ACCOUNTING FOR ATTENTION CHANGES IN DISCRETE CHOICE EXPERIMENTS AND MODELING ADVERSE SELECTION IN THE CATTLE PROCURMENT MARKET

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Abstract: This first paper conducts a discrete choice experiment to estimate turfgrass producers' willingness to accept (WTA) values using different logit models and specifications to capture respondents' attention. We first estimate the mixed logit model and a generalized multinomial logit model with and without eye-tracking variables to demonstrate the importance of accounting for individuals' differing levels of attention during an experiment. Our study finds that marginal WTA values are biased when individuals' attention changes are not properly accounted for in the model specification. This finding leads to our second objective, to determine whether attention changes can be fully captured in the absence of eye tracking data by testing six alternative model specifications. All six models are able to detect learning and fatigue effects but are unable to fully capture changes in attention. Of the six alternative models tested, the two models that implement panel data offer more reliable and significant results, suggesting the type of data and model specification used may play an important role in diagnosing attention changes when compared to various heterogeneity models.

In the second paper, a potential adverse selection problem is hypothesized in the beef packing industry. Adverse selection arises from information asymmetry between buyers and sellers, where we suspect feeders may have an information advantage compared to packers regarding cattle quality. Assuming that higher quality cattle are sold through alternative marketing agreements and lower and/or unknown quality cattle are sold through the cash market, we expect to find adverse selection is present in the cash market due to uncertainty regarding quality. We expect to find no or a lower level of adverse selection in the alternative market as premiums and/or discounts alleviates information asymmetries. Using a rare feedlot transaction dataset as well as a private regional aggregate dataset, we begin our analysis employing both Heckman's two-step model and the generalized Roy's model to determine the presence of selection bias. We then calculate cash price differences that a randomly selected lot would receive versus a lot that was sold in the cash market to determine the potential impact quality may have on market prices. We ultimately find the cash market has a negative adverse selection issue where lower quality cattle receive lower prices.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER I

DOES CHANGE IN RESPONDENTS' ATTENTION AFFECT WILLINGNESS TO ACCEPT ESTIMATES FROM CHOICE EXPERIMENTS?

Abstract

This study conducts a discrete choice experiment to estimate turfgrass producers' willingness to accept (WTA) values using different logit models and specifications to capture respondents' attention. We first estimate the mixed logit model and a generalized multinomial logit model with and without eye-tracking variables to demonstrate the importance of accounting for individuals' differing levels of attention during an experiment. Our study finds that marginal WTA values are biased when individuals' attention changes are not properly accounted for in the model specification. This finding leads to our second objective, to determine whether attention changes can be fully captured in the absence of eye tracking data by testing six alternative model specifications. All six models are able to detect learning and fatigue effects but are unable to fully capture changes in attention. Of the six alternative models tested, the two models that implement panel data offer more reliable and significant results, suggesting the type of data and model specification used may play an important role in diagnosing attention changes when compared to various heterogeneity models.

Keywords: scale heterogeneity logit models, WTA, eye tracking measures, discrete choice experiments

1. Introduction

Economists use discrete choice experiments (DCEs) to determine both producers' and consumers' imputed value of various nonmarket goods and services. By varying the attributes and price at different levels, the DCE allows for the statistical estimation of respondents' valuations of the nonmarket goods and services. Typically, respondents are asked to make a series of choices in a DCE. By presenting multiple choice tasks a researcher increases the amount of information available for analysis, but this setting comes at a risk. When facing multiple choice sets, the degree of respondents' attention paid to each choice set may differ as they become either familiar with the attributes or fatigued from answering multiple choice tasks in a survey.

A major limitation associated with the statistical analysis of DCEs is the failure to account for the potential changes in respondents' attention throughout the experiment. There is an emerging and growing literature on attributes non attended (ANA), where respondents' nonattendance to a subset of attributes has been shown to offer insight into choice selection strategies (Balcombe, Fraser, and McSorley, 2014). Although this paper considers choice selection strategies as a characteristic of learning and fatigue effects, our main focus is placed upon attention changes measured by an individual's total time spent fixating on attributes across choice tasks.[1] We believe ranges in attention changes across respondents can dramatically impact model estimates. Consequently, results for estimating respondents' preferences represented by willingness to pay (WTP) or willingness to accept

[1] Although there is a variety of ways to measure the "total time spent" a respondent spent on a choice task, we chose to implement total eye fixation durations. The advantage of using eye fixations versus a survey timer is it allows a greater degree of accuracy in recording what attributes a respondent paid attention to and for how long. A survey timer would not be able to offer that detailed of information, and more importantly it would not be able to recognize if a respondent took a break during a survey and would inaccurately account that extra time as attention spent on answering a choice task.

(WTA) may be biased if these changes in attention, sometimes referred to as learning and fatigue effects, are not properly considered in the estimation procedure.

The first objective of this study is to examine the importance of accounting for changes in respondents' attention when estimating choice experiment models. Unlike previous studies that have focused on ANA as the main measure of attention, we define attention by a respondent's total eye fixation duration per attribute. Similar to ANA, it is possible for an attribute to receive zero eye fixations and be considered non attended, however our paper puts a greater emphasis on the change and the range of total eye fixations across the sequence of choice tasks to expand beyond the simple binary classification of attended versus non attended attributes. Using this more detailed attention measure should improve estimation procedures. Realizing most researchers will not have access to an attention-related measure like eye tracking fixation measures lead us to our second objective to explore if researchers can properly account for attention changes by implementing different estimation methods and specifications.

In the decision theory literature, the role attention plays in the decision-making process is largely disregarded. It has been assumed that heuristics or simple selection and comparison of alternatives drive choice selection (Meyerding and Merz, 2018).[2] Therefore, there have been limited research focused on how respondents' attention is related to decision-making. Visual attention is one way to characterize an individual's attention in choice experiments.[3] In normal viewing situations attention and eye movements are closely related to one another. This means eye movements and

[2] A heuristic strategy is where the respondent chooses to only focus on a certain set of attributes to make a choice selection (Campbell et al., 2015).

[3] Other surveys may employ "trap" questions to determine if a respondent is paying attention, where the common convention is to delete inattentive respondents as their responses can substantively bias policy measurements such as WTP (Malone and Lusk, 2018). Deleting respondents may be costly and restrict representativeness. Other studies have used time spent per choice task as an attention measure (Börger and Cook, 2016), yet there is no way to distinguish between a respondent taking a short break in between choice tasks or if they spent the time considering all presented information.

fixations are not random but are rather guided by an individual seeking information (Behe et al., 2014, Balcombe, Fraser, and McSorley, 2015).

2. Literature Review

2.1. Learning and Fatigue Effects

Choice models derived from random utility theory assume respondents behave rationally and select the option that maximizes utility. The models also assume individuals fully attend to and costlessly process all information that is presented in a choice scenario (Cameron and DeShazo, 2010). This assumption may be violated if learning and fatigue are present in surveys with multiple choice tasks. The learning phase is defined once a respondent develops preferences and increases the accuracy of their responses. The learning effect produces lower variances while also improving data quality (Savage and Waldman, 2008). The fatigue effect typically increases with the number of choice tasks and is characterized by randomness in responses that results in a higher variance of the error term (Czajkowski, Giergiczny, and Greene, 2014).

Respondents may choose not to pay full attention to all given information and develop a decision-making strategy (Cameron and DeShazo, 2010). Incomplete attention to any attribute, due to either choice selection randomization or forming a decision-making strategy, can generate biased results (Cameron and DeShazo, 2010; Malone and Lusk, 2018). Factors that lead to learning and fatigue effects range from the survey administration method (e.g., mail versus online survey, Savage and Waldman, 2008; amount of information given prior to survey, Day et al., 2008), changes in respondent decision-making strategies (Swait and Adamowicz 1996; DeShazo and Fermo, 2002), choice set complexity in terms of the number of alternatives and attributes presented (DeShazo and Fermo, 2002; Fiebig et al., 2010; Chung, Boyer, and Han, 2011), as well as path dependent ordering (Day et al., 2008; Czajkowski, Giergiczny, and Greene, 2014). The variety of factors that cause learning and fatigue effects in welfare measures has led to a wide range of methods used by researchers to evaluate results of DCEs.

2.2. Measures of Attention Changes

Visual attention may offer the most insight on how choice behavior relates to changes in attention. Previous research employing eye tracking technology focused on attributes non-attended (Balcombe, Fraser, and McSorley, 2015; Spinks and Mortimer, 2016; Meyerding and Merz, 2018), as well as choice certainty (Uggeldahl et al., 2016). Sprinks and Mortimer (2016) found the average time taken to answer each question as recorded by eye tracking exhibited a broad U shape suggesting the time taken to make a choice decreases to a certain level.[4] This relationship has been analyzed graphically by plotting both fixation counts (Meibner and Decker, 2010; Balcombe, Fraser, and McSorley, 2015; Meibner, Musalem, and Huber, 2016; Meyerding and Merz, 2018) and fixation duration (Meyerding and Merz, 2018) against the sequence of choice tasks. It has been shown lesser attention towards a choice task should increase the error variance (i.e. decrease scale) within a model to signal fatigue (Cameron and DeShazo, 2010). Whereas the more time an individual takes to complete a choice set results in more consistent responses and a lower error term variance (Börger and Cook, 2016).

[4] When both learning and fatigue are present, a convex U shape relationship between the variance and the number of choice tasks may be observed (Swait and Adamowicz, 1996; Czajkowski, Giergiczny, and Greene, 2014; Campbell et al., 2015). The convex U shape is consistent with learning and fatigue, as it is expected the variance will be greater when the respondent first begins the survey, become smaller once preferences are formed, and become large again as the respondent becomes bored answering the end of the survey. Certain studies did not observe the U shape depending on if fatigue ever sets in. Also, the functional form used within the scale parameter specification may play a role in observing a U shape. For instance, most studies which found an inverted U shape employed a quadratic specification within the scale parameter in an attempt to find some optimal measure (Caussade et al., 2005 Chung, Boyer, and Han, 2011; Czajkowksi, Giergiczny, and Greene, 2014; Sprinks and Mortimer, 2016).

2.3. Scale Heterogeneity Models

Previous studies have used scale heterogeneity models to accommodate changes in respondents' attention by relaxing the assumption of a constant error term variance. This enables the scale for some observations to differ from others. Heteroskedastic multinomial logit models have formerly been used to determine how choice complexity may affect the variance (Swait and Adamowicz, 1996; Fermo and DeShazo, 2002), as well as determine the optimal number of choice sets to present (Chung, Boyer, and Han, 2010). The heteroskedastic multinomial logit model allows the scale parameter to be a function of observable survey characteristics. This approach is a simple addition to the traditional multinomial logit model. Despite identifying sources of heterogeneity in the form of choice set complexity, the scale specification is not respondent specific.

The scaled multinomial logit model is more flexible in its scale function being both respondent specific and allowing for additional explanatory variables to measure scale heterogeneity. It has previously been used to test changes in learning and fatigue from choice task to choice task (Czajowski, Giergiczny, and Greene, 2014; Balcombe, Fraser, and McSorley, 2015). The choice task specification can follow a linear and/or sinusoidal trend to map out when learning ends and fatigue begins. Campbell et al. (2015) presented a similar specification for detecting learning and fatigue by grouping the choice tasks into early, middle, and late phases. Other observable traits of entropy such as demographic characteristics have been proposed to be used in heterogeneity-based models (Fiebig et al., 2010; Campbell et al., 2015). A limitation of the scaled multinomial logit is that it only takes into consideration heterogeneity resulting from scale changes, and not heterogeneity resulting from preference changes.

Some DCE studies that used scale heterogeneity models reported welfare estimates were not sensitive to different scale specifications (Fiebig et al., 2010; Czajkowksi, Giergiczny, and Greene, 2014). By contrast, Campbell et al. (2015) found different treatments of learning and fatigue did have an impact on these estimates. This contradiction in literature further supports our investigation in determining the potential bias in econometric estimates that fail to account for changes in attention.

3. Methodologies

3.1. Mixed Logit Model

The multinomial logit (MNL) model is one of the most commonly used methods by economists when evaluating DCEs. An advantage of using the MNL model is it allows a choice set with multiple alternatives to be analyzed. Drawbacks include the assumption of independence of irrelevant alternatives (IIA). The IIA assumption states that the probability ratio between two alternatives does not depend on the characteristics of any other alternatives (Wittink and Haensel, 2011). Another shortcoming of the standard MNL model is it assumes the scale coefficient for each respondent, choice task, and alternative is the same.

The most popular extension from the MNL model is the mixed logit (MIXL) model. The main attraction to the MIXL model is that it allows preference heterogeneity to be measured, meaning it captures how respondents' preferences may vary among attributes and from other respondents. By assuming the heterogeneity of respondents' preferences, the MIXL allows parameters to vary randomly over respondents, where the parametric heterogeneity distribution allows the derivation of conditional parameter estimates to be individual specific (Sarrias and Daziano, 2017). The utility function for the MIXL model is given by:

$$U_{ijt} = (\beta + b_i)y_{ijt} + \varepsilon_{ijt,} \tag{1}$$

where β is a parameter vector of utility weights, b_i is the vector of individual specific deviations from the mean, y_{ijt} is the vector of observed attributes which represents individual i choosing alternative j

for choice set t, and ε_{ijt} is independently and identically distributed (i.i.d.) type I extreme value distributed error (Sarrias, Daziano, and Croissant, 2017).[5] The probability for MIXL is given by:

$$P(j|J) = \frac{1}{R}\sum_{r=1}^{R} \frac{\exp\left[(\beta+b^r)y_{ijt}\right]}{\sum_{k=1}^{J}\exp\left[(\beta+b^r)y_{ikt}\right]}, \qquad (2)$$

where the logit model is averaged out over R number of draws (Fiebig et al., 2010). With parameters being estimated as individual specific, the MIXL model allows for preference heterogeneity to be observed within a DCE. Despite capturing heterogeneity in model estimation, the MIXL does not account for scale heterogeneity, including that brought forth by attention changes. Failing to capture scale heterogeneity leaves the MIXL model unable to generate lexicographic or random behavior that is represented by a small or large scale parameter. Rather, respondents' change in attention can be modelled within a MIXL model only if such a variable (e.g. eye-tracking variable) is provided by the researcher. Otherwise, any influence attention may have on parameter estimates needs to be assumed to be captured within the error term.

3.2. Generalized Multinomial Logit Model

The generalized multinomial logit (G-MNL) model incorporates both taste (preference) and scale heterogeneity, allowing it to fit both lexicographic and random behavior better. Because of this added flexibility, the G-MNL is often the preferred model across information criterion compared to other logit models (Fiebig et al., 2009). The G-MNL extends the MIXL model by allowing scale to vary

[5] The variance of ε_{ijt}, σ_{ε}^2, is $\frac{\pi^2}{6\nu^2}$ where ν^2 is the scale parameter. When the scale parameter increases the error variance decreases, and vice versa. The variance of the error term may change to be higher or lower as a respondent progress through a survey, representing the learning and fatigue effects. For example, the longer a respondent spends on a choice task should cause a higher scale parameter value, and consequently would result in a lower variance. This would be consistent with the learning effect given a respondent is taking the time to develop preferences while considering all available information. Within estimation, the unobservable scale parameter is typically set equal to $\frac{\pi^2}{6}$ to create a constant variance equal to one (Campbell et al., 2015).

across respondents through a parametric specification of heteroscedasticity (Sarrias and Daziano, 2017). With the scale coefficient being individual specific, one can expect the G-MNL model to control for attention changes through observing changes in the error term's variance across choice tasks.

To control for scale heterogeneity and individuals' preference heterogeneity the utility function for the G-MNL model is given by:

$$U_{ijt} = [\sigma_i \beta + \gamma b_i + (1 - \gamma)\sigma_i b_i]\, y_{ijt} + \varepsilon_{ijt}, \tag{3}$$

where the addition of a new coefficient γ is a scalar that controls how variance of the residual taste heterogeneity varies with scale.[6] The variance of the error term is expressed by $\sigma_i = \exp(\bar{\sigma} + \tau\varepsilon_i)$ where $\varepsilon_i \sim TN(-2,2)$, and the new parameter τ is the scale coefficient that accurately assesses the extent of scale heterogeneity.[7] The interpretation of the new scale variable is straightforward, where a higher τ value signals greater heterogeneity in choice selection (Fiebig et al., 2010). The G-MNL model is more flexible than both the scaled multinomial logit model and MIXL model as we can extend the scale parameter function to be a characteristic of some observable trait to capture both preference and scale heterogeneity.[8]

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[6] The scaled multinomial logit (S-MNL) model is given by:

$$U_{ijt} = \beta y_{ijt} + \varepsilon_{ijt}/\sigma$$

and allows scale to differ by respondent. The S-MNL utility function may be multiplied by σ_i to become:

$$U_{ijt} = (\beta\sigma_i) y_{ijt} + \varepsilon_{ijt}$$

implying utility weights of β to be scaled up or down proportionately across respondents by the scale factor. The scale factor is the inverse of the variance. To measure both preference and scale heterogeneity, the S-MNL model may be nested with the MIXL model from equation (1) to obtain the G-MNL model. Specifically, individual utility weights is given by:

$$\beta_i = \sigma_i \beta + [\gamma + (1 - \gamma)\sigma_i]\, \vartheta\eta_i$$

where $\vartheta\eta_i$ varies with scale. If in the above equation $\gamma = 0$ and $\sigma_i = 1$ then the function reverts back to the MIXL model where $\beta_i = \beta + \vartheta\eta_i$. If the variance of $\eta_i = 0$ then the model reverts back to the S-MNL model where $\beta_i = \sigma_i\beta$ (Sarrias and Daziano, 2017).

[7] In the case where τ is too large, numerical problems may cause extreme draws for the error term; to avoid this ε_i is drawn from a truncated normal distribution with truncation at ± 2 (Fiebig et al., 2010; Greene and Hensher, 2010; Sarrias and Daziano, 2017).

[8] When compared to MIXL, G-MNL generally offers a better model fit for Type I and Type III people. Type I people are characterized as extreme with preferences close to lexicographic, meaning a certain attribute may dictate the respondent's decision making. Behavior is not random, and a small scale for the error term is observed (i.e. the learning effect). Type III people exhibit the fatigue effect, being extremely random in their decision-making behavior (Fiebig et al., 2010). The G-

3.3. Scale Parameter Functions and Specifications

Due to both time and financial costs, eye tracking data may not be feasible for all studies. It is important to determine if a scale specification within the variance function is able to properly consider learning and fatigue effects. However, respondents' attention changes may not be properly controlled if inappropriate specifications or assumptions are placed on the estimated model. Czajkowski, Giergiczny, and Greene (2014) state that "overly restrictive specification and failing to include enough choice tasks may draw incorrect conclusions in terms of whether scale dynamics are observed" (p. 340).

In the literature, most studies specified their data as pooled (Swait and Adamowicz, 1996; DeShazo and Fermo, 2002; Hess and Rose, 2012), while a few studies specified their data as panel (Savage and Waldman, 2008; Greene and Hensher, 2010; Czajkowski, Giergiczny, and Green, 2014; Campbell et al., 2015). Panel data may be used in a DCE to control for certain characteristics within a population when studied as longitudinal data; cross sectional heterogeneity and behavioral characteristics may be captured in estimation methods (Greene, 2015). Although panel data is traditionally used for time series data, a DCE with multiple choice tasks may also qualify to be treated as panel data as each respondent has multiple observations over the specified period it took to complete the survey.

Following Greene and Hensher (2010), we first attempt to find out whether one can address the issue of respondents' attention change using the panel data analysis when respondents' eye-tracking data (and/or equivalent attention related data) are not readily available. We first sort the data by choice task number followed by respondent id. Sorting the panel data this way allows dynamics of behavior and cross-sectional heterogeneity to be estimated within model convergence. We further

MNL model can better account for learning and fatigue effects by allowing scale to vary and accommodate the different types of respondents.

control for attention changes between choice tasks by dummy coding the 12 choice tasks and dropping the first choice task as a reference class. We then include the remaining 11 choice tasks as fixed effects within the panel data. The panel data analysis is then conducted for both MIXL and G-MNL models.[9]

To further observe scale changes, additional scale parameters may be introduced to the variance function in vector form to include explanatory variables that represent some observable trait (Fiebig et al., 2009), and is represented by:

$$\sigma_i = \exp(\bar{\sigma} + \tau\varepsilon_i + \phi' m_i), \tag{4}$$

where the explanatory variable, m_i, is individual specific and σ_i follows a lognormal distribution $\sigma_i \sim LN(\bar{\sigma}, \tau^2)$ (Fiebig et al., 2010; Czajkowksi, Giergiczny, and Greene, 2014; Börger and Cook, 2016). Equation (5) allows a researcher to test alternative specifications to control for learning and fatigue effects, or in our case to determine if any observable variable may be able to fully capture attention changes in the absence of eye tracking measures.[10]

We use three different types of dummy variables for the vector m_i in equation (4): (1) choice task dummy variables, (2) demographic dummy variables based on subjects' reported college degree, as well as (3) dummy variables coded by early-middle-late choice phases.[11] Similar to the fixed effects in the panel data specification, the 12 choice tasks are dummy coded with the first choice task dropped to serve as the reference class. For the next scale specification, we test whether or not a

[9] Uggeldahl et al. (2016) also used fixed effects in their model estimation to remove constant unobserved effects that span across the set amount of choice tasks presented. Unlike our use of fixed effects, however, the Uggeldahal et al. (2016) study calculated the fixed effects as a function of certainty and then included this new variable into a pooled data OLS estimation.
[10] Learning and fatigue effects are associated to the error term's variance and may be measured and analyzed by a researcher through interpreting τ and γ. The additional explanatory variable, m_i, in equation (5) further extends analysis where a researcher can measure learning and fatigue effects by a survey characteristic. For example, a choice task-specified scale function would provide additional scale parameters to be interpreted, where an increase in scale coefficients across number of choice tasks would indicate respondents becoming more deterministic in their choice selection (i.e. the learning effect) (Czajkowski, Giergiczny, and Greene).
[11] The choice task dummy scale drops the first choice task to serve as the reference class (Czajkowski, Giergiczny, and Green, 2014). The early-middle-late dummy scale drops the middle phase to serve as the reference class, in turn allowing differentiation between learning and fatigue effects to be more easily observed between the early and late phase (Campbell et al., 2015).

demographic characteristic may be associated with learning and fatigue effects. We hypothesize a subject of a college degree to be closely related to decision making; specifically, for our survey we choose to explore if as a respondent's educational background may lend them to make more informed decisions regarding turf grass management. Our next dummy coded scale specification splits up choice tasks evenly or by weighting the early phase heavier than the middle and late phase (i.e. allowing the first half of the survey to be categorized as the early phase and the second half of the survey to be evenly split up as the middle and late phase) (Campbell et al., 2015). To assist in splitting up our DCE's choice tasks into phases, we examine the visual breaks when average TFD is plotted against choice task number as a guide (Figure 2). We ultimately designate the early phase as choice tasks one to six, the middle phase as choice tasks seven to ten, and the last two choice tasks as the late phase. The middle grouping is dropped as a reference class to serve as a clear divider between what appears to be the learning and fatigue phases.

The final scale specification is an adaption from Balcombe, Fraser, and McSorely (2015) that incorporates both choice task progression and eye tracking measures. We chose not to perfectly replicate their specification as the inclusion of an eye tracking variable within the variance function would be contradictory to our second objective. We instead adopt the other linear and sinusoidal scale parameters to be used within a G-MNL model. The sinusoidal terms can allow learning and fatigue phases to appear anywhere in the sequence of choice tasks, and also allows the scale function to be both individual and task specific, resulting in a more flexible approach than equation (4). The scale function with sinusoidal terms is given by:

$$\sigma_{it} = \exp\Big(-\phi_1(\varphi_{it} - \bar{\varphi}_t) - \phi_2\big(\sin(\varphi_{it}\pi) - \overline{\sin(\varphi_{it}\pi)}\big) - \phi_3\big(\sin(\varphi_{it}2\pi) - \overline{\sin(\varphi_{it}2\pi)}\big)\Big), \tag{5}$$

where φ_{it} is calculated by $\frac{(t-1)}{(T-1)}$ with t corresponding to a specific choice task and T corresponding to total number of choice tasks, and $\bar{\varphi}_t$ being the average across choice tasks. ϕ_1 is representative of a linear measure and how the scale parameter increases (negative coefficient value) or decreases (positive coefficient value) throughout the survey. ϕ_2 is the coefficient related to a sinusoidal variable that will peak in the middle of the survey only if learning is present at the beginning half and fatigue is present at the last half; this term follows more of a quadratic specification by determining optimal minimum and maximum peaks of attention; $\overline{\sin(\varphi_{it}\pi)}$ is the average of the previous term. The coefficient ϕ_3 corresponds to another sinusoidal term and gives further flexibility in observing learning and fatigue effects as it allows the minimum or maximum scale to be at any point in the survey. $\overline{\sin(\varphi_{it}2\pi)}$ is the average of the previous term (Balcombe, Fraser, and McSorley, 2015).

4. Data

The data used in this study is from a discrete choice experiment performed in 2015 at the Turfgrass Producers International Conference in Carlsbad, California. Thirty-two sod producers took part in the survey that elicited willingness to adopt turfgrass varieties with improved hardiness attributes for a range of farm gate prices. The final sample has 22 usable and complete surveys, where all of the completed choice experiments also had complete eye tracking and demographic information. Both the time and cost constraint associated with collecting responses with eye tracking limited the total number of industry professionals who were able to complete the survey. Despite the small sample size, the data is still relatively reliable in terms of market representativeness as respondents belong to a range of geographical locations with an average production area of 1,855 acres and combined annual sales of over $254 million in 2014. In an effort to address the small sample size as well as to ensure greater accuracy during estimation procedures, we implement a Monte Carlo simulation to produce 1,000 data sets with 792 observations for each econometric model.[12]

A fractional factorial design was created with a D-efficiency score of 96.84%. There were 4 blocks of choice sets consisting of 12 choice sets from the designed 48 choice sets. Respondents were randomly directed to one of the four blocks. Blocking the choices and randomly assigning them to respondents allowed for a greater variation of choice tasks answered without overwhelming a respondent with an excessive number of choice tasks. Respondents were asked to consider six different attributes of improved turfgrass varieties including winter kill reduction, shade tolerance, drought tolerance, salinity tolerance, and a 10% maintenance reduction, as well as price. Table 1 provides attribute descriptions and levels. Each choice task included two alternatives along with a status quo option, where the status quo served as a no-purchase option. A sample choice task card that was presented to respondents is seen in Figure 1.

Respondents took the survey using a computer that had an eye tracking device, the Tobii TX 300, installed. The Tobii TX 300 software has one of the highest resolutions and is capable of recording at 0.4 accuracy (binocular) and 0.15 precision (unfiltered). A nine-point calibration was conducted prior to the start of the survey to accurately track respondents' eye movements. Once calibration was completed, each participant was presented with a series of 12 choice sets on the screen and given as much time as needed to complete each task. The Tobii TX software tracks eye movements by recording fixations on different areas of interest, where fixation is defined as the pause of eye movement on a specific area of the visual field (Bergstrom and Schall, 2014). Areas of interest (AOIs) are mapped out on the screen, representing the different boxes that contain the various attributes and alternatives. Once the survey is completed, the eye tracking device provides various

[12] Despite only having 22 usable respondents, each respondent was presented 12 choice tasks that included 3 alternatives each to produce 792 total observations in the original data set. Therefore, we replicate the original 792 sample size in each of the 1,000 simulated data sets.

measurements of individuals' eye movement including time to first fixation (TFF), fixation count (FC), total fixation duration (TFD), and total visit duration (TVD). TFF and FC measure the time that a respondent takes to fixate for the first time on an AOI and the number of fixations each respondent spends on each AOI, respectively. TFD and TVD measure the total time of each fixation a respondent spends per each AOI and the total visit duration for each respondent on each AOI.

5. Empirical Analysis

5.1. Evidence of Respondents' Change in Attention

We first analyze the eye tracking data by themselves to see if changes in people's attention are observed. Although we have data available for four different eye tracking measurements, only total fixation duration was considered as most previous studies either used fixation count or fixation duration in their calculations (Meibner, Musalem, and Huber, 2016; Meyerding and Merz, 2018). Using TFD instead of FC allows us to better account for the time a respondent spent on each choice task, as well as on the areas of interest. As can be seen in Figure 2, there were more TFDs in the earlier tasks than the last few tasks. Choice task 1 has the highest average fixation duration at 17.89 seconds, whereas choice task 11 had the lowest at 7.53 seconds. Although a visual change can be observed, a graph alone cannot determine whether the learning or fatigue effect is observed in this specific choice experiment.

TFD can be measured to be even more specific by detailing respondents' fixation regarding each attribute per choice task and alternative (Figure 3).[13] Realizing respondents may spend radically different amounts of time fixating on different attributes and completing one choice task

[13] Contrary to Meibner and Decker's (2010) finding that price appears to be the most important attribute because it garners the greatest number of fixations, our results show the opposite (Figure 3). Similar to our dataset, Balcombe, Fraser, and McSorley (2015) also found price to have the lowest average fixation counts within their study.

before progressing onto the next, we standardized all six attributes' TFDs (i.e. TFD_{Price}, TFD_{Winter}, TFD_{Shade}, $TFD_{Drought}$, TFD_{Saline}, and $TFD_{Maintenance}$) to one total unit. Therefore, the time an individual spent on each choice task and more specifically on each attribute was transformed to become a proportion of total time taken to complete the survey on a scale of 1. Standardizing total TFD to one unit per survey prevents respondent exhibiting any extreme behavior from disproportionately influencing the results by weighting each individual the same.[14] The median total TFD spent across all choice tasks and attributes was 121.46 seconds (10.12 seconds per choice set); one respondent had a total TFD measure of 10.82, and another respondent spent 255.68 seconds on total fixations. This wide range in time spent gives rise to the importance of standardizing respondents eye tracking measure—a step many previous studies skipped. When TFD per attribute is standardized, extremely small values are used for estimation. The range of the standardized total TFD ranges from 0.000 to 0.314 with a mean of 0.028. These small values result in large coefficients estimated (see the interaction terms' results in Table 3 and 4).

5.2. Estimation of Welfare Measures and Test for Bias

Demand predictions represented by welfare measures for G-MNL and MIXL have previously been shown to be almost identical (Fiebig et al., 2009). However, their predictions regarding the distribution of demand across respondent types (lexicographic versus random behavior responses) is different. We denote the model with TFDs as model A, and the model without TFDs as model B. WTA values were calculated by:

$$WTA = \frac{\partial U/\partial X_i}{\partial U/\partial P} = \frac{\beta_i + \beta_{xi} * \overline{TFD}}{\beta_p + \beta_{pi} * \overline{TFD}}, \tag{6}$$

[14] Uggeldahl et al. (2016) standardized their eye tracking variables into z-scores to remove individual variance and to minimize the difference in eye movement pattern rates between respondents.

where X_i represents the different attributes (i.e. $i = 1 = \text{winter};\ i = 2 = \text{shade};\ \text{etc}$), β_i is the coefficient for each attribute, β_{xi} correspond to the interaction variables for each attribute (i.e. TFD_{Winter}), $\overline{TFD}$ is the average total fixation duration, β_p is the price coefficient, and β_{pi} corresponds to the interaction variable TFD_{Price}. When calculating WTA values for model A, insignificant interaction terms are considered equal to zero, which causes the WTA calculation to shorten to:

$$WTA = \frac{\partial U/\partial X_i}{\partial U/\partial P} = \frac{\beta_i}{\beta_p}, \tag{7}$$

where this function is also used to calculate the WTA values for model B.

To determine if biased estimates of sod producers' WTAs are produced when attention is not considered in the model, we compare model A and model B for both the MIXL and G-MNL models by employing a complete comparison (CC) test (Poe, Giraud, and Loomis, 2005). The CC test is used over the t-test for this comparison as the WTA distributions are no longer normal and thus unknown. We first use a Monte Carlo simulation to produce 1,000 data sets for both model A and B. Each simulated dataset contains 792 observations to replicate the original sample size. We then calculate WTA values, resulting in 1,000 values for each attribute per model. The next step of a CC test requires a researcher to subtract each of the WTAs generated from model B from the WTAs generated from model A. This produces one million differences between the A and B WTA estimates for each attribute. Under the null and alternative hypotheses:

$$H_0: WTA_A - WTA_B = 0$$

$$H_a: WTA_A - WTA_B \neq 0,$$

we are able to calculate the *p*-value using the one million differences. With the one million differences, we first round to two decimal points to reflect monetary values, and then count the number of differences that equal zero before dividing this total by one million. This generates our *p*-value for each attribute, where we are then able to compare it to a specified significance level. When comparing model A to model B for both the MIXL and G-MNL models, the CC tests produce significant p-values at the 1% level for shade and drought in the MIXL model and for winter, shade, drought, and saline in the G-MNL model; winter, saline, and maintenance WTAs from the MIXL model as well as the maintenance WTA in the G-MNL model were significant at the 5% level. This suggests a model with an attention variable produces significantly different WTA values than a model that does not control for respondents' attention.

Tables 3 and 4 present estimation results for the MIXL and G-MNL models that were estimated with and without considering TFD.[15] All attributes have the expected signs, whereby winter kill reduction, shade tolerance, drought tolerance, salinity tolerance, and a 10% maintenance reduction were positive and significant within the models that included TFD. The models that did not include TFD produced insignificant estimates. The gate price per square foot, given the different combinations of attributes, was positive as expected, however it was insignificant in all models. An insignificant price coefficient may be due to our small sample size and employing random parameter logit models that use more parameters in estimation compared to the MNL or S-MNL model. TFD_{shade} was the only interaction term in both MIXL and G-MNL models that was positive, where positive TFD estimates suggest the greater amount of fixation on an attribute is related to the attribute's perceived importance in choice selection (Meibner and Decker, 2010). However, all interaction variables were insignificant and were therefore not used in WTA calculations. WTA values were all insignificant for the "A" models that did not include any eye tracking measures.[16] When including an attention related variable within the model, WTA values become significant across all attributes and both likelihood and AIC improve.

[15] All models were estimated using the R packages mlogit and gmnl. A status quo ASC was also added to the model specification to determine if the status quo option held any significance against other alternatives.

[16] WTA values' significance was calculated using the Krinsky and Robb (1986) confidence interval method. The Krinsky and Robb (1986) method expands upon our Monte Carlo experiment. First, 5,000 marginal WTAs for each attribute are calculated from simulated data. The 5,000 WTAs are then sorted from lowest to highest values. To generate 95% confidence intervals, the first and the last 125 observations are used as cut off points.

Within the G-MNL models, the coefficient τ has a negative value, where a decrease in τ signals a decrease in the degree of scale heterogeneity. The coefficient γ is negative in model "A", which suggests the variance of the residual taste heterogeneity increases with scale (Fiebig et al., 2010).

5.3. Scale Parameter Function Specifications and Changes in Attention

With evidence of biased results obtained from CC tests (Tables 3 and 4), we adapt several specifications from previous studies in an attempt to more fully capture changes in attention without using eye tracking data. Results from the two models are found in Table 5, where we first test the panel specification for both the MIXL and G-MNL model. Under this specification all attributes with the exception of price were positive and statistically significant. Winter, shade, drought, and saline marginal WTAs were all statistically significant at the 1% level from the MIXL model. WTAs for winter, drought, and saline attributes were statistically significant at the 1% level and WTAs for shade and maintenance attributes were significant at the 1% level from the G-MNL model. The G-MNL panel model was preferred over the MIXL model in both log likelihood and AIC. MIXL was preferred under the BIC criterion, where the G-MNL model was penalized for its additional scale variables.

The remaining four alternative models are run as pooled data and vary in their scale parameter specifications, where these scale specifications substitute different variables into the explanatory variable, m_i, from equation (4).[17] The first specification follows Czajkowski, Giergiczny, and Greene's (2014) paper and tests choice task sequence as a way to describe respondents' attention. All random parameters including price are assumed to be normally distributed

[17] The reason why panel data is not used alongside scale specifications is due to double controlling for respondents' attention.

(Savage and Waldman, 2008; Greene and Hensher, 2010; Czajkowski, Giergiczny, and Greene's, 2014).[18] All attributes exhibited the expected positive sign, however, the specification produced insignificant estimates and insignificant marginal WTAs. The scale coefficients within the model (i.e. the dummy coded choice task parameters) appear to decrease after the first two choice tasks, remain constant, and then substantially decrease over choice task 11 and 12. This is consistent with Figure 2 where eye tracking fixation and visitation are plotted against choice tasks. However, the choice task scale parameters are insignificant. The scale parameters, τ and γ, are also insignificant and are therefore unable to provide any analysis regarding respondents' attention changes.

We next test the sinusoidal scale specification, where all attributes produced the expected positive signs but are insignificant. The sinusoidal scale specification also produced insignificant marginal WTA values. When interpreting the model's scale parameters there appears to be evidence of learning and fatigue effects but is inconclusive due to insignificant estimates. The linear term is negative, which would suggest the scale's variance increases over choice sequence (i.e. the fatigue effect has set in). The first sinusoidal term is also negative, signaling either the learning phase or fatigue phase does not peak within their respective halves of the survey (i.e. learning should peak in the first half of the survey, and fatigue should peak in the second half of the survey). The second sinusoidal term is positive, indicating a decrease in the variance during the middle phase of the DCE. Therefore, there appears to be evidence of an overall attention change across respondents characterized by learning and fatigue effects. Furthermore, the parameter value for τ is negative, suggesting there is a decrease in the degree of scale heterogeneity that would be consistent with the occurrence of fatigue. The parameter γ is negative, suggesting the attributes' coefficients are a "mixture of normal with proportionally different means and standard deviations" versus being a

[18] Other models assumed price to be log normally distributed to ensure negative values are obtained for calculating WTP values (Fiebig et al., 2010). Balcombe, Fraser, and McSorely (2015) ran all random parameters under both normal and log normal distributions before comparing the two models. We ran all models with a normal and log normal distributions on price but found results associated to a normally distributed price as more intuitive for our analysis.

"mixture of normal with different means but equal variances" (Fiebig et al., 2010, p. 399). Due to all scale parameters being insignificant, however, we are unable to verify these conclusions. These results may be due to our limited number of observations, where future studies with larger data sets may use a similar modified scale specification (i.e. do not include eye tracking information within the sinusoidal function) from Balcombe, Fraser, and McSorley's (2015) paper.

Our next specification uses demographic information as a variable within the scale function.[19] To test if a demographic variable may be synonymous with choice behavior, we selected college degree. Degree subjects include turf management, horticulture, landscape architecture, plant and soil sciences, as well as "other". All degrees except for "other" are hypothesized to positively affect WTA for abiotic attributes increasing turf resilience. We dummy coded each degree subject and dropped "other" to serve as the reference class.[20] All attributes exhibited the expected positive sign but produced insignificant results and insignificant marginal WTA values. All demographic scale variables except degree in landscape architecture were significant at the 10% significance level. Contrary to what was expected, the scale demographic variables exhibited negative values, with a degree in landscape architecture having the greatest impact on choice outcome.

The final scale specification splits up the choice tasks into early, middle, and late sections. Once again, the model produces estimates with the expected positive signs, but they are significant across all attributes and they also produce insignificant marginal WTAs. Both the early and late terms included in the scale function are positive but insignificant.

Although half of the models produced insignificant results (most likely due to our small sample size), we continue on with our analysis and outline how to compare the six different scale

[19] Campbell et al. (2015) suggested including socio-economic variables to extend the modeling of learning and fatigue. It may be plausible certain demographic characteristics are synonymous with respondent behavior (i.e. type I vs type III respondents), and thus may be useful to model attention changes.

[20] Additional demographic information collected included age, gender, race, and highest level of education obtained. For this specific topic, we chose to only investigate subject of college degree as it was the most relevant to the survey's questions.

model specifications to the original “B” models that included eye tracking data. Specifically, to determine which models may be appropriate to use in the absence of an eye tracking variable we follow a similar procedure to section 5.2 after estimating our six alternative model specifications. A Monte Carlo simulation is used to generate 1,000 data sets for each model before performing a CC test against the G-MNL model that includes TFD. Resulting p-values from the CC test can be found in Table 6. All marginal WTAs across all six alternative specifications are statistically different from the marginal WTA values that include TFD. This suggests all six alternative specifications are unable to synonymously capture changes in attention to eye tracking technology, and therefore are not suitable substitutes.

Conclusions

Respondents’ attention allocation is largely disregarded in DCEs as it is assumed simplified decision-making strategies compose respondent’s choice behavior. Although heuristics may be one form of the learning phase, the commonly used MIXL model may only be able to capture this effect within the error term. Realizing attention changes may be a major factor influencing choice selection, we first determine if ignoring attention changes in model estimation affects parameter estimates and welfare measures.

We prove that failing to account for a respondent’s attention change in model estimation produces biased WTA measures. A complete comparison test shows marginal WTA values in both MIXL and G-MNL models are statistically different from WTA values calculated from MIXL and G-MNL models that include an average eye fixation duration variable. In other words, many DCEs may be producing inaccurate and biased WTA and WTP values if a researcher fails to control for attention changes. Correcting such estimation methods to include attention changes is important to ensure proper conclusions and policy implications are formed by the researcher. Eye tracking is just one alternative to measure entropy during a survey.

Realizing most researchers will not have access to eye tracking data due to time constraints and added costs prompted us to test six alternative model specifications. Specifically, we wanted to determine if attention may be captured by a different data type (i.e. pooled vs panel data) or through including additional scale parameters within the scale function. Although the models that were estimated with panel data produced significant estimates for all attributes, the marginal WTA values were statistically different when compared to the models that included eye tracking data to fully capture changes in attention. The remaining four scale parameter specifications all produced insignificant attribute values, rendering their analysis irrelevant. Regardless, the use of panel data provided more meaningful results than the pooled data heterogeneity models, suggesting the first step towards capturing attention changes may be related to the type of data used. Panel data and heterogeneity models may not be combined as this would lead to the researcher double controlling for attention and model misspecification. More research is needed to determine if any of these alternative specifications can accurately capture changes in attention in ways similar to eye tracking data.

This study, like many eye tracking studies, is limited due to small sample size. Cost of implementation and lengthy survey sessions associated with gathering eye tracking data limited the number of respondents that could complete this survey at the turfgrass convention. In an attempt to try and improve estimation, we also estimated the MIXL and G-MNL models without including an alternative specific constant (ASC). Testing these additional model specifications did not improve results, and in some cases produced erroneous estimates that did not match theory.

Additional extensions to this research may include investigation into the effects of socio-demographic characteristics on learning and fatigue effects and further testing of scale parameter specifications. The addition of an observable variable to the scale specification may not be enough to capture changes in attention. Propensity score matching may also be introduced to determine if respondents with similar socio-demographic backgrounds exhibit similar patterns not only in choice selection but also with learning and fatigue effects. Attention changes may also be better captured if the G-MNL variance function was expanded to also be choice task specific. Allowing for scale heterogeneity to be measured at both the respondent and choice task level may improve results to be unbiased and offer greater insight into detecting attention changes within DCEs.

Options A and B represent two different sets of sod/turf grass Bermuda or zoysia marketing characteristics and reductions in buyers' maintenance such as weed control, mowing, and fertilizer. Which option (A, B, or C) would you be most likely to produce to market to consumers?

Attributes	**Option A**	**Option B**	**Option C**
Winter Kill Reduction	NO	NO	If A or B were the only available options, I would NOT purchase new sod for my facility.
Shade Tolerance	YES	NO	
Drought Tolerance	NO	YES	
Salinity Tolerance	NO	YES	
10% Maintenance Reduction	YES	NO	
Farm Gate Price per Square Foot	$0.25	$0.35	
I would choose	☐	☐	☐

Figure 1. Sample choice task card for turf grass study

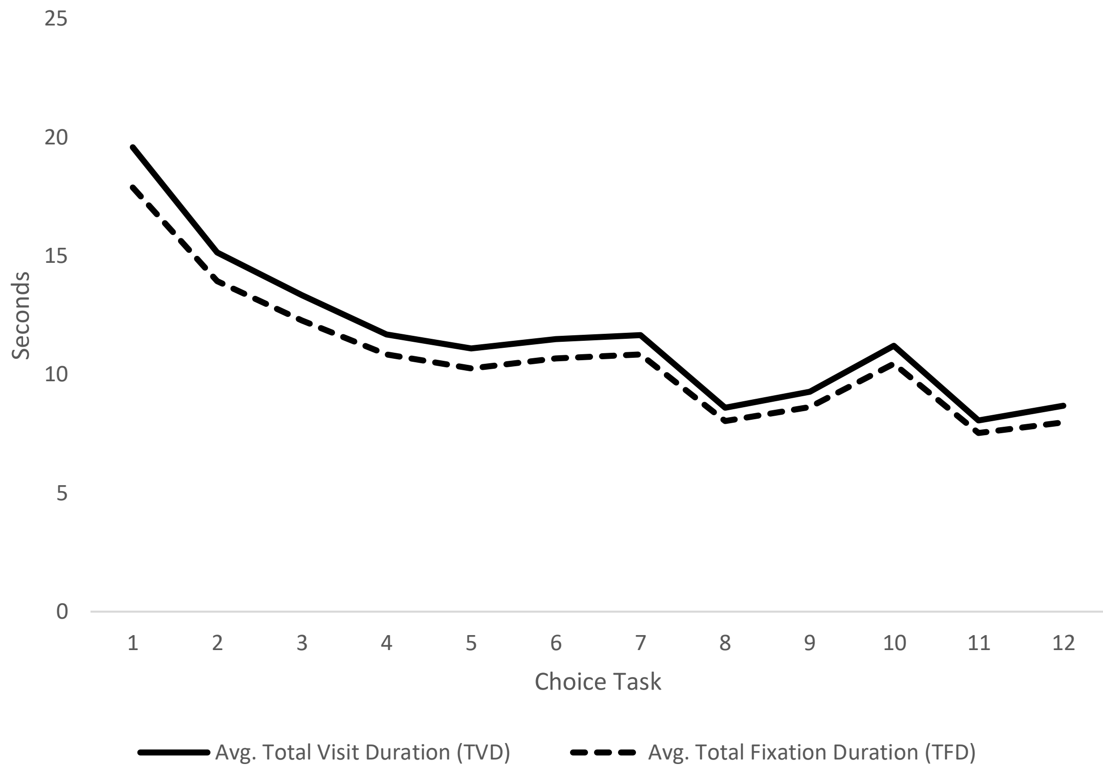

Figure 2. Average Total Visit Duration (TVD) and Average Total Fixation Duration (TFD): Seconds per Choice Task

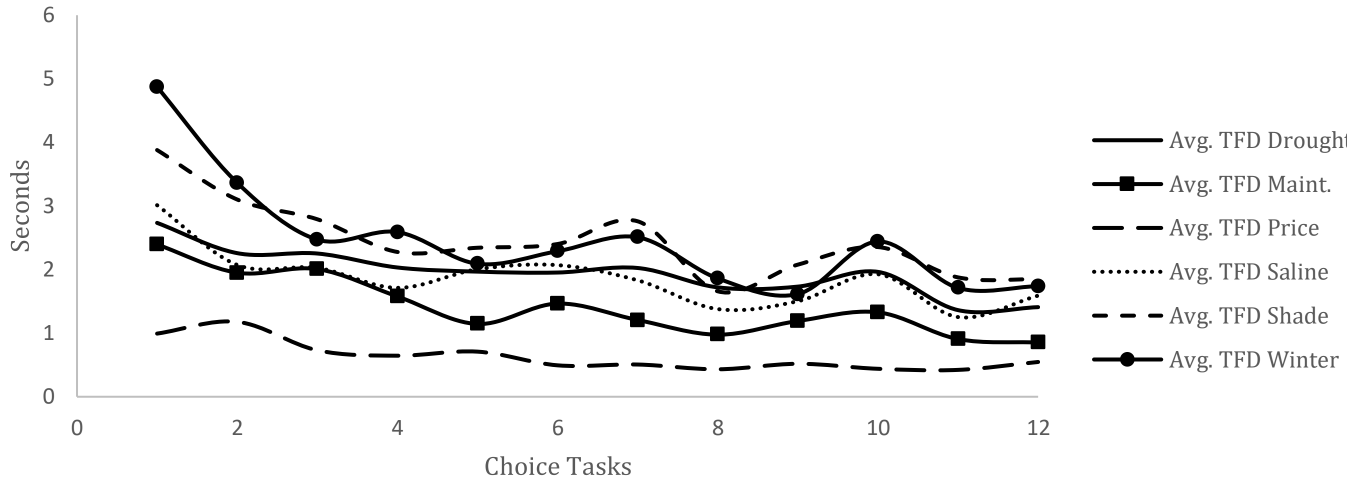

Figure 3. Average total fixation duration of attributes by the sequence of choice tasks

Table 1. Attributes and Attribute Levels for the Turf Grass Choice Experiment

Attribute	Description	Attribute Levels
Winter	Winter kill reduction	Yes
		No
Shade	Shade tolerance	Yes
		No
Drought	Drought tolerance	Yes
		No
Saline	Salinity tolerance	Yes
		No
Maintenance	10% maintenance reduction	Yes
		No
Price	Farm gate price received in dollar per square feet	\$0.15
		\$0.25
		\$0.35
		\$0.45
		\$0.55

Table 2. Selected sample demographic summary statistics

Characteristic	Mean	Count	Minimum	Maximum
Education level				
<12th grade	0.000	0		
High school diploma	0.000	0	N/A	N/A
Some college	0.363	8		
B.S./B.A. or higher graduate	0.637	14		
Degree				
Turfgrass management		4		
Horticulture		1		
Landscape architecture	N/A	1	N/A	N/A
Plant and soil science		2		
Other		14		
Gender				
Male	N/A	4	N/A	N/A
Female		18		
Age	46.136	22	26	65
Race				
White		22		
Black/ African American	N/A	0	N/A	N/A
Native American		0		
Asian		0		

Table 3. Mixed Logit Model Parameter Estimates with and without Eye Tracking

Variable	Parameter	Estimation without Eye Tracking Variables (TFD)	Estimation with Eye Tracking Variables (TFD)	Complete comparison test between WTA with and without TFD (p-value)
Status quo ASC	α	35.096 (53.369)	0.780 (0.604)	---
Price	β_1	30.985 (73.644)	0.859 (1.630)	---
Winter	β_2	47.735 (66.949) [$1.54]	0.832*** (0.218) [$0.97]***	0.003***
Shade	β_3	54.694 (77.163) [$1.77]	0.756** (0.231) [$0.88]***	0.002***
Drought	β_4	66.525 (92.812) [$2.15]	1.109*** (0.230) [$1.29]***	0.002***
Saline	β_5	32.555 (45.420) [$1.05]	0.666** (0.213) [$0.78]***	0.004***
Maintenance	β_6	25.006 (35.260) [$0.81]	0.506* (0.219) [$0.59]***	0.005***
TFD_{Price}	β_7	---	57.574 (107.666)	---
TFD_{Winter}	β_8	---	-8.035 (16.629)	---
TFD_{Shade}	β_9	---	5.915 (17.398)	---
$TFD_{Drought}$	β_{10}	---	-17.569 (18.536)	---
TFD_{Saline}	β_{11}	---	-16.542 (21.431)	---
$TFD_{Maintenance}$	β_{12}	---	-9.961 (22.553)	---
Log likelihood	---	-218.59	-203.340	---
AIC	---	463.19	444.684	---
BIC	---	509.67	512.267	---

Note: Numbers in parentheses are standard errors. Numbers in brackets are willingness to accept in dollars per square foot. Standard deviations of estimates are not presented in this table as they are not relevant to our research objectives. Interaction terms between the TFD variables and their respective attributes were also estimated but are not included in the table or WTA calculations as they were insignificant.

***,**,* indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 4. Generalized Multinomial Logit Model Parameter Estimates

Variable	Parameter	Estimation without Eye Tracking Variable (TFD)	Estimation with Eye Tracking Variable (TFD)	Complete comparison test between WTA with and without TFD (p-value)
Status quo ASC	α	28.710	0.836	
		(41.357)	(0.611)	
Price	β_1	43.564	0.922	---
		(66.411)	(1.651)	
Winter	β_2	26.598	0.848***	
		(38.503)	(0.270)	0.007***
		[$0.61]	[$0.92]***	
Shade	β_3	30.553	0.766**	
		(43.792)	(0.234)	0.006***
		[$0.70]	[$0.83]***	
Drought	β_4	37.386	1.121***	
		(53.612)	(0.233)	0.005***
		[$0.86]	[$1.22]***	
Saline	β_5	17.768	0.691*	
		(25.021)	(0.216)	0.009***
		[$0.41]	[$0.75]***	
Maintenance	β_6	16.521	0.522**	
		(24.255)	(0.221)	0.011**
		[$0.38]	[$0.57]***	
TFD_{Price}	β_7	---	35.941	---
			(108.488)	
TFD_{Winter}	β_8	---	-8.546	---
			(16.774)	
TFD_{Shade}	β_9	---	5.996	---
			(17.580)	
$TFD_{Drought}$	β_{10}	---	-16.967	---
			(18.782)	
TFD_{Saline}	β_{11}	---	-18.888	---
			(21.740)	
$TFD_{Maintenance}$	β_{12}	---	-11.003	---
			(22.803)	
Tau	τ	-0.033	-0.015	---
		(0.091)	(0.489)	
Gamma	γ	-19.015	4.582	---
		(54.014)	(235.553)	
Log likelihood	---	-217.51	-203.42	---
AIC	---	465.02	448.83	---
BIC	---	518.66	523.93	---

Note: Numbers in parenthesis are standard errors. Numbers in brackets are willingness to accept in dollars per square foot. Standard deviations of estimates are not presented in this table as they are not relevant to our research objectives.

***,**,* indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 5. Alternative Model Specifications to Account for Changes in Attention when Eye Tracking Data is Absent

Variable	Parameter	MIXL Panel	GMNL Panel	Choice Task Order Dummy Variables	Sinusoidal Scale Function	Demographic Scale Function	Early-Middle-Late Scale Function
Status quo ASC	α	-0.198 (0.732)	0.210 (0.780)	8.989 (31.129)	4.611 (14.818)	15.304 (27.836)	1.939 (2.775)
Price	β_1	0.854 (2.244)	2.907 (2.570)	17.529 (66.232)	11.013 (34.689)	16.885 (44.631)	2.016 (5.264)
Winter	β_2	1.167** (0.371) [$1.37]***	1.454*** (0.426) [$0.50]***	18.829 (69.719) [$1.07]	8.426 (26.204) [$0.77]	25.271 (41.882) [$1.50]	2.644 (2.637) [$1.31]
Shade	β_3	1.302*** (0.346) [$1.52]***	1.312** (0.454) [$0.45]**	19.709 (72.605) [$1.12]	9.942 (29.811) [$0.90]	23.846 (39.271) [$1.41]	3.178 (3.242) [$1.58]
Drought	β_4	1.490*** (0.383) [$1.74]***	1.199*** (0.343) [$0.41]***	22.223 (81.353) [$1.27]	11.172 (34.062) [$1.01]	32.927 (54.408) [$1.95]	3.706 (3.862) [$1.84]
Saline	β_5	0.838** (0.260) [$0.98]***	1.167*** (0.353) [$0.40]***	13.034 (46.295) [$0.74]	6.098 (18.550) [$0.55]	17.592 (28.470) [$1.04]	1.865 (1.954) [$0.92]
Maintenance	β_6	0.620* (0.245) [$0.73]**	0.827** (0.287) [$0.28]**	10.284 (38.757) [$0.59]	4.989 (15.429) [$0.45]	11.275 (18.727) [$0.67]	1.496 (1.618) [$0.74]
Scale Estimates							
Choice Task 2	m_2	---	---	-3.105 (3.914)	---	---	---
Choice Task 3	m_3	---	---	-2.924 (3.737)	---	---	---
Choice Task 4	m_4	---	---	-2.654 (3.827)	---	---	---
Choice Task 5	m_5	---	---	-2.909 (3.813)	---	---	---
Choice Task 6	m_6	---	---	-2.742 (3.771)	---	---	---
Choice Task 7	m_7	---	---	-2.653 (3.761)	---	---	---
Choice Task 8	m_8	---	---	-2.642 (3.796)	---	---	---
Choice Task 9	m_9	---	---	-2.264 (3.655)	---	---	---
Choice Task 10	m_{10}	---	---	-2.757 (3.746)	---	---	---
Choice Task 11	m_{11}	---	---	-2.699 (3.788)	---	---	---
Choice Task 12	m_{12}	---	---	-0.755 -0.728	---	---	---

				(3.549)			
Linear term	ϕ_1	---	---	---	-0.373 (0.446)	---	---
First sinusoidal term	ϕ_2	---	---	---	-2.018 (1.912)	---	---
Second sinusoidal term	ϕ_3	---	---	---	0.550 (0.540)	---	---
Turf management	m_{13}	---	---	---	---	-3.048 (1.690).	---
Horticulture	m_{14}	---	---	---	---	-3.297 (1.771).	---
Landscape architecture	m_{15}	---	---	---	---	-11.785 (74.008)	---
Plant and soil sciences	m_{16}	---	---	---	---	-3.124 (1.710).	---
Early choice tasks	m_{17}	---	---	---	---	---	0.676 (0.565)
Late choice tasks	m_{18}	---	---	---	---	---	0.557 (0.579)
Tau	τ	---	0.462 (0.499)	-0.032 (0.273)	-0.897 (1.811)	-0.008 (0.267)	-0.662 (0.461)
Gamma	γ	---	3.603 (2.611)	-0.165 (0.701)	0.042 (0.247)	-0.080 (0.142)	-2.622 (5.226)
Log likelihood	---	-191.64	-189.29	-214.07	-217.89	-213.02	-217.78
AIC	---	409.28	408.58	480.14	471.77	464.05	469.57
BIC	---	455.77	462.22	573.11	536.14	531.99	530.36

Note: Numbers in parenthesis are standard errors. Numbers in brackets are willingness to accept in dollars per square foot. Standard deviations of estimates are not presented in this table as they are not relevant to our research objectives.

***,**,* indicate statistical significance at 1%, 5%, and 10% levels, respectively.

Table 6. Alternative Model Specifications Complete Comparison Tests Against G-MNL with TFD[a]

Test	MIXL Panel	GMNL Panel	Choice Task Order Dummy Variables	Sinusoidal Scale Function	Demographic Scale Function	Early-Middle-Late Scale Function
Winter	0.004***	0.008***	0.002***	0.003***	0.003***	0.004***
Shade	0.005***	0.008***	0.002***	0.003***	0.003***	0.003***
Drought	0.003***	0.005***	0.002***	0.003***	0.002***	0.002***
Saline	0.004***	0.010***	0.003***	0.004***	0.003***	0.005***
Maintenance	0.008***	0.013**	0.005***	0.007***	0.006***	0.007***

Note: ***,**,* indicate statistical significance at 1%, 5%, and 10% levels, respectively.
[a] The MIXL Panel was compared back to the MIXL model with TFD, not the G-MNL with TFD.

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CHAPTER II

ADVERSE SELECTION IN THE CATTLE PROCUREMENT MARKET

Abstract

We hypothesize a potential adverse selection problem in the beef packing industry. Adverse selection arises from information asymmetry between buyers and sellers, where we suspect feeders may have an information advantage compared to packers regarding cattle quality. Assuming that higher quality cattle are sold through alternative marketing agreements and lower and/or unknown quality cattle are sold through the cash market, we expect to find adverse selection is present in the cash market due to uncertainty regarding quality. We expect to find no or a lower level of adverse selection in the alternative market as premiums and/or discounts alleviates information asymmetries. Using a rare feedlot transaction dataset as well as a private regional aggregate dataset, we begin our analysis employing both Heckman's two-step model and the generalized Roy's model to determine the presence of selection bias. We then calculate cash price differences that a randomly selected lot would receive versus a lot that was sold in the cash market to determine the potential impact quality may have on market prices. We ultimately find the cash market has a negative adverse selection issue where lower quality cattle receive lower prices.

1. Introduction

Since the introduction of alternative marketing agreements (AMAs), some researchers and producers have suggested meat packers could strategically use AMAs to suppress fed cattle prices (Ward, 1999). Within the cattle procurement market, feeders can sell their cattle to packers through either AMAs or the cash market. It has been hypothesized that packers negatively influence prices either through oligopsony power and/or an over-use of AMAs. With an emphasis on packer power as well as quantity of transactions, little has been done to study the impact that feedlots and their marketing choices may have on fed cattle prices. Specifically, feeders can select which market to send a specific lot of cattle to, dictating the distribution of cattle quality between the cash and AMAs markets. The quality difference of cattle between these two markets, although acknowledged in previous studies, has been omitted from analyses despite being one of the key components of fed cattle price formation (Koontz, 2010).

The AMA market, sometimes known as the captive supply market, refers to cattle that are committed to a certain buyer at least two weeks in advance of slaughter, and typically fall within three categories: packer owned and fed, forward contracts, and formula-based agreements such as grid-based pricing or futures-based pricing (Ward, 1999; Ward, Schroeder, and Feuz, 2004; Xia and Sexton, 2004; Xia, Crespi, and Dhuyvetter, 2019; Dennis, 2020). The cash market comprises all other live market sales negotiated between packers and feeders. Although the two markets are separate, AMAs and negotiated cash sales are connected through price formation. Cattle that are procured through AMAs are ultimately priced using either the weekly regional cash price or the plant's average cash price as the base to which premiums and/or discounts are applied (Schroeter and Azzam, 2003; Zhang and Brorsen, 2010; Adjemian et. al, 2016; Peel, et. al, 2020). If the cash market were to be inaccurately priced at a lower value than what should be observed based off the quality of cattle found in this market, then past studies have been biased in their findings about market power as they were unable to account for quality differences for their estimation. Studying the impact that quality distribution between markets may have on cattle procurement prices has not previously been done and serves as the main topic of our analysis.

AMAs can provide significant economic benefits to both packers and feeders, and dissuade participation in the cash market (Peel, et. al, 2020).[21] As a result, trends over the past few decades have shown an increased usage of contracted procurement methods and consequently a thinning cash market (Sabasi, et. al, 2013). In 1998 and 1999, AMAs accounted for 23.6% to 32.2% of all fed cattle sales among the top four packers (GIPSA, 2002; Schroeter and Azzam, 2003).[22] Between 2007 to 2016, however, cash market and captive supply market percentages switched as cash market sales decreased from roughly 60% to 30% of all cattle sales (Koontz, 2010; Zhang and Brorsen, 2010; Xia, Crespi, and Dhuyvetter, 2019).[23] The issue of a thinning cash market and consequently the matter of price discovery has become a widely researched topic (Koontz, 2015; Adjemian, et. al, 2016; Peel et. al, 2020). Up to this point, however, quantity—not quality—has been the primary basis of these analyses. Disregarding and failing to control for quality attributes among cattle sold between the two markets may bias current conclusions.

Contrary to popular opinion, feeders hold the power over packers when it comes to dictating which market to send a pen of cattle (Koontz, 2015). Not only do feeders dictate how each pen of cattle are marketed, but feeders also hold an information advantage over packers in

[21] Feedlots have strong incentives to use formula marketing methods over the cash market. Incentives include supply-chain-management, increased meat quality, and reduction of production costs. Packers also benefit from formula marketing in terms of improving week-to-week supply management, securing higher quality cattle, and allowing for product branding opportunities in retail stores (Koontz, 2010). Although both producers and feeders within a focus group agreed the cash market offers greater independence, flexibility, as well as quicker response times to changing market conditions, the cash market has disincentives in the forms of large costs of use and disorganization related to planning for the future (Koontz, 2010; Koontz, 2015). Specifically, cattle may miss being marketed in either an optimal or predicted week, negotiations over sales may fail, and/or pen marketing may be delayed (Sabasi, 2013; Koontz, 2015; Peel, et. al, 2020).

[22] As of 2002, the top four packers, Cargill, Tyson, JBS, and National Beef, have accounted for 80% of cattle sales (Zhang and Brorsen, 2010). I suggest you update this number; might be higher these days.

[23] The thinning of the cash market has coincided with the 2004 institution of mandatory price reporting (Koontz, 2015).

the form of knowing the of origin of cattle, genetics, medical records, and other characteristics of their animals. Feeders can therefore better predict carcass quality and performance compared to packers.[24] This information advantage introduces a potential information asymmetry concern in the fed cattle industry where we hypothesize the adverse selection problem in the cash market. Specifically, packers assume feeders will send their higher quality cattle to the AMA market to capture price premiums. This assumption consequently suggests lower quality cattle will be sent to the cash market, prompting packers to establish a cash base price off of low quality stock. This may or may not be true as smaller feeders are more likely to utilize the cash market (Koontz, 2010), making the quality distribution in the cash market unknown. As a result, the cash market price may not be an accurate assessment of quality, and consequently establish a lower base price than what should be observed.

Objectives of this study are to test for adverse selection in the cattle procurement market and to determine the impact of the adverse selection on cattle prices. Unlike previous studies, our paper employs a unique dataset from a single feedlot that details both cash and AMA transaction prices. The individual AMA prices reported from the feedlot provides post-harvest prices that are directly based off known carcass attributes, which is typically only known between the feedlot and the packer; to our knowledge such detailed information has not been used in a fed cattle study. With this rare price data, we expand the discussion of AMA versus cash markets by providing clear evidence of difference in prices between the two markets. More importantly, we discover a potential adverse selection issue in the cash market using both Heckman's and the generalized Roy's sample selection models. We extend our cash market findings from the feedlot level to a regional market by introducing a secondary industry-level dataset. Ultimately, we find a clear difference in quality between the two markets, where market prices reflect these quality differences.

[24] While completing this research, we spoke with feedlot managers who confirmed the strong record keeping and knowledge regarding the cattle they fed out.

2. Literature Review

In the past two decades, researchers have used various theoretical and empirical frameworks to evaluate price formation and discovery in the fed cattle industry. Most of the existing literature has placed an emphasis on either packer's oligopsony power or the thinning cash market without controlling for quality attributes. Arguments have ranged from claiming the elimination of AMAs would decrease the effect of market power on prices to suggesting a specified volume of cash sales is needed to ensure accurate price discovery (Koontz, 2010; Koontz, 2015). Quality, although often left out of such analyses, plays an equally important role alongside supply and demand characteristics in price formation (Koontz, 2010).

2.1. Packer Market Power

The potential negative impact of packer market power on fed cattle prices has been heavily hypothesized since the introduction of AMAs. AMAs, such as formulas, are created to lower packers' risk on the livestock's carcass performance, where feeders ultimately hold most of the power in accepting or rejecting AMA terms. To model this relationship, Xia and Sexton (2004) outlined three stages of the beef packing procurement process where feeders can either agree to top-of-market-prices (TOMP) or sell in the cash market. Although this study serves as a benchmark for modelling a link between the two markets, the use of aggregate data and duopsony assumption restrict its precision.[25] Also, by solving with respect to quantity the study

[25] The assumption of a duopsony is inaccurate for the fed cattle industry, where four firms comprise the majority of transactions to represent an oligopsony case. The use of aggregate data potentially diminishes individual feedlot trends as well as regional trends, where the ratio of cash versus AMAs sales vary greatly across the five cattle regions (i.e. the Oklahoma-Texas-New Mexico region typically conducts 4-10% of their cattle business within the cash market, whereas the Nebraska region conducts 15-35% cash trade (Koontz, 2015)). Also, this weekly aggregate data does not disclose detailed information about different types of sales.

consequently assumes quality of cattle is consistent between cash and TOMP transactions, which does not reflect reality.

Zhang and Brorsen (2010) extended the previous work to the oligopsony case to further investigate how the increased use of captive supplies by meat packing firms may lead to negative impacts on prices, while also studying price depression effects in both the short-run and long-run market. More recently, Xia, Crespi, and Dhuyvetter (2019) also expanded Xia and Sexton's (2004) paper by analyzing the relationship between cash and captive supply prices through tied-to-futures-prices (TFP) contracts and introduced a framework that allowed for substitutability between TFPs and tied-to-cash-prices. Ultimately, the study suggested packers may be able to act strategically in their quantity of AMA and cash market purchases to "manipulate" prices, but oligopsony power does not have a severe impact on prices.

2.2. Thinning Cash Market

The issue of a thinning cash market and the effect of trade volume on cattle prices has also been heavily studied. An early study by Schroeter and Azzam (2003) used 1995-1996 data to investigate the hypothesis that an increased volume of captive supplies led to lower average prices in the cash market.[26] More recently, Koontz (2015) studied the volume of cash trade necessary for price discovery in the five regional cattle markets.[27] Policymakers and cattlemen have both called for a more extensive analysis regarding the volume of trade, looking for a specific answer in terms of optimal ratios of doing business between the two markets. Peel et. al (2020) claimed "negotiated transactions and the price discovery they support benefit everyone in

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[26] It is important to note AMAs were relatively new and comprised less than 30% of transactions at the time of the study.

[27] Cash versus captive supply sales vary by region where there are varying options depending on region in which cattle may be traded (Koontz, 2015). In simplest terms, when a region has more options for trading, there becomes an increased need of cash sales for price discovery to occur.

the market and sensible efforts to increase the volume of negotiated transactions in the fed cattle market are well-founded and worth supporting" (pg. 7). However, the paper warned against implementing any policy for a minimum quota regarding volume of negotiated cash sales as the quality of price discovery would most likely worsen.

Peel et al. (2020) also discussed how a market with perfect information does not require price discovery as all parties have access to all information. The paper argues that an increased amount of cash negotiations is needed to accurately reveal prices, however, the issue of information availability may apply to more than just quantity of sales. If market information were symmetric and cattle quality were fully known between the two markets, then packers would be able to randomly select cattle in the cash market to establish a base price to produce more accurate average price. However, if adverse selection exists in the cash market, then this result will not hold true.

2.3. Adverse Selection

Sabasi et. al (2013) suggested that if AMAs were widely used, then competition between markets would be reduced and depress not only cash market prices but also all procurement method prices as well. We argue that the distribution of cattle quality between AMA and cash markets leads to a potential adverse selection concern, which could play a significant role in price formation.[28]

Akerlof (1970) was the first to introduce the theory of the lemons problem regarding information asymmetry, where a seller knows the true quality of a good and the buyer only knows the distribution of the quality of goods. We argue feeders hold an information advantage with

[28] Peel et. al (2020) supports this argument, claiming "differences in the type or quality of cattle traded by negotiated cash arrangement compared to formula cattle could be evidence of adverse effects of thin markets" (pg. 6).

respect to cattle quality based off knowledge of cattle genetics, origin, and/or medical records. With the information advantage, feedlots send their perceived higher quality cattle to the captive supply market and their remaining cattle to the cash market to best optimize their profits and avoid the risk of receiving discounts in AMA markets. Specifically, larger feedlots may strategically split up lots of cattle and sell the perceived lower quality cattle to the cash market to avoid a single to a few head of cattle from negatively influencing a pen's overall price. Smaller feedlots and businesses, however, exclusively use the cash market (Koontz, 2010). Packers may overlook this quality discrepancy of cattle supplied to the cash market from small and large feedlots. This discrepancy may then lead to an unknown quality distribution where the adverse selection problem is created; consequently, cattle sold through the cash market may receive lower cash prices than what should be observed.

The U.S. cattle market is probably one of the most complex industries characterized by long biological production times, limited and short hold-over time for slaughter-ready cattle, and most importantly thousands of beef products processed and marketed. To our knowledge, fed-cattle prices have not been analyzed from an adverse selection perspective; we are unaware of any livestock price studies that take such approach. Studies, however, have been conducted within the thoroughbred horse industry focusing on a breeder's strategic approach in marketing horses (Chezum and Wimmer, 1997; Wimmer and Chezum, 2003). Such studies have implemented sample selection models as these models allow a researcher to test and account for the adverse selection problem when estimating price equations (Wimmer and Chezum, 2006).

Like fed-cattle having two correlated markets, cash and AMA markets, the thoroughbred horse industry has a certified market whose price is established off the expected quality of horses sold in the non-certified auction market. As a result, breeders are expected to only sell their low quality horses and keep their higher quality horses for breeding purposes to avoid receiving low prices. This type of seller behavior creates a selectivity bias in price formation. Using the

Heckman selection (Type 2 Tobit) model, Wimmer and Chezum (2003) found adverse selection was present in the non-certified market (the market where lower quality horses were sold) but was not present in the certified market. This makes theoretical sense, as the certified market alleviates an information asymmetry problem as horses are inspected from a quality standpoint before being admitted into a certified market.[29]

The Heckman's two-step correction method is arguably the most utilized model to study adverse selection (Winship and Mare, 1992; Bushway, Johnson, and Slocum, 2007). Therefore, we begin our analysis following Wimmer and Chezum's (2003) argument that systematic censoring occurs when producers adversely select the animals they sell in each market. We model this systematic adverse selection as a case of selectivity bias and examine the correlation between the errors of the selection and price equations. However, we question if our research problem is appropriately characterized by the incidental selection captured by Heckman's two-step procedure (Type 2 Tobit). Specifically, incidental selection is defined by selection that occurs when truncation is applied to a stochastic function of the dependent variable where the observed predictor variable is not the actual selection variable but is correlated with it (Berk, 1983; McGuire, 1986; Winship and Mare, 1992; Bushway, Johnson, and Slocum, 2007).

As an alternative, we also employ the generalized Roy's model (Type 5 Tobit) to test for the existence of adverse selection in the cattle procurement market as it better captures self-selection by estimating the correlation between the selection equation and the two price equations simultaneously. Self-selection may more accurately describe the fed cattle market where producers and feeders make rational, optimizing decisions regarding which markets to participate (Autor, 2003). The theory behind Roy's model originated from an example of optimizing wealth in the labor market where Roy hypothesized workers given varying skillsets may self-select into a

[29] The study inaccurately implemented a logit instead of a probit during the first stage of estimation (Bushway, Johnson, and Slocum, 2007).

specific sector to participate depending on expected comparative advantages (Roy, 1951; Heckman and Honoré, 1990; Autor, 2003). The theory was then transformed by Borjas (1987) into a switching-regression model to analyze how immigrant workers may decide which country to work in given expected wages. The generalized Roy's model assumes the individual compares opportunity costs to make an optimal choice, which is more in line with the decision process feeders face when choosing how to market a lot of cattle to maximize their profit.

To the best of our knowledge, the impact that adverse selection has on cattle procurement prices has never been researched or reported. To better assess the extent of an information asymmetry problem, we follow Lee's (1995) procedure of opportunity cost analysis. Using the estimated parameters from Heckman's and generalized Roy's models, we calculate expected prices for various scenarios concerning a randomly selected lot of cattle (or a specified lot of cattle). Such analysis will convey the impact adverse selection has on prices and demonstrate lower quality cattle receive lower prices.

3. Data

We implement two different unique fed cattle datasets. The first dataset covers the sales transactions of a single Oklahoma feedlot between November 2018 to July 2019. The feedlot has a 32,000 head capacity with facilities that can hold anywhere from 60 to 300 head per pen.[30] The data includes 398 lots of cattle whose head count ranged from 1 to 212.[31] Carcass and price data cover a total of 18,097 head of cattle. The second dataset is proprietary information from an

[30] Due to the confidentiality agreement with the feedlot, the name of data sources cannot be disclosed. We obtained the data by traveling to the feedlot on two separate occasions and transferring printed records into our own data sheet.
[31] Certain lots were split up and sold over different time periods. Therefore, we report a minimum head per lot of one because one head of cattle was part of a larger lot of cattle but were sold either at a different time period and/or through a different marketing method.

industry organization and includes weekly aggregate sales for an unnamed region between 2013 to 2019. These transactions occur over two different sub-regions for a total of 3,870 observations and 1,073,078 head of cattle.

3.1. Single Feedlot Transaction Level Dataset

Summary statistics for the single Oklahoma feedlot are found in Table 1. Approximately 6.92 percent head of cattle were sold through the cash market, which is consistent with the 4-10% cash trade typically found in the Oklahoma-Texas-New Mexico region (Koontz, 2015). The average cash market price was $66.55 per hundred weight with a minimum price of $10.41 and a maximum price of $136.82. We acknowledge our cash prices are lower than the average prices reported by the USDA for the same period (USDA NASS).[32] We attribute this to the low head count of some lots (the average price for the 128 single-headed lots in our dataset is $58.66), whereas the lots that contain 15 head or more have a much higher average price that is more in line with the typical USDA average (the average price for the 20 lots that had 15 head or more is $114.80). However, if we were to delete lots with less than 15 head for the analysis then we would be ignoring the potential adverse selection issue that is the direct result of feedlots using their private information in strategically deciding to split off certain cattle from their original lot to sell in a different market and at a different time than the rest of the lot. The remaining lots were AMA transactions where 161 lots were sold through the U.S. Premium Beef (USPB) grid, 74 lots were sold through the negotiated grid, and 1 lot was sold via formula pricing. Cattle sold through AMAs on average received $122.45 per hundred weight, with a minimum price of $99.32 and a maximum price of $134.70.

[32] Between November 2018 to July 2019, USDA monthly feeder cattle prices ranged from $113 to $126 per hundred weight (USDA NASS).

Other variables include lot gender, packer, location of plant, primary breed of lot, as well as carcass specific variables that were reported after AMA cattle were slaughtered. This specific feedlot primarily conducted business with National Beef, selling 235 of their AMA lots and 15 of their cash lots to this packer. The feedlot also conducted business with Tyson (0 AMA lots, 4 cash lots), Cargill (1 AMA lot, 2 cash lots), and Other buyers (0 AMA lots, 142 cash lots).

Arguably the most unique aspect of this dataset is the lot-specific carcass reports for the AMA sales. These reports include both the lot's live and hot weight, hot yield (i.e. dressing percentage), average live and hot weight, net live and net hot price, net live premium and discount per head, and difference in price per hundred weight. Base price variables such as the region's weekly average, formula and grid allowance, base live price, hot yield threshold, and base hot price are also provided. Detailed breakdowns for each adjustment variable are also listed on these reports, where quality is broken down into different grades: prime, choice or higher, select, no roll, hard bone, or dark cutter. Carcass adjustments are based off branded beef programs such as certified Angus beef and certified Hereford beef upper 2/3 choice, as well as a discount related to age of animals over 30 months. Yield grade adjustments are broken down by numerical yield grade 1-5 (1 corresponding to thin layer of fat and 5 corresponding to a carcass covered in extensive fat). Weight adjustments refer to hot carcass weight brackets (below 575lbs, 1050-1099lbs, 1100 lbs and over), and other adjustments refer to premiums for steers, condemned livers, and open abscess livers. We solely focus on quality and yield grade measures as these carcass traits heavily dictate premiums and/or discounts.[33] These two carcass measures should allow us to effectively control for cattle quality in our study which, to the best of our knowledge, have not previously been used in any cattle procurement price study.

[33] At the time of slaughter, each head of cattle receives its own individual quality and yield grades. The lot's total premiums and/or discounts are then based off the cumulative quality performance of all cattle where a single, poor-preforming carcass can negatively influence the entire lot's price.

Our summary statistics also provide insight into cattle prices that has not previously been available. Specifically, transactional data that reports post-harvest prices to account for quality measures are not easily found at the lot level let alone the feedlot level. Our data show the clear difference in prices between cash and AMA markets, as for the period of 2018-2019, cattle lots with an average of 72 head were sold for roughly $122/cwt in the AMA market. However, in the same period, cattle lots with roughly the same number of head were sold in the cash market for about $119/cwt and $117/cwt based on the feedlot dataset and the industry dataset, respectively. This $3-$5/cwt difference produces a large impact on calculated profits, further providing evidence of a quality difference, or at least a quality perception difference, between the two market that may be explained by an information asymmetry and adverse selection problem.

3.2. Regional Feedlot Dataset

Summary statistics for the industry organization proprietary data are found in Table 2. Observations are on a weekly basis by packer, region, gender type, and procurement type; therefore, a feedlot may have multiple observations per week depending on if cattle differ in gender or are purchased through a different procurement method. Although this specific organization reports that AMA sales account for 79-100% of all cattle trades on a weekly basis since January 2019, it does not include cattle sales price for AMA sales. As a result, the regional feedlot dataset is used solely for the cash market analysis. In this dataset, the average cash price received was $122.10 per cwt with a minimum price of $94.00 and a maximum price of $172.00.

Other variables include cattle gender, packer, and sub-region. Cash market sales were 2,089 observations for steers, and 1,703 observations for heifers that were sold in the cash market in this specific region. Cargill purchased 1,618 observations, JBS purchased 846 observations, Tyson purchased 500 observations, National Beef purchased 827 observations, and Other purchased 79 observations from the cash market. 2,666 observations originated from sub-region "A" and the other 1,204 observations originated from sub-region "B".

4. Model

The two datasets are used to estimate Heckman's two-step procedure and the generalized Roy's model. Each model incorporates a hazard rate measure that can capture selection bias created from the adverse selection problem by calculating the correlation between the selection equation and price equation error terms. This measure ultimately examines the adverse selection problem under information asymmetry, where we hypothesize directly reported quality-related measures may help alleviate such issues during price formation.

Fed cattle prices are influenced by supply and demand characteristics as well as cattle quality attributes (Koontz, 2010). Depending on the transaction type, different market signals are used to capture quality effects in pricing. Negotiated cash trades do not have any direct signals for quality, leaving packers to build quality estimates into their bids based off limited information. AMAs have more direct quality signals in the form of reported quality statistics per lot as well as established, long-term relationships between feeders and packers (Peel et. al, 2020).

We recognize some researchers may recommend conducting a propensity score matching study versus sample selection models like we have chosen to compare the two markets. However, propensity score matching's conditional independence assumption limits the procedure from allowing the estimated average treatment effect from being subjected to unobserved selection bias (Makepeace and Peel, 2013). Employing both Heckman's and the generalized Roy's models will allow us to measure selectivity bias and the impact of the selectivity bias on cattle prices. The selectivity bias should be brought forth from feeders' market selection and unobserved characteristics (such as carcass quality).

4.1. Heckman's Adverse Selection Model

The Heckman's two-step procedure tests the adverse selection that is characterized by selectivity bias and estimates the effect feedlots' market selection on observed prices. This selectivity bias can cause observed prices to be lower than prices that are formed through a random selection process. Feeders can sell their cattle in either the cash market or the captive supply market. Given this dichotomous choice and the assumption that feeders select the market they believe will maximize profit for a specific lot of cattle, our analysis begins with the following probit model:

$$z_i^* = \boldsymbol{w}_i'\boldsymbol{\gamma} + \mu_{i,} \tag{1}$$

$$z_i = \begin{cases} 1 \text{ if } z_i^* > 0 \\ 0 \text{ if } z_i^* \leq 0 \end{cases}$$

where z_i^* is a latent variable associated with the choice of market; z_i denotes the feeders binary choice of pricing method ($z_i = 1$ corresponds to cattle sold in the cash market and $z_i = 0$ corresponds to cattle sold in the AMA market); i corresponds to the lot of cattle that is sold; $\boldsymbol{w}_i'\boldsymbol{\gamma}$ is a vector of specific attributes related to factors that may influence a feeder's market selection and their corresponding estimated coefficients; and μ_i is the normally distributed error term $\mu_i \sim N\ iid\ (0, \sigma_\mu^2)$.

The second step of Heckman's procedure involves the estimation of a specified regression equation, where the inverse Mills ratio (IMR) is included to account for incidental truncation caused from the feeders' selection process. The IMR, also known as a hazard rate measure, is calculated from the above predicted variables:

$$\lambda(\boldsymbol{w}_i'\boldsymbol{\gamma}) = \frac{\phi(\boldsymbol{w}_i'\boldsymbol{\gamma})}{\Phi(\boldsymbol{w}_i'\boldsymbol{\gamma})}, \tag{2}$$

where $\phi(\boldsymbol{w}_i'\boldsymbol{\gamma})$ is the probability density function divided by the cumulative distribution function, $\Phi(\boldsymbol{w}_i'\boldsymbol{\gamma})$ (Heckman, 1979). The inclusion of the IMR in the second-step regression equation is necessary as it ensures estimates are consistent, unbiased, and does not suffer from omitted variable bias. The transaction price, y_i^z, is specified as:

$$y_i^z = \boldsymbol{\alpha}'\boldsymbol{X_i} + \rho\sigma\lambda(\boldsymbol{w}_i'\boldsymbol{\gamma}) + \varepsilon_i, \tag{3}$$

where $y_i^{z=1}$ corresponds to cash market, $\boldsymbol{\alpha}'\boldsymbol{X_i}$ are the observable attributes used in a market's price formation and their respective estimated coefficients. If lots of cattle are adversely selected into the cash market, then unobservable factors (such as post-harvest carcass quality characteristics) that decrease (increase) cattle prices increase (decrease) the probability that a lot is sold in this specific market. The non-randomness in choosing a market could lead to the selection bias without incorporating IMR, $\lambda(\boldsymbol{w}_i'\boldsymbol{\gamma})$, in equation (3). The selection bias is captured by the coefficient of IMR where ρ represents the correlation between error terms of selection equation, (1) and price equation, (2) and is calculated as:

$$\rho = \frac{\sigma_{zy_i^z}}{\sigma_z \sigma_{y_i^z}}, \tag{4}$$

where $\sigma_{zy_i^z}$ is the covariance between error terms of selection and price equations, σ_z and $\sigma_{y_i^z}$ are the square root of error variances from selection equation, (1), and price equation, (3), respectively; σ is the variance of the price equations error term, and ε_i is the normally distributed error term $\varepsilon_i \sim N\ iid\ (0, \sigma_{\varepsilon_i}^2)$.

As stated by Wimmer and Chezum (2003), "when observable seller characteristics are correlated with seller incentives to select goods adversely, prices should reflect these differences…first, we isolate the effect seller characteristics have on price through the decision to sell [in a specific market]. Second, we compare the effect seller characteristics have on observed prices in [the different markets]" (pg. 280). These effects are captured in $\rho\sigma$ and are used to interpret the impact of IMR on the variation of cash prices. A large and significant IMR value suggests there is a higher probability that the market is chosen. A negative and significant IMR coefficient indicates unobservable factors that would increase the probability of a cattle lot selling in the cash market is inversely correlated with unobservable factors that would increase price. A positive and significant IMR coefficient corresponds to unobservable characteristics being positively correlated with unobservable factors that would increase price. An insignificant IMR coefficient indicates no selection bias.

The traditional Heckman model includes a single regression equation in the second stage, solely focusing on data points that are above a certain cut off point. Our research problem consists of two price regressions: cash market price and AMA market price equations. The current IMR is based off the probability that the cash market is selected and needs to be re-solved with respect to the probability that a lot of cattle is sent to the AMA market. To estimate the AMA market price equation, equation (4) must be re-estimated with the new calculated probability in terms of selecting the AMA market. We hypothesize that the premiums and/or discounts applied in the AMA market alleviates problems of adverse selection. Specifically, cattlemen are incentivized by premiums to commit their perceived higher quality lots to the captive supply and are punished by discounts for sending cattle that are below average quality. Therefore, we expect that the IMR coefficient becomes statistically either less significant or insignificant indicating less or no adverse selection problem in the captive supply market.

4.2. Generalized Roy's Model

Alongside Heckman's model, we also implement the generalized Roy's model to similarly test for the adverse selection issue where we believe Roy's methodology may better characterize the self-selection caused by feeders and motivated by comparative advantages versus the systematic truncation that defines Heckman's procedure. A limitation to Heckman's approach is the truncation that causes one market to be completely removed during estimation, where implementing the generalized Roy's model will allow us to evaluate if selection biased results are consistent between estimation methods. The generalized Roy's model begins the same as Heckman's where the IMR is calculated from the selection equation, (1). Once this first step is completed, the resulting price equations, $y_i^{z=1}$ and $y_i^{z=0}$, are estimated simultaneously for cash and captive supply markets. Although only one price may be observed for each sale, it is important to remember the two price equations are connected because the cash price serves as the base price for the AMA price. The interpretation of the coefficient of IMR is like the Heckman's case. A positive and significant ρ signifies positive selection where cattle lots are positively selected into a market and are above the average of that market's quality distribution. Negative selection is characterized by cattle lots selected for a market having below the average quality distribution of overall markets. Negative selection would ultimately suggest lower quality cattle are sent to the cash market in attempt to try and garner higher prices without providing full quality information (Eran, 2004).

4.3. Effect of Adverse Selection Problem

We estimate the extent of the adverse selection effect on cattle price using Lee's (1995) opportunity cost approach regarding unchosen alternatives in sample selection models. Unlike Lee's (1995) paper, we continue with the probit selection model instead of switching to a logit for two reasons: to stay consistent with our two previous adverse selection models, as well as to properly estimate a hazard rate variable (Bushway, Johnson, and Slocum, 2007). To estimate the magnitude that adverse selection has on prices, we first calculate the expected price a random lot of cattle would receive if sold to the cash market, $E[P_{cash}|\alpha, X]$. To calculate this measure, the cash price regression results are used to calculate a predicted cash price for all lots of cattle in our dataset (i.e. both AMA and cash lots); the average of these new predicted prices is then taken to establish the expected price a randomly selected lot would receive in the cash market. We follow a similar procedure to estimate the expected price a lot of cattle would receive given the lot was sold in the cash market $E[P_{cash}|\alpha, X, Z = 1]$; to do this, we once again use the cash price regression results to calculate a predicted cash price for any lot that was sold in the cash market (i.e. exclude the AMA lots from this estimation) before averaging the predicted prices to estimate the expected cash price of a lot that was selected into the cash market. Opportunity costs is then calculated by taking the difference between the expected price of a randomly selected cash lot and the expected price of a lot that was sold through the cash market:

$$E[P_{cash}|\alpha, X] \text{ - } E[P_{cash}|\alpha, X, Z = 1]. \quad (6)$$

where the calculated difference should represent the impact of the unmeasured quality difference on cattle price.

5. Results

All models are estimated using SAS QLIM procedure, and corrected standard errors are also automatically calculated under the procedure (SAS Institute Inc., 2014). To test our hypothesis that the adverse selection problem is present in the cash market but reduced or nonexistent in the AMA market, we first analyze the cash market using both the industry organization data and the single feedlot data. We then test for the adverse selection issue in the AMA market using the single feedlot data. As a final test to measure the impact of the adverse selection problem, we compare the expected price difference of a randomly selected lot sold in the cash market to a lot that was in fact sold in the cash market, where we cannot conclude an absolute price difference between the two markets but rather conclude cattle sold in the cash market are of lower quality.

The industry data is excluded from the last two tasks as AMA prices are not available from the industry data.

Before estimating the price equation to test for the hazard rate coefficient for signs of adverse selection, we first estimate the selection equation for both the Heckman and the generalized Roy models. Table 3 reports parameters of the selection equation estimated using the single feedlot data. Variables considered in this equation include Head Count (the number of cattle for each lot), ADG (the average daily gain from each lot), Liberal (a dummy variable with 1 when the cattle lot is sent to a packer plant located in Liberal, KS and 0 otherwise), Steer (a dummy variable with 1 when the cattle lot is for steers and 0 otherwise), Weekly Avg. Price (weekly average cattle price in the region where the feedlot is located), Quarter 1, Quarter 2, and Quarter 4 (quarterly dummy variables to represent the specific calendar quarter a given lot was sold; Quarter 3 serves as the reference). Estimating the selection model allows one to determine if there exists a systematic difference in the decision of marketing cattle between cash market versus non-cash market options. It is important to consider systematic differences between the two market options as it may detect potential selection bias (Cuddeback, et al., 2004). Both Heckman and generalized Roy models show similar estimates and standard errors, presenting only slight differences. The coefficient for head count is negative and significant at the 1% level for both models, suggesting lots with a greater number of head of cattle are less likely to be selected into the cash market (selection = 1) than to be sent to the AMA market (selection = 0). The result is consistent with feeders strategically culling poorer quality cattle from their initial lot and selling in the cash market to prevent from incurring discounts in the AMA market. The coefficient for average daily gain (ADG) is also negative and significant at the 1% level, suggesting lots of cattle that gain more efficiently are likely to be sent to the AMA market. This indicates that fleshier and easier gaining cattle are better suited to be priced in a premium/discount market, whereas poorer gaining or lighter weight cattle are more likely sold in the cash market. The coefficient for Liberal is also negative and significant at the 1% level, suggesting that lots of cattle sold to the AMA market are more likely to be sent to a packer in Liberal, KS whereas a cash lot is more likely to be sent to a packer elsewhere (i.e. Dodge City, KS, Holcomb, KS, or unknown location). The coefficient of Steer is positive and significant at the 1% level, which indicates that steers are more likely to be sent to the cash market compared to heifers or mixed lots of cattle. Estimate of Weekly Avg. Price is negative but insignificant, suggesting the region's weekly price does not significantly affect feedlot's decision regarding market selection. Coefficients for Quarter 1 and 2 are positive but insignificant. However, Quarter 4 is positive and significant at the 5% level, compared to Quarter 3, which suggests that cattle are more likely to be sent to the cash market over the AMA market in Quarter 4 at least for this single feedlot's behavior.

5.1. Adverse Selection in the Cash Market

Table 4 includes estimates from price equations of Heckman and generalized Roy models that are estimated with the single feedlot data. The existence of the adverse selection is examined by testing the coefficient of IMR, λ, which corrects for selection bias by controlling factors that discriminate between selection of cash market and non-cash market sales (Cuddeback, et al., 2004). In our case, we test to see if carcass quality characteristics and the disparate knowledge of such cattle characteristics between buyers and sellers may contribute to the selectivity and consequently the adverse selection problem. Under Heckman's model, the estimate of IMR is -26.362 and is significant at the 5% level. The negative coefficient of IMR supports our hypothesis of the adverse selection concern: unobservable factors that increase the probability that a lot of cattle is sold in the cash market negatively correlates with unobserved factors that increase cash prices (Wimmer and Chezum, 2006). The IMR coefficient from Roy model is also negative and significant at -21.548 (Roy's model does not provide a value for lambda, but it can be calculated by multiplying rho, -0.756, and sigma, 28.491) where both rho and sigma values are significant at the 1% level (Certo, et al., 2016). This result of negative and significant estimates of IMR is consistent with the presence of adverse selection (Wimmer and Chezum, 2006). Specifically, a nonrandom sample combined with the lack of information regarding cattle quality leads to omitted variable bias that influences both the probability of a lot entering the cash market and the resulting price (Certo, et al., 2016). Omitting carcass quality characteristics in the cash market transactions leads packers to establish prices off limited information, which in turns negatively affects cash prices. Alongside unknown quality differences, cash prices may also be negatively impacted by other factors such as packer risk aversion, however, such an effect should only be measured if quality differences are also considered to avoid biased conclusions.

Table 4 also reports estimates of Intercept, Head Count, Average Pay Weight, Steer, Liberal, and Quarter one, two, and four. Head Count coefficient is positive and significant at the 5% level, indicating that lots with a greater number of cattle receive higher prices. The result makes intuitive sense, as single headed lots have typically lower cattle quality. Liberal is positive and significant at the 10% level, suggesting cattle that are sent to packers in this location receive higher prices compared to other packer locations (i.e Dodge City, KS and Holcomb, KS). Average Pay Weight coefficient is positive and significant at the 1% level, where heavier weight lots receive greater prices than lighter weight (which may be a result of light muscled or sickly livestock) lots of cattle. The coefficient value for Quarter one and Quarter four are insignificant, while Quarter two is positive and significant at the 10% level.

Testing for the presence of the adverse selection problem in the cash market is extended from the feedlot level to the regional level. Our study estimates the Heckman model with our proprietary industry dataset from an unnamed region; we are unable to estimate the generalized Roy model with this dataset as all the AMA transactions have missing price information. Table 5 reports results from both selection and cash price equations. From the selection equation, the parameter estimate of Steer is negative but insignificant where a lot's gender does not play a significant role in market selection. Coefficient of Head Count is positive but insignificant in market selection. Dummy variables representing sales years, 2014, 2016, and 2018, are negative and significant, when compared to the reference year 2017. Packers included in the regional analysis include Cargill, Tyson, and JBS, where National Beef (and Other) is dropped to serve as the reference class. Only Cargill is negative and significant at the 1% level.

The IMR coefficient from the cash price equation is -40.624 when the regional data are used. This result is like the findings from the single feedlot data reported in Table 5 and indicates the presence of adverse selection. The importance of performing this procedure and ultimately obtaining a similar conclusion as the single feedlot is that it allows us to extend our findings from a single firm to the regional level.

Other variables considered in the regional data's cash price equation are Steer and dummy variables representing sales year and quarter, and cattle buyers. Steer is positive and significant at the 10% level, suggesting steers receive higher cash prices compared to sale observations that are heifers or Holsteins (the dairy breed was included as a gender category in the regional data set; there was no additional information regarding gender of the Holstein cattle). The coefficients for dummy variables, 2013, 2014, and 2015, are all positive and significant (compared to the reference year 2017), while coefficient of 2018 and 2019 are negative and significant. Quarter one, two, and four are all positive and significant at the 1% level, suggesting higher prices are received during these periods compared to quarter three. Estimates of dummy variables representing packers suggest that Tyson pays higher cash prices than National Beef (and Other), while JBS pays lower cash prices.

5.2. Adverse Selection in the AMA Market

The single feedlot dataset is also used to examine if adverse selection is also a concern when captive supply procurement methods are used. Table 6 reports coefficient values for the AMA price regression, where the same parameters as the cash price equations were used in the AMA prices along with quality-related, post-harvest variables. We hypothesize that the post-harvest quality attributes used in premiums and discount pricings minimize any potential information asymmetries regarding cattle quality. Like the previous analyses, IMR related variables are interpreted as measures of adverse selection concerns. Under Heckman's model, the AMA market produces -0.262 and is insignificant. Under Roy's model, the rho variable associated to IMR is 0.055 and is also insignificant. These results are in line with Roy's theory of feeders self-selecting which lots to send to each market based upon their information advantage in terms of having a more thorough knowledge of their cattle's quality.

Estimates of Head Count, Liberal, and quarter dummy are all positive but insignificant, suggesting these factors do not play a significant role in AMA price formation. Average pay weight coefficient is negative and significant at the 1% level, suggesting heavier weight lots do not necessarily receive higher prices in the AMA market. Steer coefficient is positive and significant at the 5% level, being consistent with lots receiving a premium for all-steer lots. The Base Live Price is the average price used to apply premiums and/or discounts to, and its coefficient is positive and significant at the 1% level which suggests that a higher base price helps generate a higher AMA price. Negotiated Grid corresponds to if an AMA lot was marketed through the negotiated gird (versus the USPB grid or formula marketing). Estimate of Negotiated Grid is negative and significant at the 1% level, suggesting this specific feedlot received higher prices through this procurement method compared to USPB grid and formula-based pricing. Quality Adjustments details the potential premiums or discounts a lot may receive given the average and range of carcass quality grades received by individual cattle within a lot; the coefficient for carcass quality is positive and significant at the 1% level, where better grading lots (i.e.cattle average Choice or higher) receive greater prices. Yield Adjustments correspond to a lot of cattle's average and range of yield grades based off of fat depth, where the negative and significant coefficient indicates that higher yielding cattle (i.e. cattle with excessive finish compared to frame size and muscle mass) receive lower AMA prices.

5.3. Effect of Adverse Selection Problem in the Cash Market

Finally, to estimate the impact that adverse selection may have on prices we follow Lee's opportunity costs methodology to compare expected prices of randomly selected lots versus lots that were sold specifically in the cash market. Results are reported in Table 7. Lee (1995) shows that price regression estimates can be used to calculate expected values and be used to estimate opportunity costs based off the probability that a specific choice was not chosen.[34] Performing this analysis calculates the differences in expected market prices per hundred weight and empirically demonstrates cattle sold within the cash market are of lower quality. The expected price difference per hundred weight differs from $3 to $60 depending on the lot size being analyzed. However, it is important to consider other lot information regarding these price differences to gain better understanding of the drastic price differences. For example, the $60 difference found for the category of 11 to 20 head-lot size is not an accurate representation of the cattle market. Multiple observations create the expected price of a randomly selected lot, however, only one cash lot of similar size was found in our dataset to be used for comparison. The respective lot had an average weight of 456 pounds and was only on feed for 51 days, which is not typical. Although this example does not provide a realistic price difference that may be used as a general conclusion, it still provides evidence of a feedlot strategically culling a low

[34] Corrected prices refer to the regression results from the Type 2 and 5 Tobit models that used corrected standard errors in estimation. This does not affect estimates; do you still need to say, corrected price or just say as estimates from cash price equation?

quality lot to the cash market early in the feeding phase to avoid losing potential profit brought forth by discounts or slow growth.

Analysis may also be expanded to calculate the expected profit change. To do this, we multiply the expected price for each lot by the lot's average pay weight (weight was divided by 100 to be consistent with price measured per hundred weight) and by the lot's total number of head. Results are also reported in Table 7. As lot sizes increase, so do the expected profits. However, profits for lot sizes of 50 head or more may have been exaggerated due to high per hundred weight prices; if the sales had occurred around 2014 the expected prices and profits would have been more believable as the period following the high cattle prices in 2013 mostly due to the drought. Given the sales occurred at the end of 2018 through July 2019, therefore one needs to interpret expected profits with caution. We attribute this inaccurate price estimation to the numerous single-head sales found in our dataset that may have forced our models to overcompensate for price differences dependent on head count.

6. Conclusion

Fed cattle prices have traditionally been analyzed with respect to volume of trade or from an oligopsony point of view. Although the discrepancy in quality between markets has been discussed in previous papers, its impact on prices has been rarely studied up to this point. We hypothesized that an information asymmetry problem may exist between feeders and packers, and consequently lead to the adverse selection problem in the cash market, which could potentially lower all cattle prices. To test our hypothesis, we applied Type 2 (Heckman) and Type 5 (Roy) Tobit models to two rare fed cattle datasets. Our results ultimately suggest there exists the adverse selection issue in the cash market, which is characterized by the negative selection. The results also suggest that the negative selection due to unobservable attributes, such as carcass quality that is not known until after the completion of the sale, negatively affect cash sale prices. Our results support the overall belief that packers establish cash sale prices off the assumption that cattle of lower and/or unknown quality are marketed through cash sales, which causes lower cash prices than what is observed. Following Lee's opportunity cost methodology (Lee, 1995), we further examine the impact the adverse selection problem has on cash prices by comparing the expected cash price from randomly selected lots of cattle and the expected cash price from cattle lots that were sold in the cash market. Although we are unable to give a definitive price difference of the adverse selection impact, we conclude there is a quality difference between markets where lower quality cattle are sent to the cash market and receive lower prices. Detecting the adverse selection problem and proving the difference in quality between markets should leave one to interpret past AMA prices studies regarding market power with caution (Ward, Koontz, and Schroeder, 1998). Specifically, studies that report the impact market power and the percentage of AMA sales has on cattle prices may change when quality differences are also considered for estimation.

Without knowing the prices associated to AMA sales in our industry organization data, our AMA analysis is restricted to the prices reported by a single feedlot. This consequently limits our findings for AMA sales to a single feedlot versus a larger population of feeders. Therefore, it is recommended that future studies include multiple feedlots and/or regions as different regions offer different AMA methods as well as have drastically different trade ratios between cash and AMA sales. Given the significance of our findings, we suggest future studies on cattle procurement prices consider characteristics of cattle quality more carefully rather than solely focusing on a packer's market power or the number of transactions that occur in each market.

Currently, implementing price reporting and/or a minimum number of transactions in the cash market is a major topic of discussion among researchers, feeders, and packers, as well as policymakers for a better price discovery. One way to improve the price discovery in the cattle procurement market might be to improve the flow of market information on cattle quality using well-developed quality certification programs. The Oklahoma Quality Beef Assurance (OQBA) is one example of a current certification program which applies to producers who practice productive and ethical management techniques to enhance their herd's performance and profitability. Expanding a similar program to the feeder-packer level may help alleviate information asymmetries and consequently help establish more accurate prices based off cattle quality regardless of how the cattle are marketed.

Table 1. Summary Statistics of Variables from the Single Feedlot Data for Cash Market Sales

	Mean (Standard Deviation)	Minimum Maximum	Lot Observations	Mean (Standard Deviation)	Minimum Maximum	Lot Observations
Number of Head per Lot	8 head (19.97)	1 head 125 head	163	71 head (38.13)	6 head 212 head	236
Lot Price (cwt)	$66.55 ($37.128)	$10.41 $136.82	163	$122.45 (7.16)	$99.32 $134.70	236
Pay Weight (lbs)	1,052 (293.62)	510 1,576	163	1,321 (122.74)	1,061 1,625	236
Average Daily Gain (lbs)	2.03 (1.88)	-1.64 3.93	163	3.08 (0.54)	0.08 4.56	236
Gender:						
Heifer	$63.86 (35.82)	$10.41 $126.00	57	$123.22 (7.43)	$99.32 $133.73	116
Steer	$68.93 (36.86)	$15.40 $136.82	91	$121.44 (6.70)	$107.04 $134.70	110
Mixed	$62.29 (44.71)	$11.96 $121.17	15	$124.67 (7.97)	$108.82 $131.04	10
Buyer:						
National Beef	$119.36 (5.44)	$110.75 $124.43	15	$122.50 (7.14)	$99.32 $134.70	235
Tyson	$129.08 (5.21)	$125.50 $136.82	4	--	--	0
Cargill	$111.33 (0.84)	$110.73 $111.92	2	$111.78 (0.00)	$111.78 $111.78	1
Other	$58.58 (32.87)	$10.41 $132.41	142	--	--	0
Plant Location:						
Liberal, KS	$103.10 (30.48)	$30.90 $124.36	12	$121.95 (7.34)	$107.04 $133.73	178
Dodge City, KS	$118.73 (6.48)	$110.73 $124.43	7	$124.00 (6.38)	$99.32 $134.70	58
Holcomb, KS	$129.08 (5.21)	$125.50 $136.82	4	--	--	0
Unknown	$59.10 (33.30)	$10.41 $132.41	140	--	--	0
AMA Method:						
Negotiated Grid	--	--	--	$120.95 (7.70)	$107.04 $133.65	74
USPB Base Grid	--	--	--	$123.23 (6.82)	$99.32 $134.70	161
Formula	--	--	--	$111.78 (0.00)	$111.78 $111.78	1

Table 2. Summary Statistics for Proprietary Industry Data for Cash Market Sales

	Mean (Standard Deviation)	N = 3,870 obs. Minimum Maximum	Lot Observations
Avg. Lot Price (cwt)	$122.10 (12.04)	$94.00 $172.00	--
Average Head per Transaction	299 (297.98)	5 2,781	--
2013 Avg. Price	$125.87 (3.68)	$119.00 $134.00	526
2014 Avg. Price	$149.55 (8.19)	$139.00 $172.00	239
2015 Avg. Price	$143.15 (13.18)	$135.00 $160.00	122
2016 Avg. Price	$119.03 (11.58)	$97.00 $140.00	732
2017 Avg. Price	$122.05 (8.85)	$105.00 $145.00	952
2018 Avg. Price	$117.13 (6.59)	$99.00 $130.00	799
2019 Avg. Price	$119.97 (6.80)	$97.00 $128.00	500
Gender:			
Heifer	$122.38 (11.78)	$97.00 $172.00	1,703
Steer	$123.72 (11.85)	$98.00 $172.00	2,089
Holstein	$106.33 (11.21)	$94.00 $132.00	8
Buyer:			
JBS	$123.18 (13.52)	$98.00 $172.00	846
Tyson	$123.17 (9.92)	$104.00 $164.00	500
Cargill	$122.17 (11.24)	$97.00 $166.00	1,618
National Beef	$124.91 (11.88)	$98.00 $170.00	827
Other	$120.79 (14.01)	$94.00 $162.00	79
Region:			
Region A	$123.07 (11.90)	$94.00 $172.00	2,666
Region B	$123.10 (11.77)	$97.00 $172.00	1,204

Table 3. Estimates of Heckman's and Roy's Selection Equations with Single Feedlot Data

Variable	Heckman	Roy
Intercept	5.398	6.416
	(3.369)	(3.327)*
Head Count	-0.307	-0.329
	(0.041)***	(0.043)***
ADG	-0.665	-0.667
	(0.214)***	(0.203)***
Liberal	-1.710	-1.653
	(0.267)***	(0.254)***
Steer	0.770	0.716
	(0.254)***	(0.246)***
Weekly Avg. Price	-0.022	-0.030
	(0.027)	(0.027)
Quarter 1[a]	0.327	0.564
	(0.425)	(0.427)
Quarter 2[a]	0.461	0.393
	(0.398)	(0.398)
Quarter 4[a]	0.961	0.996
	(0.484)**	(0.481)**
Log Likelihood	-74.624	-1327
AIC	167.248	2719

Note: *, **, *** correspond to the 10%, 5%, and 1% significance levels, respectively.
[a] Quarter 3 was dropped as the reference period.

Table 4. Estimates of Heckman's and Roy's Price Equations for Cash Market Sales with Single Feedlot Data

Variable	Heckman	Roy
IMR Related Variables		
Cash Lambda	-26.362 (11.989)**	--
Cash Sigma	--	28.491 (1.801)***
Cash Rho	--	-0.756 (0.143)***
Other Variables		
Intercept	8.364 (8.717)	7.097 (8.600)
Head Count	7.899 (2.609)***	6.587 (1.498)***
Liberal	20.737 (12.244)*	17.383 (9.182)*
Average Pay Weight (cwt)	6.961 (1.035)***	7.061 (1.020)***
Steer	-9.044 (4.886)*	-9.272 (4.712)**
Quarter 1[a]	2.938 (7.191)	4.516 (7.096)
Quarter 2[a]	13.788 (7.473)*	13.519 (7.312)*
Quarter 4[a]	-4.089 (7.682)	-3.335 (7.430)
AIC	1089	2719

Note: *, **, *** correspond to the 10%, 5%, and 1% significance levels.
Due to the different commands used within the SAS program to solve the different Tobit models, the Type 2 model reported the IMR values as the parameter λ, whereas the Type 5 model reported the IMR values as σ and ρ.
[a] Quarter 3 was dropped as the reference period.

Table 5. Estimates of Heckman's Model with Industry Organization Data

Variable	Heckman
Selection Equation	
Intercept	3.107 (0.283)***
Steer	-0.097 (0.130)
Head Count	0.007 (0.234)
2013[a]	-0.103 (0.310)
2014[a]	-0.595 (0.300)**
2015[a]	-0.403 (0.412)
2016[a]	-0.636 (0.229)***
2018[a]	-0.482 (0.236)**
2019[a]	-0.362 (0.249)
Cargill[b]	-0.513 (0.193)***
Tyson[b]	0.176 (0.359)
JBS[b]	-0.117 (0.237)
Cash Price Equation	
Lambda	-40.624 (20.475)**
Intercept	115.768 (0.586)***
Steer	0.084 (0.364)*
2013[a]	4.015 (0.632)***
2014[a]	27.090 (0.991)***
2015[a]	24.986 (1.122)***
2016[a]	-0.414 (0.887)
2018[a]	-3.544 (0.688)***
2019[a]	-4.886 (0.610)***
Quarter 1[c]	11.304 (0.321)***
Quarter 2[c]	10.589 (0.313)***

Quarter 4[c]	2.429 (0.292)***
Cargill[b]	0.160 (0.737)
Tyson[b]	1.070 (0.634)*
JBS[b]	-1.060 (0.536)**
AIC	15147

Note: *, **, *** correspond to the 10%, 5%, and 1% significance levels.
Due to the different commands used within the SAS program to solve the different Tobit models, the Type 2 model reported the IMR values as the parameter λ, whereas the Type 5 model reported the IMR values as σ and ρ.
[a] 2017 was dropped as the reference period.
[b] National Beef and other packers were dropped as the reference group.
[c] Quarter 3 was dropped as the reference period.

Table 6. Estimates of Heckman's and Roy's Price Equations for AMA Market Sales with Single Feedlot Data

Variable	Heckman	Roy
IMR Related Variables		
Captive Supply Lambda	-0.383 (0.516)	-
Captive Supply Sigma	--	1.922 (0.089)***
Captive Supply Rho	--	-0.130 (0.194)
Other Variables		
Intercept	2.583 (4.198)	3.365 (3.845)
Head Count	0.129 (0.144)	0.038 (0.040)
Liberal	0.112 (0.819)	-0.359 (0.350)
Average Pay Weight (cwt)	-1.127 (0.202)***	-1.203 (0.174)***
Steer	1.438 (0.566)**	1.696 (0.412)***
Base Live Price	1.102 (0.032)***	1.102 (0.031)***
Negotiated Grid	-0.819 (0.289)***	-0.827 (0.289)***
Quality Adjustment	0.884 (0.090)***	0.882 (0.090)***
Yield Adjustment	-0.013 (0.030)	-0.013 (0.30)
Quarter 1[a]	0.657 (0.651)	0.564 (0.427)
Quarter 2[a]	0.420 (0.541)	0.393 (0.398)
Quarter 4[a]	0.758 (0.853)	0.996 (0.481)**
AIC	331.781	2719

Note: *, **, *** correspond to the 10%, 5%, and 1% significance levels.

Table 7. Impact of Adverse Selection on Cattle Procurement Market Prices

	Heckman		Roy	
	Randomly[a] Selected Lot	Lot Sold in Cash Market	Randomly Selected Lot	Lot Sold in Cash Market
Lots with 1 to 3 head				
Expected cash price (cwt)	$36.01 (19.54)	$36.01 (19.54)	$40.53 (19.35)	$40.53 (19.35)
Expected total lot price	$340.63 (327.92)	$340.63 (327.92)	$377.74 (334.18)	$377.74 (334.18)
Average weight	766 lbs	766 lbs	766 lbs	766 lbs
Days on feed	135 days	135 days	135 days	135 days
Lots with 4 to 10 head				
Expected cash price (cwt)	$56.25 (47.17)	$30.33 (20.50)	$59.33 (46.35)	$33.80 (19.69)
Expected total lot price	$4,266.77 (5,003.64)	$1,429.34 (1,329.31)	$4,429.87 (5,047.31)	$1,568.33 (1,349.16)
Average weight	969 lbs	687 lbs	969 lbs	687 lbs
Average days on feed	163 days	139 days	163 days	139 days
Lots with 11 to 20 head				
Expected cash price (cwt)	$87.20 (27.05)	$29.32 (0.00)	$89.18 (25.88)	$32.81 (0.00)
Expected total lot price	$18,016.25 (8,581.99)	$2,139.23 (0.00)	$18,341.92 (8,510.77)	$2,393.90 (0.00)
Average weight	1,202 lbs	456 lbs	1,202 lbs	456 lbs
Average days on feed	197 days	51 days	197 days	51 days
Lots with 21 to 30 head				
Expected cash price (cwt)	$110.59 (10.36)	$116.60 (2.20)	$109.88 (9.20)	$114.96 (1.54)
Expected total lot price	$37,175.52 (6,865.69)	$38,080.83 (3,743.59)	$36,953.00 (6,741.12)	$37,562.92 (3,923.97)
Average weight	1,264 lbs	1,289 lbs	1,264 lbs	1,289 lbs
Average days on feed	240 days	189 days	240 days	189 days
Lots with 31 to 40 head				
Expected cash price (cwt)	$126.10 (11.54)	$111.12 (17.97)	$123.32 (10.23)	$111.15 (15.04)
Expected total lot price	$58,614.65 (9,661.96)	$54,841.66 (15,337.00)	$57,304.71 (9,093.51)	$54,771.54 (13,907.39)
Average weight	1,288 lbs	1,397 lbs	1,288 lbs	1,397 lbs
Average days on feed	233 days	206 days	233 days	206 days
Lots with 41 to 50 head				
Expected cash price (cwt)	$127.24 (16.41)	$95.84 (14.81)	$124.11 (14.90)	$96.27 (15.33)
Expected total lot price	$75,320.91 (15,657.71)	$51,588.73 (15,261.75)	$73,460.09 (14,901.69)	$51,836.44 (15,568.95)
Average weight	1,310 lbs	1,230 lbs	1,310 lbs	1,230 lbs
Average days on feed	226 days	276 days	226 days	276 days
Lots with 51 to 60 head				
Expected cash price (cwt)	$135.08 (12.17)	$131.66 (15.46)	$130.93 (10.90)	$128.35 (14.20)
Expected total lot price	$99,948.63	$103,471.19	$96,910.87	$100,875.51

	(15,349.13)	(19,945.93)	(14,681.14)	(19,018.83)
Average weight	1,342 lbs	1,411 lbs	1,342 lbs	1,411 lbs
Average days on feed	193 days	159 days	193 days	159 days
Lots with 61 to 70 head				
Expected cash price (cwt)	$140.67 (15.01)	$137.18 (15.16)	$135.43 (13.23)	$133.16 (12.29)
Expected total lot price	$118,974.80 (20,0016.41)	$116,404.69 (7,770.29)	$114,582.61 (18,870.41)	$113,050.65 (5,527.26)
Average weight	1,294 lbs	1,283 lbs	1,294 lbs	1,283 lbs
Average days on feed	215 days	184 days	215 days	184 days
Lots with 71 to 80 head				
Expected cash price (cwt)	$149.28 (13.97)	--	$142.78 (12.38)	--
Expected total lot price	$151,678.54 (24,530.56)	--	$145,070.83 (22,902.60)	--
Average weight	1,344 lbs	--	1,344 lbs	--
Average days on feed	221 days	--	221 days	--
Lots with 81 to 90 head				
Expected cash price (cwt)	$157.28 (11.63)	--	$149.30 (9.80)	--
Expected total lot price	$173,650.98 (22,197.63)	--	$164,903.95 (20,776.51)	--
Average weight	1,291 lbs	--	1,291 lbs	--
Average days on feed	227 days	--	227 days	--
Lots with 91 to 100 head				
Expected cash price (cwt)	$169.92 (13.30)	--	$159.49 (12.52)	--
Expected total lot price	$222,281.28 (36,296.85)	--	$208,664.69 (34,232.04)	--
Average weight	1,370 lbs	--	1,370 lbs	--
Average days on feed	200 days	--	200 days	--
Lots with 101 to 120 head				
Expected cash price (cwt)	$178.32 (16.08)	--	$166.79 (14.43)	--
Expected total lot price	$267,170.97 (47,109.42)	--	$249,918.32 (43,751.54)	--
Average weight	1,377 lbs	--	1,377 lbs	--
Average days on feed	427 days	--	427 days	--
Lots with 121 to 150 head				
Expected cash price (cwt)	$188.15 (12.19)	$176.14 (6.51)	$175.12 (10.11)	$165.88 (7.32)
Expected total lot price	$334,300.62 (38,208.55)	$332,020.17 (16,821.24)	$312,197.89 (35,366.74)	$312,704.75 (18,075.79)
Average weight	1,389 lbs	1,520 lbs	1,389 lbs	1,520 lbs
Average days on feed	190 days	176 days	190 days	176 days
Lots with 180 head or more				
Expected cash price (cwt)	$238.71 (9.60)	--	$216.63 (9.80)	--
Expected total lot price	$625,594.80 (113,343.25)	--	$568,094.50 (105,800.61)	--
Average weight	1,331 lbs	--	1,331 lbs.	--

Average days of feed	212	--	212	--

[a]Randomly Selected Lot calculation includes all lots, i.e. all AMA and cash transaction observations have a new predicted price estimated based off of the corrected cash price regression results from the Heckman and Roy models.
[b]Expected total lot prices calculated by multiplying the lot's expected price (for given market) by the lot's pay weight (pay weight is divided by one hundred to match expected price per cwt) and by lot's total head count.

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