 3.1is independent across each of the nine cattle factors in table 3.2. For example, does the stocker producers’ region influence producer rating of importance of the nine cattle purchase preferences? Are importance ratings independent of different educational levels? Specifically, we examine whether producer ratings of importance are independent across six demographic categories, including production region, educational level, single or multiple counties, age, types of operation, and annual capacity. Chi-square test results shown in table 3.4. Results suggest that production region does not impact rankings, with the exception of certified preconditioned cattle where ($\chi^2 = 11.11, p = 0.011 < 0.05$), suggesting rejecting the null hypothesis of independence between production region and preconditional. The importance of specific breed is influenced by producer education level where ($\chi^2 = 10.74, p = 0.030 < 0.05$), while ranking of the other eight cattle characteristics are independent of educational level. Whether stocker producers maintain cattle on land in multiple counties has no relationship with their importance ranking of the nine cattle characteristics. Stocker producer age does impact importance ranking of distance shipped where ($\chi^2 = 1.17, p = 0.045 < 0.05$); however, importance ranking of other characteristics are independent of producer age. The importance ratings of general animal type, distance shipped and avoiding "trader" cattle are not independent of operation type where ($\chi^2 = 17.21, p = 0.028 < 0.05$) ($\chi^2 = 17.51, p = 0.025 < 0.05$) and ($\chi^2 = 21.98, p = 0.005 < 0.05$) respectively. Similarly, annual capacity/operation size does impact producer ratings of importance for avoiding "trader" cattle where ($\chi^2 = 9.55, p = 0.020 < 0.05$).

Factors Exploratory Latent Class Analysis

Exploratory latent class analysis models were estimated using MLE in SAS 9.4. To facilitate class enumeration of stocker producer importance ratings for cattle purchase characteristics, models were estimated for up to five classes. In order to understand and more easily explain the latent class model fit for stocker purchasing preferences, the original data was re-categorized from a five-point scale importance rating to a two-point scale rating of Important and Unimportant. The Important group includes 1 (very important) and 2 (important). The other three importance ratings of 3 (indifferent), 4 (slightly important) and 5 (not important) are placed in the Unimportant group. Table 3.5 reports both five-point scale (1-5) and two-point scale (1-2) class enumeration results.

According to the literature and theory for class enumeration, smaller criteria values indicate a better fit. The Bayesian Information Criterion (BIC) index is considered more reliable with large samples (Liu et al. 2017). In table 3.5, smaller values for each information criteria are bolded which indicate the "best" fit. We can see that the results of five-point scale and two-point scale are consistent. BIC and Consistent Akaike information criterion (CAIC) point to the 2-class latent class model, while the 4-class model is indicated by the Akaike information criterion (AIC) and the Sample-sized adjusted Bayesian Information Criterion (SBIC) statistics. Though BIC is the most important index in deciding the class enumeration generally, according to Nylund et al. (2007), the BIC underestimates the number of classes when samples are small. Since our data sample is relatively small, the SBIC will be emphasized in our class enumeration process. Overall, 4-class enumeration is concluded to be the best fit of the original data.

Interpreting Latent Class Analysis

Since results for class enumeration are consistent for both the two-point scale data and the five-point scale data, the two-point scale data was used in the latent class analysis model for easier interpretation and explanation of results. Latent class membership probabilities ($\gamma_{c)}$ and item-response probabilities (ρ) are estimated for the 4-class model. These two parameters help explain the response pattern for each class. Latent class membership probability ($\gamma_{c)}$ indicates the membership probability in each latent class for any randomly selected producer. All latent class membership probabilities sum to 1across classes because latent class membership is estimated simultaneously with the overall model and is mutually exclusive and exhaustive. Item-response probability reflects the likelihood that a stocker producer in the selected class gives that specific response regarding a specific purchase preference (Law and Harrington, 2016). Item-response probabilities for a specific characteristic sum to 1 within a class.

Latent class membership probability

Figure 3.1 shows the percentage of producers in each latent class. Class 1 has the lowest membership at 7.25%, while class 3 has highest percent of producers at 43.96%. Classes 2 and 4 have similar probabilities at 22.71and 26.09%, respectively.

Item-response probability

Table 3.6 shows item-response probabilities, which indicates the differences in response patterns that help to distinguish among classes. For example, producers in class 1 choose specific breed as important with 17.1% probability and with 82.9% probability as unimportant. In contrast, producers in classes 2, 3 and 4 tend to place more importance on breed with probabilities of considering breed as important at 62.1%, 79.4% and 74.3%, respectively. Similarly, producers in class 1 have lower probability of choosing general animal type as important with 25.7%, and producers in class 2, 3, and 4 have very high probabilities to consider animal type as as important at 90.8%, 97.8% and 99.9%, respectively. For the cattle characteristic of certified preconditioned, all the four classes have comparatively lower probabilities of considering it as important at 7.8%, 29.7%, 36.4% and 17.9%, respectively. The graphical depiction of the table 3.6 results in figure 3. illustrates the primary differences among the four classes.

Stocker producers in classes 2, 3 and 4 have higher probability (60% to 80%) of choosing specific breed as important, while stocker producers in class 1 have only a 17% probability of considering specific breed as important. The pattern of probabilities is similar for animal type and size/weight with producers in class 2, 3 and 4 have a high probability (80% to 99%) of thinking animal type and size/weight is important. Class 1 stocker producers are only 25% likely to think animal type and size/weight is, substantially less than the other three classes. Regarding certified preconditioned cattle, all four of the classes have comparatively low probabilities of considering it to be important. Geographic region of stocker calves is very important for producers in class 3. The probabilities of purchasing and avoiding cattle from a specific region in class 3 are 97% and 90%, respectively. It can be understood that class 4 producers have specific requirements on calf origin. In contrast, producers in class 1, 2, and 4 are much less likely to care about calf origin. Some of them have little probabilities to consider the region to be important thing in their purchasing process. Stocker producers in class 2 have a 15% probability of thinking shipping distance is important, which is significantly lower than stocker producers in classes 1, 3 and 4, at 54%, 82% and 80%, respectively. Stocker producers in all four latent classes have high probabilities of avoiding “trader” cattle when they purchase calves, with producers in class 2 having the lowest probability of deeming it important at 50%. Source of purchase indicates where producers buy calves, for example, from auction or through other methods. Stocker producers in class 3 and 4 have 81% and 63% probabilities of considering the source of purchase for calves as important. Meanwhile the probability of saying source is important is less than half for class 2 producers, and only 22% in class 1.

Probabilities of the Individual Stocker in Each Latent Class

The procedure PROC LCA (Lanza et al. 2007) can be used to predict class membership for an individual stocker producer. Table 3.7 shows the first ten stockers’ importance ratings in the original data and the estimated probabilities of specific class membership predicted for the ten stockers. For example, the first stocker responded to all nine items as unimportant except avoiding “trader” cattle, which means his primary concern is to not purchase “trader” cattle. Stocker 1 has 99.9% probability of belonging to class 1 and no probability of belonging to class 2, 3 or 4. For such a situation, the best estimate is that this stocker belongs to class 1. Other stocker producers could also be categorized into a single class using the same kind of rule.

Multiple-group Latent Class Model

Stocker producers are distributed across four regions of the state, including Northwest (NW), Northeast (NE), Southwest (SW) and Southeast (SE). Region was added to the four-class model as a grouping variable. In order to test whether there is probabilities difference across regions, model 1 is estimated with all parameters freely estimated and then with parameters constrained to be equal across groups. The G^2 statistic was 287.77 (df = 1891) for the unconstrained model and 411.04 (df = 1999) for the constrained model, the likelihood-ratio difference test statistic of 123.27 (df = 108) were calculated which is distributed χ^2. The resulting p-value is 0.15, indicating that the null hypothesis is failed to rejectand suggests that the item-response probabilities were held equal across region.

Table 3.8 shows the result of the latent class membership probabilities for each of the four regions. NW and SE have a similar pattern to class membership probabilities stocker producers as a whole which reported in figure 3.1

In NW and SE regions, few are likely to belong to class 1, with most of stocker producers were classified into class 3. The probability that stocker producers belong to class 2 is less than that in class 3. Stocker producers in NE are the least likely belong to class 1 and class 4, which consistent with producers from NW and SE, while they have high and even probabilities of belonging to class 2 and 3. Results suggest that stocker producers in NW, SE, and SW are most risk averse, as they place importance on most of the characteristics, or at least the cattle are with good breed, type and size or weight. SW is most distinct with comparatively even probabilities among class 1, 2 and 3, but has a relatively high probability of belonging to class 4. Stocker producers in class 4 have high rating of all characteristics except certified preconditioned, specific region or avoid specific region to purchase cattle. Stocker producers in SW have 16.4% of probability to be risk takers, which is much higher than the other regions. This might be explained by producers in SW have more dynamic weather, unstable grass quality and marketing, they prefer taking risk than the producers from the other three regions.

Demographic Distribution in Each Class

It is interesting to examine demographic distributions across classes, such as producers' region, annual capacity, single vs. multi-county operation, producers' age and educational level. Figure 3.3 reports the region distributions in each class. In class 1, close to half of producers are located in Southwest Oklahoma, and 23%, 16%, and 15% are in the Northwest, Northeast and Southeast, respectively. In the contrast to producers in class 1, producers in class 2 have least number from the Southwest at 18%. Class 2 has relatively more producers located in the other three regions, which are 31%, 27%, and 24% in Northwest, Northeast and Southeast, respectively. For class 3 and 4, 34% and 35% of producers are from the Northwest, similar to class 2. Class 4 has the most producers from the Southeast (29%) and least from Northeast (15%). Figure 3.4 illustrates capacity distributions for each class. Class 1 is comprised of 50% small (1-100 head) operations, 43% have medium (101-500 head) operations, and no very large operations (> 2500 head). Class 2 has the largest percentage of very large capacities relative to other classes at 8% and fewer small and medium operations with 34% and 30%. Class 3 has 33% of producers with large capacities of 501-2500 head, which is the highest compared with the other classes. Almost half of (46%) producers in class 4 running medium operations, the most across the four classes. Figure 3. 5 shows the percentages of producers in single versus multi-county operations. Class 3 has the highest percentage of multi-county with 44%, while 20%, 33% and 42% of producers have multi-county operations in class 1, 2 and 4, respectively. In figure 3.6, the age distributions are similar among the four classes, with the exception of class 1 which has no producers younger than 34 years old. Figure 3.7 reports producers' education distributions, where 37% and 38% of producers in class 1 have high school or below and bachelor's degree of education, respectively, and a quarter of them have a vocational or 2-year degree, with no producers having graduate degree. From figure 3.7, we find that producers in class 1 have the highest percentage of high school or below education with 37% and no producer has a graduate degree. The number of producers with a bachelor's degree in class 1 is the least and with vocational or 2-year degree is the most among four of them. Class 2, 3 and 4 have similar distributions on producer education level, with the biggest percentage of producers with graduate degree in class 3 and bachelor's degree in class 4.

Conclusion

Latent class analysis suggests that stocker producers can be divided into four classes based on purchase preferences. Class 1 producers have comparatively low probabilities for all nine purchase characteristics compared with the other three classes, except for a higher probability of rating avoiding "trader" cattle as important. Overall, these producers are not picky about the details. Since stocker producers in class 1 seem to be least risk averse, we label class 1 as the "Risk taker" group. In contrast, Class 3 producers seem to be most risk averse. They have a high probability of rating everything as important except for certified preconditioned (36%). However, that is the highest probability across all groups for preconditioning. This is an interesting result to consider in the context of heavy promotion of third-party verified preconditioning programs. Multiple research studies report premiums for preconditioning feeder cattle (Avent, Ward and Lalman 2004; Williams et al. 2012) yet the majority of stocker producers in this study place less importance on it that on other characteristics. However, it is also important to note that our study measures only importance and not willingness to pay for preconditioning. We label class 3 as the "Risk averse" group. Both class 2 and 4 have high probabilities of rating specific breed, animal type and the size/weight important, that is, the physical characteristics of the cattle. However, class 4 producers are more likely to rate the distance shipped of cattle, avoiding "trader" cattle and the cattle source to also be very important, compared with producers in class 2. Class 2 producers care primarily about the physical attributes when they purchase cattle, but without other strong preferences. We label class 2 as the "Amazon shopper" group as they care more about the look and function of the cattle but less about where it was sourced or the sale venue. Class 4 is consistent with class 2 in regarding physical attributes of cattle as important, but class 4 producers care do about cattle geographic attributes and market source. We label class 4 as the "Upscale shopper" group. It is worth noting that all subgroups have less than 50% probability to consider certified preconditioned cattle important and no class likes "trader" cattle, but class 2 producers are most likely to consider them.

The latent class analysis approach adds important information to our understanding of Oklahoma stocker producers' purchasing preferences. Different among classes, regions, and sizes reflect the flexibility necessary for the stocker sector and its position in the beef supply chain.

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Table 3. 1 Demographic Characteristics of Survey Respondents.

Characteristic		**%**
Region	Northwest	32.80%
	Northeast	21.20%
	Southwest	24.70%
	Southeast	21.30%
Educational Level	High school	29.60%
	Vocational, Technical, or 2-year degree	14.30%
	Bachelor's degree	42.90%
	Graduate degree	10.20%
	None of these	3.10%
Operation on land in multiple counties	Yes	38.90%
	No	61.10%
Age	<25	0.00%
	25-34	8.70%
	35-44	12.20%
	45-54	15.80%
	55-64	33.70%
	65-74	18.90%
	>75	10.70%
Operation	Cow/Calf, Retain calves through feedlot	3.40%
	Cow/Calf: and Stocker/Background calves	34.30%
	Cow/Calf, Sell calves at weaning	19.10%
	Stocker/Background, Retain calves through feedlot	3.40%
	Stocker/Backgrounder	33.10%
	Custom feeder	1.70%
	Purebred seedstock	1.70%
	Freezer beef	1.70%
	Other	1.70%
Capacity	1-100	26.60%
	101-500	39.20%
	501-2500	28.10%
	>2500	6.10%

Table 3. 2 Importance of Purchase Characteristics in Stocker Purchase Decisions.

Description	**Value**	**%**
Specific Breed	1=Very Important	31.13
	2=Important	37.74
	3=Indifference	8.02
	4=Slightly Important	8.02
	5=Not Important	15.09
General animal type	1=Very Important	46.95
	2=Important	43.19
	3=Indifference	2.82
	4=Slightly Important	3.76
	5=Not Important	3.29
Animal size/ weight	1=Very Important	39.72
	2=Important	43.93
	3=Indifference	7.01
	4=Slightly Important	4.67
	5=Not Important	4.67
Certified preconditioned cattle	1=Very Important	10.14
	2=Important	17.39
	3=Indifference	21.74
	4=Slightly Important	14.98
	5=Not Important	35.75
Purchasing animals from a specific geographic origin	1=Very Important	20.39
	2=Important	25.73
	3=Indifference	15.53
	4=Slightly Important	12.14
	5=Not Important	26.21
Avoiding animals from a specific geographic origin	1=Very Important	24.27
	2=Important	22.33
	3=Indifference	14.56
	4=Slightly Important	13.11
	5=Not Important	25.73
Distance shipped	1=Very Important	23.41
	2=Important	40
	3=Indifference	16.59
	4=Slightly Important	7.32
	5=Not Important	12.68
Avoiding trader cattle	1=Very Important	73.43
	2=Important	12.08
	3=Indifference	6.28
	4=Slightly Important	3.38
	5=Not Important	4.83

Source/method of purchase	1=Very Important	25.25
	2=Important	36.36
	3=Indifference	22.72
	4=Slightly Important	7.58
	5=Not Important	8.08

Table 3. 3 Mean and Standard Deviation of Importance Ratings of Stockers Purchase Preferences.

Cattle Purchase Characteristic (1=Very important. 5=not at all important)	**Mean**	**Standard deviation**
Specific breed	2.415	0.465
General animal type	1.741	0.297
Animal size/weight	1.918	0.376
Certified preconditioned cattle	3.488	0.448
Purchasing animals from a specific geographic origin	2.970	0.501
Avoiding animals from a specific geographic origin	2.900	0.501
Distance shipped	2.460	0.480
Avoiding "trader" cattle	1.535	0.346
Source of purchase	2.394	0.485

Table 3. 4 Chi-square tests of independence between stocker producer demographic information and nine cattle purchase characteristics.

	Region		Educational level		Multiple county	
Cattle Purchase Characteristic	χ^2	p-value	χ^2	p-value	χ^2	p-value
Specific breed	1.32	0.72	10.74	0.03	0.00	0.99
General animal type	5.72	0.13	5.16	0.27	0.65	0.42
Animal size/weight	0.42	0.94	8.33	0.08	0.20	0.65
Certified preconditioned cattle	11.11	0.01	1.43	0.84	0.95	0.33
Purchasing animals from a specific geographic origin	3.36	0.34	2.96	0.57	2.02	0.15
Avoiding animals from a specific geographic origin	0.36	0.95	1.30	0.86	1.27	0.26
Distance shipped	1.01	0.80	1.21	0.88	0.3	0.58
Avoiding "trader" cattle	1.32	0.73	6.22	0.18	2.21	0.14
Source of purchase	0.49	0.92	0.54	0.97	0.12	0.72

	Age		Operation		Annual capacity	
Cattle Purchase Characteristic	χ^2	p-value	χ^2	p-value	χ^2	p-value
Specific breed	2.01	0.85	8.26	0.41	0.27	0.97
General animal type	0.21	0.99	17.21	0.03	6.8	0.08
Animal size/weight	2.08	0.84	9.28	0.33	5.73	0.13
Certified preconditioned cattle	8.32	0.14	15.12	0.06	1.39	0.71
Purchasing animals from a specific geographic origin	8.55	0.13	13.46	0.097	2.55	0.47
Avoiding animals from a specific geographic origin	4.29	0.51	10.19	0.25	4.94	0.18
Distance shipped	1.17	0.04	17.51	0.03	2.52	0.47
Avoiding "trader" cattle	2.45	0.78	21.98	0.01	9.55	0.02
Source of purchase	0.25	0.39	8.64	0.37	1.6	0.66

Table 3. 5 Comparison of latent class model enumeration fit indices between five-point scale and two-point scale.

k	LL	AIC	BIC	CAIC	SBIC	Entropy
Five-point						
1-Class	-2468.25	2847.11	2967.09	3003.09	2853.02	1
2-Class	-2341.64	2667.89	**2911.18**	**2984.18**	2679.88	0.9
3-Class	-2257.13	2572.88	2939.48	3049.48	2590.95	0.87
4-Class	-2199.14	**2530.89**	3020.8	3167.8	**2555.04**	0.88
5-Class	-2186.39	2579.4	3192.68	3376.63	2609.63	0.89
Two-point						
1-Class	-1025.98	461.43	491.42	500.42	462.90	1
2-Class	-940.58	310.62	**373.94**	**392.94**	313.74	0.78
3-Class	-918.63	286.73	383.38	412.38	291.50	0.81
4-Class	-905.83	**281.13**	411.11	450.11	**287.54**	0.77
5-Class	-895.54	281.55	443.85	492.85	288.60	0.79

Note. K = number of classes; LL = log-likelihood; BIC = Bayesian Information Criterion; SABIC = Sample-size adjusted BIC; CAIC = Consistent Akaike Information Criterion. Values are bolded points to the “best” fit for each respective statistic. Entropy is an omnibus index where values > .80 indicate “good” classification of individual cases into classes (Clark & Muthén, 2009)

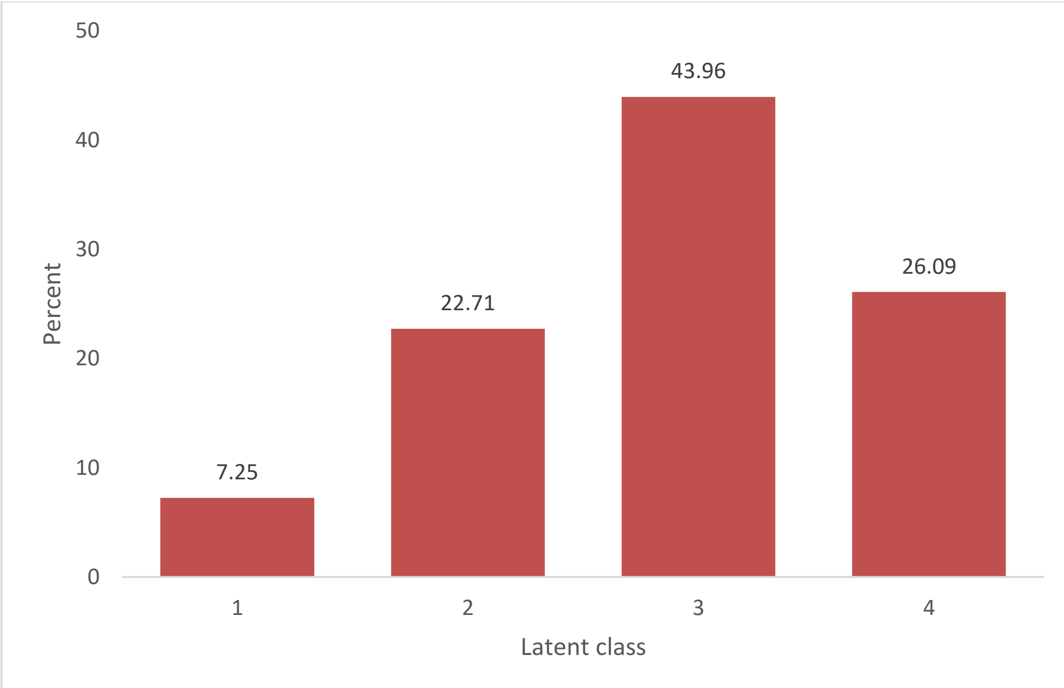
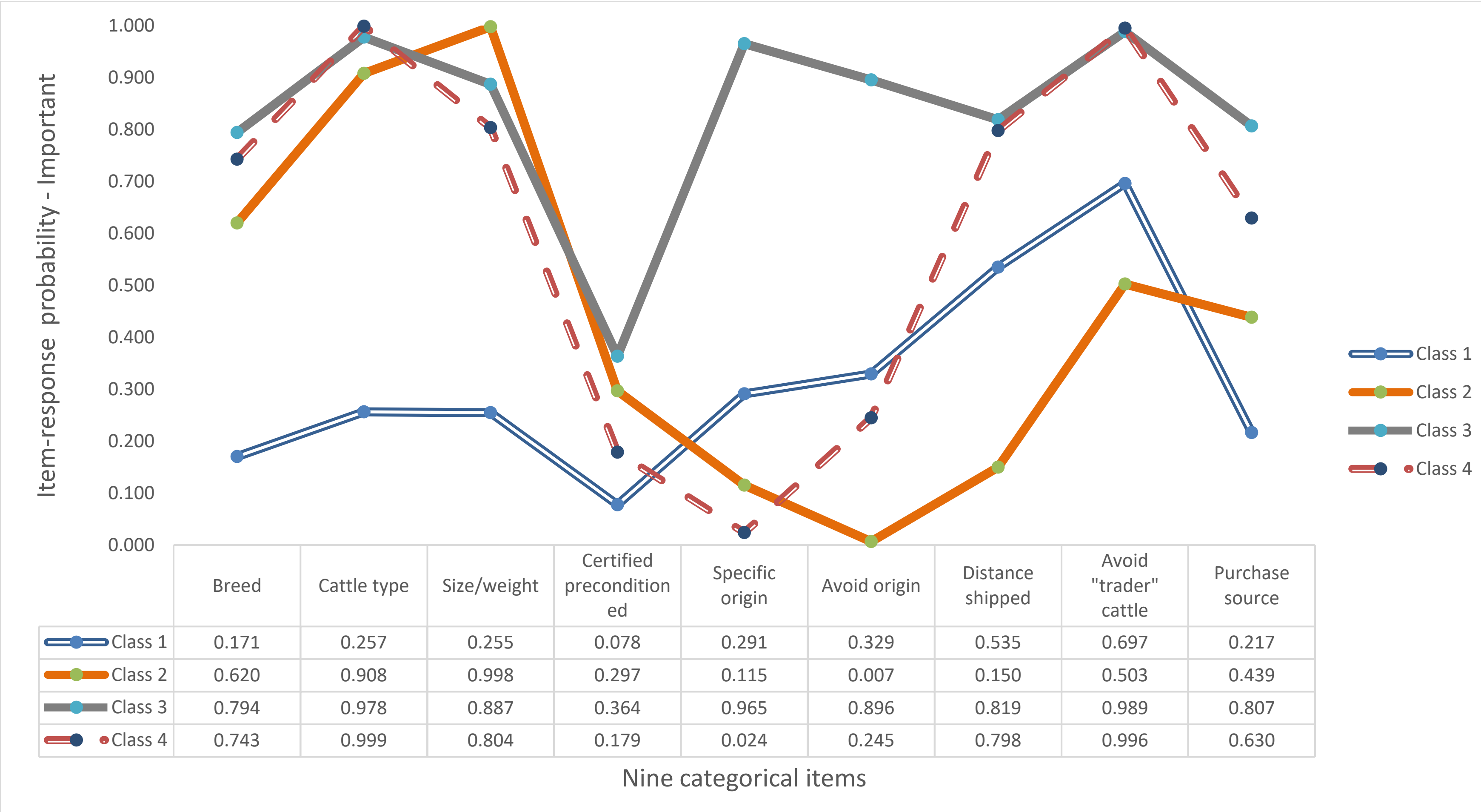


Figure 3. 1 Latent Class Membership Probabilities for Stockers based on Purchasing Preferences

Table 3. 6 Item-response Probabilities for Stocker Purchasing Preferences.

Purchase characteristics	**Item-response probability**			
	Class 1	Class 2	Class 3	Class 4
Specific breed				
Important	0.171	0.620	0.794	0.743
Unimportant	0.829	0.380	0.206	0.257
General animal type				
Important	0.257	0.908	0.978	0.999
Unimportant	0.743	0.092	0.022	0.001
Animal size/weight				
Important	0.255	0.998	0.887	0.804
Unimportant	0.745	0.002	0.113	0.196
Certified preconditioned cattle				
Important	0.078	0.297	0.364	0.179
Unimportant	0.922	0.703	0.636	0.821
Purchasing animals from a specific geographic origin				
Important	0.291	0.115	0.965	0.024
Unimportant	0.709	0.885	0.035	0.976
Avoiding animals from a specific geographic origin				
Important	0.329	0.007	0.896	0.245
Unimportant	0.671	0.993	0.104	0.755
Distance shipped				
Important	0.535	0.150	0.819	0.798
Unimportant	0.465	0.850	0.181	0.202
Avoiding "trader" cattle				
Important	0.697	0.503	0.989	0.996
Unimportant	0.303	0.497	0.011	0.004
Source of purchase				
Important	0.217	0.439	0.807	0.630
Unimportant	0.783	0.561	0.193	0.370



	Breed	Cattle type	Size/weight	Certified preconditioned	Specific origin	Avoid origin	Distance shipped	Avoid "trader" cattle	Purchase source
Class 1	0.171	0.257	0.255	0.078	0.291	0.329	0.535	0.697	0.217
Class 2	0.620	0.908	0.998	0.297	0.115	0.007	0.150	0.503	0.439
Class 3	0.794	0.978	0.887	0.364	0.965	0.896	0.819	0.989	0.807
Class 4	0.743	0.999	0.804	0.179	0.024	0.245	0.798	0.996	0.630

Figure 3. 2 Item-response Probabilities for “Important” across Stocker Purchase Characteristics and Latent Classes

Table 3. 7 Estimated Probabilities of Class Membership for Individual Stocker Producers.

ID	Breed	Cattle type	Size/ Weight	Certified pre-conditioned	Specific origin	Avoid origin	Distance shipped	Avoid "trader" cattle	Purchas source	Prob C1	Prob C2	Prob C3	Prob C4	Best
1	2	2	2	2	2	2	2	1	2	0.999	0	0	0	1
2	2	1	1	2	1	1	2	1	.	0.018	0.002	0.973	0.007	3
3	1	1	1	1	2	2	2	1	1	0	0.687	0.007	0.305	2
4	1	1	1	2	2	1	1	1	1	0.001	0.001	0.203	0.795	4
5	2	2	1	2	2	2	2	2	1	0.186	0.814	0	0	2
6	2	1	1	1	1	1	1	1	1	0	0	0.998	0.002	3
7	1	1	1	1	1	1	1	1	1	0	0	0.999	0.001	3
8	1	1	1	2	1	1	1	1	1	0	0	0.996	0.003	3
9	1	1	1	2	1	2	1	1	1	0.001	0.022	0.894	0.082	3
10	2	1	1	2	1	2	2	1	2	0.121	0.754	0.092	0.032	2

Table 3. 8 Class Membership Probabilities for each of the Four Regions.

Region	Class 1	Class 2	Class 3	Class 4
NW	0.063	0.336	0.431	0.170
NE	0.026	0.426	0.418	0.130
SW	0.164	0.185	0.238	0.413
SE	0.049	0.332	0.411	0.208

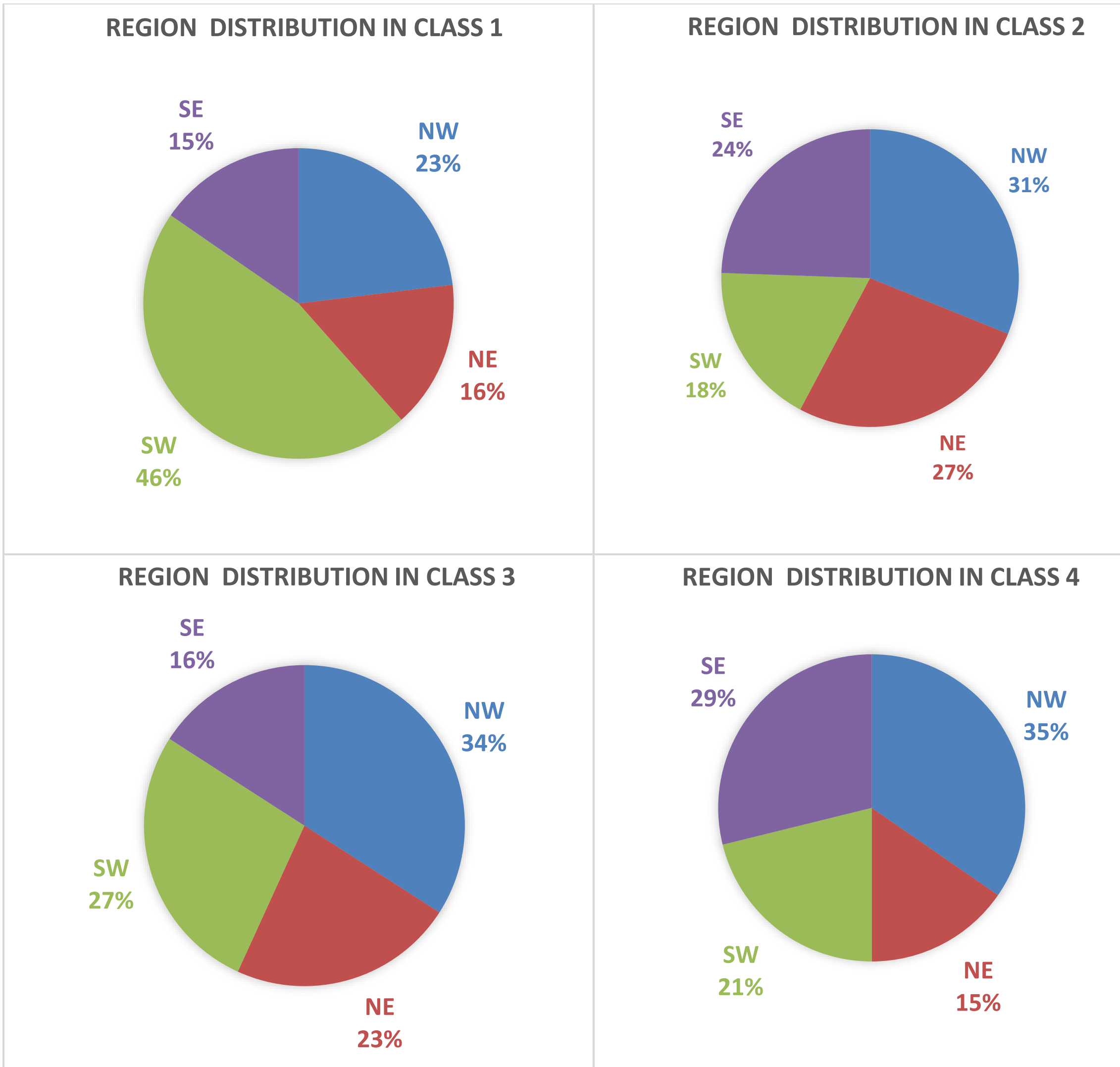


Figure 3. 3 Region Distributions in Each Class.

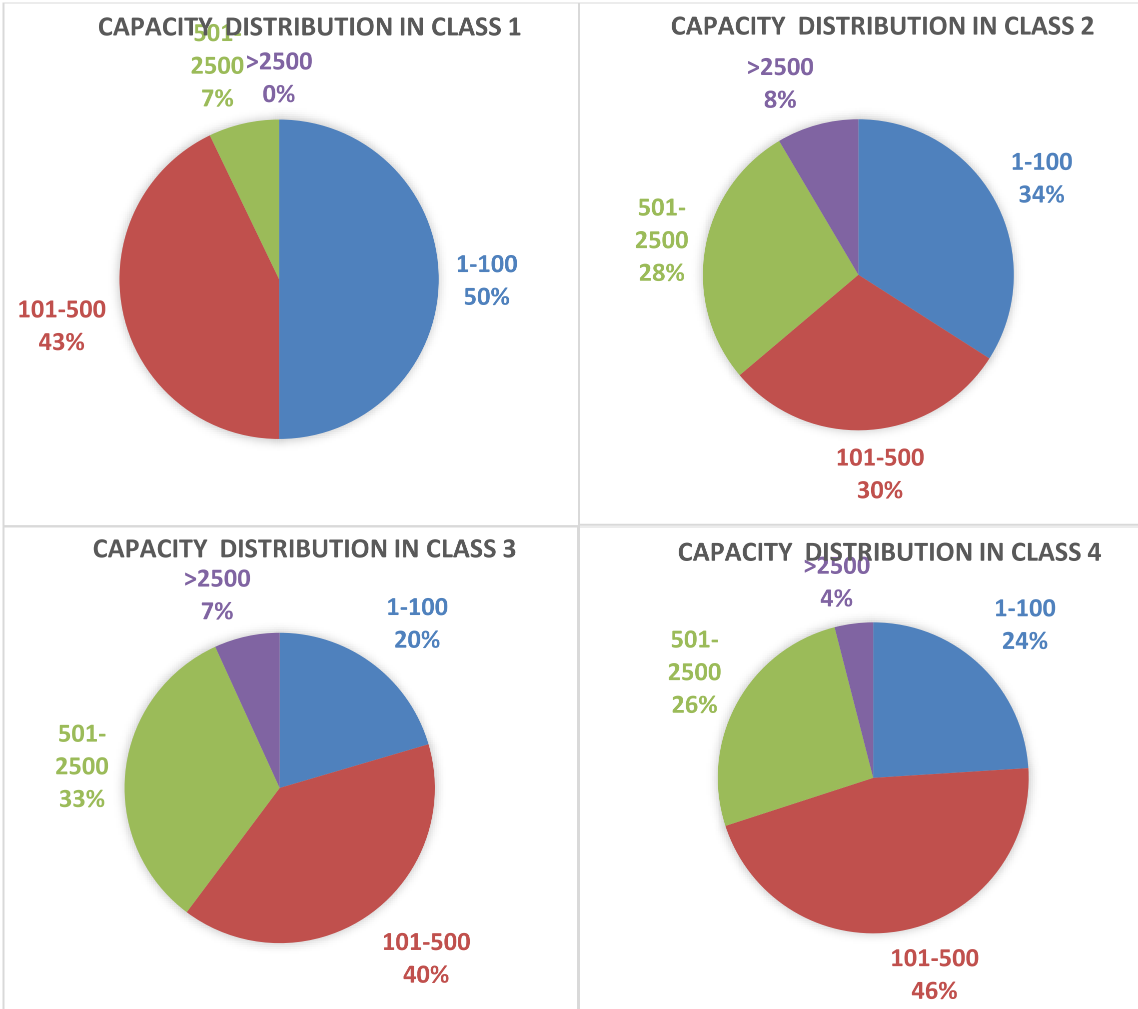


Figure 3. 4 Capacity Distributions in Each Class.

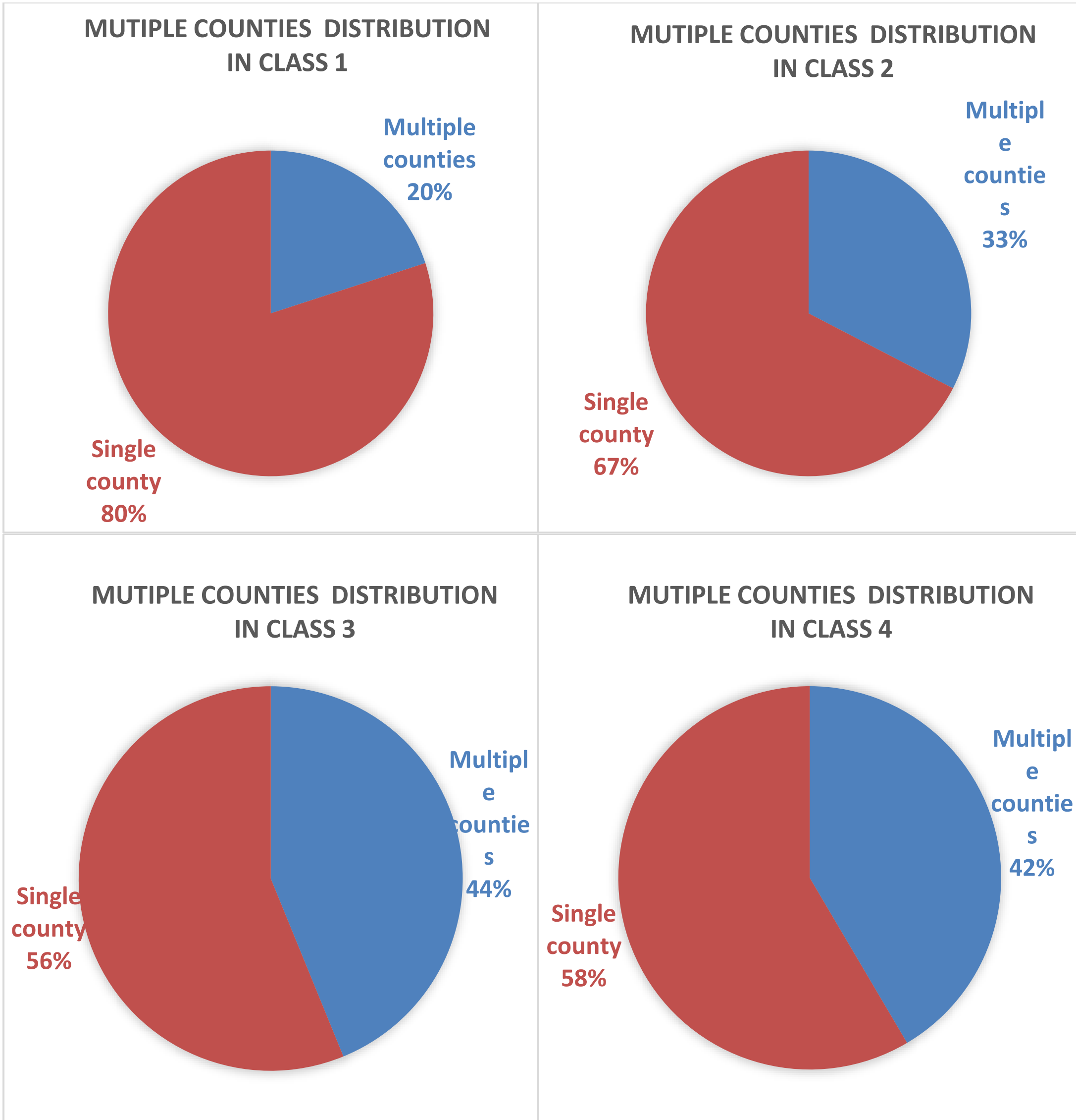


Figure 3. 5 Multiple County Distributions in Each Class.

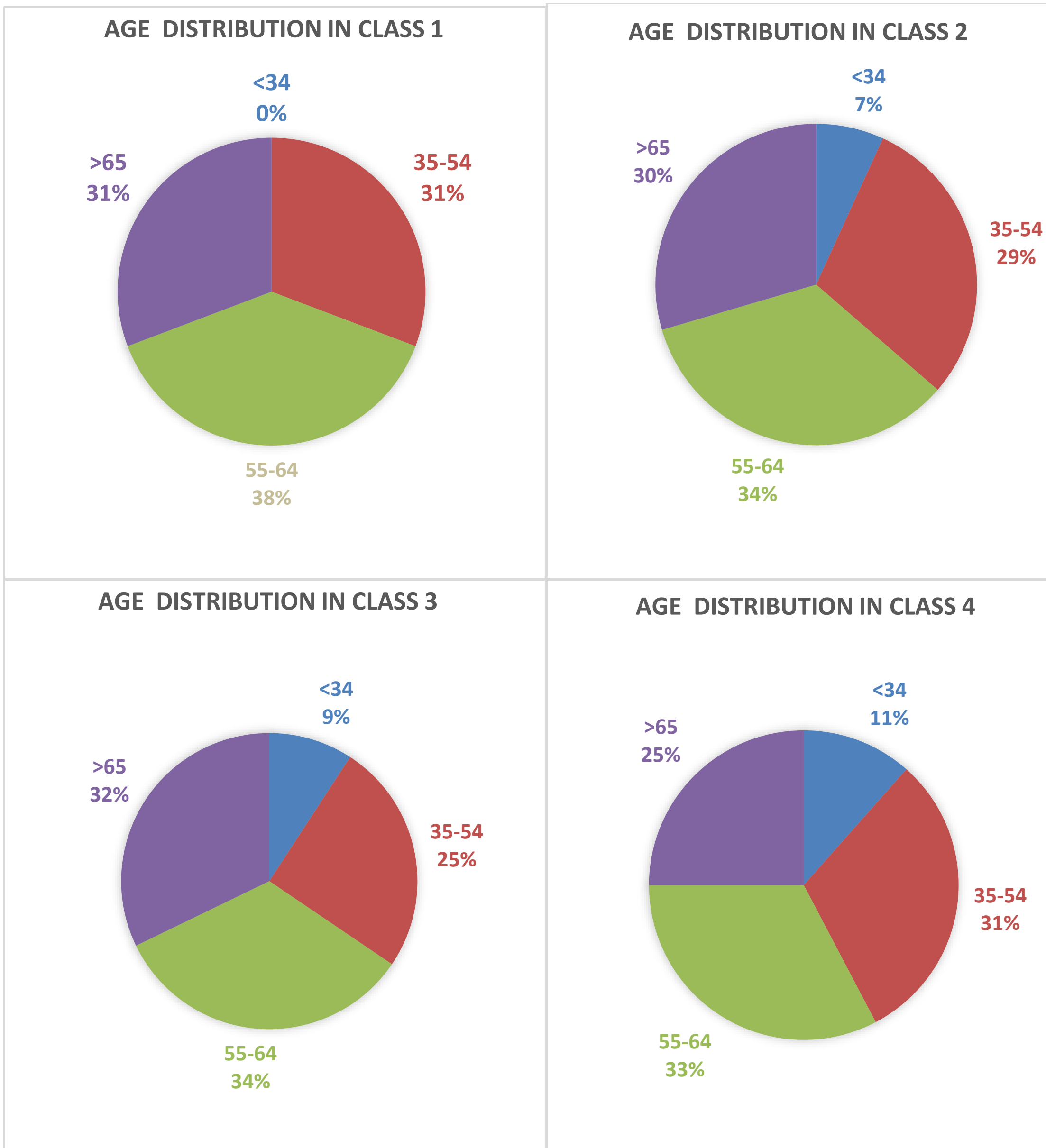


Figure 3. 6 Age Distributions in Each Class.

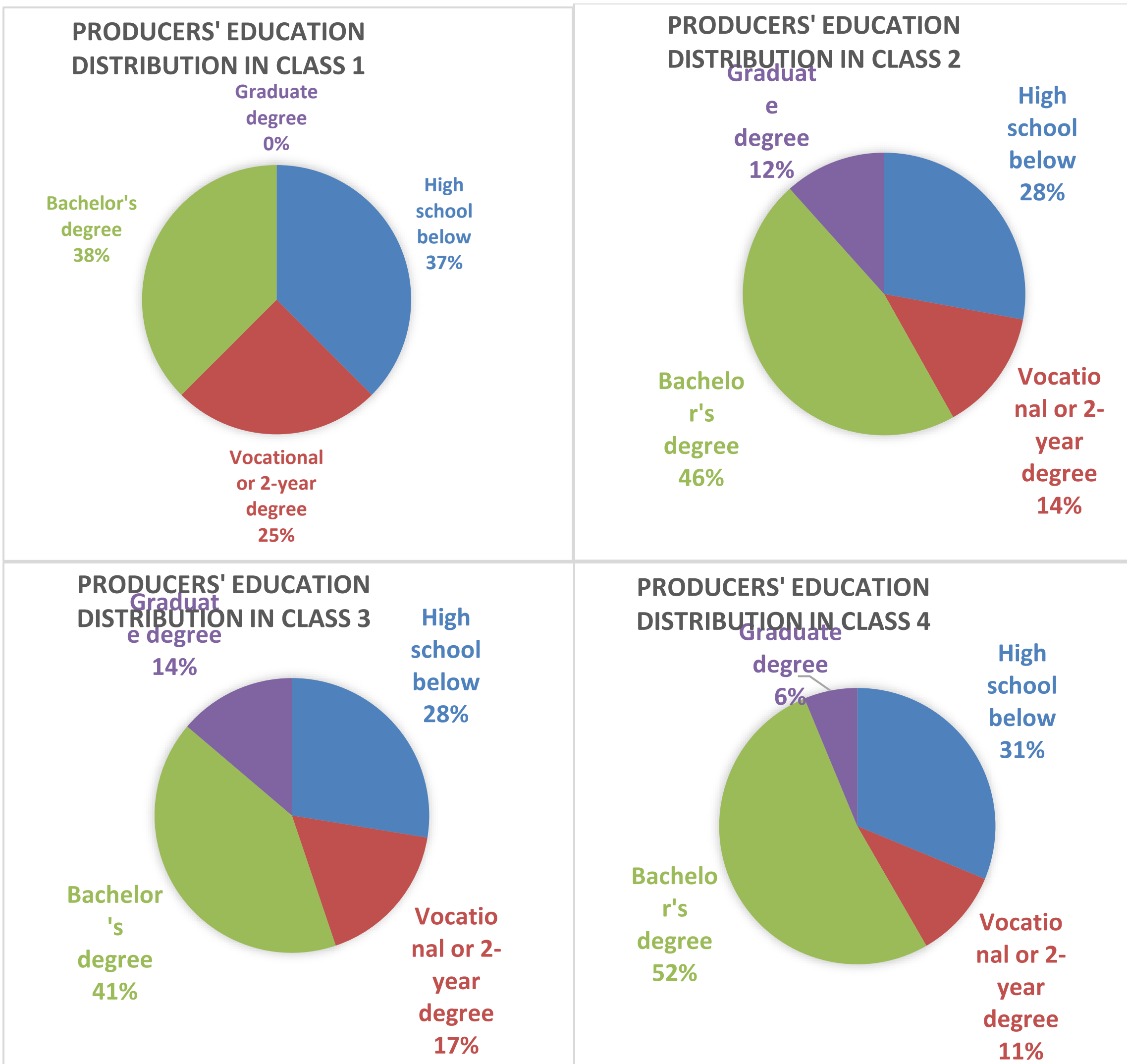


Figure 3. 7 Education Distributions in Each Class.

CHAPTER IV

FOOD INSECURITY DURING THE COVID-19 PANDEMIC

Introduction

In an effort to contain the COVID-19 virus, the Wuhan city of China announced a quarantine beginning at 10:00 AM on January 23rd, 2020. People were to remain indoors, and at 2 PM on the same day the highways were blocked. The epicenter of the pandemic transferred from China to Europe and then to the United States. On January 21st, United States confirmed the first case of COVID-19 infection, which rapidly spread across the country, and with other countries experiencing similar infections the COVID-19 pandemic was deemed a global health emergency by WHO on January 30.

Schools went online, businesses that are not essential closed, and masks and social distancing quickly become a social norm. However, the virus continued to spread. The United States became the leader of the world in confirmed COVID-19 cases (Taylor 2020), and the United States government declared a national emergency on March 13 after the first person died because of the virus. Part of this response entailed establishing a system of data collection to gauge the severity of the pandemic and its impact not only to the health of people, but their employment and food security status.

There were indeed impacts on people's ability to acquire food. In addition to job and income loses food retailers experienced a shortage of certain foods. The unemployment rate jumped to 14.7% in April 2020 from 4.4% in the previous months (USBLS 2020); forty million United

States residents lost their jobs in the first two months of the Covid-19 pandemic in 2020 (Raifman et al. 2020). Though existing and new government programs were available for assistance, response was slow both due to the nature of the programs and government agencies' inability to accommodate such large number of people seeking assistance. Fortunately, the US has an extensive food pantry system that was prepared to help. Feeding America is a nonprofit organization that coordinates the 200 food banks and their 60,000 food pantries, and they reported on April 19, 2020 that requests for food assistance were expected to rise by almost 50%, and that they has spent more money on food in the previous six months combined (CBS 2020).

Food insecurity rate has positive relationship with the unemployment rate, according to Schanzenbach and Pitts (2020), a 0.7-0.79 percentage point increase in food insecurity was predicted with one percentage point increase in the unemployment rate. According to Kent et al. 2020 "A household is classified to be food secure if people have physical, social, and economic access to sufficient, safe, and nutritious food that meets their food demand and preferences for a healthy life". Four dimensions are necessary to measure if a household is food security: availability, accessibility, utilization, and stability of food (Jones et al. 2013). Meanwhile, food insecurity is defined as a healthy and active life cannot be achieved because of limited or uncertain access to sufficient, nutritious food (Owens et al. 2020). Laborde et al. estimated that without interventions, over 140 million people could fall into extreme poverty (measured against the $1.90 poverty line) in 2020 globally— an increase of 20% from pre-COVID levels. However, there were interventions in most countries. The question is whether the interventions were sufficiently rapid and properly funded to prevent a rise in food insecurity. To determine whether this was the case, a number of different organizations administered surveys to track food insecurity.

In the US, the United States Department of Agriculture (USDA) regularly measures food insecurity. Every December a Food Security Supplement is included in the Current Population

Survey. This survey is referred to in this study as the CPS-FSS survey, and it is a highly representative survey due to the scientific—and expensive—sampling procedure. It employs a probability sample with a two-stage sample technique and the food security questionnaire underwent extensive scrutiny in ensuring it truly matters food insecurity. This makes it difficult to administer rapidly in response to unexpected events like pandemics. As it would not be administered until December of 2020, it was of little use for monitoring the pandemic's impact in the spring and summer of 2020.

As such, organizations have attempted to measure food insecurity by implementing expedited internet surveys, such as the COVID Impact Survey that conducted by National Opinion Research Center (NORC) at the University of Chicago, referred to in this study as the NORC survey. Beside implementing the surveys by internet, these surveyors do phone calls and face to face interviews for people that have difficulty accessing the internet. While certainly informative, the expedited nature of the NORC survey presents some difficulties as it did not measure food insecurity using the same method as the CPS-FSS survey, making it difficult for the NORC survey to truly determine how much the food insecurity rate rose compared to past years in the CPS-FSS survey. The main purpose of this paper is to analyze the results of the NORC survey and provide some adjustments to its food insecurity rate so that it can be compared to rates in past years measured by the CPS-FSS survey. We thus provide a measure the state of food insecurity in the United States during the first few months of the COVID-19 outbreak. The rate measured during COVID-19 is then compared to rates during relatively normal years prior to the pandemic and during the Great Recession.

Macroeconomic Events and Food Insecurity

Adverse macroeconomic events such as the COVID-19 pandemic and the Great Recession have led to great impact for the world, including the whole economic environment, and the household's financial situation, physical and mental health. These impacts on different aspects are not independent but related to each other. Measuring the impact for the whole society and each household from the adverse macroeconomic events is one important job of economic researchers. Food security is one of the important indexes that is worth to measure, because the food security rate reflects the situation of the households getting access the foods they want. And the ability of obtaining foods one family needs reflets the condition of the employment and income of each household.

The Great Recession

The Great Recession began in 2007 and ended in June 2009, which was seemed to be the worst major recession after the Great Depression in the United States (Birkenmaier et al. 2016). It resulted in large increases in unemployment and economic output (Seyfried 2011; Schmitt and Baker 2008). It also led to a rise in food insecurity (Ziliak 2020; Birkenmaier et al. 2016; Coleman-Jensen and Gregory 2014; Pilkauskas 2012; Andrews and Nord 2009). Researchers have investigated the impact of the Great Recession on food insecurity rates for different regions, like Mexico, Detroit metropolitan area. They reported that low-income households' food insecurity remains prevalent in Detroit metropolitan area and a worse food insecurity happened to the the households in Mexico who were more vulnerable before the Great Recession. Other reports that seniors or children are the most vunerable groups, and the health of children were harmed during the economic crisis (Vilar-Compte et al. 2015; Wolf and Morrissey 2017; Rajmil et al. 2014; Oberg 2011). Flores-Lagunes et al. (2018) analyzed the severity of food insecurity by racial, ethnic, and immigrant groups during the Great Recession in the United States and reported that blacks and Hispanics have higher food insecurity rates than whites, and nonimmigrants have lower food insecurity rate than immigrants.

In terms of the US as a whole, though, the CPS-FSS survey provides the best indication of the Great Recession's impact. The number of households with food insecurity as measured by the CPS-FSS survey increased to almost 15% during the Great Recession, up from the normal 12%

and the highest observed rate since the survey began in 1995 (Nord et al. 2010). This three-percentage point increase may seem small, but the survey represents over a hundred million surveys; what this increase tells us is that even in unprecedented difficult economic years food insecurity may only rise a few percentage points. This gives us a benchmark by which to compare the impact of COVID-19 on food insecurity, for if the pandemic caused food insecurity to rise three percentage points, we can say it has similar impacts to a large recession.

COVID-19

COVID-19 is a crisis that might be compared with the Great Recession in myriad ways. Both were unexpected, impacted the economy rapidly, and left households and government scrambling to respond. Considerable research has studied the pandemic's impact on food insecurity in different regions of the world, including Erokhin and Gao (2020), Power et al. (2020), Manfrinato et al. (2020), and Gaitan-Rossi et al. (2021). According to Loopstra, April 2020 incomes decreased in Britain due to job loss, having an immediate impact on food insecurity. The number of adult Britains experiencing food insecurity is estimated to have quadrupled under the COVID-19 lockdown. Zidouemba et al. (2020) suggested that the pandemic of COVID-19 contributed to a worsening of food security for households at the poor rural and urban areas, due to the rise of food prices and the fall in household incomes and remittances. Households in South Africa with low levels of education and high dependence on labor income would face to income shock and less food security (Arndt et al. 2020). School closures exacerbate food insecurity, because the students living in the poor households rely on the school lunch to obtain enough and healthy food (Lancker and Parolin 2020; McLoughlin et al. 2020). Considerable research has documented the pandemic's impact on food insecurity in the US (Ahn and Norwood 2020; Niles et al. 2020; Leddy et al. 2020; Fitzpatrick et al. 2021; Wolfson and Leung 2020; Gundersen et al. 2021; Schanzenbach and Pitts (2020). Typical findings indicate that the COVID-19 pandemic resulted in high levels of unemployment, higher food prices, and loss of business sales. Household economic disorder, household stress, and interruptions in healthcare will contribute to acute chronic disease complications. Households with children are more vulnerable to food insecurity among the whole society. COVID-19 pandemic is increasing the existing disparities and negatively affecting low-income, food-insecure households that already hard to meet their basic food needs.

The COVID Impact Survey conducted by NORC at the University of Chicago, and referred to here as the NORC survey, is a particularly powerful survey for studying the immediate impact of the pandemic on food insecurity. The NORC survey is not as representative as the CPS-FSS survey because it relies more on respondents volunteering to take the survey, either on the internet or by phone, and is thus referred to as an 'opt-in' survey. Contrast this with the CPS-FSS where enumerators will personally go to the residences of subjects to administer the interview and where completing the survey is required by law. However, it utilized a high sample size and a number of survey and statistical procedures that increases its ability to represent the US as a whole. Given that the survey had to be designed and administered with just a few months of planning (at the most) it is as accurate of a survey one can expect.

Two aspects of the NORC survey makes it difficult for comparing to previous food insecurity rates measured by the CPS-FSS: (1) the NORC survey does not ask all the standard food insecurity questions used by the CPS-FSS survey and (2) the CPS-FSS does not actually ask the food insecurity questions of every household, but instead assumes certain households are food secure, whereas the NORC survey does ask the questions of everyone. Though the two surveys may be difficult to compare, adjustments can be made to make them more comparable, as explained in subsequent sections.

Data

Two data sets were used to assess and compare the rates of food insecurity in United States. The data for the pre- COVID period come from the 2001 to 2007 and 2012 to 2016 Current Population Survey Food Security Supplement survey that is referred to as CPS-FSS survey, which is the US government's official source of official estimates of food insecurity (Coleman-Jensen et al. 2019). The data for the Great Recession was from the 2008 to 2011, because the food insecurity rates during these four years were found keeping lower than other period (Coleman-Jensen et al. 2019)also using the CPS-FSS survey. The data used for the COVID-19 period was obtained from the Covid Impact Survey, administered by NORC in in the spring of 2020.

The CPS-FSS Survey

CPS-FSS survey provides food insecurity statistics from the national and state-level. This survey is administered in December as an addendum to the monthly Current Population Survey that is conducted by the US Census Bureau. The Food Security Supplement is funded by the United States Department of Agriculture, even though it is administrated by the US Census Bureau. The Current Population Survey (CPS) is the source of the official government statistics on employment and unemployment, using an expensive and highly representative sampling procedure. The CPS-FSS survey asks a series of questions about food expenditures, food security, and nutrition assistance programs. The CPS-FSS survey was first administered in 1995 and has been conducted every year since. The survey entails 10 questions for the households that have no children, and eight extra questions for the households with children, which is shown in figure 4.1. Each question is designed to assess the ability of a household to access food and/or their anxieties over food access in the future. For example, the response was asked to make a choice between four answers, which are 'Often true', 'Sometimes true', 'Never true' and 'Don't know or refuse to answer' for the statement, "I was worried whether my food would run out before I got money to buy more." Another question asks whether the food they bought didn't last and have no money to get more. Based on the responses, each household is grouped into of four categories: high food security, marginal food security, low food security, or very low food security.

The CPS-FSS survey is considered the gold standard for measuring food insecurity, for two reasons. The first reason is the sampling technique used by Current Population Survey ensures it is as close to a truly representative sample as possible. It employs a probability sample with a two-stage sample technique. The first stage is to sample primary sampling areas, like a region of the US, and the second stage is to sample housing units among the primary sampling areas. For example, it randomly selects home addresses from a comprehensive list of all US home addresses, with updates from the United States Postal Service twice a year. As virtually everyone living in the US has a home address, they have an equal probability of being selected for the survey. The second reason is that the food security questionnaire underwent extensive scrutiny in ensuring it truly matters food insecurity.

In order to understand how the USDA interprets responses from participants, two particular details should be recognized. The first regards their screening procedure. In order to reduce respondent burden, the households who meet two criteria would not need to answer the questions and be classified as food secure. One criterion is if their income is above 185% of the poverty threshold for their state of residence, and the other criterion is they answer 'enough of the kinds of food I want to eat' to the preliminary question in the previous figure, which states, "Which of these statements best describes the food eaten in your household, with four answers as enough of the kinds of food (I/ we) want to eat, enough but not always the kinds of food (I/ we) want to eat, sometimes not enough to eat, or often not enough to eat?." If both criteria are met the household is assumed to be food secure is thus not administered questionnaire. However, it recognized that some households who are screened and assumed food secure would actually be food insecure if they were administered the 10 or 18 questions (ERS 2012a).

The second detail warranting recognition is the standard used to classify households among the four food security levels. According to the definition of USDA reported in 2019, households who are able to buy the foods they need are classified as food secure, even though they might be slightly worried on if they can obtain foods in the future. Meanwhile, the households that cannot acquire the amount and kinds of foods they desire are food insecure. The correspondence between respondents' answers to the food security questions and their food security status is given in figure 4.1.

The NORC Survey

The Covid Impact Survey conducted by the National Opinion Research Center (NORC) was established in response to the COVID-19 pandemic and the need to provide timely information on the virus' impact. Since its founding in 1941 as a nonpartisan information source, NORC has partnered with myriad organizations to deliver information useful for decision makers to improve the lives of people. NORC has three offices, University of Chicago campus, Chicago's downtown, and Bethesda, MD. The Covid impact survey is conducted at the University of Chicago and was funded by the Data Foundation with support from the David & Lucile Packard Foundation, the Federal Reserve Bank of Minneapolis, and the Alfred P. Sloan Foundation. The Covid Impact Survey, hereafter referred to as the NORC survey, was designed to provide national and reginal data and analysis for physical and mental health, economic security, and social dynamics in United States.

The NORC survey was administered three different times to capture conditions for three different weeks: April 20-26, May 4-10, and May 30- June 8. Each time the data collection process was design to provide a representative snapshot of (1) the household population nationwide (2) for 18 regional areas including 10 states (CA, CO, FL, LA, MN, MO, MT, NY, OR, TX) and (3) eight Metropolitan Statistical Areas (Atlanta, Baltimore, Birmingham, Chicago, Cleveland, Columbus, Phoenix, Pittsburgh) (Islam et al. 2020). From COVID Impact Survey report, AmeriSpeak

Panel® was used to collected data for national estimates which is a based panel that is designed to representthe whole U.S. household population. The survey can be completed through online or telephone interview for households not available to be online. Address-based (or ABS) approach was used to collect the reginal data by web or telephone interview. All sampled households are invited to complete the survey with a unique PIN or toll-free calling by mailing a postcard.Approximately 400 interviews in each region were conducted with adults aged 18 and over n each week.

The NORC survey was designed to track the impacts of the pandemic on a variety of well-being measures, such as whether they were laid off, if they communicate less with family, if they experienced negative emotions, whether they wore a mask, and—pertinent to this study—food insecurity. Most of these questions were asked in two parts: first, their life before the pandemic, and second, their life after the pandemic. For example, regarding communicating with family, they were first asked how often they communicated with family in the past month, and then how often they communicate now, which was during the pandemic.

Recall that the CPS-FSS survey asks 10 – 18 questions regarding food insecurity, depending on whether the household contains children. Because the NORC survey addresses numerous issues in addition to food insecurity it could not ask the full CPS-FSS questionnaire shown previously in figure 4.1. Instead, they opted to ask only two of the questions asked in the CPS-FSS survey. The two questions posed are the first two questions shown in figure 4.1. NORC generally deemed a household as food insecure if they answered ‘often’ or ‘sometimes true’ to either question. These two questions were only asked in regard to the last thirty days and was not also asked in reference to before the pandemic.

Methods

As mentioned before, The NORC survey was conducted for three weeks.. Two questions related to food insecurity ask respondents which were also asked in the CPS-FSS survey. Figure 4.1 shows these two questions also asked in the CPS-FSS survey. Answers to these two questions regarding food insecurity were compared to the answers to the same two questions in the CPS-FSS survey. However, this comparison is not ideal because while the NORC survey asked it of all respondents, whereas the CPS-FSS asked it of only a subset.

The CPS-FSS survey used the screening procedure discussed previously. Before the respondents answer the 10 or 18 questions, their household income was elicited, and they were asked the preliminary question shown in figure 4.1. They were then ‘screened’ according to the following rule: if (1) the respondent’s income was above 185% of the poverty threshold and (2) they answered they have enough to the food that they want, the household was not asked the food security questions and was deemed to be food secure. If the respondent did not pass one or both (the actual screening process varies across years) of the screening criteria, they were administered the 10 – 18 food security questions. The USDA recognizes that some of these individuals who are assumed to be food secure and are not administered the questionnaire will in fact be food insecure had they answered the questions (ERS 2015). As such, it is likely that the sample in the NORC survey will contain a higher proportion of food insecure individuals than those in the CPS-FSS survey.

In order to facilitate a fairer comparison between the CPS-FSS and the NORC survey responses, the screening procedure used in the CPS-FSS is mimicked when analyzing responses to the NORC survey. This mimicking is achieved by assuming any household in the NORC survey with a household income higher than 185% of poverty threshold is food secure regardless of their actual answers to the two questions. While this would seem to be a more stringent screening process, potentially resulting in lower food insecurity rates than those measured by the CPS-FSS, other research has shown it can actually provide food insecurity estimates strikingly similar to the CPS-FSS survey (Ahn, Smith and Norwood 2020; Ahn and Norwood 2021).

Statistical weights were provided as part of NORC dataset and used for the calculation of all statistics. These weights help ensure the sample results reflect the demographics of the US, and not just the demographics of the sample. The NORC dataset contains six weights variables, in which that the NATIONAL_WEIGHT or NATIONAL_WEIGHT_POP was applied when generating national estimates, when generating region estimate, the REGION_WEIGHT or REGION_WEIGHT_POP is applied. NATIONAL_WEIGHT and REGION_WEIGHT are normalized weights that total to the sample size and were used in this paper.

Results

Recall the NORC survey measures food insecurity in three separate weeks. The results for each week are shown in tables 4.1-4.3, shown by the percent of the sample who select often, sometimes, or never true for each question. These percentages do not employ the method where the screening process of the CPS-FSS survey is mimicked. Confidence intervals for these percentages are obtained by conducting 1000 nonparametric bootstraps, where at each simulation a new sample is acquired from the original sample by random sampling the observations with replacement. The standard deviation of the responses is then calculated, and the percent of times respondents select a response is reported by the original sample percentage plus/minus two standard deviations.

As households with children are often found to be more vulnerable to food insecurity (Gundersen et al. 2021), in addition to the responses for the entire sample, the responses for households with children is also reported. A household is said to be food insecure if the household answers ‘often true’ or ‘sometimes true’ to either question, and this food insecurity rate is reported. Then, the

CPS-FSS screening process is mimicked to provide an estimate of food insecurity that is more comparable to the CPS-FSS.

From the table 4.1, we can see that about 28% and 23% of the respondents selected 'often true' or 'sometimes true' for the first and the second question, respectively. This results in a food insecurity rate of 29.6% for all households. When the CPS-FSS screening process is mimicked, many of the food insecure households are reclassified as food secure, producing a lower food insecurity rate of 16.37%. This rate is not only smaller but closer to the range of rates published by both the CPS-FSS survey, which never exceeds 16%, and the Ahn and Norwood (2020) survey conducted at roughly the same time as the NORC survey. Similar to other studies, table 4.1 shows that food insecurity rates are much higher among households with children compared to those without children. Households with children have a 25.44% of food insecurity rate compared to just 9.51% for those without children. This result is consistent with other studies reporting that with less job opening, people with children have a more difficult time working. Meanwhile, because of the close of school, children have hardship on accessing the lunch at school, which make the situation of households with children worse (McLoughlin et al. 2020; Lancker and Parolin 2020). Policy makers need to consider the extra difficult from households with children. Compare the rates of food insecurities that were mimicked with the CPS-FSS screening process among the three weeks. The rates for May 4 - 10 and May 30 - June 8th are 13.46% and 15.93%, which is slightly less than the April 20-26 rate of 16.37%. Several kinds of the nutrition programs from the federal and states could explain the sharp decrease from 16.37% at the end of April to 13.46% at the beginning of May, such as the National School Lunch Program, the Child and Adult Care Food Program, the special Supplemental Nutrition Program for Women Infants and Children, and the Supplemental Nutrition Assistance Program. The American Academy of Pediatrics recommends pediatricians see the risks related to food insecurity are minimized by providing families with easy to access to those nutrition programs

(Frank et al. 2020). According to Schanzenbach et al. (2019): "participation in these programs can mitigate food insecurity, decrease the risk of hospitalizations, and improve health and academic achievement". Several stimulus programs provided funds to mitigate the hardship during the Covid-19 pandemic, includes Economic Impact Payments (EIP), the Child Tax Credit, and other refundable tax credits. Four Economic Impact Payments were received by eligible people, and the Child Tax Credit payments included in stimulus efforts began in 2021.

2008 Crisis, Pre-COVID and COVID-19

Tables 4.1 – 4.3 suggest that about 15% of US households were food insecure during spring of 2020, when COVID-19 wreaked its havoc. Is this rate higher than what would have been observed if there was no COVID-19? During periods where there is no economic recession food insecurity as measured in the CPS-FSS survey tends to be between 10 – 12% (Coleman-Jensen et al. 2021), so yes, this 15% is higher than what one would expect in normal times. Is a rise of about three percentage points large? This can be addressed by recognizing that the CPS-FSS survey measured insecurity rates as high as 15% during the Great Recession (Coleman-Jensen et al. 2021), caused by the 2008 Financial Crisis. This suggests that COVID-19 had approximately the same impact on food insecurity as the largest recession since the Great Depression. So, yes, COVID-19 did increase food insecurity rates and the increase was large.

Another way of assessing the pandemic's impact on food insecurity is to compare responses to the two questions on the NORC survey to the responses to those same questions when asked in the CPS-FSS survey. As mentioned previously this comparison alone is problematic because, due to its screening procedure, the households answering these two questions in the CPS-FSS have lower incomes than those in the NORC survey. However, no households with an income less than 185% of the poverty threshold would be screened in the CPS-FSS survey, so comparing only households below this threshold in the two surveys should provide a better comparison. If more of these lower-income households report food insecurity during COVID-19 than compared to ‘normal’ times, this would indicate that food insecurity did indeed rise. As such, responses to the two questions are calculated only for those households with incomes below 185% of the poverty threshold.

The dataset from CPS-FSS conducted by USDA from 2008 to 2011 was used to measure the rate of food insecurity in the 2008 financial crisis. The food insecurity rate of pre-Covid period were measured by the dataset of CPS-FSS from 2001 to 2007 and 2012 to 2018, because there was no noticeable crisis related to a big change of the food status in those years. The three weeks data from NORC were combined to measure the rate of food insecurity for COVID-19 period. In order to be able to compare the responses of NORC with the CPS-FSS survey, the responses from the households who have income that are higher than the 185% of the poverty threshold were not included in this analysis.

The results are shown in table 4.4. The percentages of food insecurity in the CPS-FSS are interpreted as fixed numbers with no variance, while the NORC percentages are reported as a point estimate plus/ minus two standard deviations. From table 4.4, the responses from Great Recession and Pre-COVID period that selected ‘often true’ and ‘sometimes true’ for the two questions is higher than that from COVID-19 period. Because the respondents in COVID-19’s food insecurity rate is 52.56%± 2.40%, which is 5.5 percentage points higher than during the Great Recessions, and 9.5 percentage points higher than the pre- COVID period. These results suggest that, at least for households making less than 185% of the poverty threshold, not only did COVID-19 increase food insecurity among US households but had a greater negative impact than the Great Recession.

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Food Security Questionnaire used in the CPS-FSS Survey

Note: responses to each question affirming a food security problem are highlighted to illustrate how the food security scale is calculated, but is not highlighted in the questionnaire. The pronouns used varied from "I" to "We" based on the household size.

Please answer the following questions concerning your ability to acquire adequate food.

Preliminary Question. Which of these statements best describes the food eaten in your household in the last 12 months?
- ○ Enough of the kinds of food I want to eat
- ○ Enough but not always the kinds of food I want to eat
- ○ Sometimes not enough to eat
- ○ Often not enough to eat
- ○ Don't know or refuse to answer

Below are several statements that people have made about their food situation. For these statements, please indicate whether the statement was often true, sometimes true, or never true for you.

1. "I was worried whether my food would run out before I got money to buy more." Was that often, sometimes, or never true for you in the last 12 months?
- ○ Often true
- ○ Sometimes true
- ○ Never true
- ○ Don't know or refuse to answer

2. "The food that I bought just didn't last, and I didn't have money to get more." Was that often, sometimes, or never true for you in the last 12 months?
- ○ Often true
- ○ Sometimes true
- ○ Never true
- ○ Don't know or refuse to answer

3. "I couldn't afford to eat balanced meals." Was that often, sometimes, or never true for you in the last 12 months?
- ○ Often true
- ○ Sometimes true
- ○ Never true
- ○ Don't know or refuse to answer

4. In the last 12 months, did you ever cut the size of your meals or skip meals because there wasn't enough money for food? (Yes/No)

5. If you answered 'yes' to the previous question, how often did this happen?
- ○ Almost every month
- ○ Some months but not every month
- ○ Only 1 or 2 months
- ○ Don't know or refuse to answer

6. In the last 12 months, did you ever eat less than you felt you should because there wasn't enough money for food? (Yes/No)

7. In the last 12 months, were you ever hungry but didn't eat because there wasn't enough money for food? (Yes/No)

8. In the last twelve months, did you lose weight because there wasn't enough money for food? (Yes/No)

9. In the last twelve months, did you ever not eat for a whole day because there wasn't enough money for food? (Yes/No)

10. If you answered 'yes' to the previous question, how often did this happen?
- ○ Almost every month
- ○ Some months but not every month
- ○ Only 1 or 2 months
- ○ Don't know or refuse to answer

(Questions 11-18 were asked only if the household included children age 0-17)

11. "We relied on only a few kinds of low-cost food to feed the children because we were running out of money to buy food." Was that often, sometimes, or never true for your household in the last 12 months?
- ○ Often true
- ○ Sometimes true
- ○ Never true
- ○ Don't know or refuse to answer

12. "We couldn't feed the children a balanced meal, because we couldn't afford that." Was that often, sometimes, or never true for your household in the last 12 months?
- ○ Often true
- ○ Sometimes true
- ○ Never true
- ○ Don't know or refuse to answer

13. "The children in my household were not eating enough because we just couldn't afford enough food." Was that often, sometimes, or never true for your household in the last 12 months?
- ○ Often true
- ○ Sometimes true
- ○ Never true
- ○ Don't know or refuse to answer

14. In the last 12 months, did you ever cut the size of any of the children's meals because there wasn't enough money for food? (Yes/No)

15. In the last 12 months, did any of the children ever skip a meal because there wasn't enough money for food? (Yes/No)

16. If you answered 'yes' to the previous question, how often did this happen?
- ○ Almost every month
- ○ Some months but not every month
- ○ Only 1 or 2 months
- ○ Don't know or refuse to answer

17. In the last 12 months, were the children ever hungry but you just couldn't afford more food? (Yes/No)

18. In the last 12 months, did the children ever not eat for a whole day because there wasn't enough money for food? (Yes/No)

Calculating Food Security Rates

For households with no child, the food security status is high, marginal, low, or very low if the number of affirmative responses to questions 1-10 are 0, 1-2, 3-5, or 6-10, respectively.

For households with one or more children the status is high, marginal, low, or very low if the number of affirmative responses to questions 1-18 are 0, 1-2, 3-7, or 8-18,

The six question short-form questionnaire includes only the questions 2, 3, 4, 5, 6, and 7.

These two questions are asked in the NORC survey also

Figure 4. 1 Description of the CPS-FSS and NORC surveys.

Table 4. 1 Food Insecurity Status in April 20-26, 2020, NORC Survey.

	April 20-26	
	Q1: We worried our food would run out before we got money to buy more	Q2: The food that we bought just didn't have money to get more
Food Insecurity Status[a]	Refers to past thirty days Point estimate ± two standard deviations[b]	
All households(N=2181)		
Often true	6.94% ± 1.10%	6.31% ± 1.04%
Sometimes true	20.87% ± 1.70%	16.52% ± 1.54%
Never true	72.19% ± 1.98%	77.17% ± 1.78%
Percent food insecure without screening	*29.67% ± 1.98%*	
Percent food insecure with screening	*16.37% ± 1.60%*	
Households without children(N=1231)		
Often true	5.81% ± 1.36%	4.79% ± 1.24%
Sometimes true	16.23% ± 2.00%	13.66% ± 1.90%
Never true	77.97% ± 2.40%	81.55% ± 2.20%
Percent food insecure without screening	*24.83% ± 2.40%*	
Percent food insecure with screening	*9.51% ± 1.74%*	
Households with children(N=950)		
Often true	8.44% ± 1.74%	8.31% ± 1.84%
Sometimes true	27.00% ± 2.80%	20.29% ± 2.60%
Never true	64.56% ± 3.00%	71.40% ± 3.00%
Percent food insecure without screening	*36.05% ± 3.20%*	
Percent food insecure with screening	*25.44% ± 2.80%*	

[a] Includes only respondents who answered the questions. Calculations are made using data provided by Wozniak, et. al., 2020 at https://www.covid-impact.org/results, using the observations design to represent the nation at-large, along with the sample balancing weights provided.
[b] Standard deviations calculated using bootstrap. For 2,000 simulations the original data are sampled with replacement.

Table 4. 2 Food Insecurity Status in May 4-10, 2020, NORC Survey.

	May 4-10	
	Q1: We worried our food would run out before we got money to buy more	Q2: The food that we bought just didn't have money to get more
Food Insecurity Status[a]	Refers to past thirty days Point estimate ± two standard deviations[b]	
All households(N=2222)		
Often true	6.23% ± 1.04%	3.74% ± 0.80%
Sometimes true	20.83% ± 1.72%	17.98% ± 1.64%
Never true	72.94% ± 1.86%	78.28% ± 1.74%
Percent food insecure without screening	*25.27% ± 1.88%*	
Percent food insecure with screening	*13.46% ± 1.42%*	
Households without children(N=1333)		
Often true	5.09% ± 1.22%	2.71% ± 0.88%
Sometimes true	16.59% ± 2.00%	14.08% ± 1.92%
Never true	78.32% ± 2.20%	83.20% ± 2.20%
Percent food insecure without screening	*21.16% ± 2.20%*	
Percent food insecure with screening	*8.25% ± 1.52%*	
Households with children(N=889)		
Often true	8.02% ± 1.84%	5.35% ± 1.52%
Sometimes true	27.54% ± 3.00%	24.14% ± 2.80%
Never true	64.43% ± 3.20%	70.51% ± 3.00%
Percent food insecure without screening	*31.40% ± 3.20%*	
Percent food insecure with screening	*21.26% ± 2.80%*	

[a] Includes only respondents who answered the questions. Calculations are made using data provided by Wozniak, et. al., 2020 at https://www.covid-impact.org/results, using the observations design to represent the nation at-large, along with the sample balancing weights provided.
[b] Standard deviations calculated using bootstrap. For 2,000 simulations the original data are sampled with replacement.

Table 4. 3 Food Insecurity Status in May 30-June 8, 2020 NORC Survey.

	May 30-June 8	
	Q1: We worried our food would run out before we got money to buy more	Q2: The food that we bought just didn't have money to get more
Food Insecurity Status[a]	Refers to past thirty days Point estimate ± two standard deviations[b]	
All households(N=2002)		
Often true	5.76% ± 1.04%	4.48% ± 0.94%
Sometimes true	19.48% ± 1.74%	16.07% ± 1.62%
Never true	74.76% ± 1.92%	79.45% ± 1.80%
Percent food insecure without screening	*27.32% ± 1.92%*	
Percent food insecure with screening	*15.93% ± 1.66%*	
Households without children(N=1115)		
Often true	4.61% ± 1.22%	3.80% ± 1.14%
Sometimes true	15.60% ± 2.20%	12.96% ± 1.98%
Never true	79.79% ± 2.40%	83.25% ± 2.40%
Percent food insecure without screening	*20.99% ± 2.40%*	
Percent food insecure with screening	*8.79% ± 1.70%*	
Households with children(N=887)		
Often true	7.32% ± 1.76%	5.40% ± 1.50%
Sometimes true	24.68% ± 2.80%	20.25% ± 2.80%
Never true	68.00% ± 3.20%	74.35% ± 3.00%
Percent food insecure without screening	*35.29% ± 3.20%*	
Percent food insecure with screening	*24.92% ± 2.80%*	

[a] Includes only respondents who answered the questions. Calculations are made using data provided by Wozniak, et. al., 2020 at https://www.covid-impact.org/results, using the observations design to represent the nation at-large, along with the sample balancing weights provided.

[b] Standard deviations calculated using bootstrap. For 2,000 simulations the original data are sampled with replacement.

Table 4. 4 Comparison of the Food Insecurity Rates among 2008 Crisis, Pre-COVID and COVID-19 Periods for All Households with Incomes below 185% of the Poverty Threshold.

	Q1: We worried our food would run out before we got money to buy more	Q2: The food that we bought just didn't have money to get more
Food Insecurity Status[a]		
2008 Crisis (N=222,366) as measured by the CPS-FSS survey from 2008 to 2011		
Often true	10.31%	6.37%
Sometimes true	31.10%	25.70%
Never true	58.58%	67.93%
Percent food insecure if dropping the households with income higher than 185% of the poverty threshold	*47.02%*	
Pre-Covid (N=624,400) as measured by the CPS-FSS survey from 2001 – 2007 and 2012 - 2018		
Often true	8.76%	5.60%
Sometimes true	29.15%	24.24%
Never true	62.09%	70.16%
Percent food insecure if dropping the households with income higher than 185% of the poverty threshold	*43.08%*	
Covid-19 (N=6405) as measured by the NORC survey		
	Refers to past thirty days Point estimate ± two standard deviations[b]	
Often true	6.32% ± 0.62%	4.84% ± 0.52 %
Sometimes true	20.42% ± 1.02%	16.89% ± 0.94%
Never true	73.25% ± 1.14%	78.27% ±1.02%
Percent food insecure if dropping the households with income higher than 185% of the poverty threshold	*52.56% ± 2.40%*	

CHAPTER V

CONCLUSIONS

Recall the NORC survey measures food insecurity in three separate weeks. The results for each week are shown in Table 4.1-3 The first two essays included in this dissertation are concerned with producer decision making. The first essay focuses on the profitability of different insecticides for controlling horn flies in stocker cattle, and the second essay focuses on stocker producers' preferences when they make decisions on purchasing stocker cattle. The third essay focuses on food insecurity during the COVID-19 pandemic.

In the first essay, two insecticides (Corathon® and LongRange®) were used to control the number of horn flies on stocker cattle and the average daily gain of the cattle were measured as well. Results show that compared with the control group, horn fly populations from groups treated with Corathon® and LongRange® were on average 34% and 50% lower, respectively. The economic effectiveness of each treatment was determined by comparing the marginal benefits of increases in average daily gain with the marginal costs of horn fly control. The marginal benefits were calculated by multiplying the average daily gain of the stocker cattle with the value of weight gain incorporating "price slide" (Brorsen et al. 2001). Additional profits from the application of Corathon® and LongRange® were $11.83/head and $9.95/head, respectively. The group treated with LongRange® has a greater reduction of horn flies and achieved greater increase in pounds of gain than the Corathon® group, while because of its higher costs of product and labor, additional profit using LongRange® is lower than that of Corathon®. With price slides 50% steeper than the price slide used originally, additional profit decreased to $4.26/head and $0.93/head for the Corathon® and LongRange® gourps, respectively, because the steeper slide reduces the value of weight gain. In contrast, with price slides 50% flatter than the original price slide, the profit of each insecticide is higher relative to the control group ($19.39/head for Corathon® and $18.97/head for LongRange®). The results estimated in this paper can be useful to stocker producers as they make decisions on application of each insecticide.

In the second essay, stocker producer purchasing preferences are analyzed using collected in the 2017 Oklahoma Beef Calf/Stocker Movement Survey. Chi-square tests results indicate that preference for certified preconditioned cattle is related to the region in which stocker producers are located. Stocker producers' educational level impacts their rating of importance for cattle's specific breed. Stocker producers' age and operation type are not independent of preferences for distance shipped of cattle. Operation type and annual capacity of stocker producers impacts their importance ranking on avoiding "trader" cattle. Lastly, operation type was related to producer rating of importance on general animal type. From the results of independence tests, we can see stocker producers' operation type influence their decisions on purchasing cattle than other demographic information.

Oklahoma stocker producers were divided into four latent classes according to purchasing preferences using latent class analysis. Latent class membership probabilities for class 1 through class 4 are 7.25%, 22.71%, 43.96% and 26.09%, respectively. From the item-response probability (figure 3.2), we can see that stocker producers in class 1 have lower probabilities of rating each of the nine cattle purchase characteristics as important than the other three classes, with the exception of avoiding "trader" cattle. Producers are not picky about details, stocker producers in class 1 seem to be least risk averse. Based on this, we can label class 1 as "Risk taker" group. In contrast, Class 3 producers are the most risk averse. They are pickiest and have high probabilities of rating all items as important except for lower importance rating for certified preconditioned. However, this group has the highest item-response probability of any group for rating certified preconditioned important at 36%. Thus, class 3 is named the "Risk averse" group. Class 2 has high probabilities of rating cattle physical attributes including specific breed, animal type and size/weight important, but has low probabilities of rating the other 6 items as important. Thus, class 2 can be labeled as the "Amazon shopper" group as they care more on the look and function of the products but less on where it was made or come from. In class 4, stocker producers not only have high probabilities of rating cattle physical attributes, but they also rate cattle's geographic attributes and market source including shipping distance, avoiding "trader" cattle, and purchasing source as important, Thus, class 4 might be named as "Scale shopper" group as they do care about geographic and marketing resource except for physical attributes.

The third essay focuses on food insecurity during the COVID-19 pandemic and compares of food insecurity across 2008 Crisis, pre-COVID and COVID-19 pandemic periods. Results of food insecurity rates for three separate weeks in the spring of 2020 from the NORC survey that mimicked the screening procedure of CPS-FSS survey were reported as 16.37%, 13.46% and 15.93%, respectively. Nutrition programs from the federal and states governments such as the National School Lunch Program, the Child and Adult Care Food Program, the special Supplemental Nutrition Program for Women Infants and Children, and the Supplemental Nutrition Assistance Program could explain the sharp decrease from 16.37% at the end of April to 13.46% at the beginning of May. Meanwhile, several stimuluses are funds to mitigate the hardship during the Covid-19 pandemic, includes Economic Impact Payments (EIP), the Child Tax Credit, and other refundable tax credits. Four Economic Impact Payments were received by eligible people, and the Child Tax Credit payments have been started to fund from July until now.

When comparing households with children or not, households with children are more vulnerable to be food insecure. During pandemic, unessential businesses and schools closed and people lost their jobs and incomes; meanwhile, the school lunches were not available to many children.

In order to compare food insecurity rates across 2008 Crisis, Pre-COVID and COVID-19 periods, the households with income higher than 185% of the poverty threshold were deemed to be food secure and were dropped when calculating food insecurity rates. As expected, the pre-COVID period has the lowest food security rate with 43.08%, and the Covid-19 period has the highest food security rate with 52.56%. The 2008 Crisis' food insecurity rate was 47.02%. Though the 2008 Crisis had a huge impact on people's lives, the impact on food access in COVID-19 is still higher than the 2008 Crisis. As food access data continues to be collected, future studies will be needed to monitor food insecurity rates for federal, state, and local policy decisions.

Oklahoma State University Institutional Review Board

Date:	Tuesday, September 06, 2016
IRB Application No	AG1619
Proposal Title:	Oklahoma beef calf/stocker movement survey
Reviewed and Processed as:	Exempt

Status Recommended by Reviewer(s): Approved Protocol Expires: 9/5/2019

Principal Investigator(s):

Derrell Peel	Kellie Raper
	514 Ag Hall
Stillwater, OK 74078	Stillwater, OK 74078

The IRB application referenced above has been approved. It is the judgment of the reviewers that the rights and welfare of individuals who may be asked to participate in this study will be respected, and that the research will be conducted in a manner consistent with the IRB requirements as outlined in section 45 CFR 46.

☒ The final versions of any printed recruitment, consent and assent documents bearing the IRB approval stamp are attached to this letter. These are the versions that must be used during the study.

As Principal Investigator, it is your responsibility to do the following:

1. Conduct this study exactly as it has been approved. Any modifications to the research protocol must be submitted with the appropriate signatures for IRB approval. Protocol modifications requiring approval may include changes to the title, PI advisor, funding status or sponsor, subject population composition or size, recruitment, inclusion/exclusion criteria, research site, research procedures and consent/assent process or forms
2. Submit a request for continuation if the study extends beyond the approval period. This continuation must receive IRB review and approval before the research can continue.
3. Report any adverse events to the IRB Chair promptly. Adverse events are those which are unanticipated and impact the subjects during the course of the research; and
4. Notify the IRB office in writing when your research project is complete.

Please note that approved protocols are subject to monitoring by the IRB and that the IRB office has the authority to inspect research records associated with this protocol at any time. If you have questions about the IRB procedures or need any assistance from the Board, please contact Dawnett Watkins 219 Scott Hall (phone: 405-744-5700, dawnett.watkins@okstate.edu).

Sincerely,

Hugh Crethar, Chair
Institutional Review Board

VITA

MENGYU YIN

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Doctor of Philosophy

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